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Digital Maintenance in the Digital Twin Era

Proceedings of the 64th ESReDA Seminar & Doctoral Workshop

Deusto

Engineering

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Abstract

These proceedings are the outcome of the 64th ESReDA seminar and Doctoral Workshop “Digital Maintenance in the Digital Twin Era” that took place at the University of Deusto in Bilbao, on 29-31 May in 2024. The 64th ESReDA Seminar covered a wide array of topics centered around the integration of Digital Twin technologies in maintenance and asset management across multiple sectors, including civil engineering, aerospace, railway, oil & gas, and smart buildings. Key topics included applications of digital twins in lifecycle management, the use of artificial intelligence and predictive maintenance strategies —such as machine learning, edge-based AI, and data-driven analytics— human factors and human-machine interfaces in safety-critical systems, and addressing skill gaps for the digital era. The seminar also addressed cybersecurity challenges in remote maintenance infrastructures, digital skills development and training using AR/VR, sustainable maintenance practices and environmental impact, resilience planning and performance management for critical infrastructures, as well as industrial servitization and business transformation through digitalization. The seminar plus doctoral workshop attracted a good mix of academic and industrial participants from many European and overseas countries, and provided a platform for stimulating discussion and debate on resilience techniques and their applications in practice.

Foreword

European Safety, Reliability & Data Association (ESReDA)

European Safety, Reliability & Data Association (ESReDA) is a European Association established in 1992 to promote research, application and training in Reliability, Availability, Maintainability and Safety (RAMS). The Association provides a forum for the exchange of information, data and current research in Safety and Reliability.

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Introduction

Focus, Locus, Scope and Structure of the Book

We would like to extend our heartfelt thanks to all participants of the 64th ESReDA Seminar, “Digital Maintenance in the Digital Twin Era”, held at the University of Deusto in Bilbao, Spain, on 30-31 May 2024. We hope the seminar served as a fruitful platform for insightful dialogue, knowledge exchange, and new collaborations among professionals working at the intersection of digitalization, engineering, and maintenance.

The seminar proceedings feature a rich collection of contributions from both academic and industrial participants, addressing a wide spectrum of themes. Among the key topics explored were cybersecurity issues in remote maintenance environments, the evolution of industrial servitization and digital business models, and sustainable maintenance practices with a focus on environmental impact. Other areas of interest included human factors and human-machine interaction in safety-critical settings, digital skills development through tools like AR/VR, and the identification of skill requirements for the digital age. Additionally, several presentations examined the role of artificial intelligence —including machine learning, edge computing, and data-driven methods —in predictive maintenance, as well as the practical implementation of digital twins for lifecycle and asset management. Critical infrastructure resilience and performance optimization were also prominent areas of discussion throughout the seminar.

Participants represented a diverse community from numerous European and international institutions. Contributions came from universities and organizations across Europe and beyond, highlighting the global interest and collaborative efforts in advancing digital maintenance practices. Industrial stakeholders included representatives from various research and innovation-driven entities, further emphasizing the practical applications and industry relevance of the discussed topics.

We would like to thank the Technical Programme Committee for their dedicated work in reviewing and curating the contributions, as well as all authors for their valuable presentations and commitment throughout the preparation and publication process. We look forward to seeing this momentum continue and to welcoming you to future ESReDA events.

Aitor Goti, Antonio Guillén, Juan Chiachío, Manuel Chiachío

Chairman of the Seminar

Dr. Aitor Goti, Associate Professor in Department of Mechanical, Design and Industrial Management Department University of Deusto.

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Self-powered sensors for IoT and Industry 4.0 applications

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Abstract

This paper analyses the interest of residual energy for use in measurement systems located in remote locations where the power supply is not easily accessible. It can also be very interesting for maintenance 4.0 in installations or machines that present the same problem of powering measurement systems and monitoring of certain variables. Different ways of capturing residual energy from the environment are analysed, as well as their use to power ultra-low consumption electronic systems. A possible application oriented to maintenance 4.0 is analysed.

1. Introduction

The development of "Energy Harvesting" techniques makes it possible to create an autonomous system independent of the electrical grid and disposable batteries (Meng-Lin Ku, W. *et al.*), by obtaining energy from environmental sources such as solar, thermal, electromagnetic, and mechanical. Energies that are available practically anywhere, can be natural or artificial and can be considered unlimited (Ming-Yan Fan, P. *et al.*). Table I shows the types of energy discussed, with the range of power that can be captured with each of them.

Table 1
Power of environmental energy sources

Energy Source	Power
Light	10.0 μW/cm^2 ~ 100 mW/cm^2
Thermal	10.0 μW/cm^2 ~ 1 mW/cm^2
RF	0.2 nW/cm^2 ~ 5 μW/cm^2
Mechanical	0.4 μW ~ 100 mW

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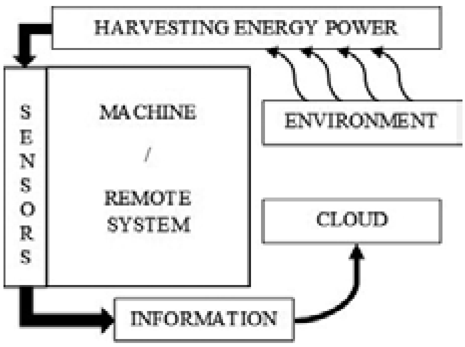
One of the main applications of this type of systems is the power supply of wireless sensors (Meng-Lin Ku, W. *et al.*), which are of great interest, among other applications, for the measurement of environmental variables, both in applications in remote locations (land, sea, etc.), as well as in industrial environments, due to lack of accessibility or high hazard index. It may also be of interest in other applications for the measurement of different physical variables can provide machine information that through a self-powered system to facilitate diagnosis and prognosis tasks for maintenance 4.0. Figure 1 shows the block diagram of such a system, self-powered by residual energy, which can measure variables and send the information.

Figure 1

General block diagram of a self-powered measuring system



An autonomous system of this type has a system for capturing, conditioning, and storing the energy captured from the environment and the electronic system itself, which measures certain variables, processes this information, and transmits it through the corresponding electronic system (Ahmed Khan, M. *et al.*). The first part is responsible for transforming the energy captured from the environment into electrical energy. It consists of a conditioning circuit that is responsible for adapting the energy to the voltage and current required to make it useful, and an intermediate storage system (Viehweger, C. *et al.*). Li-ion batteries and supercapacitors have been tested as storage systems (Quintáns, C. *et al.*). In both cases they are charged for a long period of time with a very weak current and they provide enough instantaneous power for the system to perform its function for a short period of time.

2. **Autonomous Power Systems**

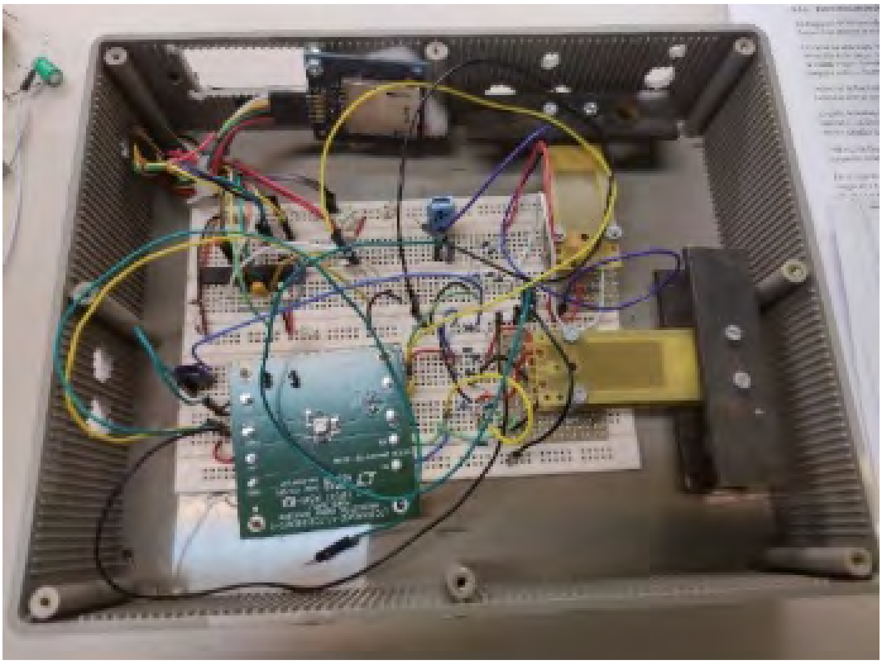
This section describes three power supply systems based on residual energy capture, which have been used in our laboratories.

2.1. *Mechanical energy*

Mechanical energy can be converted into electrical energy by taking advantage of the mechanical vibrations of the environment or the deformations that can be captured with piezoelectric devices (Soo Kim, H. *et al*.). There are a multitude of devices of this type on the market that work at different oscillation frequencies, depending on their elasticity constant and the maximum allowable deformation. In this work, the PPA-1011 device has been selected, which allows a maximum deformation of 21 mm and has an elastic constant of 267.45 N/m, figure 2.

Figure 2

Complete mechanical generation system



2.2. *Electromagnetic energy*

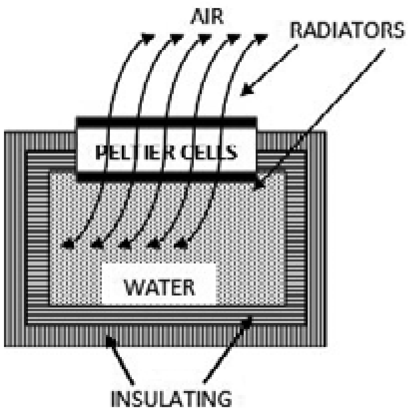
This system captures radio frequency energy via an antenna and transforms it into electrical energy that is stored for later use. Space is largely permeated by electromagnetic radiation due to telecommunication signals, although this type of residual energy generates very little electrical power.

2.3. *Thermal energy*

This option is based on the daily variation that occurs in the ambient temperature anywhere on earth. This is the basis for this type of electricity generation from thermal variation. The system consists of a small thermally insulated water tank (figure 3). The tank has a small window in which Peltier cells are located and through them heat passes from the environment to the water when the ambient temperature is above the temperature of the water in the tank and vice versa when the water temperature is above the ambient temperature. This causes heat flow through the Peltier cells, which gives rise to the generation of electrical power proportional to the heat flow through the cells. The complete system is described in (Quintáns, C. *et al.*).

Figure 3

Sketch section of the proposed thermoelectric generator [7]



3. **Data selection and submission process**

The process of sending/receiving sensing data using wireless media is one of the most energy-consuming processes in the systems. The most serious studies that compile the consumption of this type of transmission estimate transmission energy costs in the order of 10 mW/bit in WiFi technologies (Gomez, K. *et al.*), to less than 2 uW/bit in LoRa technologies (Bouguera, T. *et al.*). LoRA (Long Range) technology (Wixted, A.J. *et al.*) is specifically designed for wireless data transmission over medium to long distances (between 2 and 40 km) in battery-operated devices. This involves two fundamental transmission characteristics:

— Very low power consumption in the data transmission/reception process of the order of 2 uW/bit.

— A low transmission rate, between 0.3 kbits/sec and 50 kbits/sec. At the architecture level, LoRa has two fundamental components:

- LoRa devices of the sensor and/or actuator type (LoRa-Dev).
- The LoRa gateway (LoRa-GW). The LoRa devices send data packaged in messages to the LoRa-GW, which receives them and redirects them to other networks.

The LoRa-GW also serves as a sender of data to the devices from any other device. The topology of the LoRa architecture is therefore a star topology, with the LoRa-GW as the central element. In (Bouguera, T. *et al.*) the power consumption of LoRA technology was studied depending on various factors, reaching results in some cases around 2 uJ/bit. A comparison of both technologies in the energy aspect is presented in (Klimiashvili, G. *et al.*). One of the most interesting solutions for sending data using autonomous energy sources is the Send-on-Delta (SoD) techniques, which basically sends a data when the difference between that data and the last data sent is greater than a value called delta. The combination of the use of autonomous power sources, SoD-type data selection techniques and low-power, low-flow wireless transmission systems such as LoRA can be leveraged for the implementation of complete sensing and data transmission solutions for Industry 4.0 paradigms or directly on the Maintenance 4.0 paradigm, in environments where conventional and stable power sources would not be available.

4. **Application case: Maintenance 4.0**

Data sensing with low energy consumption is particularly interesting for the Maintenance 4.0 paradigm, especially when the system to be maintained is a biological or environmental system or is in environments where conventional power supplies are not available. The term Maintenance 4.0 uses the tools and resources of Industry 4.0 to improve the industrial maintenance process. On the one hand it uses current data networking capabilities embedded in sensor devices, actuators, or controllers, and on the other hand it leverages the high processing and decision-making capabilities of central systems for trend identification and predictive maintenance support. Maintenance 4.0 has four fundamental parts:

— Identification of the architecture of the system to be maintained.
— Identification of the type of maintenance (corrective, preventive and predictive) in the plant, with the aim of selecting the type of decision algorithms and data acquisition:

- Data acquisition process (sensorization), selection of the necessary energy source (power supplies), data selection and data transmission, identification of hot and cold data streams, monitoring, and processing tools in the control system.

— Decision-making action system based on the results of remote analysis processes (BigData, Artificial Intelligence, etc.).

In parallel, six functional blocks are considered in the OSA-CBM (Open System Architecture for Condition-Based Maintenance):

— Data acquisition.
— Data manipulation.
— State detection.
— State assessment.
— Prognosis.
— Recommendation generation.

The first two blocks can be implemented both in the self-powered smart sensor and in the intermediate gateway installed in the edge server, as it is basically a reactive control system that would generate alarms or emergency stops based on conditional monitoring by comparing data with expected results already defined. The LoRa-GW would also be located on the edge servers in case the transmission technology is LoRa technology. The state detection and estimation as well as the prognosis project the future situation of the plant based on the estimation of trends and previous experiences, so that they can be implemented in the Edge-Servers or in the Cloud-Servers. Finally, the creation of recommendations is a high-level action, which creates recommendations based on trends, history, and experiences with similar environments and past and studied situations, so it is an action developed exclusively in the Cloud-Servers.

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— Identification of the architecture of the system to be maintained.
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— Data acquisition process (sensorisation), selection of the necessary energy source (power supplies), data selection and data transmission, identification of hot and cold data streams, monitoring, and processing tools in the control system.
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5. Conclusions

A study has been presented which shows the feasibility of creating a system for measuring various variables that is self-powered by ambient energy and, therefore, suitable for measuring remote variables and variables in machines. This requires the use of elements with very low power consumption and their appropriate management, so that energy efficiency makes it possible. Piezoelectric transducers generate an alternating signal with an amplitude in the order of volts and a current of a few μA, and therefore require a step-down converter. In contrast, the radio frequency energy generated requires a boost converter. From the tests carried out, it can be deduced that the prototype needs 2.3 mJ to perform the power supply and sensor measurements, which translates into a consumption of 38 μW for a sampling period of one minute.

Acknowledgements

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SELF-POWERED SENSORS FOR IoT AND INDUSTRY 4.0 APPLICATIONS

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64th ESReDA Seminar ***Bilbao, May 30th – 31th, 2024***

OUTLINE

- Introduction
- Self-powered measuring system
- Mechanical energy
- Thermoelectric energy
- Sending/receiving detected data
- Application case: maintenance 4.0
- Conclusions

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INTRODUCTION

- Self-powered sensors for IoT and Industry 4.0 applications
- Interest of residual energy for use in measurement systems located in remote locations
- Autonomous system independent of the electrical grid and disposable batteries
- Interesting for Maintenance 4.0 and sensors for IoT

Harvesting Energy Source	Power
Light	10 µW/cm2 ~100 mW/cm2
Thermal	10 µW/cm2 ~ 1 mW/cm2
RF	0.2 nW/cm2 ~ 5 µW/cm2
Mechanical	0.4 µW ~ 100 mW

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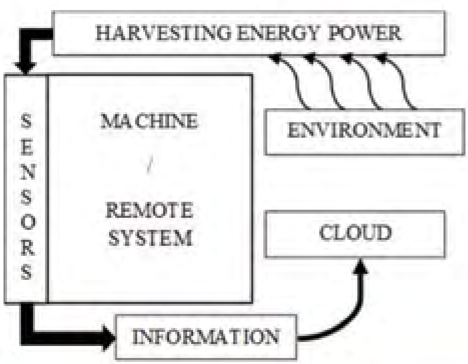
SELF-POWERED MEASURING SYSTEM



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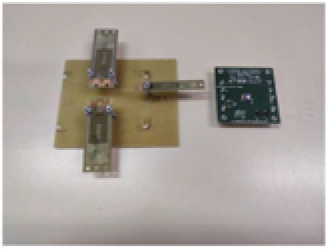
MECHANICAL ENERGY (I)



- Mechanical energy (vibrations) can be converted into electrical energy by piezoelectric devices.
- The electrical energy generated depends on the oscillation, the frequency, the constant of elasticity of the piezoelectric device and the maximum allowed deformation.

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MECHANICAL ENERGY (II)

- In this system we use the PPA-1011 piezoelectric device that allows a maximum deformation of 21 mm and has an elastic constant of 267.45 N/m.
- The figure shows the complete system.

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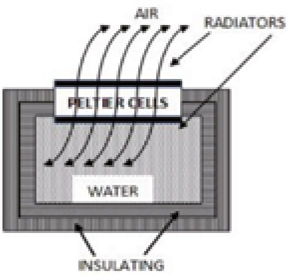
THERMOELECTRIC ENERGY



- The system is based on the daily variation that occurs in the ambient temperature anywhere on Earth.
- The heat passes from the environment to the water when the ambient temperature is above the temperature of the water and vice versa when the water temperature is above the ambient temperature.
- The heat flow through the Peltier cells generate electrical power proportional to the heat flow through the cells.

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SENDING/RECEIVING DETECTED DATA

- The sending/receiving sensing data is the most energy-consuming processes.
- The transmission energy costs is about 10mW/bit in WiFi technologies and less than 2uW/bit in **LoRa** (Long Range) technologies.
- LoRa Technologies is specifically designed for wireless data transmission over medium to long distances (between 2 and 40 km).
- LoRa has two fundamental components:
  - ✓LoRa devices of the sensor and/or actuator type (LoRa-Dev)
  - ✓The LoRa gateway (LoRa-GW).

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APPLICATION CASE: MAINTENANCE 4.0

- Data sensing with low energy consumption is particularly interesting for Maintenance 4.0, especially when the system is in environments where conventional power supplies are not available.
- Six functional blocks are considered in the OSA-CBM (Open System Architecture for Condition-Based Maintenance):
  - ✓ Data acquisition - Data manipulation
  - ✓ State detection - State assessment
  - ✓ Prognosis - Recommendation generation

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CONCLUSIONS

- A study has been presented that shows the viability of a sensor and transmission system with their power supply based on harvesting energy.
- This system is suitable for measuring remote variables and variables in machines and other applications.
- This requires the use of electronic systems with very low power consumption .
- Power supplies based on Piezoelectric devices and thermoelectric systems with Peltier cells can solve the problem.
- Lora technologies are suitable for sending and receiving data for maintenance 4.0 applications.

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Thank you very much for your attention
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Self-Powered Sensors for IoT and Industry 4.0 Applications

Vulnerabilities in the human factor-digital technology relationship in the railway system

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Abstract

This paper presents the findings of an investigation that was carried out following an incident of a train overtaking a red-light signal. In addition to identifying the issues that led to the incident, the investigation commission found that the staff on duty (signalman) at the railway station did not report the incident, even though the station was equipped with an electronic traffic control system, with the automatic recording of all activities carried out in the station, both by the signalman and by the trains running. The investigation commission concluded that the main cause of the incident, which has not been reported, was the lack of effective monitoring of the movement clerk's activity over time, by not using/checking the records provided by the digital device at each departure of the movement clerk. Thus, it can be said that the benefits of digital devices were only half used, ignoring from a certain point of view the existent safety component.

1. Introduction

On 08.06.2023, at around 04:30 a.m., while freight train no.66691-007 (hereinafter referred to as train A) was running through CFR Sighisoara station —figure 1— which had made a stop on line no. 5 - the towing locomotive and a number of 6 wagons overtook the exit signal X5 which displayed a red-light unit towards the train with the indication "*STOP without overtaking the signal!*". After passing the signal, the train entered the entry path of another freight train, no. 57700-005 (hereafter referred to as B train), running from the opposite direction.

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Figure 1

After overtaking the signal and stopping the two trains at a distance of about 30÷40 m between the towing locomotives, without notifying the incident and without ordering the necessary checks to be carried out, the signalman ordered train A to reverse until the locomotive reached signal X5. After this action, he proceeded to secure train B through the station and then dispatched train A. With these actions, the incident conditions were reversed.

> The time elapsed from the time the train passed the X5 “on stop” signal to the time the two trains left CFR Sighisoara station was 12 minutes.

There was no damage to the railway infrastructure or to the two trains and no delays to passenger trains. The incident was not reported until 4:30 p.m. (12 hours later).

2. What/how did it happen?

Train A was supposed to stop at CFR Sighisoara station on line 5 (red in figure 2). In order to achieve this, the signalman gave the necessary command for the line exit signal (X 5) to have a red light, which forced the driver to stop the train before it.

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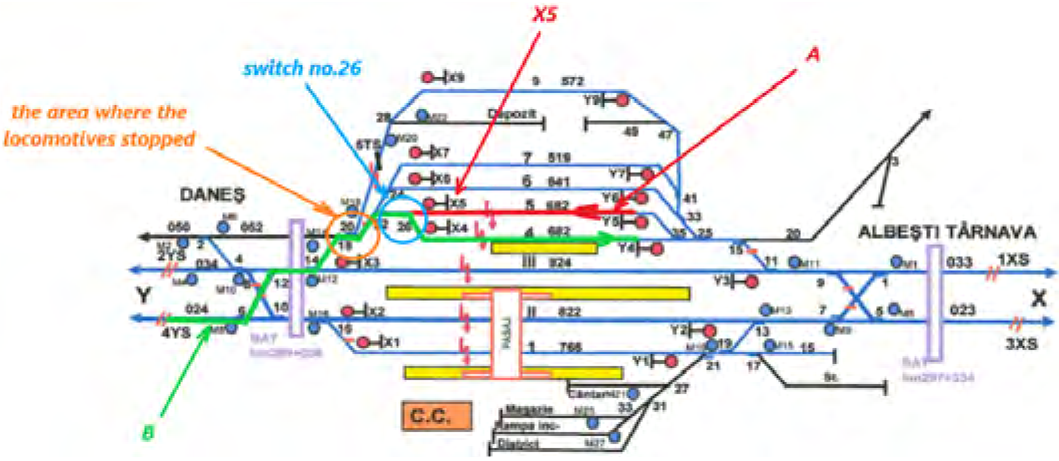
Figure 2

Sighisoara railway station



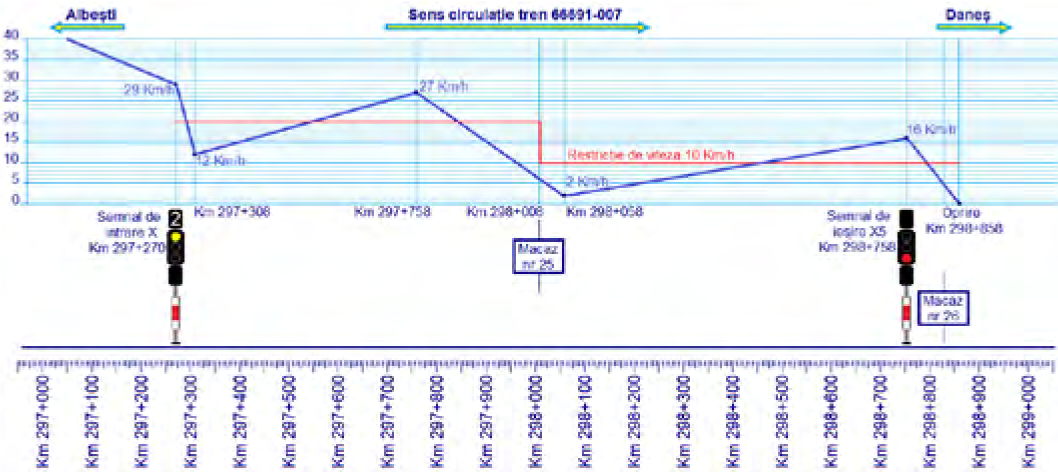
Train B had to stop at the station on track No. 4 on the route shown in green in figure 2. To do this, the switch no. 26 was manipulated to allow train B to run on its track. It could not allow train A to run or train B to enter over train A.

After entering the station (yellow light signal in figure 3), the driver of train A had to run at a maximum speed of 20 km/h until entering line 5, from where he had to run at a maximum speed of 10 km/h. The driver did not respect this speed, so that after reaching a speed of 2 km/h (almost stopping), instead of continuing at the same speed and stopping, he increased his speed above the required 10 km/h. During the investigation, it was found that by the time the locomotive reached the exit signal, the train speed was 16 km/h and the driver took the measure to bring the train to an emergency stop - figure 3.

The investigation revealed that the way the driver acted was due to a state of fatigue caused by the fact that he was on duty for longer than the maximum time allowed by the legislation in force, i.e. from 07.06.2023 at 5.00 p.m.

After the trains had stopped, without notifying the incident and without checking the cause of the overrun of signal X5, the signalman asked the driver of train A to turn the train back and then retraced the route for train B to enter the station.

Figure 3



3. **Technical equipment in the station**

In the Sighisoara railway station, an electronic centralization system based on SIMIS W type computer technology has been in operation since 2008.

In the signalman's office there is - among other things related to the case under investigation —a command post and a disturbance printer— photo 1.

Photo 1

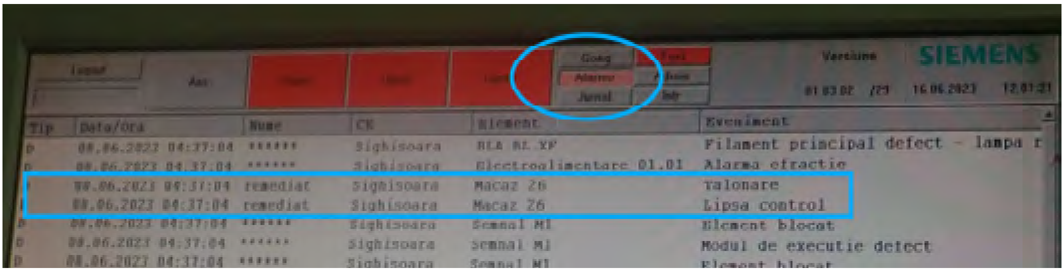
Command (control) post

The control post - photo 1, is used to carry out the movement and shunting runs by the movement employee, to check how the runs are carried out, to follow the movement of the trains, as well as for optical and acoustic signalling of any faults/alarms in the installation.

All faults, malfunctions and alarms are displayed in the ”fault list”. If at least one fault message appears, the “alarms” button in the basic log window is shown in red and will be accompanied by a beep - photo 2.

Photo 2

Screenshot of the reported defect



The alarm contains the following information: type of alarm, time of the alarm, name of the operator who acknowledged the alarm, name of the central unit, item that triggered the alarm, cause of the alarm.

An alert remains on the list until it has been confirmed and its cause has been removed. Once the cause has been removed, alarms are found in the ”log” window. Events recorded in the ”log” book are: faults recorded by the electronic control centre, faults recorded by the control centre, operator actions, movements of isolated trains or rail vehicles, login and logout operations. The query of the “log” window can be done by: alarm type, date/time, item, event.

Alarm/defect indications can be printed on demand, they are not automatically printed when they occur, nor they are distinctly highlighted (different colour from black or a special column), in order to be quickly identified by the human factor that should check them.

There is no such printer in the office of the movement clerk at CFR Sighisoara station and therefore the alarm indications could not be printed even if a person had been established to do so.

According to the documents provided by the infrastructure manager, there was such a printer when the facility was commissioned in 2008. It was subsequently taken out of service due to failure. Since alarms/defects are signalled optically and acoustically when they occur and the movement clerk is obliged to record them in the special register, it was considered that the installation of the printer was no longer necessary.

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4. Conclusions

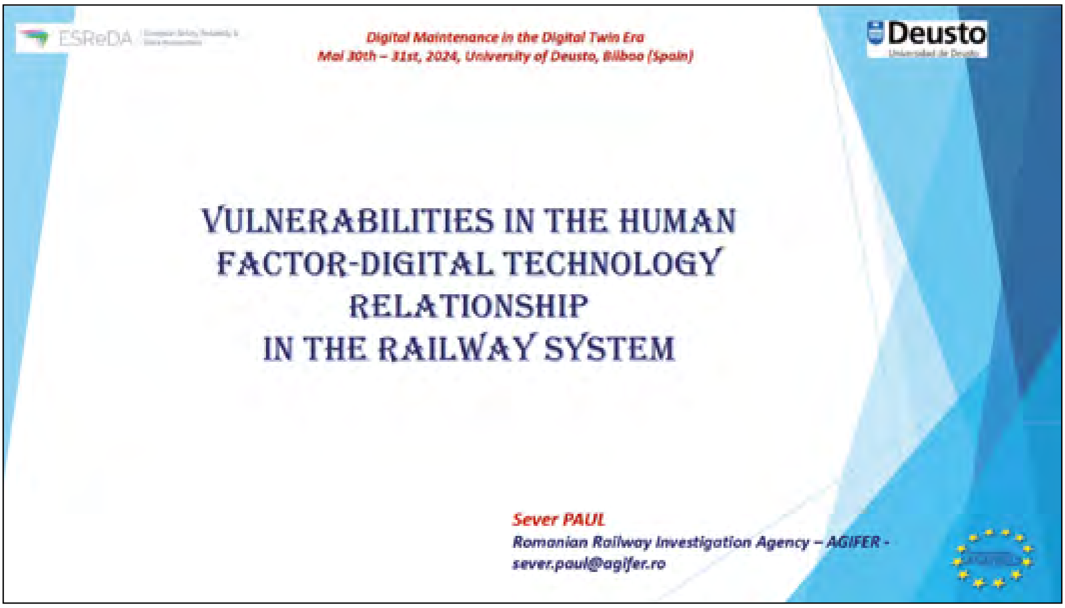
In its analysis of how the signalman acted, the investigating commission also identified that there was no monitoring of the signalman's activity when leaving work by the station management or by the safety monitoring staff of the Brasov Branch.

Thus, no facility log information was ever checked to identify a situation similar —and unadvised— to that identified in the incident under investigation.

In other words, although the station had an electronic centralisation system designed to facilitate the work of staff and prevent accidents/incidents, that was designed as a technical barrier to prevent human error, its benefits were not used. The facility was incomplete in that there was no printer for printing faults and there was no effective monitoring by checking the information provided by the facility computer.

5. Bibliography

Investigation report on the railway incident occurred on 08.06.2023 within the area of activity of the Regional Railway Branch Brasov, at the CFR Sighisoara station, in the movement of freight train no. 66691-007, by overtaking the exit signal X5 displaying towards the train the indication "STOP without overtaking the signal!" - www.agifer.ro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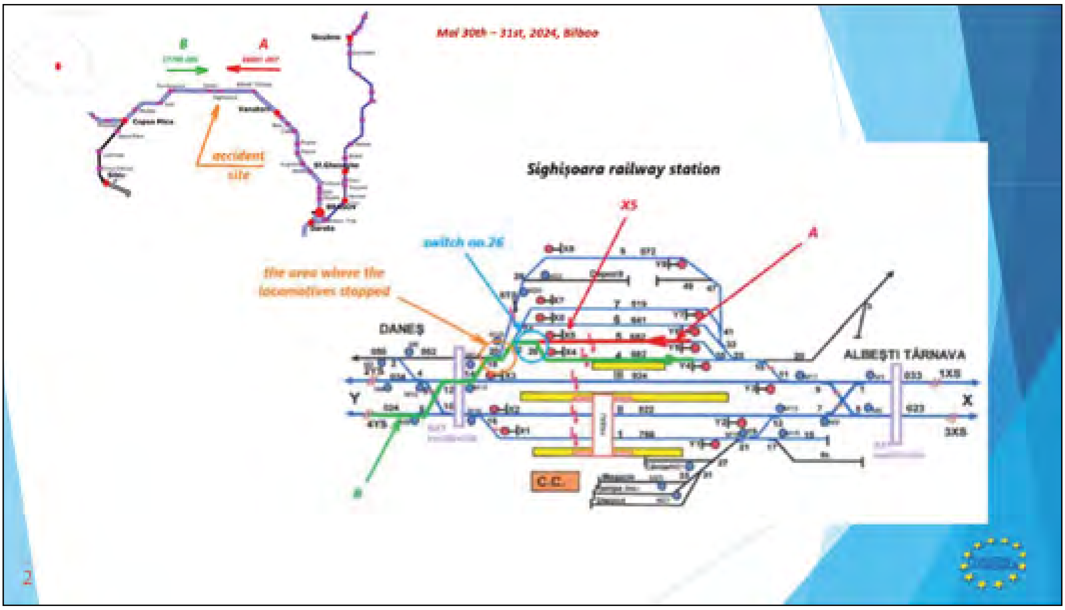
Sever PAUL
Romanian Railway Investigation Agency – AGIFER -
sever.paul@agifer.ro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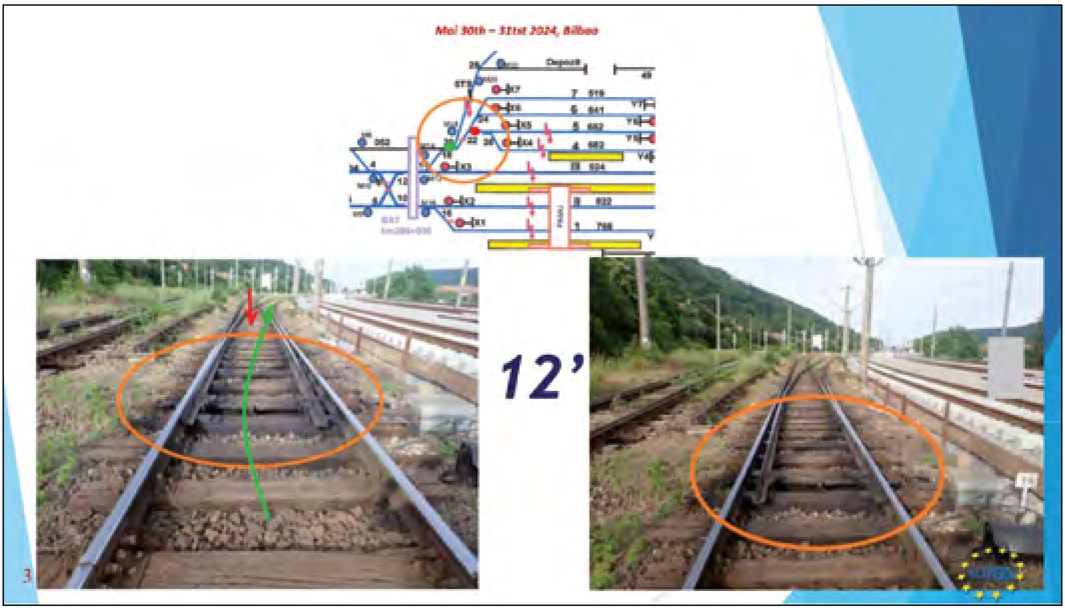
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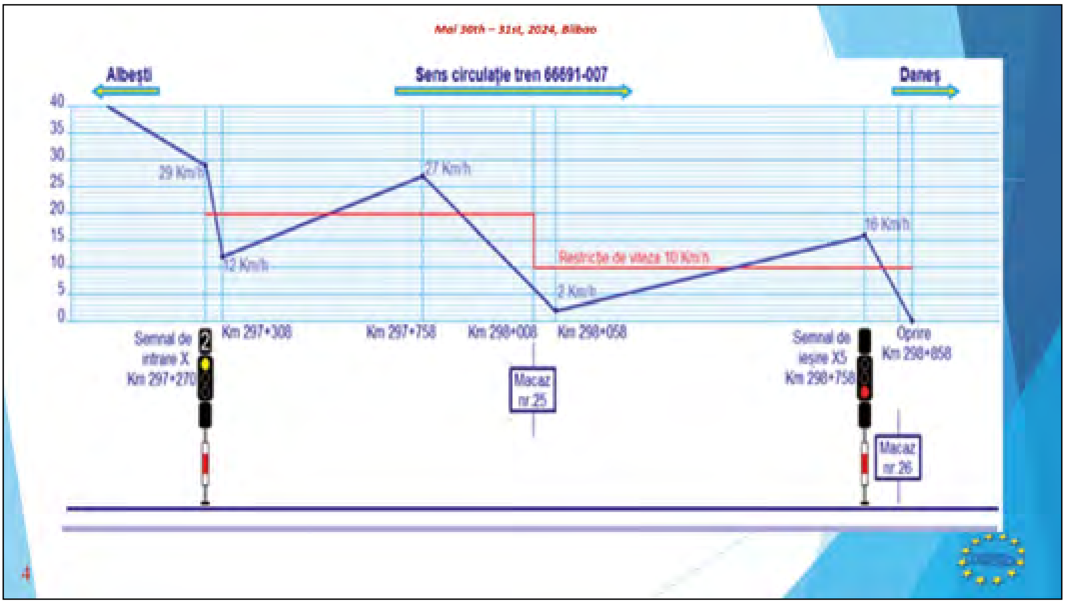
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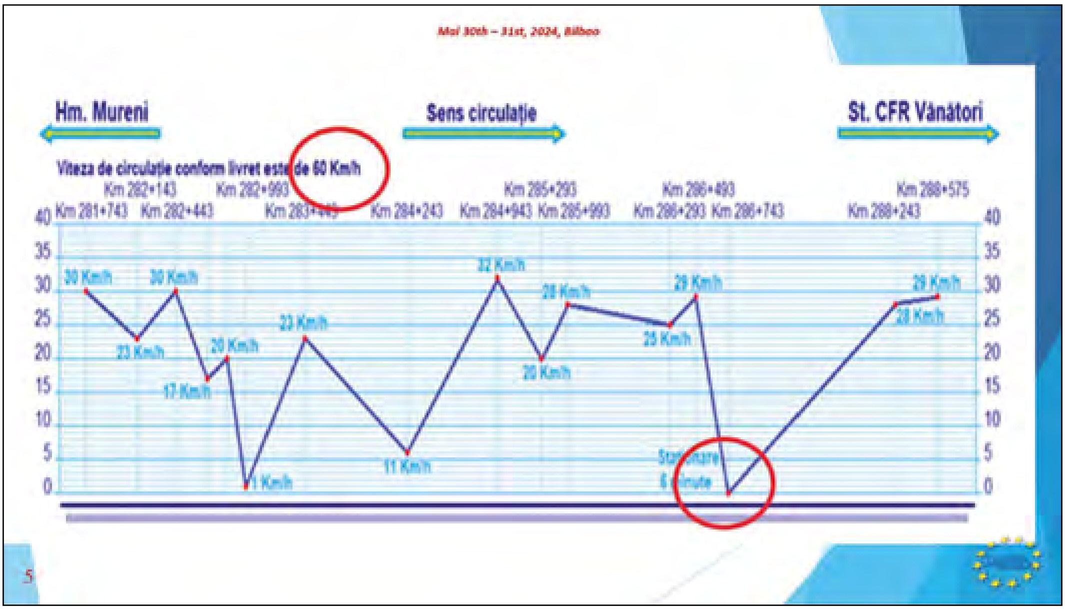
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Km 286+293
Km 286+493
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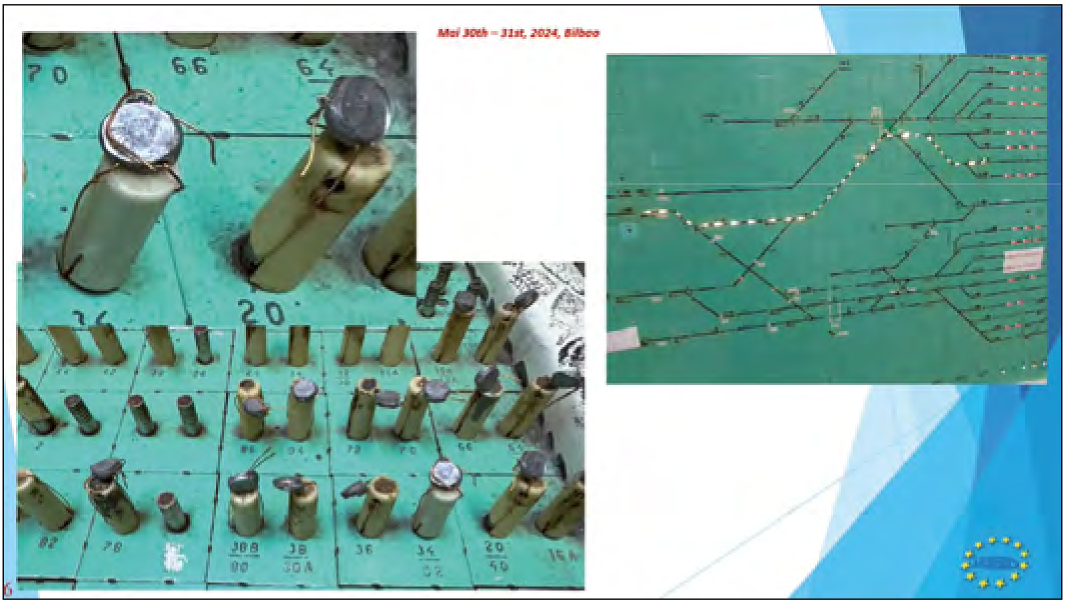
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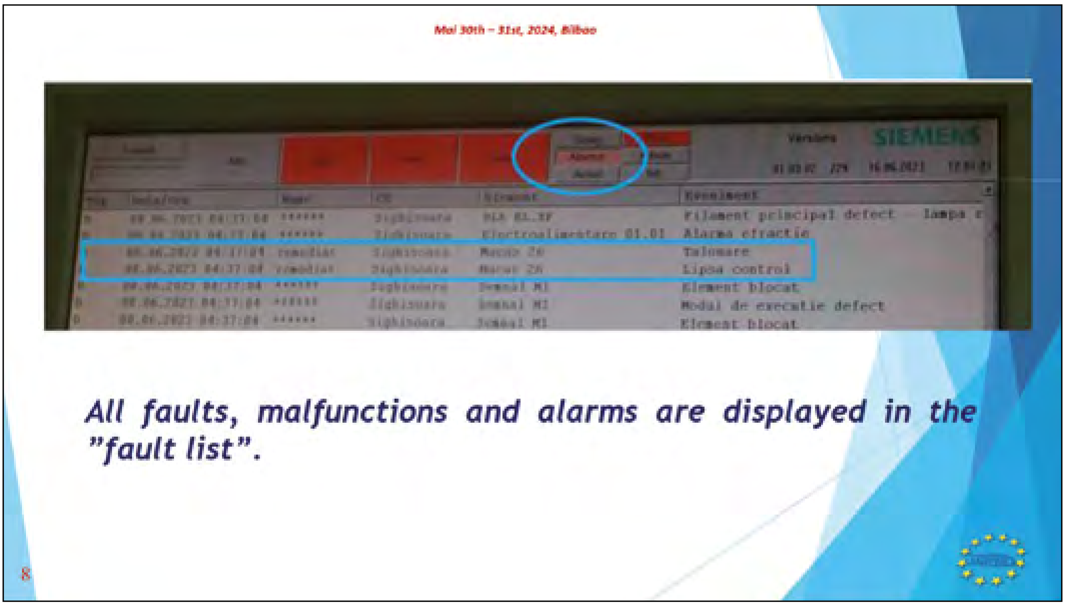

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Thank you!
Muchas gracias!
10

Recalibration of Digital Twins via Mobile Agents

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Abstract

Digital twins are based on the combination of virtual models and real sensor data. Applied to cities, digital twins can be used for situational representation of crises and hence can provide decision makers with holistic pictures of large-scale emergencies. Digital twins can be linked to coupled simulations for critical infrastructures to determine high risk areas for infrastructure failures and to efficiently direct emergency responses to minimize damages and to quickly restore infrastructures.

However, simulations will naturally become less precise as simulation time progresses and require real world data to realign the digital twin with its real-world equivalent. This data can be recorded by sensors, which for instance measure voltage or pressure at certain key points, or by mobile agents. Mobile agents are, in the context of this paper, drones and spontaneous volunteers that collect live input data. They can contribute information in large emergency situations when infrastructures operate outside their typical parameters or when other channels, such as sensors, fail due to their dependence on damaged infrastructures.

The significance of volunteers, which are not affiliated with aid organizations, has increased in the last years due to the internet and social media enabling an easy and quick (self-)organization. Spontaneous volunteers are typically already on site and can provide a substantial work force very quickly. Information that is collected by volunteers performing dedicated information collection tasks can be used to obtain a broad overview of publicly available information.

Drones are already used by emergency services. They can be dispatched quickly and can reach locations that are inaccessible by humans. They are carrier systems for not only optical cameras but also other sensors such as thermal and multispectral imaging or lidar scanners. Collected data can be processed automatically to detect and georeference objects using AI methods. This makes drones a powerful tool for enhancing situational awareness in emergency scenarios.

We present a concept for the maintenance of a digital twin by updating the simulators with real world data. The simulators define the input data they require: the initial conditions, constraints, and observable predictions of the simulations. We discuss which input data can be extracted from data submitted by the mobile agents studied here and which data must be obtained from other sources. We present a concept for updating the coupled infrastructure simulators. The corresponding interfaces are designed to be easily extendible to other input sources to facilitate a modular and flexible simulator architecture.

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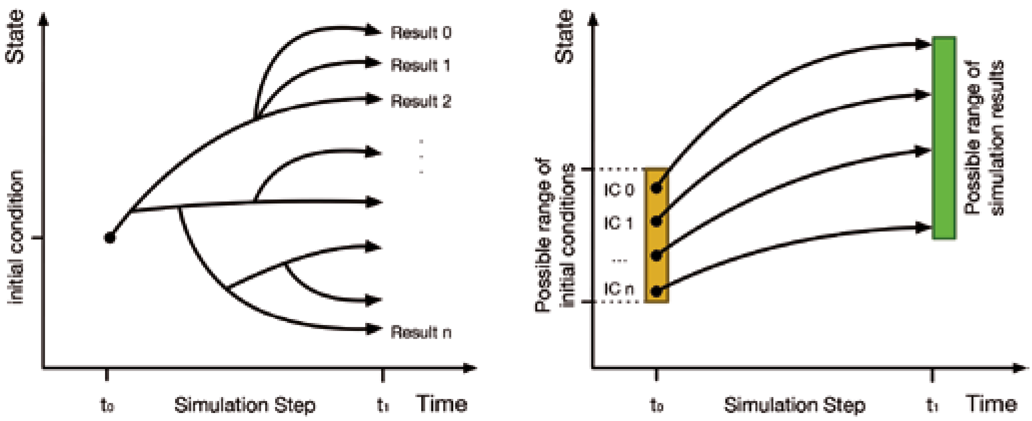
1. Introduction

A digital twin is a virtual model of a real object. The real object is equipped with sensors to measure its various states and this data is used to enrich the virtual model [1]. This model can be used to optimize processes or identify faults at an early stage. In an urban environment, parking space utilization can be monitored [2], or predictive maintenance can be carried out on buildings [3]. Furthermore, digital twins of cities can be used for public safety. By simulating different damage scenarios and identifying high-risk areas, emergency forces can plan efficient responses and the restoration of critical infrastructures. However, creating a complete digital twin of a city is challenging due to the complex interconnections between infrastructures. Damage to one infrastructure can result in unforeseen failures in adjacent ones, leading to unpredictable cascading effects [4]. To address this challenge, a co-simulation framework was presented in [5]. This framework combines simulators for urban critical infrastructures, such as power grids, natural gas, water, and communication networks, built structures, with a simulator for emergency response forces. By simulating cascading effects, decision makers can take targeted preventative steps or prepare a response efficiently. This information can also be used to build more resilient infrastructure systems and train emergency response forces for crisis situations.

However, this co-simulation approach poses a problem: The prediction of the simulation will diverge from reality with increasing simulation time and lose its predictive power. There are three main reasons for this. Firstly, simulations are only an approximation of reality. Secondly, the presented co-simulation incorporates probabilistic and non-deterministic components yielding a multitude of possible outcomes in each simulation step. The simulation of built structures, for example, only gives probabilities for building damages. The corresponding divergence of the simulation results is illustrated in the left-hand side of figure 1.

Figure 1

Illustrated divergence of simulation results based on probabilistic and non-deterministic simulations (left) and based on uncertain initial conditions (right)



Source: Fraunhofer SIRIOS, 2024.

Thirdly, not all input information is available and initial conditions as well as boundary conditions of the simulations have uncertainties. For example, it might be unknown how long an emergency power supply lasts, but it might be possible to give a reasonable estimate based on legal regulations and technical limitations, e.g., from 12 h to 18 h. The corresponding divergence of the simulation results is illustrated in the right subfigure of Figure 1. The initial conditions might also be sampled from a probability density.

It is consequently necessary to recalibrate the co-simulation with external data. The maintenance of digital twins is often based on sensors and self-reporting of technical systems. This input source might not be sufficient in the case of natural disasters resulting in cascading infrastructure failures since sensors and technical monitoring systems might be damaged themselves or might depend on other damaged infrastructures, such as electricity and communication networks. Some infrastructures, such as most buildings and road networks, do not have any automatic monitoring systems in place. Additionally, monitoring systems might be designed for typical operation conditions but might be insufficient when infrastructures operate outside their normal parameters. In such cases, mobile agents, such as drones or spontaneous volunteers, can provide additional data.

This paper examines how and which data collected by mobile agents can be incorporated into a digital twin to recalibrate the co-simulation of different critical infrastructures.

This paper is structured as follows: Chapter 2 introduces the setup of the digital twin under consideration. The components of the co-simulation, their required input data and results are presented. In addition, the mobile agents considered in this paper, the drones, and spontaneous helpers, are introduced. Chapter 3 describes the proposed scheme for including mobile agents to recalibrate a co-simulation and illustrates it with an example. Finally, chapter 4 discusses and concludes the presented scheme.

2. **Digital Twin Setup**

2.1. *Co-simulation environment*

The co-simulation presented in [5] consists of coupled simulations for different critical infrastructures. The co-simulation includes simulators for electricity, water, natural gas, and communication networks as well as built structures and emergency response services. Each simulation requires specific input data. This paper distinguishes static and non-static input data. Static data comprises all data that does not change during the simulation, as for example, the power line network or pipeline networks. Non-static data on the other hand can change. For example, the operational state of an electrical transformer can be affected by the structural soundness of the building it is in and the water usage depends on outside factors. A visibility and audibility simulation, used to simulate the perceptibility of warning messages for the public, is also part of the co-simulation but does not require any non-static input data. Emergency response forces can

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also assume the role of mobile agents contributing information, but this possibility is not considered in this work.

2.2. *Input requirements*

Table 1 shows the required input data for the individual simulators of the co-simulation, their possible sources, as well as the results of the individual simulators and options for validating these results. The content of Table 1 was determined by interviewing experts for the respective simulators.

For example, the simulators for the utility networks —electricity, natural gas, water, and communication— require information about production and demand, the network topology, and its changes, as well as element-specific operating parameters. The simulators can obtain these values from various sources: Sensors that are connected to a central control system can collect information about current operating conditions. Customer calls, on the other hand, can be used to find out where there are changes in the topology, e.g., in the form of damaged power lines. The results of the individual simulators describe the supply of the population with the respective medium. In the case of electricity, this can be through spontaneous volunteers, drones, but also customer calls in the event of a power outage. The input variables and results of the simulators for the buildings and emergency response can be validated in a similar way to the values of the utility network simulators.

2.2.1. Drones as input source

Specialized emergency response teams deploy drones on a regular basis to improve situational awareness, not only during natural disasters. After reaching their designated mission area, emergency responders can set up and start drones within minutes and gather an array of survey information. There are established solutions to acquire and share drone data via the internet or messengers [6]. In this work, we assume a functioning communication network, which easily allows sharing data with relevant units and decision makers.

Depending on their technical equipment, drones can provide a wide range of data, e.g., optical, thermal, multi-spectral, and lidar[1] data. Drone data typically consists of videos, streams, and pictures in various resolutions as well as global navigation satellite system (GNSS) data, like GPS coordinates, and gimbal[2] meta data. This data can be used raw, i.e. without further processing (e.g. live video streaming) and then requires qualified human operators for analysis and interpretation [7].

[1] Light detection and ranging (lidar) is an optical method to measure ranges and velocities.
[2] A 3D-pivoted technical support unit to stabilize the sensor payload which also provides data about its pitch, yaw and roll angles.

Table 1

Required input, possible sources, and results for each simulator under consideration. Numbers are used to map which inputs and results can be validated by which source

	Electricity	Natural Gas	Water	Communication	Building	Emergency Response
Required Input	1. Power production. 2. Power demand. 3. Changes of topology (damages, failures). 4. Operational parameters. 5. Topology.	1. Source pressures. 2. Demand rates. 3. Changes of topology (damages, failures). 4. Operational parameters. 5. Topology.	1. Filling levels of tanks and reservoirs. 2. Demand rates. 3. Changes of topology (damages, failures). 4. Operational parameters. 5. Topology.	1. Transmission capacity. 2. Band width2. 3. Electricity supply. 4. Changes of topology (damages, failures) 5. Operational parameters. 6. Topology.	1. Scenario-dependent external impacts. 2. Topology. 3. Changes of topology.	1. Number and position of units. 2. State of institutions (e.g., hospitals). 3. Workload of control centres. 4. Road network state. 5. Changes of functionalities of units. 6. Changes of the state operations (normal operations *vs*. state of emergency).
Sources of Input	— Control centre sensors[1,2,3,4]. — Technical parameters[4,5]. — Consumer calls[3]. — Spontaneous volunteers[3]. — Drones[3].	— Control centre sensors[1,2,3,4]. — Technical parameters[4,5]. — Consumer calls[3]. — Spontaneous volunteers[3]. — Drones[3].	— Control centre sensors[1,2,3,4]. — Technica[1] parameters[4,5]. — Consumer calls[3]. — Spontaneous volunteers[3]. — Drones[3].	— Contro[1] centre sensors[1,2,3,4,5]. — Technical parameters[5,6]. — Consumer calls[4]. — Spontaneous volunteers[4]. — Drones[4].	— Technical parameters[2]. — Spontaneous volunteers[1,3]. — Drones[1,3].	— Self-reported[1,2,3,4,5,6]. — GPS sensors1. — Drones[1,4]. — Spontaneous volunteers[2,4]. — Events and incidents triggering the changes[1,2,3,5,6].
Results	1. Power supply.	1. Gas supply.	1. Water supply.	1. Mobile phone and internet availability.	1. Deformations. 2. Component failures. 3. Buildings failures.	1. Number and position of units. 2. State of institutions. 3. Workload of control centres. 4. Road network state.
Validation Sources of Results	— Consumer calls[1]. — Spontaneous volunteers[1]. — Drones[1].	— Consumer calls[1]. — Spontaneous volunteers[1].	— Consumer Calls[1]. — Spontaneous volunteers[1].	— Base station status[1]. — Consumer calls[1]. — Spontaneous volunteers[1].	— Drones[1,2,3]. — Spontaneous volunteers[1,2,3].	— Drones[1,4]. — Spontaneous volunteers[1,2,4].

Source: Fraunhofer SIRIOS, 2024.

Beyond that, the data can serve as the basis for further processing using sophisticated algorithms. In particular, algorithms based on artificial intelligence (AI) technologies can assist human operators and partially perform important tasks. Examples for use cases are (near-)real-time mapping, 3D models, or detection and classification purposes [8]. The YOLO models are an example of commonly used AI detectors [9]. The merging of multiple sensor inputs as well as meta data enables even more sophisticated analyses.

Using these methods, drone data can be transformed from the raw footage without any abstraction to a high level of abstraction. The level of abstraction influences how well operators must be trained and experienced and how data can be shared with other parties. The interpretation of live video streams, for example, requires experienced operators whereas structured data with geocoordinates can be processed automatically.

Principal use cases for drones include search and rescue operations or mapping of damage to buildings, roads and bridges in a wide area. For this purpose, a raw video stream can be processed with an AI detector to detect people or damaged structures. In combination with the drone metadata, it is possible to reference the detections with real geo data and remotely triangulate their exact locations. These georeferenced detections can be further used to generate tactical maps or can be shared with decision makers.

For the co-simulation presented here, drones can be used to map areas affected by natural disasters and their impact on infrastructures, e.g., power outages. This data is used to verify the current state of the simulation and to update the digital twins of structures, infrastructures, and position of emergency responders.

2.2.2. Spontaneous volunteers as input source

We investigate a setup in which spontaneous volunteers use a smartphone app for volunteer coordination. The volunteers receive dedicated requests to submit situational information on the app. The submitted information is then collected, processed, optionally visualized, and incorporated into the co-simulation.

Emergency response forces formulate the requests and send them to the volunteers using the app system. Volunteers can be asked to fill out a questionnaire and to submit pictures or videos of the situation. Using chatbots to interact with spontaneous volunteers is a promising approach to increase usability [10]. Other crowdsourcing approaches use information that is submitted via social media and collected by dedicated units, like the virtual operations support team (VOST) in Germany [11].

Table 1 includes several use cases for volunteer-submitted input to the digital twin and the co-simulation. For electricity, natural gas, water, and communication infrastructures, spontaneous volunteers can report on damages to the infrastructure networks, such as damaged power lines and broken water pipes, and can report on the state of supply. Damage close to the consumer, e. g. in the low voltage electricity networks, is typically reported by consumer calls [12] and nowadays with dedicated apps and websites, which arguably also constitute a form of information crowdsourcing.

Weather information and information about disaster events, such as floodings, storms, hail, and landslides, can be used to calculate probabilities for building damages and to estimate incident rates triggering emergency responses. Spontaneous volunteers can report on building damages and the usability of transport infrastructures, e.g., streets, railways, bridges, and tunnels. Information of possible transport infrastructure issues is crucial for directing relief efforts. Most buildings are not monitored by sensors or automated systems. Spontaneous volunteers can also report on the state of certain institutions, e.g. whether hospitals or other medical facilities are inaccessible. Moreover, spontaneous volunteers can also report on a variety of other relevant topics not covered here, for example, social and psychological issues of the population [13].

However, the large amount of volunteer-submitted information and the resulting large workload for data processing are a challenge for emergency response services. Specialized tools might help to reduce the additional workload [14]. Moreover, the trustworthiness of crowdsourced information when comparing to authoritative information sources is an issue of concern. Using dedicated information gathering solutions rather than using data sourced from social media might help to improve data quality [15].

Using dedicated information gathering solutions, such as crowdsourcing apps, for this task could be beneficial since the submitted information can be collected and analyzed in a centralized system. This data can be enriched with important meta-information, such as identity information and personal capabilities of volunteers, as well as detailed location information. Submitted pictures and videos allow response forces to obtain a clearer picture of the situation. Volunteers can be directly contacted, e.g., asked to provide additional information using follow-up questionnaires. Crowdsourcing apps for information gathering can also be closely integrated in warning and risk communication systems, e.g., volunteers can provide feedback to warnings.

Several comparable use cases have already been researched and partially implemented in real-world applications. For example, crowdsourced information gathering has been studied for weather data [16], various natural disaster events [17-21], transport infrastructures [22], and supply infrastructures, ranging from power and communication outages to drinking water quality [23-27]. A system to evaluate the structural stability of school buildings after natural disasters by non-experts has been presented in [28].

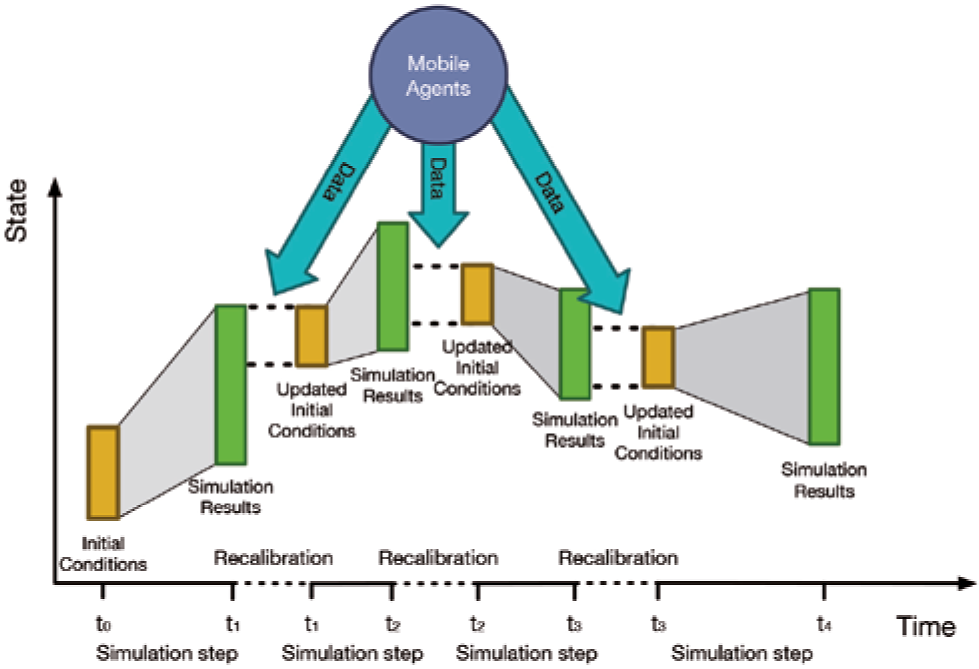
3. **Maintenance scheme**

3.1. *Proposed scheme*

We propose the following simulation-update scheme to capture the possible outcomes of the simulation and recalibrate the simulation with new input data submitted by mobile agents. This input data is neither submitted in real-time nor continuously as sensor data would be. The simulation is hence performed in steps. The proposed scheme is illustrated in figure 2. The x-axis shows the time, and the state of the simulation is illustrated as a one-dimensional variable on the y-axis.

Figure 2

Proposed maintenance scheme to enrich a simulation with input data from mobile agents



Source: Fraunhofer SIRIOS, 2024.

The first step starts at t_0 and ends at t_1. In the following recalibration phase, the current simulation results are combined with external data from mobile agents yielding the updated initial conditions for the subsequent simulation step.

Figure 3 shows a single simulation step starting at time t_0 and ending at time t_1. In Figure 3, input data is categorized as initial conditions and boundary conditions. Initial conditions are start values of observables at a specific time t_i. Initial conditions are typically not exactly known and might fall within a range or follow a probability density. For example, the height of a flood might be based on a hydrological model yielding a range of probable water depths between l_{min} and l_{max}. In this scheme, the different parameter configurations are sampled using multiple simulation runs, comparable to a Monte Carlo simulation. The possible parameter space is illustrated as a yellow band and simulator runs are illustrated as arrows.

Furthermore, boundary conditions might be imposed on the simulations. Boundary conditions are illustrated as blue band, which restricts the simulation arrows in the y-direction. In this scheme, boundary conditions are conditions that are imposed for the simulation time. Boundary conditions might be deduced from external information or can arise from technical limitations, e.g., an electricity network simulation might define a maximal amount of power that can be supplied. Simulator runs that make contradicting predictions are cancelled, as indicated with red, crossed lines in figure 3. Boundary conditions are implemented in this scheme using observer services, which monitor whether the conditions are fulfilled.

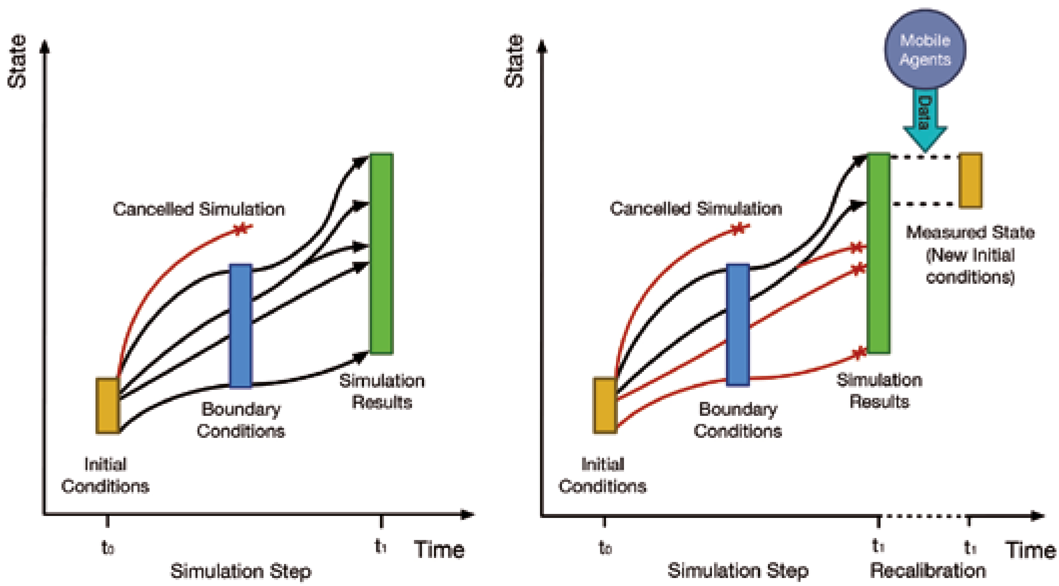
Some of the coupled simulations yield probabilistic predictions, which result in non-deterministic simulation steps. For example, a structural simulation of a building yields a damage probability and non-deterministic agent simulations are used to model emergency response forces. Based on the probabilities, one outcome is chosen in a single co-simulation run. Multiple simulation runs can be used to sample the possible outcomes. This behavior is illustrated in figure 3 with an arrow splitting into two parts.

The space of all possible simulation results is shown as a green band. The simulations will typically diverge from reality and are hence recalibrated with external data, as indicated on the right-hand side of figure 3. Simulator runs whose results are incompatible with the input data are discarded. The remaining simulation results are used as new initial conditions for the subsequent simulation step.

Figure 3

Left: Illustration of different results of a single simulation step depending on initial and boundary conditions

Right: Illustration of the proposed recalibration process between two consecutive simulation steps



Source: Fraunhofer SIRIOS, 2024.

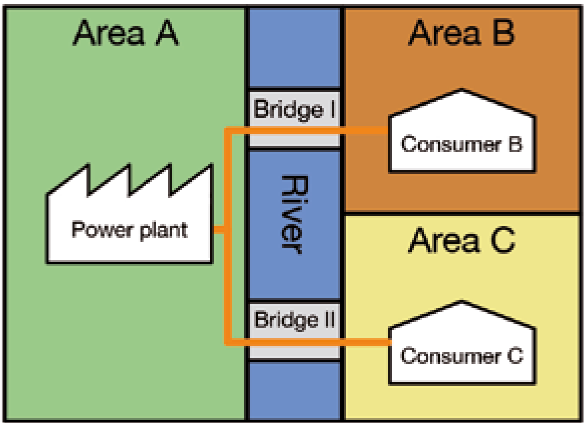
3.2. *Example scenario*

3.2.1. Setup and scenario

As an instructive example, consider the setup shown in Figure 4. There are three areas: A, B, and C. Area A and B as well as area A and C are separated by a river and connected by bridges each. An electric power plant is situated in area A and supplies area B and area C with electricity. The corresponding power lines go over the bridges.

Figure 4

Schematic representation of the example scenario under consideration



Source: Fraunhofer SIRIOS, 2024.

A flooding event that might damage the bridges is predicted. The simulation yields the following four possible states of the infrastructure system:

1. no bridge is damaged, and everything is working normally,
2. bridge I is damaged, bridge II is not damaged, and area B has no electricity supply,
3. bridge I is not damaged, bridge II is damaged, and area C has no electricity supply,
4. both bridges are damaged, and areas B and C have no electricity supply.

The advantage of the co-simulation approach is that the predictions can be used to mitigate the effects of infrastructure damages and to efficiently direct response forces. In this example scenario, simulations might reveal that

— some outcomes have more severe impact on other infrastructures and
— some outcomes are more likely than other outcomes.

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Damage to bridge I might have a higher impact because, for instance, the water supply of all areas might be interrupted if area B has no electricity. Damage to bridge I might be more likely due to its construction.

Mobile agents are used to gather information. In this scenario, spontaneous volunteers report on the state of electric power supply. The predictions of the co-simulation can be used to perform preparations, such as creating information gathering tasks and activating volunteers in advance. Spontaneous volunteers could also report on the structural state of the bridges and submit pictures of damages, but this task is not included here.

In this scenario, drones are used to assess structural damages to the bridges. Since drone capacities are limited and require deployment of specialized teams, the co-simulation can be used for efficient planning. E.g., a building simulation revealed that bridge I is more likely to be damaged and the drone team is hence deployed in advance close to bridge I. Input from other sources, such as spontaneous volunteers, can also be used to coordinate the drone teams. If, for example, volunteers report a potential for damage, drones can be used to verify the damage.

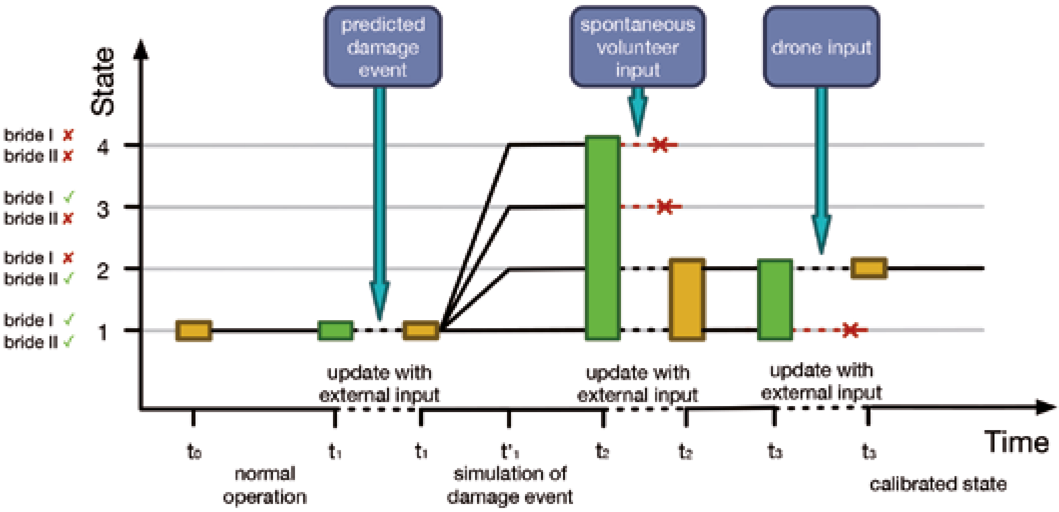
3.2.2. Co-simulation update scheme

The simulation is performed as depicted in Figure 5. The following steps happen.

1. A normal operation is simulated. The system is in state 1.
2. At time t_1, new weather information yields a prediction of a possible damage event at time t_1'.
    a) The four possible outcomes of the co-simulation are depicted on the y-axis in figure 5.
    b) A building simulation reveals, that bridge I is more at risk than bridge II.
    c) The tasks for spontaneous volunteers are prepared and a drone team is dispatched to bridge I.
3. The damage event happens at t_1', but no situational picture is available.
4. Volunteers report no electric power supply in area B and a working power supply in area C.
    a) Consequently, bridge II is not damaged.
    b) Insufficient information on bridge I is available.
    c) The co-simulation is updated at t_2: state 3 and 4 are excluded.
5. Drone observations reveal that bridge I is damaged, i.e. state 1 is excluded.
6. The co-simulation is updated and fully calibrated at time t_3.

Figure 5

Time progression of the damage forecast and its recalibration using mobile agents



Source: Fraunhofer SIRIOS, 2024.

Conclusions

In this work, we present a maintenance scheme for a digital twin of an urban environment which includes a co-simulation component for different critical infrastructures.

We collect the required input data that is necessary to update the simulations. This input can stem from different sources, such as consumer calls, sensors and monitoring systems, emergency response services, and mobile agents. Mobile agents such as drones and spontaneous volunteers can serve as a source of situational information to augment sensor data, to replace damaged monitoring systems, or for information that is not covered by other sources.

Drones can be equipped with various sensors and are a quick and flexible tool for emergency response services to obtain situational information. Modern techniques based on AI algorithms allow for automated processing of drone data. Spontaneous volunteers can perform dedicated information gathering tasks using app systems for coordination, data collection, and data analysis. Volunteers can further submit pictures and videos, along with important meta-data.

Information submitted by mobile agents can be used in particular to gain knowledge about the state of critical infrastructures such as electricity, water, natural gas, and communication networks. Other well-suited use cases include gathering information about extreme weather events, natural disasters, damages to built structures, and the state of transport infrastructures.

In the presented scheme, the co-simulations are performed in steps and updated with external information. Ambiguities due to lack of information about the infrastructure network are handled by starting multiple, parallel simulator runs with different initial conditions. Probabilistic simulations are handled by sampling over different possible outcomes. The digital twin is maintained by updating the co-simulations after each simulation step with new input data. The resulting state is then used as new initial conditions for the next simulation step.

In the future, we plan to implement the proposed maintenance scheme for the already existing co-simulation. Applications to real-world problems, which have a higher degree of realism than the current toy scenario are planned.

Acknowledgements

The authors' interdisciplinary research and development, as presented in this paper, is conducted within the Fraunhofer Center for the Security of Socio-Technical Systems (Fraunhofer SIRIOS) funded by the German federal government and the state of Berlin. We thank Hans Betke, Till Martini, and Stefan Pfennigschmidt for their input and feedback to this work.

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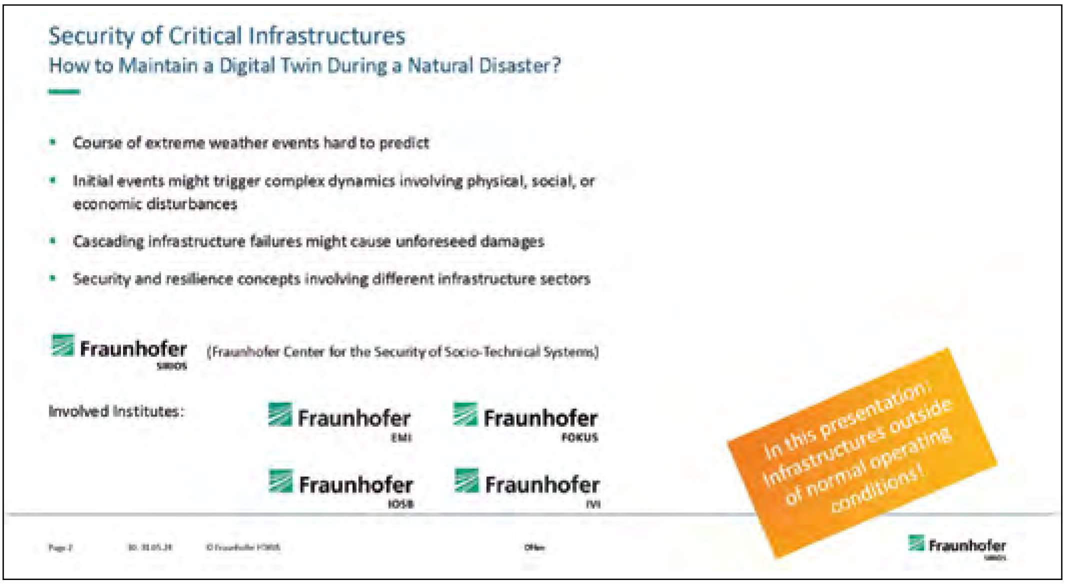

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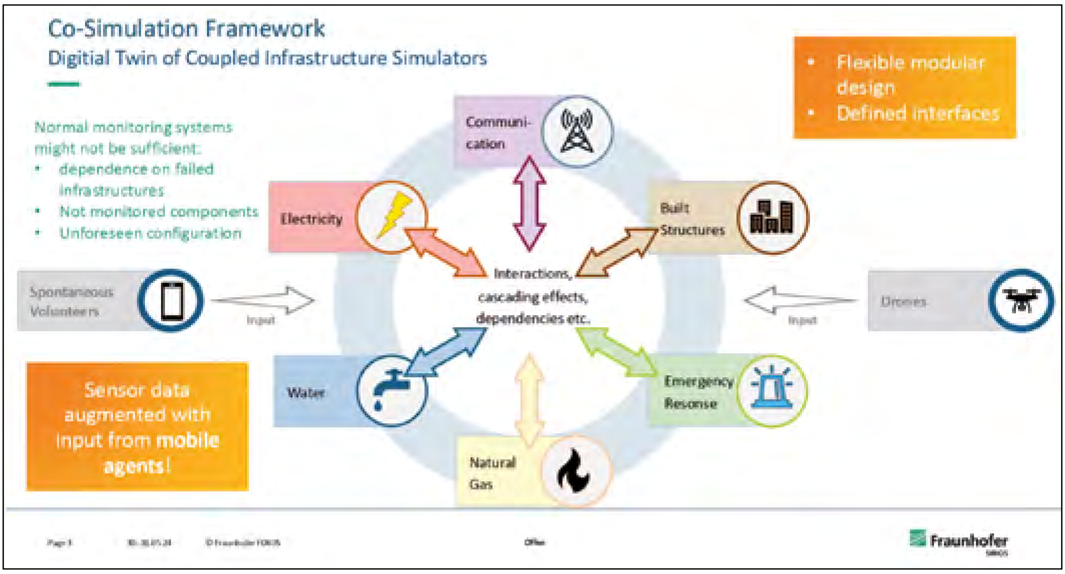

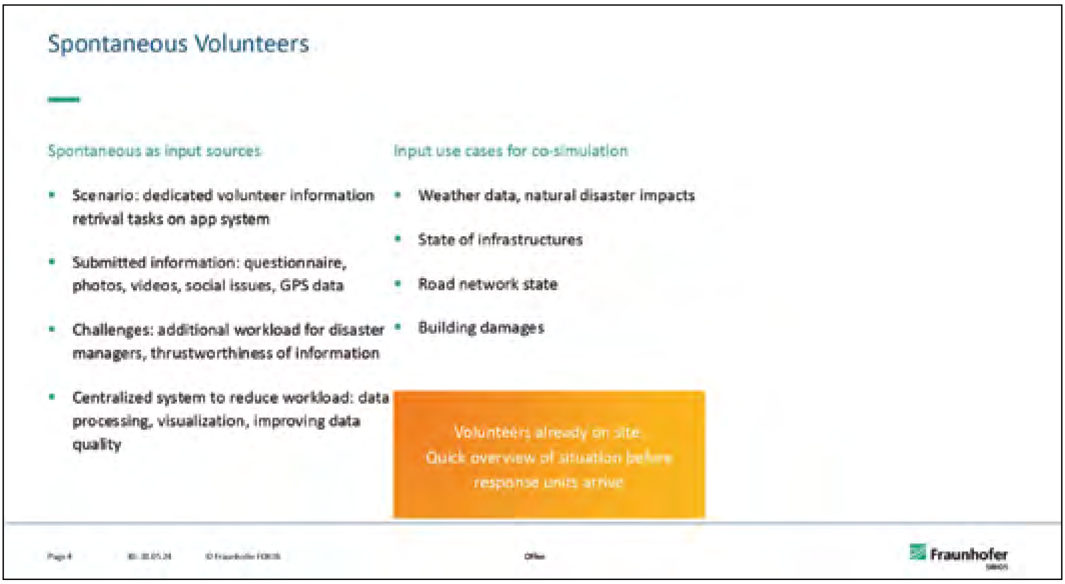

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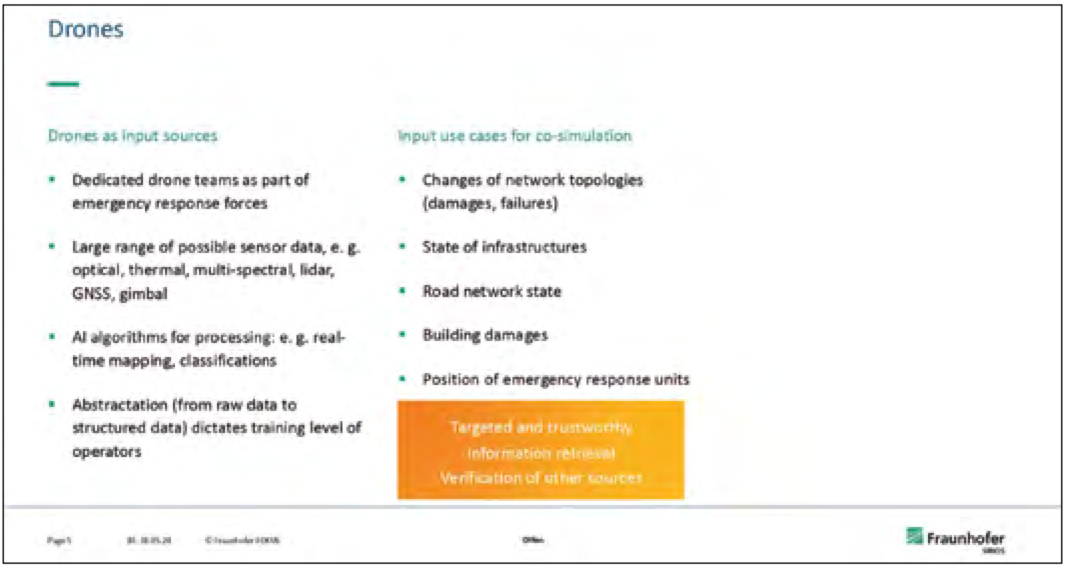

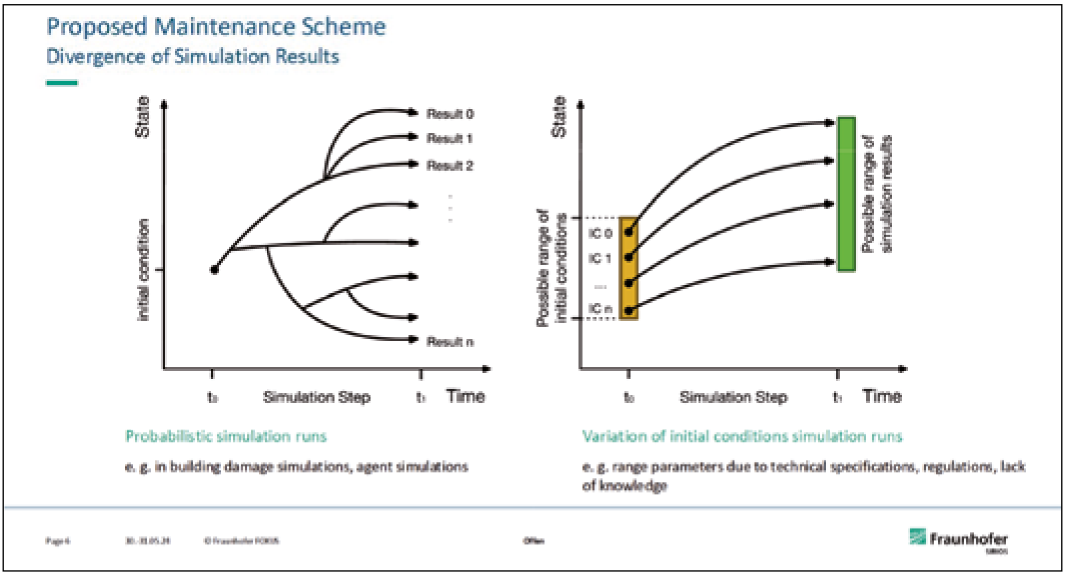

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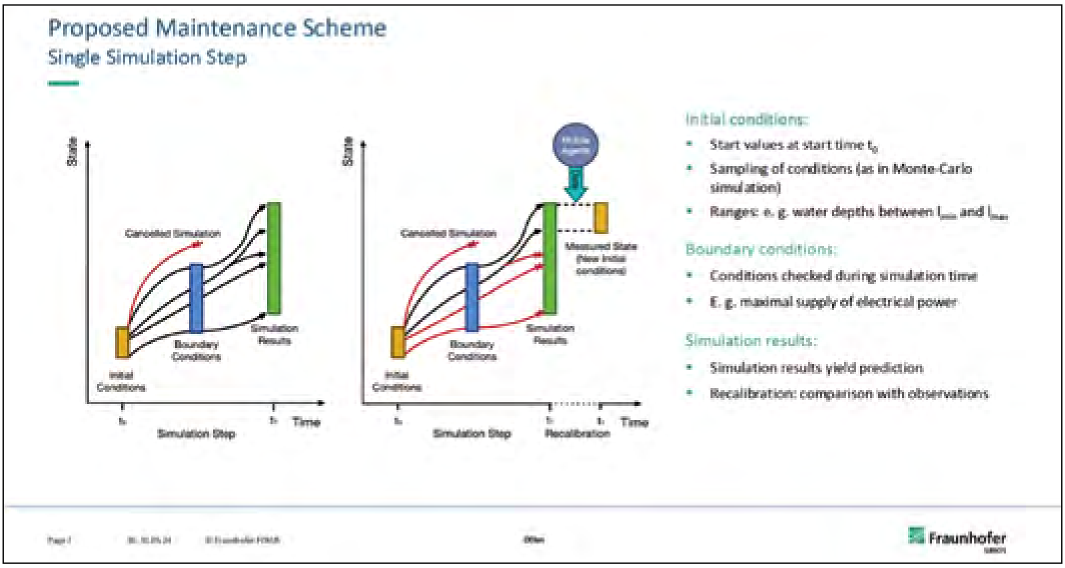
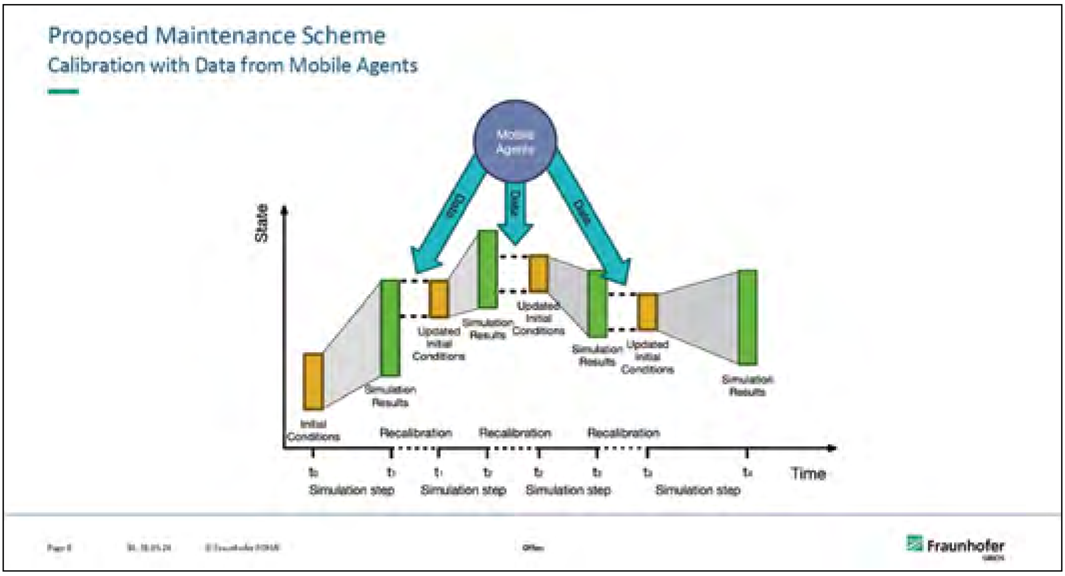
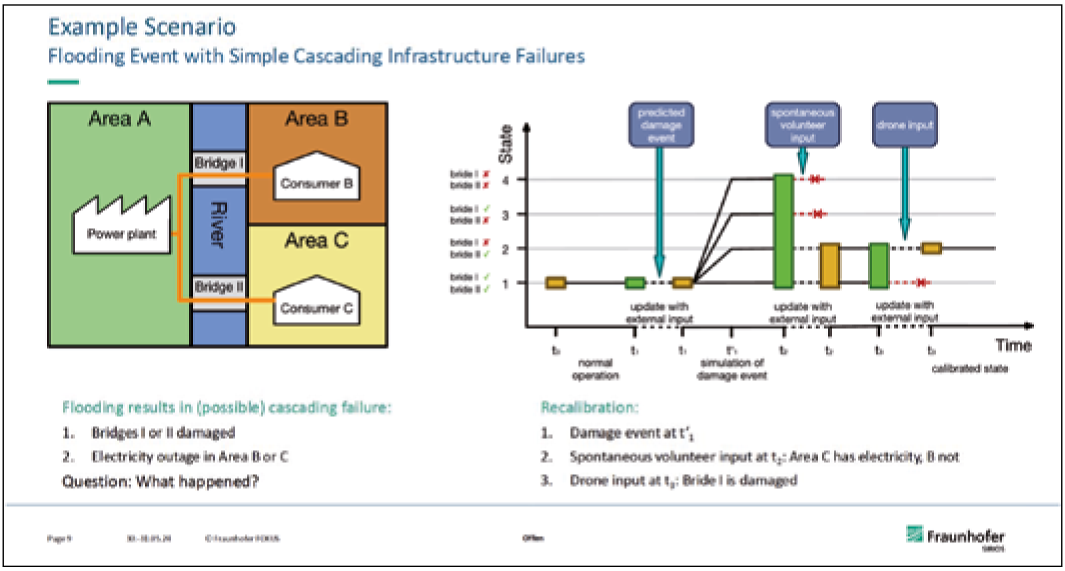

Proposed Maintenance Scheme
Single Simulation Step
State
Cancelled Simulation
Boundary Conditions
Simulation Results
Initial Conditions
Simulation Step
Time
Mobile Agents
Measured State (New Initial conditions)
Recalibration
Initial conditions:
Start values at start time t_0
Sampling of conditions (as in Monte-Carlo simulation)
Ranges: e. g. water depths between l_{min} and l_{max}
Boundary conditions:
Conditions checked during simulation time
E. g. maximal supply of electrical power
Simulation results:
Simulation results yield prediction
Recalibration: comparison with observations
Fraunhofer


Proposed Maintenance Scheme
Calibration with Data from Mobile Agents
Mobile Agents
Data
State
Initial Conditions
Simulation Results
Updated Initial Conditions
Recalibration
Simulation step
Time
Fraunhofer


Example Scenario
Flooding Event with Simple Cascading Infrastructure Failures
Area A
Area B
Area C
Bridge I
Bridge II
River
Power plant
Consumer B
Consumer C
predicted damage event
spontaneous volunteer input
drone input
State
Time
update with external input
update with external input
update with external input
normal operation
simulation of damage event
calibrated state
Flooding results in (possible) cascading failure:
1. Bridges I or II damaged
2. Electricity outage in Area B or C
Question: What happened?
Recalibration:
1. Damage event at t'1
2. Spontaneous volunteer input at t2: Area C has electricity, B not
3. Drone input at t3: Bride I is damaged
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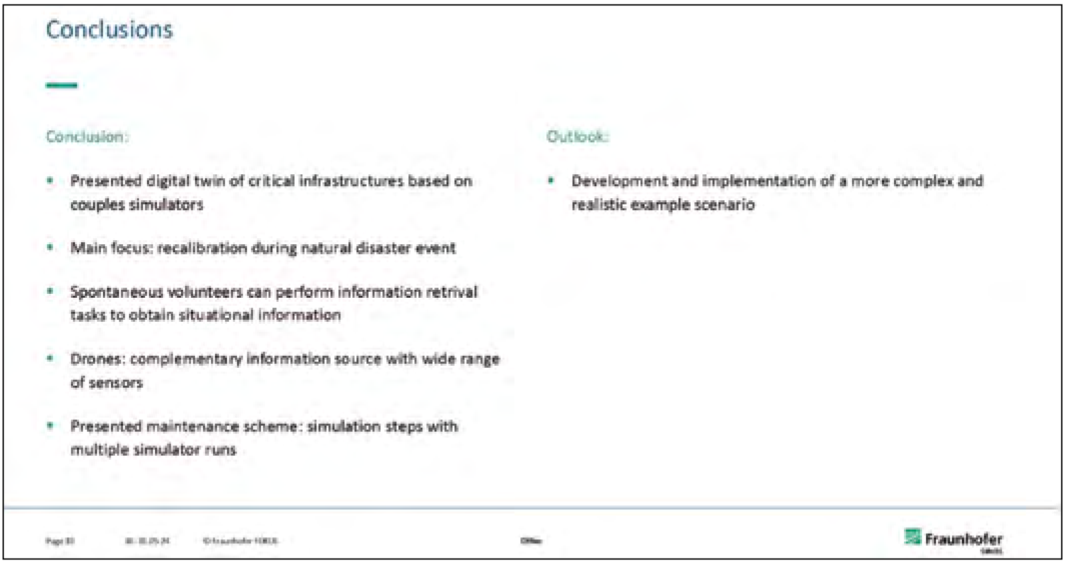
Conclusions
Conclusion:
Presented digital twin of critical infrastructures based on couples simulators
Main focus: recalibration during natural disaster event
Spontaneous volunteers can perform information retrival tasks to obtain situational information
Drones: complementary information source with wide range of sensors
Presented maintenance scheme: simulation steps with multiple simulator runs
Outlook:
Development and implementation of a more complex and realistic example scenario
Fraunhofer

Edge-Based AI for Online Health Monitoring of Critical Water Desalination Pumps: Aingura IIoT Applications in the Digital Twin Era

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Aingura IIoT

Abstract

In the dynamic landscape of digital maintenance during the Digital Twin Era, Aingura IIoT presents groundbreaking maintenance applications aimed at improving the reliability and efficiency of vital water desalination pumps. This presentation delves into a practical use case illustrating the application of Edge-based Artificial Intelligence (AI) for real-time online health monitoring. This technology enables early detection of potential issues, fostering predictive maintenance strategies. Moreover, it elevates overall system reliability, reduces downtime, and contributes to the sustainable operation of water desalination facilities. The presentation underscores the practical implementation of advanced AI algorithms at Edge devices, allowing instantaneous data analysis without the need for extensive data transfer to central servers. This not only minimizes latency but also optimizes bandwidth usage. Consequently, the seamless transfer of knowledge as valuable information can enhance the usability of digital twins without significant investment costs.

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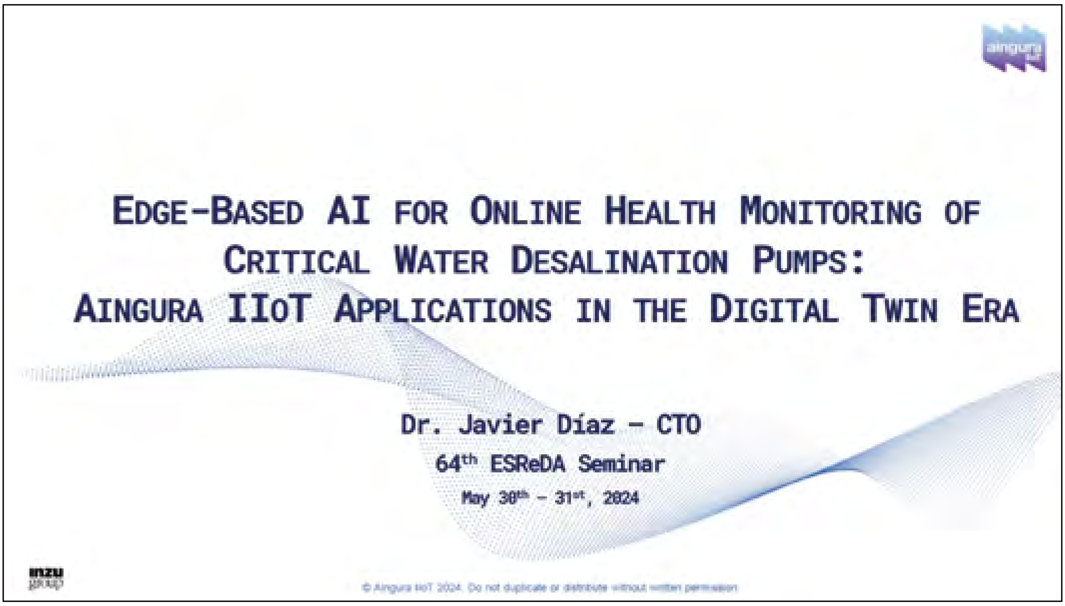

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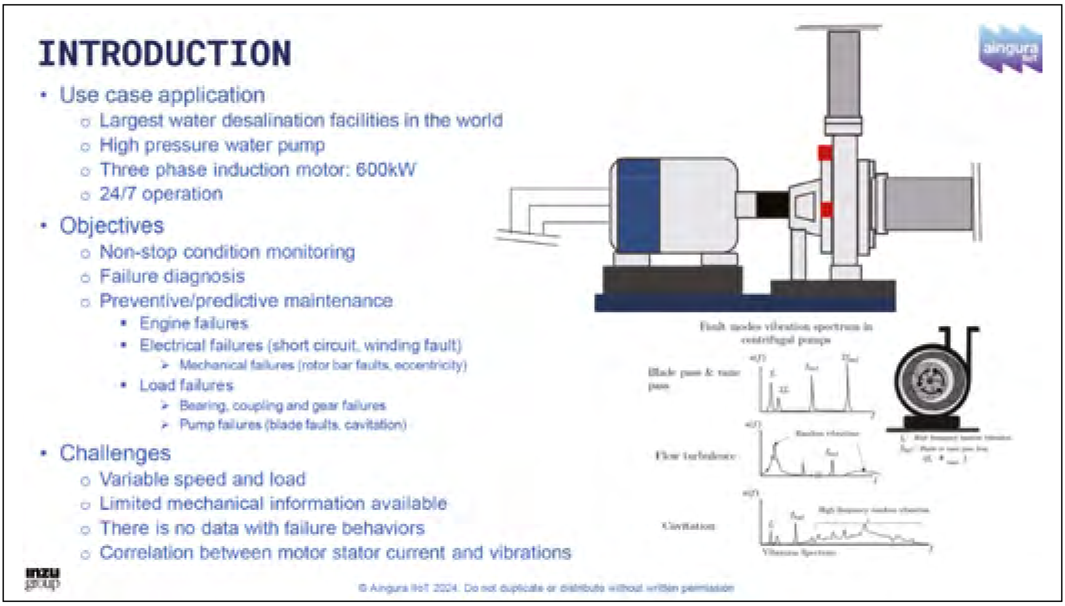

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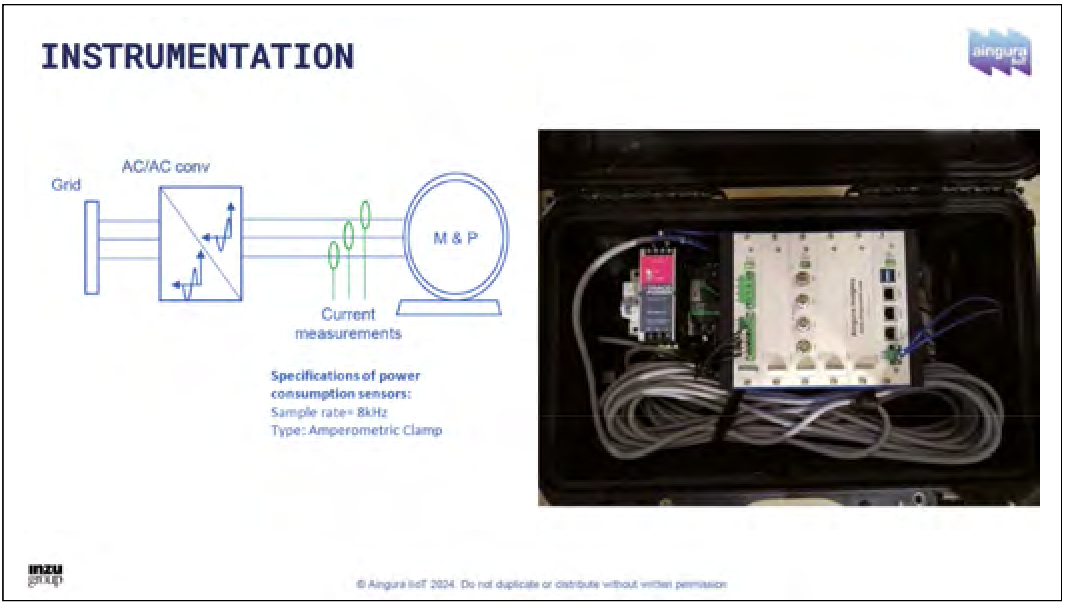

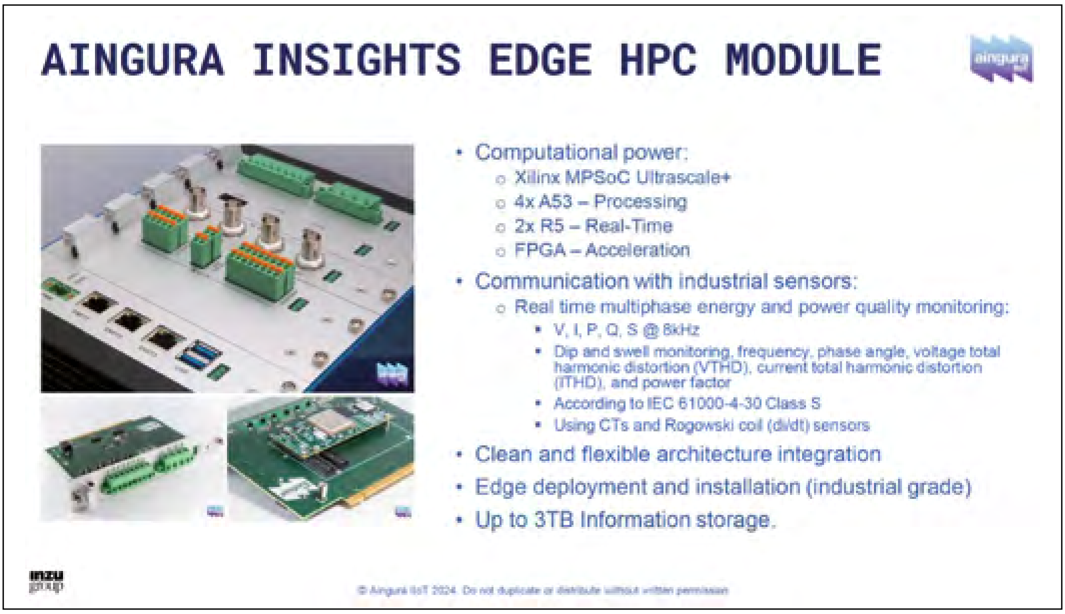

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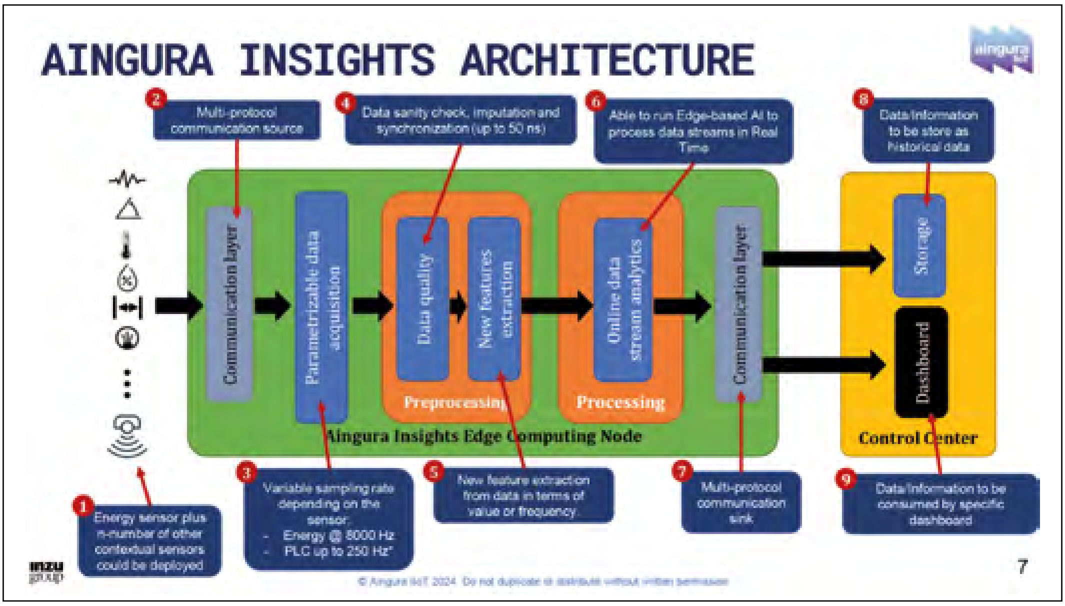

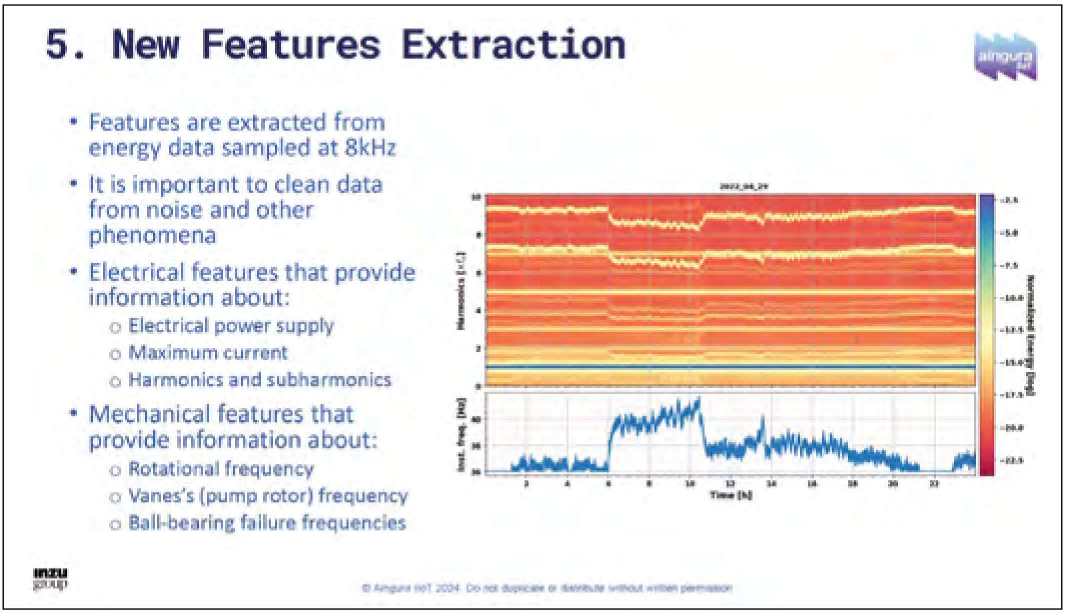

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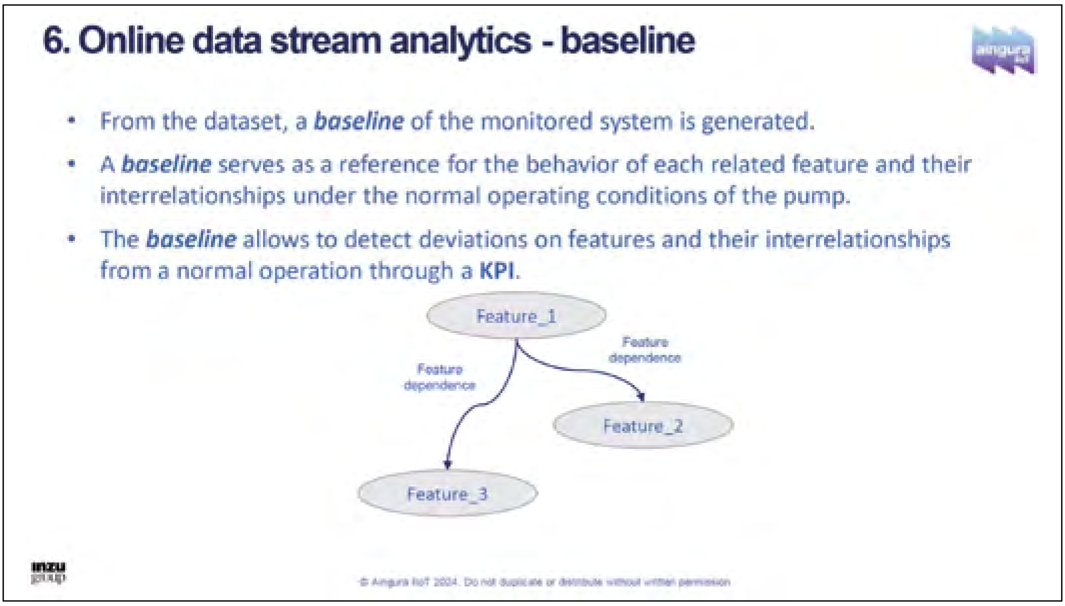
6. Online data stream analytics - baseline
• From the dataset, a *baseline* of the monitored system is generated.
• A *baseline* serves as a reference for the behavior of each related feature and their interrelationships under the normal operating conditions of the pump.
• The *baseline* allows to detect deviations on features and their interrelationships from a normal operation through a **KPI**.
Feature_1
Feature dependence
Feature dependence
Feature_2
Feature_3
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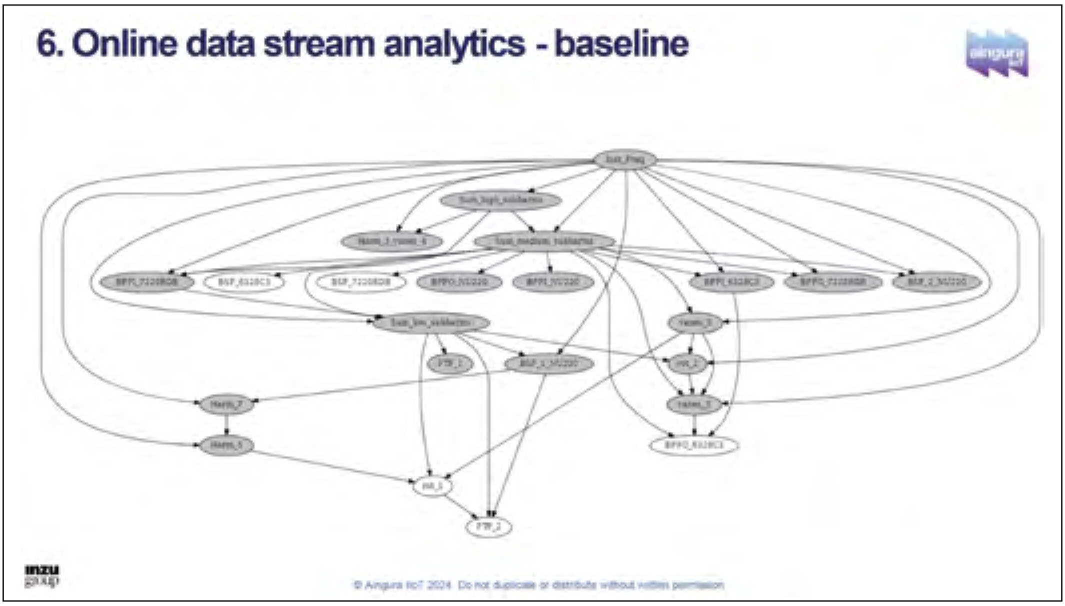
6. Online data stream analytics - baseline
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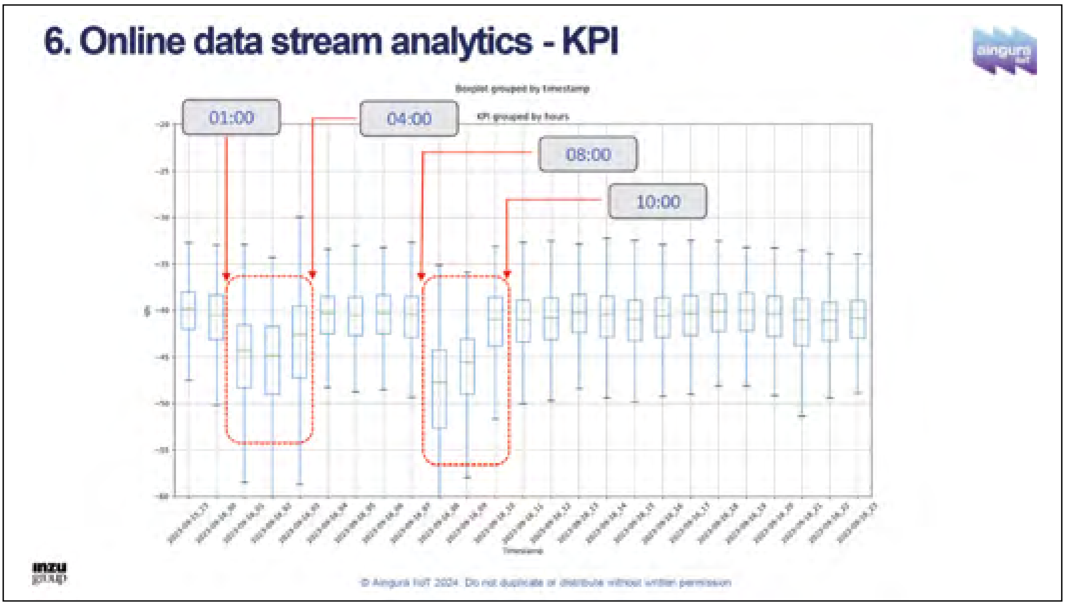
6. Online data stream analytics - KPI
Boxplot grouped by timestamp
KPI grouped by hours
01:00
04:00
08:00
10:00
Timestamp
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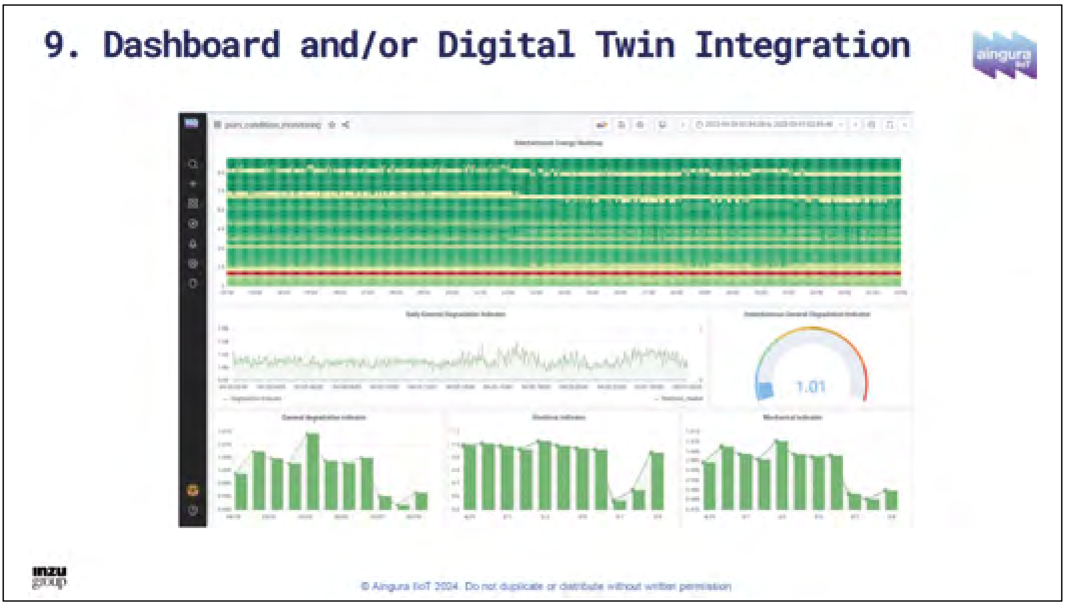
9. Dashboard and/or Digital Twin Integration
1.01
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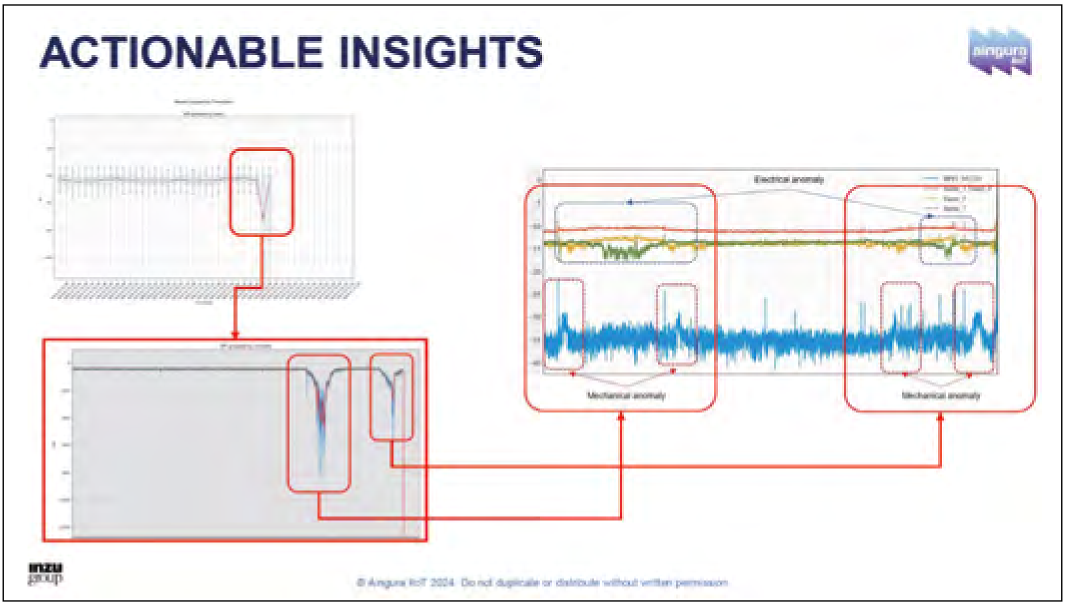

CONCLUSIONS

- The use of Edge-based Artificial Intelligence (AI) for real-time online health monitoring is demonstrated as a practical solution for early issue detection, facilitating predictive maintenance strategies.
- Implementation of this technology elevates overall system reliability, reduces downtime, and contributes to the sustainable operation of water desalination facilities, highlighting its significant impact on operational efficiency and cost-effectiveness.
- The integration of advanced AI algorithms directly into Edge devices enables instantaneous data analysis, minimizing latency and optimizing bandwidth usage. This approach streamlines the transfer of valuable information, enhancing the usability of digital twins without requiring substantial investment costs.

The consideration of the Human-Machine Interface in the Safety Management System of the process industry

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Abstract

The Seveso III Directive 2012/18/EU imposes an obligation to take into due consideration the human factors and the interfaces between operators, processes, and plants, as part of the implementation of the Safety Management System for the process industry. It is fundamental that in the risk analysis the human factor and the conditions in which significant activities for the safety of the establishment must be carried out. The national technical standard UNI 10616:2022 provides guidelines for implementing a safety management system, describing the procedures and technical tools useful for achieving specific objectives for the prevention of major accidents. In the standard, specific attention is paid to the human-machine interface, also considering the prevention and assessment of human error, as fundamental aspects of process safety management. A good, designed man-machine interface, in the control room of a process plant, allows you to minimize the possibility of operator error on the panel, both during normal operating conditions and during emergency situations. The prevention of human error cannot ignore the knowledge of the potential negative consequences deriving from non-compliance with system procedures. The assessment of the possibility of human error must be used in the reliability analysis to verify if the procedures and operational controls adopted to improve the behaviour of the operator or the instrumental controls give the best contribution to the safety of the system. In addition, a fundamental role is represented by training activities and emergency drills, which must be carried out according to a specific path that goes from design to critical analysis of results. In this way it will be possible to prepare any corrective actions, also in terms of response times and emergency management, to reduce the possibility of accidents related to human error. The consideration of the human factors and the interfaces between operators, processes, and plants, in the correct implementation of a safety management system must be based on: detecting any problems at the interfaces thanks to the feedback from both operators and maintenance technicians; monitoring the status of systems, through maintenance activities, and ensuring a good house-keeping; using proper labelling of equipment and alarm annunciators; improving the reliability of operators' performance; implementing an effective system of operational controls, that allows to prevent any human errors before they can cause accidents; the functionality of the operator/process and operator/equipment interfaces to monitor the process, identify any anomalies or emergency situations and implement the planned intervention procedures.

1. Introduction

The Seveso III Directive 2012/18/EU [1], implemented in Italy by a legislative decree issued in 2015 - D.Lgs. 105/2015 [2], is aimed at the prevention of major

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accidents involving dangerous substances. The D.Lgs. 105/2015 covers establishments where dangerous substances may be present (e.g. during processing or storage) in quantities exceeding certain thresholds. Operators of the establishments are obliged to take all necessary measures to prevent major accidents and to limit their consequences for human health and the environment.

Depending on the amount of dangerous substances present, establishments are categorised in lower and upper tier, with different obligations. The requirements include, among others: notification of all concerned establishments; deploying a Major Accident Prevention Policy (MAPP) through the implementation of a Safety Management System for Prevention of Major Accident (SMS-PMA); producing a Safety Report (SR) for upper-tier establishments; producing an Internal Emergency Plan (IEP) for upper tier establishments; providing information in case of accidents.

As part of the implementation of the Safety Management System, the D.Lgs. 105/2015 imposes an obligation to take into due consideration the human factors and the interfaces between operators, processes, and plants.

During the control activities it is in fact necessary to verify that training programs and emergency drills are implemented to improve operator behaviour. It is therefore fundamental that in the risk analysis the human factor and the conditions in which significant activities for the safety of the establishment must be carried out, giving a particular attention to the interfaces between operators and processes in the phase of operational control of the plants.

2. **The control activities: human factors and HMI**

2.1. *Human factors in the control activities*

In Italy, the SMS inspections are conducted to verify the suitability of the operator MAPP carrying out a planned and systematic examination of the systems being employed at the establishment, whether of a technical, organisational or managerial nature.

The human factors and the interfaces between operators, processes, and plants are specific items of interest during the SMS control activity [3]. In fact, the commission must:

— Verify that training and drill programs exist and are implemented to improve the behaviour of the operator.
— Verify that the work shifts, and the distribution of tasks have been established considering the psycho-physical stress to which the workers are subjected and that mechanisms are put in place to verify that the appropriate psycho-physical conditions are maintained.

Among the tools available to the inspection commission during the documentary verification, it is possible to verify directly, also by consulting the documentation relating to the health and safety at work analysis, the compliance with the indications relating to the maintenance suitable psycho-physical conditions of the workers.

During the "on-site" visit, the possible insights concern interviews with the employees both on the management methods of ordinary and extraordinary management, maintenance, emergency interventions, and on their involvement in the drafting and/or revision of the operating instructions.

2.2. *The consideration of the HMI and the human error*

The national technical standard UNI 10616:2022 (Establishments with major-accident hazard-Safety management systems-Guidelines on implementation of UNI 10617) [4] provides guidelines for implementing a safety management system, describing the procedures and technical tools useful for achieving specific objectives for the prevention of major accidents in industrial establishments (national technical standard UNI 10617:2019) [5].

It deals with most of the hazards and major accident risks present both in simple installations and in more complex installations where the process risks can be preponderant compared to those connected to the simple loss of containment. The application of the contents of the standard must be commensurate with the specificities of the major accident hazards present in the establishment.

In the standard, specific attention is paid to the human-machine interface (HMI), meaning the system that separates the operator, who is using a machine (i.e. the control panel located in the control room in the case of the process industry), from the machine itself, while ensuring a constant connection.

Among the objectives for the continuous improvement of the SMS-PMA, which arise from the results of the identification of the hazards and the assessment of the risks of a major accident, the improvement of the quality of the interface between the operator and the plant/process can also be included (i.e. promptness, accuracy and punctuality in reporting anomalies).

In close connection with the HMI, it is considered the prevention and assessment of human error, a fundamental aspect of process safety management.

To strengthen and disseminate the culture of safety, the site manager should also operate through the implementation of a company policy which clearly and transparently identifies the criteria for distinguishing acceptable behaviour from that which cannot be considered as such, distinguishing situations involving intentional misconduct from human errors attributable to organizational causes.

The awareness of the people who carry out a work activity in the plant, involved in activities relevant to safety, can in fact be verified through knowledge of the potential negative consequences deriving from a failure to comply with the specified procedures, with consequent human error, and the possibility of even a major accident. The need to verify the system procedures, on the other hand, may derive from the possible analysis of the accidents and/or near misses connected to the ascertained human error.

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3. **Design and schemes to prevent human error**

3.1. *Design of the man-machine interface*

The functionality of the interfaces between operators, process and systems, consisting of the instrumentation located in the control room with related switchboards/monitors/buttons/optical and acoustic signalling panels, including wireless devices, must be ensured through the periodic check program of the active safety systems, consisting of toxic and/or flammable gas detectors, fire detectors, alarms and blocks for critical operating parameters. The displays must report process variables, alarms, automatic blocks, recordings, as well as actuators for control actions on the process, such as starting/stopping pumps and compressors, opening/closing valves, changing the regulation and operating parameters set.

The main functions of an interface are:

— Presentation of process information.
— Immediate implementation of control actions.
— Support for diagnosis, decision making or planning.

Important elements of an interface are usability, to make the HMI easy to use (reducing the possibility of errors), and accessibility by the panel operator. A correct design of the control, alarm and automatic blocking systems must consider the analysis of the operator's tasks at the switchboard and the optimal ergonomic and specific environmental factors for correct operation of the systems and plants.

A good, designed man-machine interface, in the control room of a process plant, allows you to minimize the possibility of operator error on the panel, both during normal operating conditions and during emergency situations, throughout the process life cycle and in case of plant or process changes. These interfaces must be considered throughout the life cycle of the process and during plant or process changes.

Control provisions must in fact be adopted to manage any modifications/changes made, in conditions of necessity and under specific responsibility, to the switchboards or control equipment. Obviously, these changes must not reduce the ergonomic design characteristics as well as they must consider other project requirements, such as accessibility for maintenance or periodic checks.

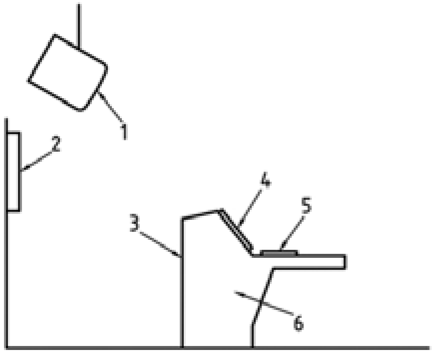
3.2. *Practical schemes of control rooms*

To represent some practical examples of control room [6], with the relative representation of process parameters and data on the screen of a DCS (Distributed Control System), the case of a typical process industry was investigated.

In the following, schemes of correct design and distribution of spaces in a control room, with the relative minimum requirements are presented [7]:

Figure 1

Illustrations of definitions associated with workstation visual display



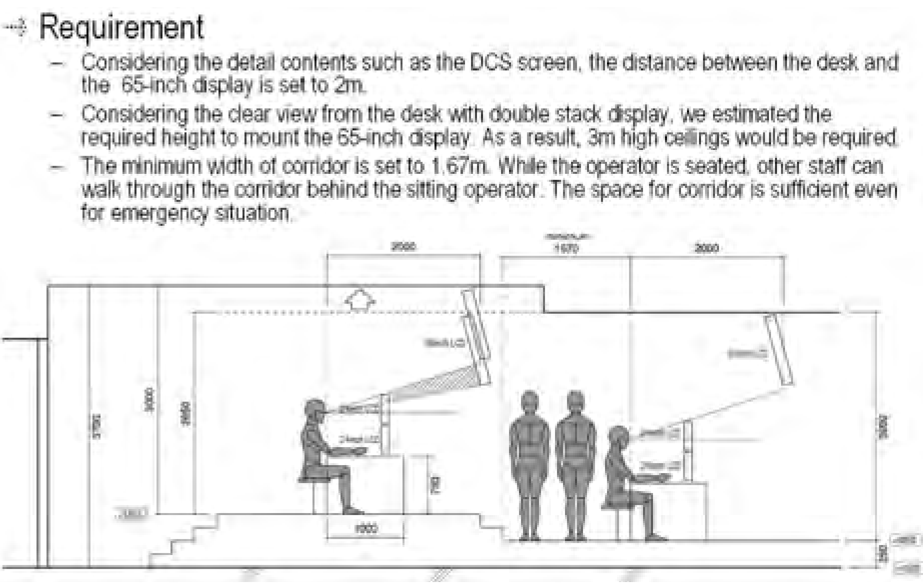
Key

1 Off-workstation visual display
2 Wall-mounted control panel
3 Control console
4 Visualdisplay
5 Control panel
6 Control workstation
(consists of 3, 4, and 5)

Source: T. Naito *et al*., 2011.

Figure 2

Visibility of large screens and the widths of corridors



Source: T. Naito *et al*., 2011.

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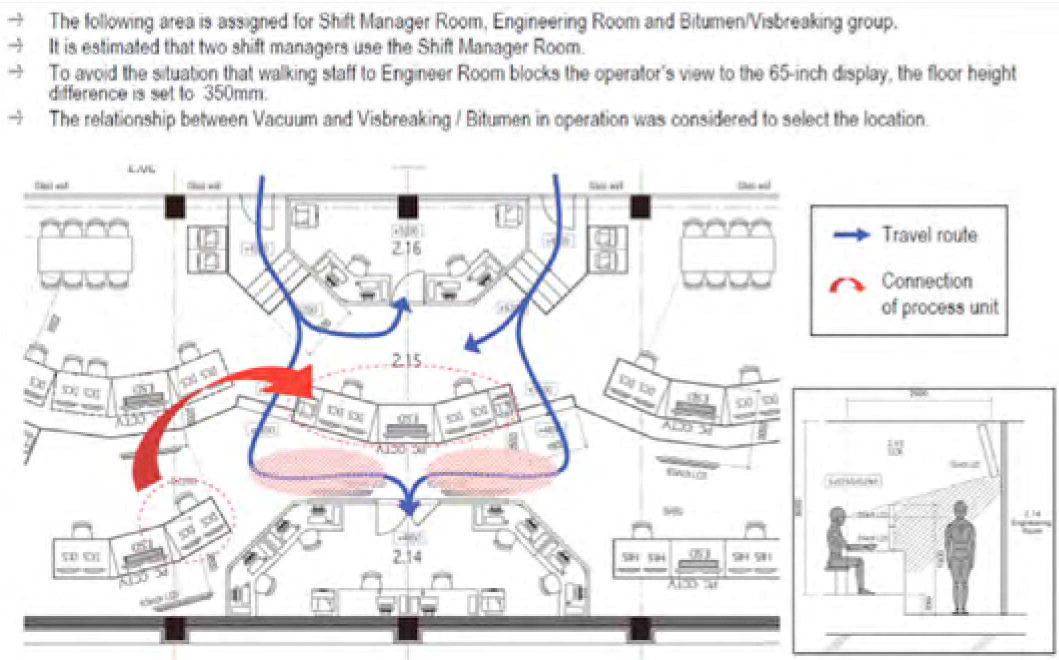
Figure 3

Travel routes and collaborative operation among units



Source: T. Naito *et al.*, 2011.

The key points for the adequate representation of data and information on a screen, in order to improve the man-machine graphic interfaces [8], are:

Figure 4

Colour graphic representation

Source: R. Kowalski *et al.*, 2017.

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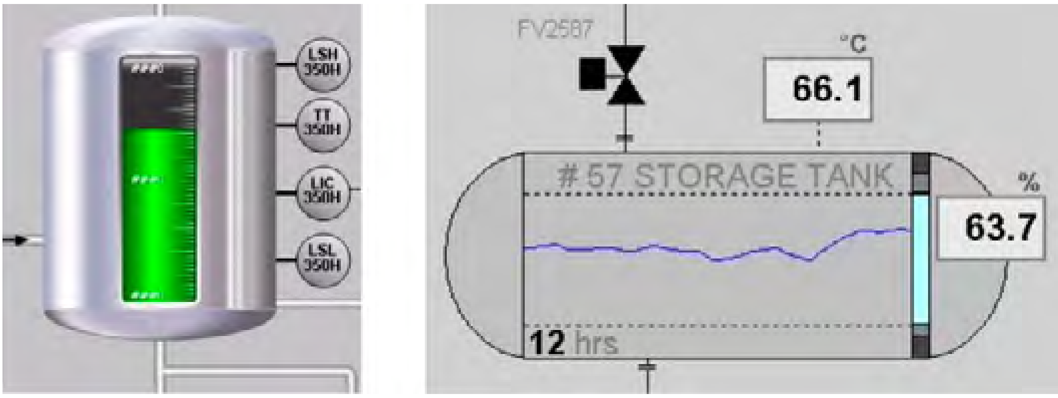
Figure 5

Device status display

Source: R. Kowalski *et al*., 2017.

Figure 6

Representation of data values

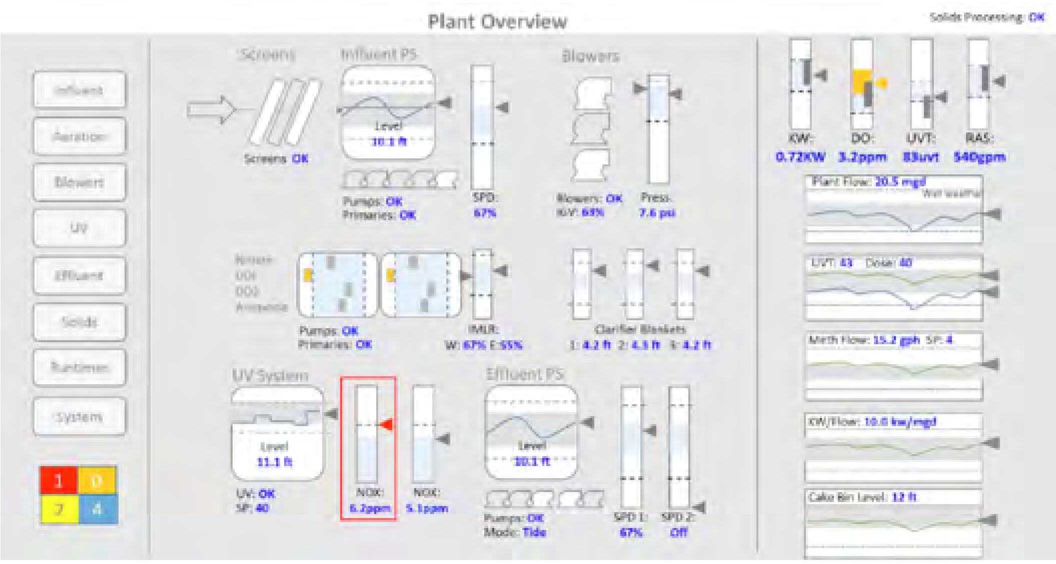


Source: R. Kowalski *et al*., 2017.

Typical examples of control panels are finally given in the following, as taken from the DCS (Distributed Control System) in the control room [9]:

Figure 7

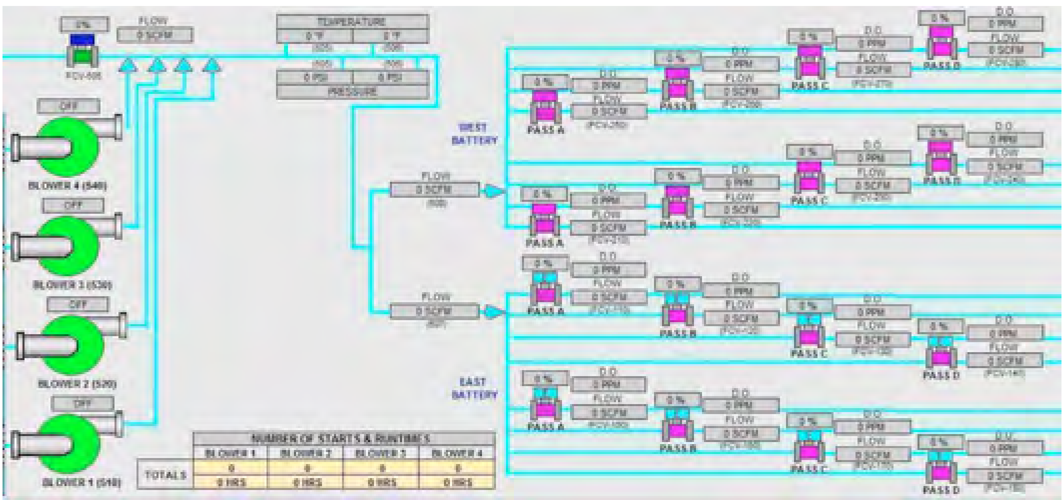
Plant overview



Source: ANSI/ISA, 2015.

Figure 8

Process Air Unit Process



Source: ANSI/ISA, 2015.

3.3. *The prevention of the human error in a process plant*

The prevention of human error cannot ignore the knowledge of the potential negative consequences deriving from non-compliance with system procedures, with the possibility of a major accident. The assessment of the possibility of human error must be used in the reliability analysis to verify if the procedures and operational controls adopted to improve the behaviour of the operator or the instrumental controls give the best contribution to the safety of the system.

The management by the workers of operating anomalies and/or emergency situations must be verified both in the actual conditions of occurrence of the events and in the simulations, in order to highlight any deficiencies connected to the human factor. The analysis of non-conformities relating to procedures, regulations, operating instructions, detected as a result of inspections and/or accidents/near-accidents, generally linked to human error, can highlight deficiencies related to the behaviour of people, the organization and the work environment. Such deficiencies must be subject to appropriate corrective actions.

Emergency drills are an important element of evaluation. They must be carried out according to a specific path that goes from planning to the critical analysis of the results, in order to prepare any corrective actions, also in terms of response times and emergency management of the operators in order to reduce the possibility of accidents related to human error.

4. **The consideration of the human factor in the SMS**

Based on the experience coming from the control activities conducted on some Seveso Italian establishments, in the following the discussion about examples and indications of particular or recurring situations are given about the consideration of the human factor in the SMS.

The inspections must mainly be aimed at evaluating how much the company policy, and therefore the management system, require that human factors are taken into consideration in the conduct of the plant's activities, identifying any deficiencies. The aspects that must be taken into consideration are the organizational elements, the policy and standards followed in the design and modification phases of the plants, the operating conditions, including problems related to process management, and the working environments.

As regards the design phases of new processes or operating systems, it must be evident that the company policy or the standards adopted foresee the consideration of human factors. Indicative of the fact that human factors have been considered is, for example, the evidence of the analysis of the aspects related to the spaces available to the operators, the accessibility of the equipment, the correct construction and location of the control panels and the use of prototypes and pilot plants also for the analysis and revision of the operator-plant interface.

At an operational level, information on work shifts must be acquired, for example by verifying that the available resources are distributed in a homogeneous manner, or in any case congruent with the workload, that the responsibilities have been clearly identified and are commensurate with the experience and ability of the employee to identify the cause of an error which may also cause a major accident. In fact, it must be considered that stress and fatigue can be the result of incorrect personnel management. To identify a possible deficiency in this sense, one could, for example, analyse the criteria for allocating resources within the various operational areas, verifying whether both the physical and aptitude characteristics and the degree of experience, which must be possessed by the person responsible for the critical tasks of the plant, have been specified.

With regard to the operating procedures available to operators, the main aspects to consider are that these are clear and complete, written in a language that operators can understand, that their involvement in drafting and revision has been envisaged and, most importantly, that these procedures provide employees with all the elements that enable them to identify and manage unforeseen situations.

It should be remembered that the conditions of the working environment (lighting, temperature, exposure to noise, vibrations or chemical agents, etc.) also play a fundamental role in the employee's ability to interact with the systems and equipment. In this regard, it will be important to verify not so much that the values of these parameters are compatible with the activity carried out, but rather that national and international standards have been considered in the organization of the activity for the definition of optimal conditions in the workplace, providing, in the procedures, the analyses to establish what are the levels that allow to guarantee efficiency and safety. Finally, it should be considered that the system must provide for the periodic measurement of these parameters, to verify that the pre-established limits are respected, adopting compensatory measures in case it is not possible to respect the limit.

5. Conclusions

The consideration of the human factors and the interfaces between operators, processes, and plants, in the correct implementation of a safety management system must be based on:

- The detection of any problems at the interfaces, thanks to the feedback information coming from both the operators and the maintenance technicians.
- Monitoring the status of equipment and systems. It is important that equipment is visually inspected throughout the work shift. Reading the instruments placed on the equipment makes it possible to verify the reliability of the parameters reported by the remote-control systems in the control room. Furthermore, only through visual inspections anomalous situations can be promptly identified. The information found must be recorded on special checklists which must be reviewed on a periodic basis by the supervisors so that what is reported is consistent with other data and that any anomalous situations are promptly resolved. In addition, it is good practice to have equipment checks integrated with normal operations.
- An adequate maintenance of work tools and equipment, including maintaining good conditions of cleanliness and order in the workplace (s.c. housekeeping).

— The use of correct labelling and signalling of containers, pipes, equipment, etc., also through appropriate color codes, to allow immediate knowledge of the risks and the identification of systems and components. Of specific importance, for example, are the methods for signalling automatic blocks to the switchboard, especially in the event of a bypass due to contingent plant requirements, with the relative operating management procedure.
— The maintenance of good lighting conditions, essential for identifying the equipment, reading the instruments and identifying possible problems.
— The improvement of the reliability of the operators' performances. Particular attention should be paid to the procedures for handing over deliveries between shift managers and/or switchboard operators during shift changes in the plant and in the control room, keeping adequate traces in the system documentation.
— The implementation of an effective system of operational controls based on procedures, permits, inspections, etc., that allows to prevent or promptly identify any human errors before they cause accidents.
— The functionality of the operator/process and operator/equipment interfaces to make it easier for the operator to monitor the process, identify any anomalies or emergency situations and implement the foreseen intervention methods. Consider, for example, the problem of managing a maximum number of alarms on screen in the event of a generalized emergency, or the problem of assessing reliability/redundancy for critical alarms (in the event of a power failure).

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[8] https://boomtsps.medium.com (20/03/2023).
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The consideration of the Human-Machine Interface in the Safety Management System of the process industry
64th ESReDA Seminar. Digital maintenance in the digital twin era
29 – 31 May 2024
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Servizio Rischi e Sostenibilità Ambientale delle Tecnologie, delle Sostanze Chimiche, dei Processi Produttivi e dei Servizi Idrici e per le Ispezioni (VAL-RTEC)
ISPRA - Istituto Superiore per la Protezione e la Ricerca Ambientale


The role of ISPRA for industrial control
ISPRA has a national role as a technical body supporting the Ministry of Environment in the national implementing of the Seveso Directives for the prevention of major accidents
• Definition of technical contents of laws and decrees to control Major Accidents
• Set-up of the National Inventory of major accident hazards establishments and other related data-bases
• Inspections of upper-tier establishments SMS-PMA on regular basis or after an accident
• Support for international activities (EU, OECD, bilateral cooperation)
• Technical coordination and addressing of Regional Agencies for the Protection of Environment (ARPA)
• Collaboration with other Authorities competent for industrial risk (Ministry of home affairs – National Fire Brigades; Department of civil protection; Ministry of infrastructures)
2
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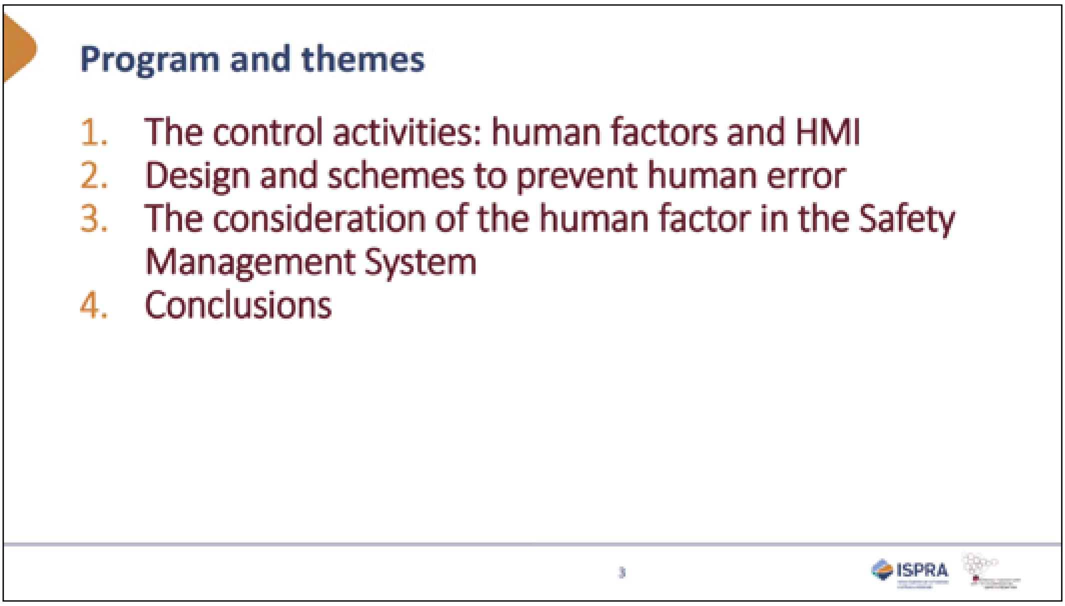

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1. The control activities: human factors and HMI

HMI in the Seveso directive

The SMS imposes taking into due consideration the human factors and the interfaces between operators, processes, and plants

In the risk analysis, particular attention must be given to the human factor and the conditions in which safety activities must be carried out

During the control activities, it is necessary to verify that training programs and emergency drills are implemented to improve operator behavior

5

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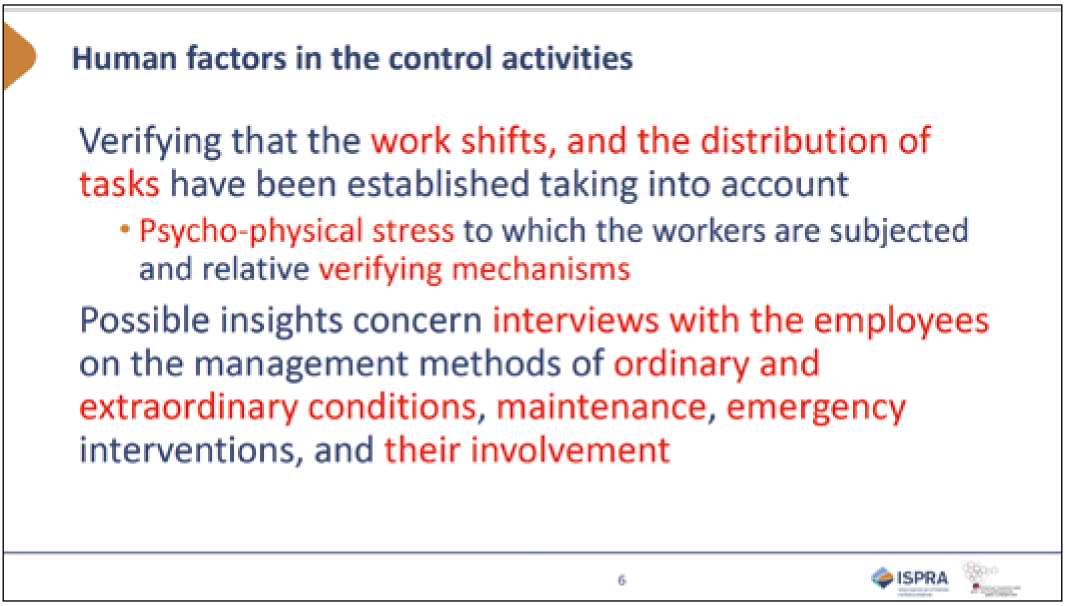

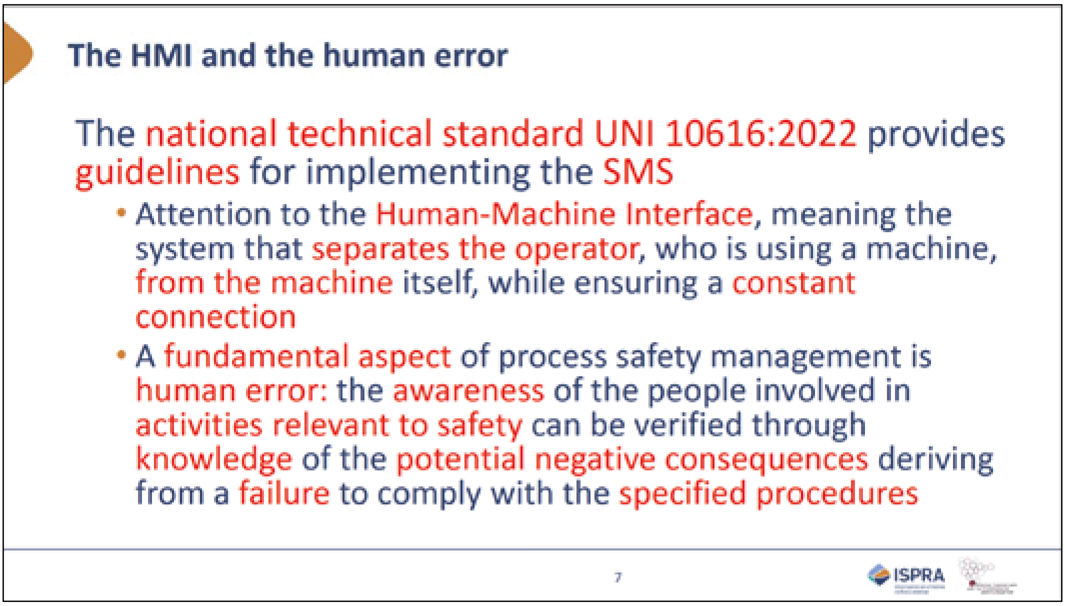

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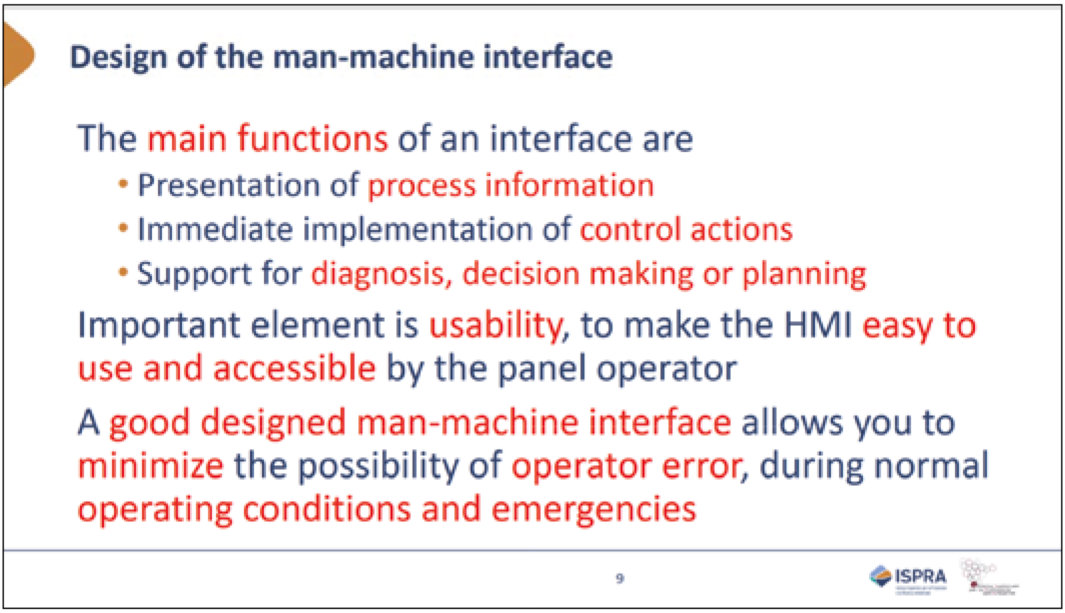
2. Design and schemes to prevent human error


Design of the man-machine interface
The main functions of an interface are
• Presentation of process information
• Immediate implementation of control actions
• Support for diagnosis, decision making or planning
Important element is usability, to make the HMI easy to use and accessible by the panel operator
A good designed man-machine interface allows you to minimize the possibility of operator error, during normal operating conditions and emergencies
9
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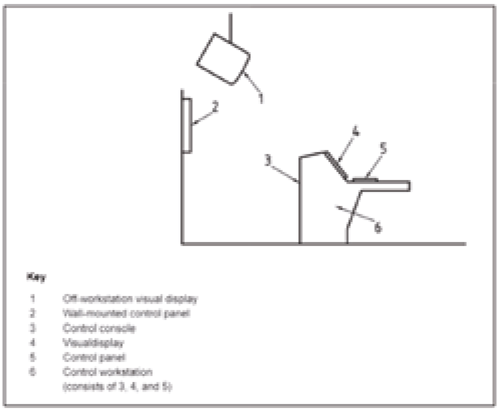
Workstation visual display

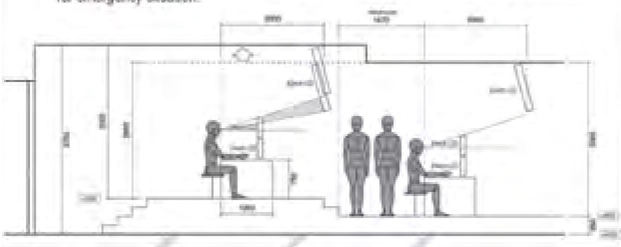


10

Large screens and corridors

→ Requirement

- Considering the detail contents such as the DCS screen, the distance between the desk and the 65-inch display is set to 2m.
- Considering the clear view from the desk with double stack display, we estimated the required height to mount the 65-inch display. As a result, 3m high ceilings would be required.
- The minimum width of corridor is set to 1.67m. While the operator is seated, other staff can walk through the corridor behind the sitting operator. The space for corridor is sufficient even for emergency situation.



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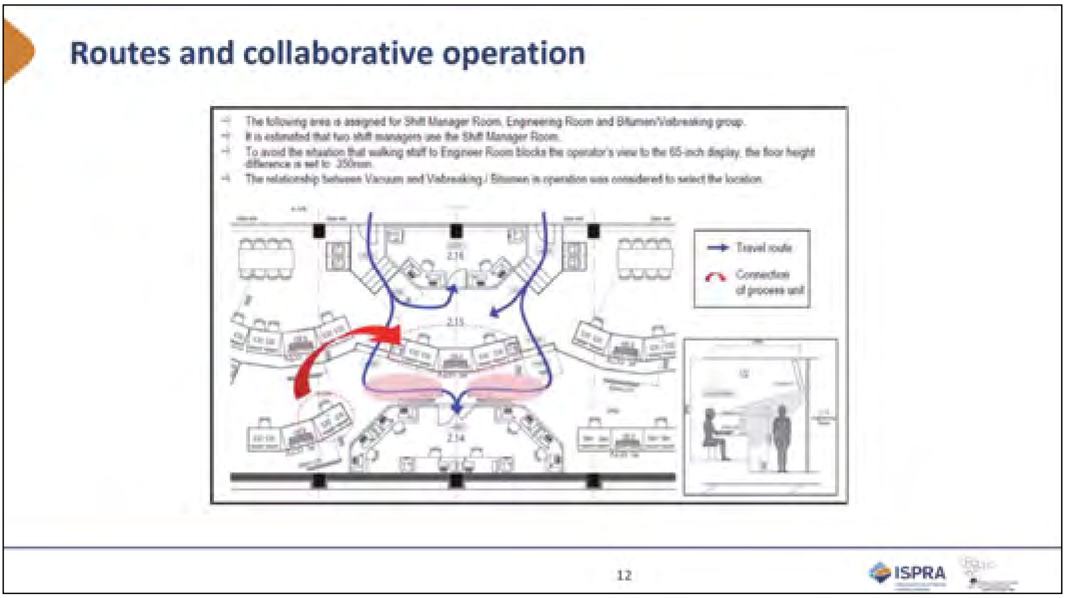
Routes and collaborative operation
The following area is assigned for Shift Manager Room, Engineering Room and Bitumen/Visbreaking group.
It is estimated that two shift managers use the Shift Manager Room.
To avoid the situation that walking staff to Engineer Room blocks the operator's view to the 65-inch display, the floor height difference is set to 350mm.
The relationship between Vacuum and Visbreaking / Bitumen in operation was considered to select the location.
Travel route
Connection of process unit
12
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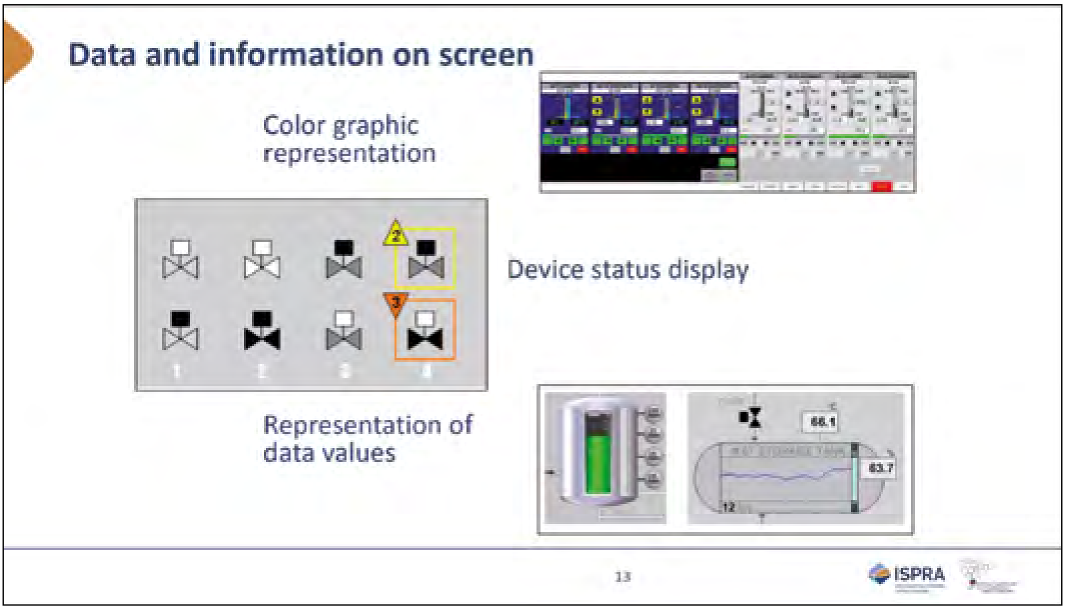
Data and information on screen
Color graphic representation
Device status display
Representation of data values
66.1
63.7
13
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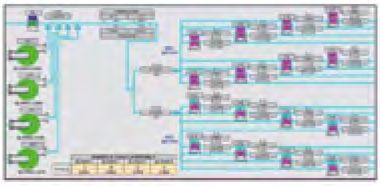
Control panels on DCS

Plant overview



Process Air Unit

14

The prevention of the human error

The assessment of human error must be used in the reliability analysis to verify if the procedures give the best contribution to the safety of system

The analysis of non-conformities, generally linked to human error, can highlight deficiencies related to the behavior of people and the work environment

Emergency drills must be carried out according to a path that goes from planning to the critical analysis of the results, to prepare any corrective actions

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3. The consideration of the human factor in the Safety Management System

The human factor in the SMS

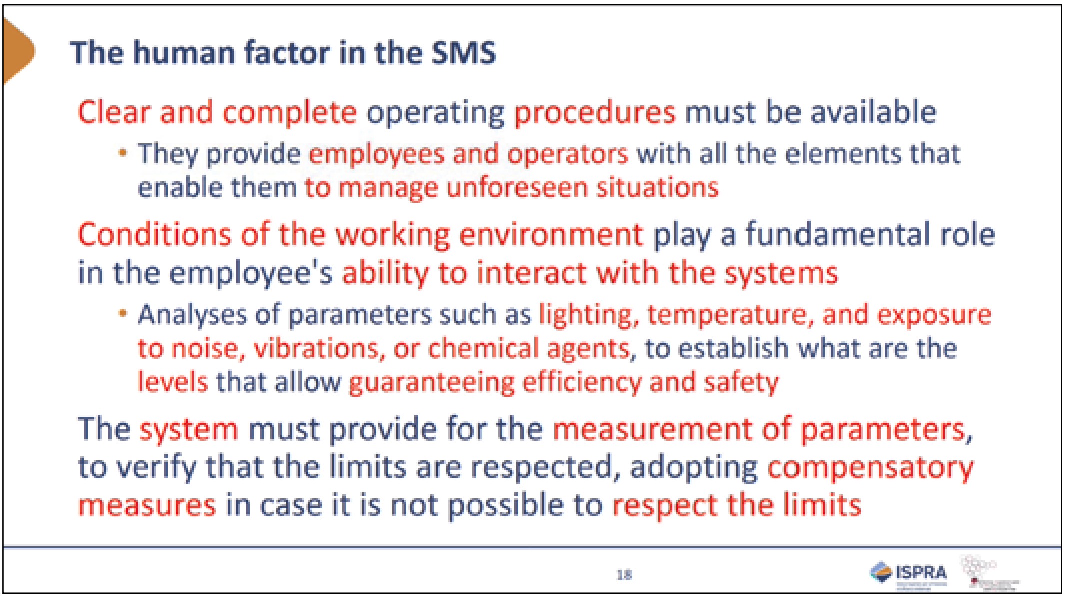
The inspections must evaluate how much the company policy requires that human factors are taken into consideration in the plant's activities

- Spaces available to the operators, accessibility of the equipment, location of the control panels

Work shifts must be distributed in a homogeneous manner and congruent with the workload

- Responsibilities have been clearly identified and are commensurate with the experience and ability of the employee to identify the cause of an error
- Stress can be the result of incorrect personnel management

17


The human factor in the SMS
Clear and complete operating procedures must be available
They provide employees and operators with all the elements that enable them to manage unforeseen situations
Conditions of the working environment play a fundamental role in the employee's ability to interact with the systems
Analyses of parameters such as lighting, temperature, and exposure to noise, vibrations, or chemical agents, to establish what are the levels that allow guaranteeing efficiency and safety
The system must provide for the measurement of parameters, to verify that the limits are respected, adopting compensatory measures in case it is not possible to respect the limits
18
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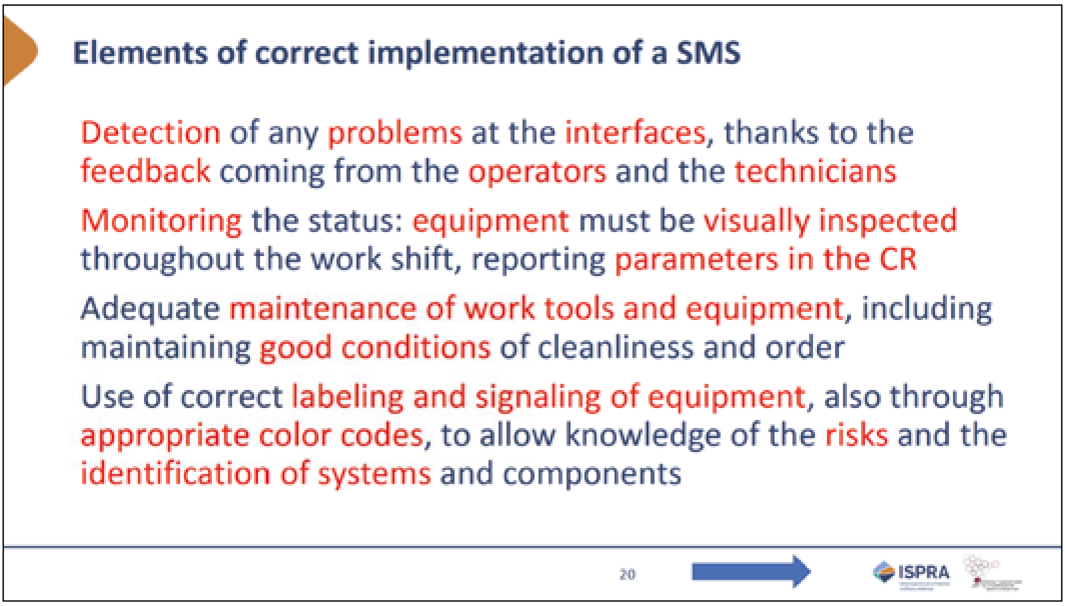
4. Conclusions


Elements of correct implementation of a SMS
Detection of any problems at the interfaces, thanks to the feedback coming from the operators and the technicians
Monitoring the status: equipment must be visually inspected throughout the work shift, reporting parameters in the CR
Adequate maintenance of work tools and equipment, including maintaining good conditions of cleanliness and order
Use of correct labeling and signaling of equipment, also through appropriate color codes, to allow knowledge of the risks and the identification of systems and components
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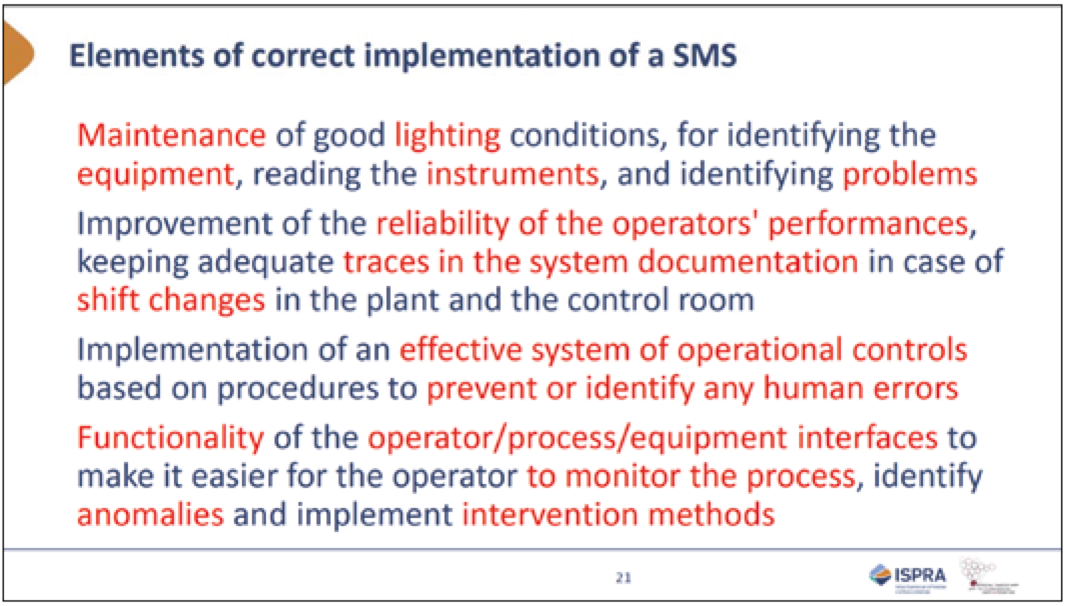

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Artificial Intelligence as a driver for Prescriptive Maintenance: Limitations

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Abstract

The primary objective of this paper is to comprehensively examine the existing obstacles hindering the expansion of prescriptive maintenance. To achieve this goal, we first conduct a literature review to compile a list of these identified barriers. Subsequently, we launch an initiative to uncover the sequences of barriers or complex interactions between them. This approach is crucial because when addressing individual barriers in isolation, the effectiveness of measures can be limited, given the potential for unexpected interactions with other interconnected barriers. In conclusion, we introduce a proposal that presents a visual, continuous sequence of distinct tasks aimed at guiding the journey toward the desired outcome. Our aim is to broaden the perspective of decision-makers, particularly those in small and medium-sized companies operating in non-cutting-edge technological sectors.

1. Introduction

The global economy has undergone significant changes due to the combined forces of globalization and technological development. Consequently, supply chain management (SCM) for companies has evolved into a complex process. Presently, it is common to observe companies operating in one part of the world while having manufacturing facilities scattered across the globe. Technology plays a pivotal role in manufacturing and supply chain processes, minimizing the time gap for information flow at a nominal cost and enhancing customer service efficiency (1). Within the supply chain (SC), logistics assumes a crucial role, translating the management's supply chain policies into practical action. Despite the revolutionary impact of technology on supply chains, there are inherent limitations to the development of logistical infrastructure, with improvements reaching a certain threshold. While information can traverse at the speed of light, the physical movement of goods is subject to its own time constraints (2).

Although the SCM is a critical success factor for an organization, it relates to its manufacturing capabilities. These capabilities are influenced by the maintenance strategy, which can significantly hinder the operational availability of equipment. Recent

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advancements in maintenance modelling, driven by data-centric methodologies like machine learning (ML), have opened a wide array of applications. In the manufacturing industry, managing functional safety throughout the product life cycle while containing maintenance costs poses a significant challenge (3). A pivotal approach in tackling this challenge is predictive maintenance (PdM). Given the substantial volume of operational data generated by modern vehicles, ML emerges as an ideal tool for implementing PdM. Despite the extensive coverage of PdM and ML applications in manufacturing systems in various review papers, there is currently no comprehensive survey specifically addressing ML-based PdM for automotive systems (4).

The natural progression for PdM involves embracing a state-of-the-art approach to asset management, leveraging advanced analytics and machine learning to anticipate maintenance requirements and optimize equipment performance. This advanced strategy is termed prescriptive maintenance. Unlike merely pinpointing potential issues, prescriptive maintenance provides concrete recommendations for maintenance actions and operational adjustments (5).

Prescriptive maintenance (PcM) leverages a combination of machine learning (ML) and artificial intelligence (AI) alongside the Industrial Internet of Things (IIoT) to provide precise recommendations for equipment maintenance. This integration encompasses technologies that scrutinize historical data, formulate assumptions, conduct tests, and iteratively analyse data. Through intricate algorithms, the software autonomously identifies and learns from data trends, efficiently recognizing and understanding data patterns. The machine learning process continuously reassesses models (files trained to recognize specific patterns) and data to accurately forecast what something will do at speeds unachievable by human analysts. Ultimately, prescriptive maintenance determines the potential outcomes of different actions and proposes the best approach (6).

From a pragmatic standpoint, there is a notable incongruity in the maturity levels of theoretical maintenance management approaches as outlined in the literature (7). While certain companies, particularly those operating in highly automated and technologically progressive sectors like the semiconductor industry, actively employ many of the cutting-edge approaches available, a significant majority of companies —particularly small and medium-sized enterprises (SME)— fail to consistently capitalize on the existing opportunities (8). Therefore, it does make sense to further analyse the limitations to the progress of the concept, both form the applied perspective, but also from the technological dimension.

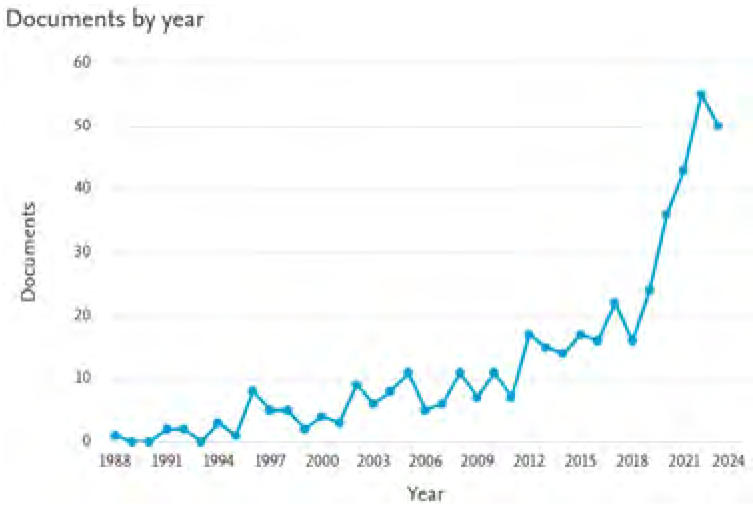
The sections proposed to address this goal are first, an estate of the art about the topic and related fields. The next section will be devoted to identifying the potential barriers and the last section addresses the Discussion and Conclusions.

2. State of the art

The literature review for the main concept "prescriptive maintenance" exhibits an increasing interest through time (see figure 1)

Figure 1

Academic interest in the prescriptive maintenance concept

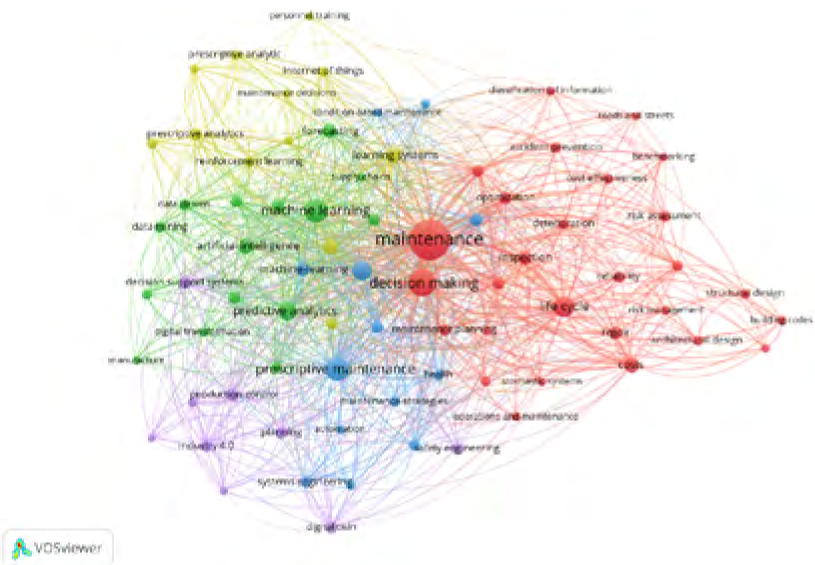


Source: Scopus.

When we analyse the co-occurrence of keywords as presented in figure 2, it becomes clear the different clusters of factors related to the main one.

Figure 2

Associated concepts to be considered according to the literature



Source: Self elaborated by using VOS viewer tool®.

It becomes clear the connection between prescriptive maintenance with a different cluster, but strongly connected, where general maintenance, risk, inspection and safety, costs, design and life cycle are the key factors. This cluster accounts for asset management as well. In closed connection to those two, the cluster for AI, machine learning and predictive analytics is strongly connected to the application to prescriptive analytics, learning systems, reinforcement learning, internet of things and maintenance decisions. Finally, but yet importantly, a significant cluster related to prescriptive maintenance involving I4.0, planning, production control and digital twin is found.

However, when the search includes the term barrier, the total number of papers jumps from 201 until just four, where just one conference paper from 2022 addresses the problem, where the focus looks in proposing a strategy to identify the action plan based on previous similar situations. This means that more research is needed to accurately identify the practical limitations for expanding the vision, because the identified ones and the promoted solutions have been not enough powerful.

3. **Analysis of potential barriers**

In theory, embracing Prescriptive Maintenance strategies has the potential to enhance the decision-making process among maintenance professionals, streamlining the planning and execution of maintenance tasks for improved efficiency. As a result, this can result in decreased downtime and the prolonged longevity of assets. The strategic application of data-driven insights positions prescriptive maintenance as a leading approach in modern maintenance methodologies (9). Within this framework, machine learning and artificial intelligence not only forecast future failures but also pinpoint potential remedies.

When transitioning the emphasis from PcM to PdM, various authors have indicated that the existing body of literature on PdM lacks coverage in the SME (Small and Medium-sized Enterprises) domain. Particularly, the financial aspects remain unclear (9-11). There exists significant untapped potential in SMEs to develop cost models for PdM and address challenges related to data availability. Additionally, there is a deficiency in the management and monitoring of PdM initiatives within SMEs, as well as a shortage of skilled personnel in this context (10).

Various axes have been identified as pertinent in elucidating the challenges associated with embracing these principles. These axes encompass Data, Financial, Knowledge Management, Organizational, Social, and Technical aspects. This differs from the more prevalent triple bottom line approach to sustainability, which primarily considers the environmental, social, and financial dimensions (11).

Recognized obstacles call for diverse approaches based on the strategies and capabilities of industrial management (12). In light of the information provided, industrial management should acknowledge the importance of maintenance practices and should opt for the most suitable management approach while maintaining a focus on their long-term vision. While previous studies have touched upon the selection of maintenance practices, they have typically focused solely on prioritizing barriers, offering a limited perspective. The underlying hypothesis in the present paper is that there exists a structural and contextual relationship among the barriers.

Table 1 summarizes different barriers to sustainable predictive maintenance collected through a literature survey and expert interaction. In this study, the identified barriers to PdM practices are organized and categorized (13).

Table 1

Identified barriers to the development of PdM in SMEs

Code	Category	Barrier	Definition	Reference
O1	Organizational	Understanding the role of maintenance for Asset Investment Planning (AIP) strategy.	Maintenance is considered as expenditure instead of investment.	Expert communication
O2	Organizational	Perceived tension about maintenance downtime.	Time spent on maintenance activities affects the scheduled delivery of products.	(14)
O3	Organizational	Lack of employee training facility.	Training the managers and employees on appropriate knowledge and skills in quality management.	(15)
S1	Social	Negligence towards the safety of workers.	Ineffective maintenance strategy affects workers.	(16)
S2	Social	Hesitant in strengthening maintenance department.	Industries not showing interest in enhancing maintenance department.	(17)
D1	Data	Lack of data analytics on sustainable maintenance.	Reliable and regular data is required for framing digital maintenance strategy.	(18)
T1	Technological	Lack of expertise to maintain advanced technology.	Difficulties with technical capabilities to implement sustainable maintenance practice.	Expert communication
T2	Technological	Fear of failure of advanced technologies.	Single point failure may spoil the entire maintenance strategy.	(19)
T3	Technological	High cost of technological architecture.	Maintenance architecture, needs to be integrated for effective maintenance management.	Expert communication
T4	Technological	High cost of advanced maintenance strategy.	Minimal requirement in term of performance and productivity for faster result generation.	(20)

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Code	Category	Barrier	Definition	Reference
F1	Financial	Shortage of financial resources.	Initial set-up cost to apply maintenance policy.	(21)
F2	Financial	High cost of implementing sustainable predictive maintenance.	Cost of installing sensor and solenoids, computer technologies.	(22)
F3	Financial	Cost of sustaining the sustainable predictive maintenance measures.	Cost in continuation of a maintenance practice.	(23)
F4	Financial	Low return on investment.	Concern over the profit which compensates their investment in maintenance.	(13)
F5	Financial	Overhead cost on maintaining the advanced systems in maintenance strategy.	Additional cost incurred in maintenance practice because of the service charges.	(24)

After identifying the primary categories and barriers, sourced from both the literature review and discussions held during semi-structured interviews, it's worth noting that while we couldn't reach the intended number of 200 experts, we did engage with 25 experts. This initial communication serves to deduce the connections between categories and barriers.

Furthermore, our planned approach involves formally conducting a survey to facilitate a comprehensive analysis of these relationships on a larger scale. Leveraging the data gathered, we will employ Structural Equation Modelling (SEM) to systematically ascertain the likelihood of our hypotheses and assess the robustness of the inferred relationships. This step is significant as it can provide valuable insights for refining strategies aimed at promoting the adoption of such technologies. Isolating these efforts would likely result in less effective measures.

The chain of barriers, as identified predominantly by experts, begins with a common issue encountered by SMEs: a shortage of financial resources. This initial challenge often leads to subsequent issues, with the high costs associated with technological architectures directly impacted by this financial constraint. These challenges in turn feed into the technological barrier, which is closely tied to the lack of expertise required for maintaining advanced technology.

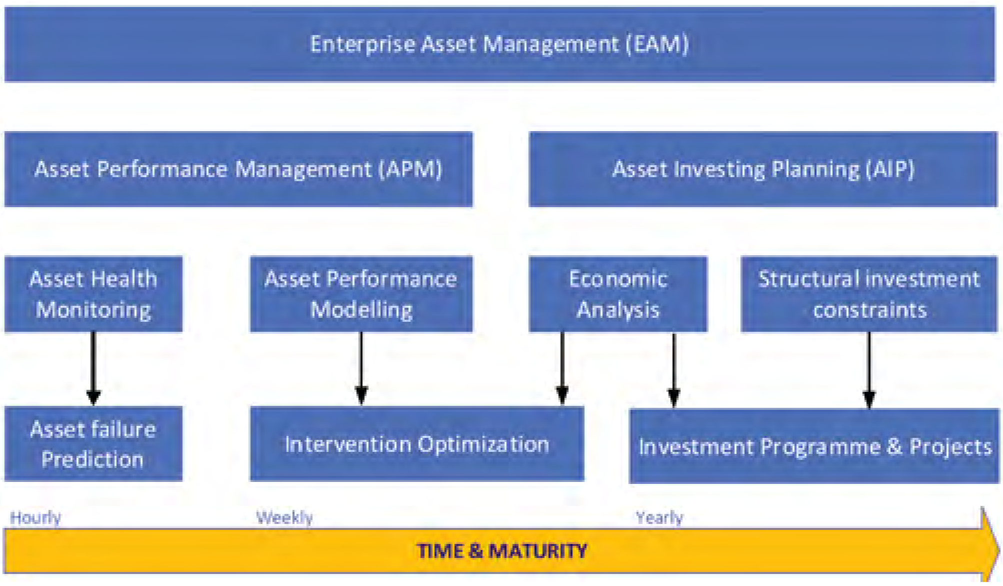
Experts emphasize that, depending on an SME's level of maturity and experience, there is often a notable disconnect between the idealized solutions presented by technology providers and the practical reality within SMEs. Consequently, there is a deficiency in data to support the learning processes associated with these technologies, which in turn affects the return on investment. This situation arises due to the organizational barrier linked to the impact of maintenance on scheduled production timelines.

SME managers often prioritize the initial implementation of a solution while inadvertently overlooking sustainability considerations. This oversight extends beyond just the technological aspect and encompasses social, organizational, and financial dimensions.

Importantly, from a strategic standpoint, there is a broader interconnected chain to emphasize. Understanding the role of maintenance within the organizational framework affects not only the organization itself but also its workforce on a social level. Regrettably, there are isolated points of failure within the overall strategy, primarily of a technological nature, which, when coupled with the substantial costs associated with the solution, further exacerbates the challenge from a financial perspective.

Figure 3

Comprehensive perspective for the different tools and expected outcomes



Based on the sequence of implications between barriers it could be useful for managers to clearly educate decision makers about the different time windows where outcome shall be expected. To this end schemas such as the one presented in figure 3 can help in understanding that different steps need to be accomplished before having the whole solution deployed and operating.

Simultaneously, providing detailed specifics about the ongoing activity, including transparently outlining its limitations and the value generated at each step, while also intensifying focus on the sustainability of the initiative, serves as a means to enhance the success rate of the endeavour.

4. **Conclusions**

This paper aims to analyse the interlinked barriers found at SMEs for the progression of the I4.0 and I5.0 maintenance techniques. In particular, the interest was to analyse the limitations for the progress of prescriptive maintenance solutions. According to the definition presented in Introduction section "Prescriptive maintenance (PcM) leverages a combination of machine learning (ML) and artificial intelligence (AI) alongside the Industrial Internet of Things (IIoT) to provide precise recommendations for equipment maintenance. This integration encompasses technologies that scrutinize historical data, formulate assumptions, conduct tests, and iteratively analyse data. Through intricate algorithms, the software autonomously identifies and learns from dat a trends, efficiently recognizing and understanding data patterns", the focus is to provide precise recommendations in an autonomous way.

The examination of the existing literature review reveals a relatively small number of contributions. Given that Prescriptive Maintenance (PcM) relies on a predictive approach as its initial phase, we have incorporated individual barriers identified by various authors as significant constraints for Predictive Maintenance (PdM). These insights have been augmented by opinions from multiple experts.

Our primary ongoing focus revolves around developing a formal Structural Equation Modeling (SEM) analysis to illuminate the consistency and relationships among these varied barriers. Initially, we utilized an approach to establish preliminary hypotheses, which will inform the design of the SEM methodology survey. These hypotheses were discussed in the "Analysis of Potential Barriers" section.

Another valuable insight emerging from our ongoing work pertains to the temporal dimension involved. Sustaining the initiative is often more challenging than its initial adoption, as per expert consensus. This challenge primarily arises due to the substantial transformations and systematic changes required in the operational, technical, social, and financial dimensions of SMEs. These transformations demand a significant amount of time for proper implementation.

To enhance managers' understanding, we have developed and presented a graphical representation in Figure 3. This diagram delineates the various steps in the process, commencing with asset health monitoring. This initial phase involves addressing technological constraints associated with the Data barrier and may necessitate several months of meticulous data collection and curation. It is crucial to note that these processes are ongoing and not one-time events, demanding continuous adaptations to policies, infrastructure, and organizational facets.

Regarding the limitations of our research, it's important to emphasize that our study is still in progress. The next steps entail collecting data from experts and constructing the SEM model. Once these steps are completed, we will have a more robust foundation for understanding the various links between barriers. Additiona lly, we plan to conduct specific case applications where a selected asset will be used to illustrate the unique significance of each barrier and its relationships within the context of that particular application.

Acknowledgements

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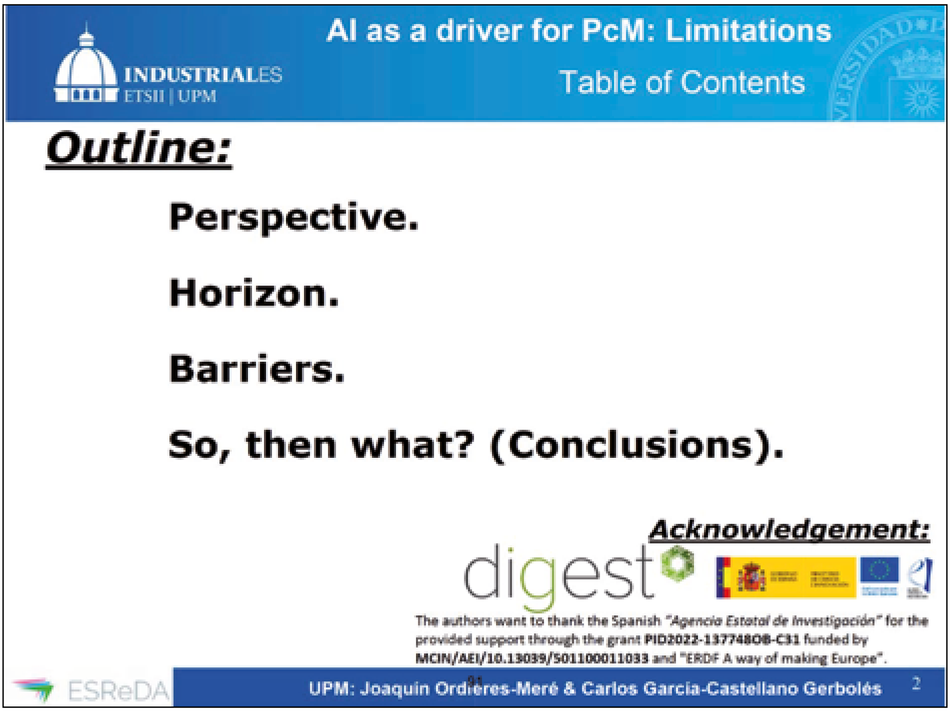
Artificial Intelligence as a driver for Prescriptive Maintenance: Limitations
Joaquín Ordieres-Meré, Carlos García-Castellano Gerbolés
Universidad Politécnica de Madrid
30/05/2024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AI as a driver for PcM: Limitations
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The authors want to thank the Spanish "Agencia Estatal de Investigación" for the provided support through the grant PID2022-137748OB-C31 funded by MCIN/AEI/10.13039/501100011033 and "ERDF A way of making Europe".
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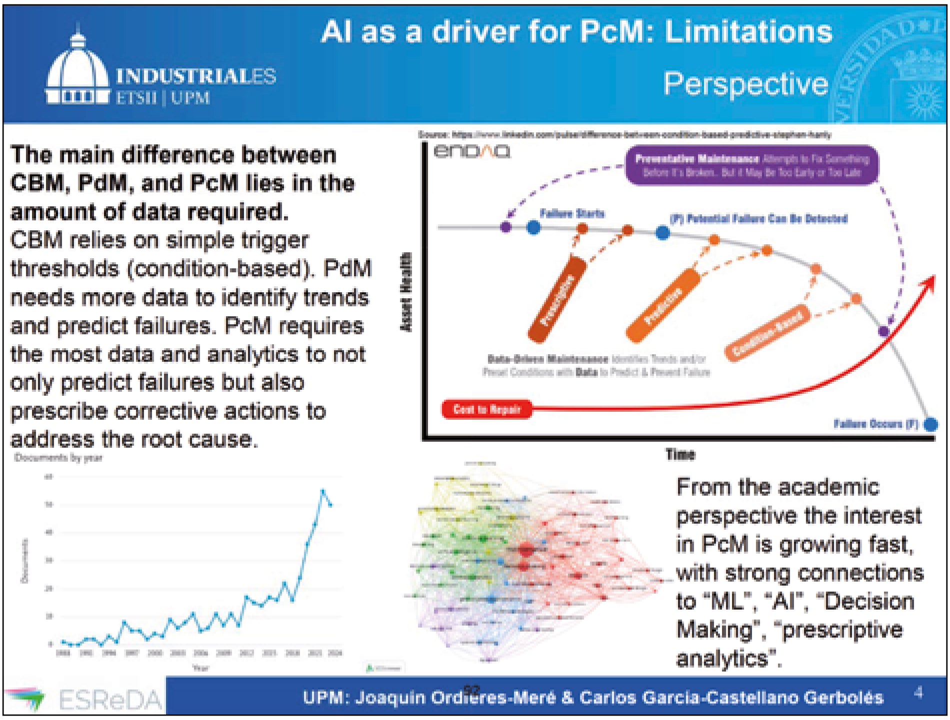

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AI as a driver for PcM: Limitations
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Horizon
Strategic Planning
All the maintenance approaches fall under the same paradigm, which is human driven actions.
Digitalization is seen as a tool to collect data, make models, etc., but nothing else.
Are Digital Twins being used effectively in Strategic Maintenance Configurations?
Source: nuclearsafety.gc.ca
"Let's have a dream"
ESReDA
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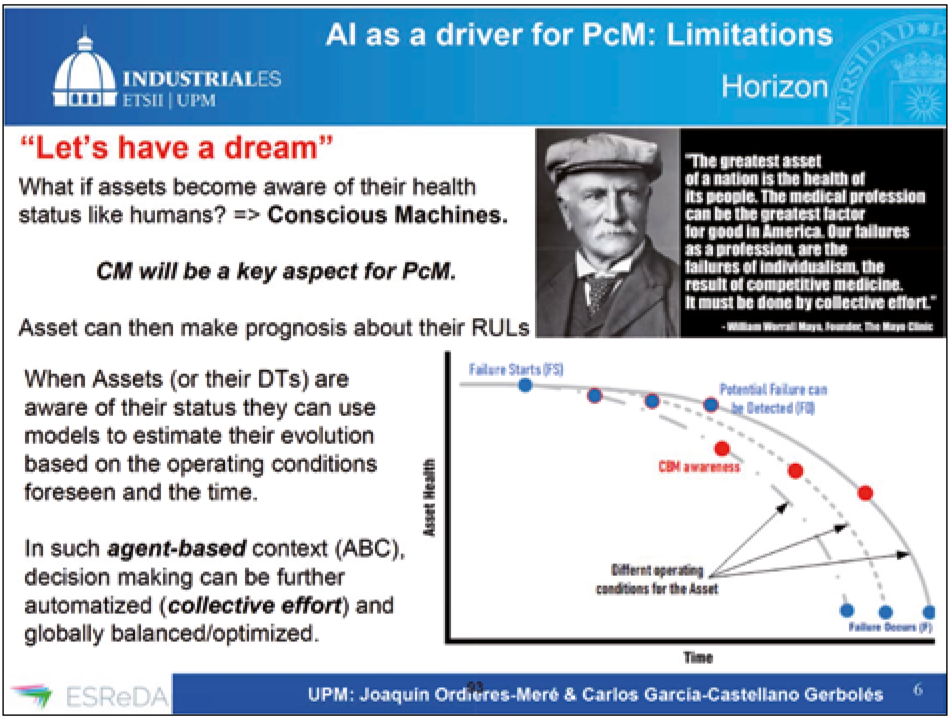
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"Let's have a dream"
What if assets become aware of their health status like humans? => Conscious Machines.
CM will be a key aspect for PcM.
Asset can then make prognosis about their RULs
"The greatest asset of a nation is the health of its people. The medical profession can be the greatest factor for good in America. Our failures as a profession, are the failures of individualism, the result of competitive medicine. It must be done by collective effort."
- William Worrall Mayo, Founder, The Mayo Clinic
When Assets (or their DTs) are aware of their status they can use models to estimate their evolution based on the operating conditions foreseen and the time.
In such agent-based context (ABC), decision making can be further automatized (collective effort) and globally balanced/optimized.
Failure Starts (FS)
Potential Failure can be Detected (FD)
CBM awareness
Different operating conditions for the Asset
Failure Occurs (F)
Asset Health
Time
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AI as a driver for PcM: Limitations

Barriers

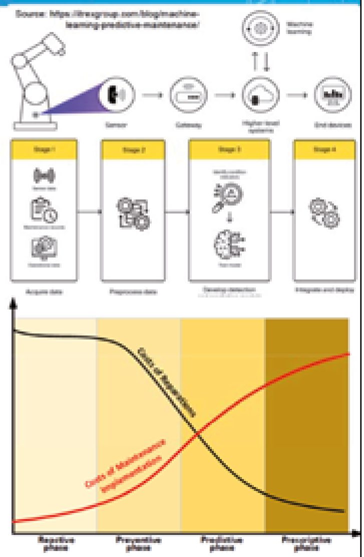
Barriers from the LR carried out

- Cost of Adoption
- Impact Estimation
- Data Availability, Quality, and Ownership
- Complexity of Prediction
- Validation, Safety Assurance, and Regulatory Challenges

Value is something to be better delimited depending on the sector and even on the company, while **Costs** (failures & maintenance) are much clear. Then **Impact** can be formulated in terms of them.

Another issue is related to Data, while most of the research work are based on sets of historical data with low quality validation of stability and robustness through time.

Standardization Bodies need to have open-mind enabling alternative approaches.



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AI as a driver for PcM: Limitations

Barriers

There is a lack of operating frameworks enabling multiple self-updated models with accuracy monitoring for robust asset's health prediction.

We are able to create data-based models relaying of data gathered from sensors, but what if a maintenance operation requires to replace several components of an asset. How the impact will be in the sensors collected data and, in the end, how the impact on the predicted evolution of the asset health.

Indeed, the decision-making process needs to consider significant number of models (as per asset subsystem) as well as their orchestration. Therefore, apart of the significant efforts to setup the DTs and relevant models, a **significant managerial effort to integrate the predictions from those models per asset and over assets in the production line**, keeping track of the individual and integrated performance, and making automatic retrains when needed.

Advantages are because of generalization, since the same methodology can be deployed in many different use cases.

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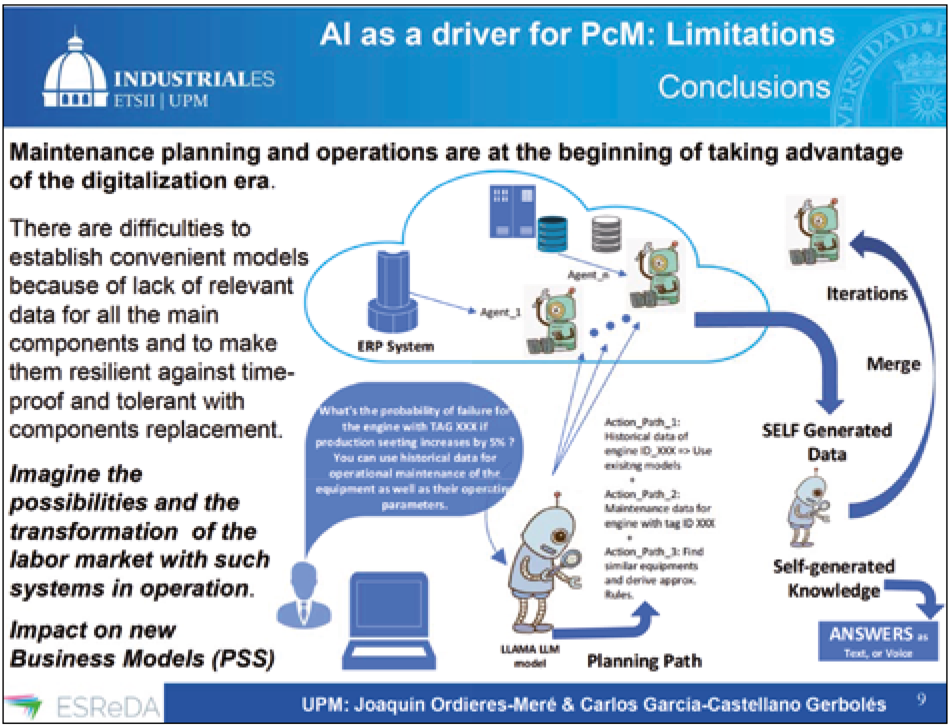
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AI as a driver for PcM: Limitations
Conclusions
Maintenance planning and operations are at the beginning of taking advantage of the digitalization era.
There are difficulties to establish convenient models because of lack of relevant data for all the main components and to make them resilient against time-proof and tolerant with components replacement.
Imagine the possibilities and the transformation of the labor market with such systems in operation.
Impact on new Business Models (PSS)
ERP System
Agent_1
Agent_n
What's the probability of failure for the engine with TAG XXX if production seeting increases by 5% ? You can use historical data for operational maintenance of the equipment as well as their operatin parameters.
Action_Path_1: Historical data of engine ID_XXX => Use existing models
Action_Path_2: Maintenance data for engine with tag ID XXX
Action_Path_3: Find similar equipments and derive approx. Rules.
LLAMA LLM model
Planning Path
Iterations
Merge
SELF Generated Data
Self-generated Knowledge
ANSWERS as Text, or Voice
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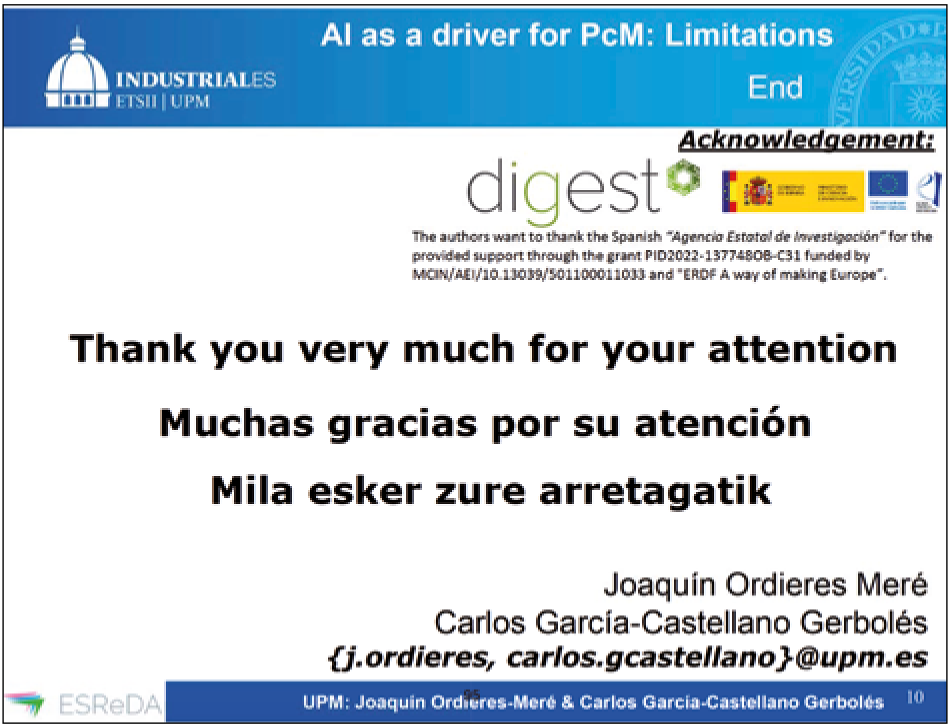
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Thank you very much for your attention
Muchas gracias por su atención
Mila esker zure arretagatik
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Sustainable maintenance and Digital Twin Technology: A Test Case for Evaluating Integration Potentialities

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Abstract

The concept of sustainable maintenance is quite recent in the industrial context, entailing a change of mindset compared to traditional models that requires integrating the three main dimensions of sustainability (i.e., economic, environmental and social) in the whole life-cycle of an asset, as well as in the design phase of the maintenance strategies and tools. Digital technologies could boost the development of sustainable maintenance models. The concept of Maintenance 4.0 refers to the integration of digital technologies to enhance reliable predictive models and support the identification of effective maintenance actions in real time. This work aims to present a prototype tool for supporting sustainable maintenance based on digital twin technologies. A test case that adopt machine learning technologies for prediction analysis integrated with assessment of safety and environmental impacts is discussed. The test case has been developed, based on a dataset of events (failures and non-conformities) collected through on-board sensors on a specific set of equipment. Using an open source tool, three different ML algorithms have been selected and their effectiveness has been analysed and compared through a set of KPIs, in order to identify the most reliable for predictive maintenance purposes.

1. Introduction

The concept of "sustainable maintenance" is quite new in the field of production systems, although some elements, which are shared with traditional maintenance policies, can be highlighted. The first issue to be considered is linked to the concept of life cycle of a process and/or a service: it is typical of the most innovative maintenance strategies, and essential to provide a reliable assessment of sustainability level of an activity. Traditionally, life cycle in maintenance activity refers mainly to the economic dimension: in sustainable maintenance models the target is also the development of models according to a long-term logic, which considers the entire life cycle of the process/product aiming to optimize all types of impacts. The second critical issue is that sustainable maintenance aims to provide maximization of effectiveness and efficiency in terms of both availability and reliability, as well as safety and environmental protection (Vatn and Aven, 2010). Thus, from one side, the contribution of an effective maintenance strategy is essential to better manage environmental, health and safety impacts of a production system or

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a service; from another side, the specific activity could determine such impacts from an environmental and social point of view. This criticality of current organizational models is confirmed by accident and injury rates associated with maintenance activities (Carrillo-Castrillo *et al.,* 2015). Thus, it is important that innovative maintenance models adopt new management and operative tools, in order to support more effective maintenance policies more in line with sustainable strategies, based on evaluating impacts on the environment, and including suitable measures for the prevention and reduction of accidents/injuries. The increasing attention towards the concept of sustainable maintenance could be also enforced by the adoption of digital and smart technologies. These tools allow real time data collection and processing aiming to carry out continuous and constant monitoring of the various impacts of the process, e.g. for redirecting maintenance activities in real time with a view to continuous improvement oriented towards productivity, energy saving, quality, but also safety and environmental protection (Kumar *et al.,* 2018; Karuppiah *et al.,* 2021). The objective of this work is to discuss a prototype tool for supporting sustainable maintenance based on digital twin technology, presenting a test case developed in the industrial sector.

2. **Sustainable maintenance and digitalization: a quick state of state of the art**

Sustainable maintenance is a quite new concept even if basic pillars of this strategy have been also evaluated —but not effectively systematized— in past and current maintenance models and strategies. Basically, sustainable maintenance models must integrate multiple dimensions, from more traditional ones —technical and economic— to environmental, social and safety dimensions (Kumar *et al.,* 2018). From a strategic point of view, an effective contribution for the design of sustainable maintenance systems is proposed in (Jasiulewicz-Kaczmarek *et al.,* 2020) through the introduction of an innovative concept: Sustainability Centered Maintenance (SCM). According to the authors of the study, the design of SCM models must be reoriented along three main lines: optimization of operating costs of production processes and maintenance activities; efficient control of environmental resources (air emissions, water consumption, waste) linked to industrial and maintenance processes; control of activities with a view to operator safety.

The study also proposes guidelines for the implementation of these processes based on:

1 The adoption of effective predictive maintenance strategies based on a life cycle approach to estimate of the residual life and aiming to optimize environmental as well as economic impacts.
2. Real-time data analysis to acquire reliable information and knowledge about actual conditions linked to the real situation in order to monitor impacts on sustainability (e.g. in terms of faults, energy consumption, unsafe conditions).
3. Definition of new metric systems, based to a more coordinated approach for monitoring the global effectiveness of maintenance processes.

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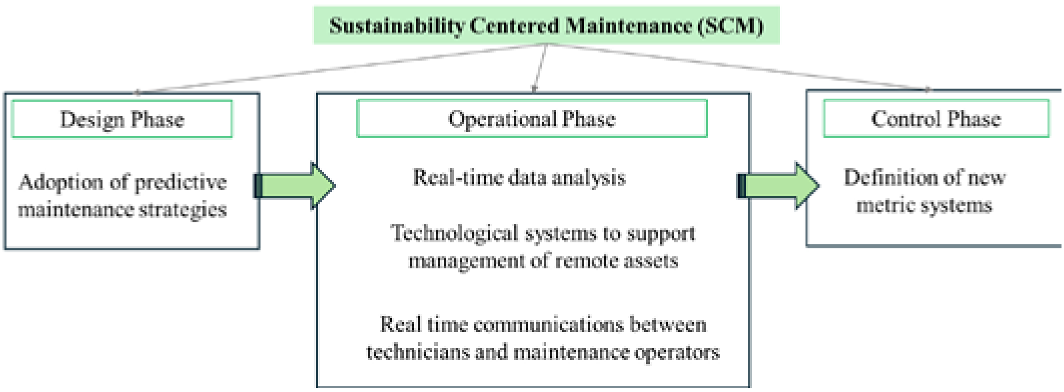
4. Development of technological systems to support effective management of remote assets aiming to provide support also in complex conditions (e.g. operator safety problems, complexity of the maintenance activity).
5. Support in identifying and communicating in real time the appropriate actions to carry out, aiming to support operators in the maintenance field with the "right" solutions.

These ideas are summarized in figure 1, adopting a life cycle —design, operational and control phases— point of view.

Figure 1

Features of Sustainability Centered Maintenance models trough the life cycle



Recently, Grijalvo Martín *et al.* (2021) focused on analyzing the need to redefine new business models to support the redesign of maintenance activities according to a sustainability perspective. Authors suggested the massive use of servitization models as a value-added strategy in order to support the development of more sustainable maintenance strategies also according to Sustainable Development Goals defined by the United Nations for the 2030 agenda. From a more operational point of view, one issue to be addressed is defining and evaluating the contribution of current digital technologies to support the diffusion of sustainable maintenance policies. New maintenance models —e.g. the so-called Maintenance 4.0 or e-Maintenance— are spreading: their main aim is to integrate a more reliable prediction of faults —based on historical data together with information acquired in real time both on the machines and on the working environment— with intelligent tools for supporting operators to identify more effective solutions in terms of maintenance interventions (Bokrantz *et al.,* 2020). These systems are based on a wide use of digital technologies, both hardware —e.g. Internet of Things (IOT) sensors, RFID technology— and software (e.g. artificial intelligence tools). Both elements can effectively contribute to the diffusion of sustainable maintenance strategies (Karki e Porras, 2021). In brief, the "traditional" approaches of descriptive maintenance —only based on the analysis of historical data— and diagnostics —focusing on analyzing causes and failure modes—

are integrated with predictive and prognostic approaches that aim to not only anticipate the prediction of the failure, estimating the residual useful life and, thus, proposing more effective corrective actions and feedback in real time (Forcina *et al*., 2021).

Very few recent papers focused on evaluating the potentiality of integrating Maintenance 4.0 models and sustainable ones. A recent study (Karki & Porras, 2021) has proposed a state of the art about the adoption of digital technologies to support sustainable maintenance strategies: the results obtained in terms of impact are very interesting on the three classic dimensions of sustainability: economic (expressed in increased productivity), environmental and social (essentially focused on the prevention of accidents/injuries). By focusing on how to support sustainable maintenance models trough digitalization, Johansson (2019) analyzed current criticalities affecting the transition towards maintenance systems characterized by a high level of digitalization and, at the same time, pursuing targets linked to the global sustainability of the process.

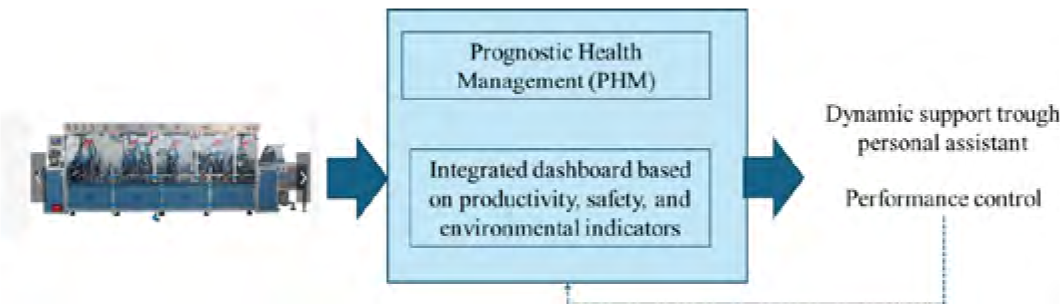
3. The proposal

The prototype tool proposed —called KNOW4I— is a digital twin based model to support sustainable maintenance in manufacturing systems: it is included in a wider cyber physical system, which has been detailed in Longo *et al*. (2022).

The prototype tool has a specific module focusing on sustainable maintenance activities (see figure 2): the module is based on a tool for prognostic health management, which forecasts —based on real time data— both data for planning maintenance activities (fault occurrence as well as down time) and environmental impact (in terms of CO_2 emissions) of the specific process.

Figure 2

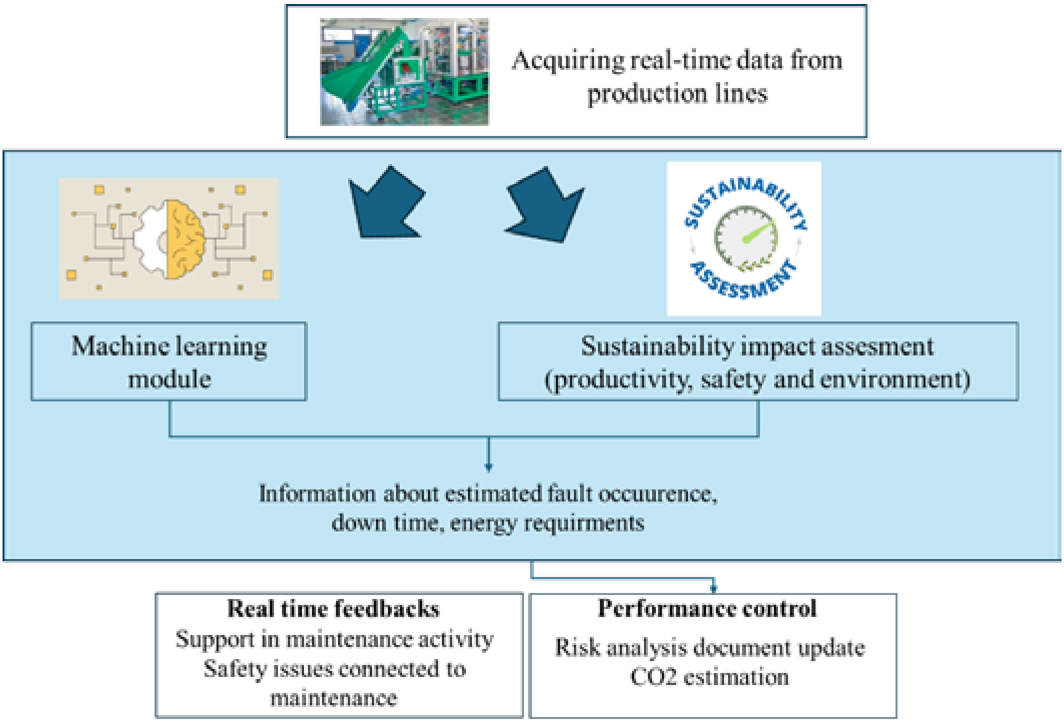
Schema of the sustainable maintenance module in the KNOW4I prototype



More details are reported in figure 3: the prototype tool acquires information about the current condition of a specific equipment (e.g. automatic production lines) trough real time sensors: information regards both occurred faults or non-conformities as well as cycle time for producing an item, and energy required for the specific production activities. Next, data are sent to the prognostic health management model in order to forecast reliability parameters to plan in a more effective way maintenance activities and cycle times and energy consumption to assess environmental impact. In addition, currently, through a manual matrix approach, each collected event is classified based on three parameters, which assess the impact on sustainability level: productivity, safety and environment. A 1-4 scale has been applied. Next, through a machine learning tool, critical data for the maintenance process are forecasted together with cycle times. Finally, feedback defined through the assessment and the machine learning tools are sent to two "destinations". Some information about e.g. how to carry out a specific maintenance task according also to safety issue related to this activity, are shared in real time with operators trough a personal assistant module. In addition, information is sent to a dashboard where data about productivity and environmental performance of the production process to assess sustainability level of the whole process and of the single item produced.

Figure 3

Information flows and tools in the KNOW4I sustainable maintenance module



4. A test case

A test case has been developed in order to evaluate the effectiveness of the prototype module. Data acquisition has been carried out on five similar assembly workstations produced and tested (before delivery to the final customer) in a company, whose core business is studying, designing and producing machines and modules for assembly processes automation for different industrial applications. Acquired data concern events —failures as well as non-conformities— occurred, in a specific time interval (one month). The total number of events observed is equal to 200: 6% of the sample have occurred in all five workstations, 79.5% of events was collected on a single station, 8.5% and 1.5% on 2 and 3 workstations respectively.

After collection, data have been directly sent to the Prognostic Health Management (PHM) module aiming to compare the efficacy of different Machine Learning (ML) algorithms. The comparison has been developed in a sub-set of events, i.e. the ones occurred in all workstations aiming to represent a significant sample of faults in analysis. The sample considered is characterized by an average failure frequency value equal to 176.86 sec, with an estimated standard deviation of 95.77 sec. Furthermore, the estimated downtime associated with the sample of events was analysed: an average value of 17.10 seconds and a standard deviation of 15.08 seconds were estimated.

Furthermore, the same sample of failure/anomaly events was analysed with a view for monitoring the impacts on the three dimensions of sustainability: three parameters were therefore defined —productivity, environment and safety— and an evaluation scale expressing the impact of the event on each of them: values for each parameter can be equal to 0 (no impact), 1 (potentially low impact), 2 (potentially medium impact), 3 (potentially high impact).

Based on the proposed scale, the events were analyzed and classified in relation to the potential level of impact on the 3 dimensions of sustainability: the summary of the results is proposed in table 1

Table 1

Fault and non-conformities collected form selected equipment
in the test case evaluated according to three dimension of sustainability

Event	Category type	Impact			Description
		Productivity	Environment	Safety	
1	Clamp failure	2	0	2	The pallet is present but has not been clamped, because the two terminals do not reach the required clamping height.
2	Clamp sensor error	2	0	0	The terminals go down but the sensor always remains on; or the terminals do not go down, but always remain in the high position.
3	Pallet presence sensor error	1	0	1	The pallet is present in the fixture but the sensor is not turned on.
4	Failure in pallet exit	2	0	2	Even though the pallet has been freed, it remains in place in the fixture.

The purpose of the test case is to evaluate the capability of the proposed prediction tool —based on an open access software— to predict occurrence of faults by adopting different ML algorithms aiming to integrate this module with one focusing on safety and environmental impact evaluation. Thus, the focus at this step of the design process is to validate the prediction module.

In order to effectively compare performance of different ML algorithms, the following steps have been developed:

1. *Definition of the decision objective*: since ML algorithms are used to make a prediction or classification, the process under analysis must be specifically identified. In the testing phase, the ML models were used exclusively to predict the trend of significant parameters with a view to sustainable maintenance. Another element of evaluation is the types of data available – e.g. they can be labeled or unlabeled: in the test, already labeled data was used.
2. *Introduction of an error function*: this step aims to evaluate the accuracy of the model's prediction with respect to the collected data; it finally defines the best fitting algorithm.
3. *Model optimization*: after evaluating the most effective ML algorithm, this step involves defining —usually with a scenario analysis— the parameter values (e.g. the weights) that allow improving the effectiveness of the ML model to reduce the discrepancy between the collected data and the model estimation until a predefined accuracy threshold is reached.

Starting from step 1, two main parameters to be estimated have been outlined, such as:

— Parameter P1: it represents the frequency (defined as error occurrence) characterizing a specific fault can occur on a specific station.
— Parameter P2: it represents the machine downtime.

Next, three types of ML algorithms have been selected: Support Vector Regression Model; Neural Network Regression Model; Random forest Regression Model.

The analysis has been carried out through an open source tool, i.e. HeuristicLab®. Finally, the error function was defined based on three well-known metrics; they have been adopted for comparing the efficacy of the past three proposed models.

The proposed metrics are:

— *Mean Square Errors (MSE):* it represents the average square error between the observed data values and the data values estimated by ML models. If the specific ML model is working as the best, this value is the lowest one.
— *Mean Absolute Errors (MAE):* it represents the distance (in absolute value) between the predicted estimated value and the actual one; also in this case, the most effective ML model is characterized by the lowest value.

— *Pearson coefficient (R^2):* it represents the coefficient of determination, i.e. the link between the variability of the data and the correctness of the adopted prediction model.

In the test case, only results obtained for a specific data set (included in table 1) have been analyzed, i.e. error 2 on station 2. In detail, a part of the total collected data (66%) was used to develop the training of the specific ML model; the complementary set (34%) has been used to test for prediction. The forecast was developed over a 24-month time horizon. Thus, the proposed metrics have been estimated for the three algorithms both in the training phase and in the testing phase: results are reported in table 2.

Table 2

Estimated values for metrics adopted to compare ML algorithms

Adoptd ML model	Evaluated Metrics					
	MAE (test)	MAE (training)	MSE (test)	MSE (training)	Pearson's R^2 (test)	Pearson's R^2 (training)
Support Vector Regression	15.465	13.953	324.277	259.479	0.921	0.915
Neural Network Regression	**3.127**	**2.171**	**17.797**	**11.444**	**0.991**	**0.974**
Random Forest Regression	7.10	5.790	63.529	55.307	0.898	0.931

Results outline that the Neural Network Regression model provides the best performance for the specific collected data sets.

5. Conclusions

The study presents a prototype tool based on a digital twin logic to support sustainable maintenance in semi-automatic production processes. Sustainable maintenance models aim to structurally integrate in current maintenance strategies assessment regarding environmental and safety impacts of these activities. The proposed system is not fully developed: thus, a test case focusing on the prognostic module that aims to forecast maintenance data based on information acquired in a real time mode is discussed in detail. Other parts of the module are being completed; further developments will be oriented to test these elements.

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Sustainable maintenance and digital twin technology: a test case for evaluating integration potentialities

Valerio Elia, Maria Grazia Gnoni, Fabiana Tornese

Department of Innovation Engineeriing– University of Salento

Agenda

1. Sustainable Maintenance: needs of new models and approaches
2. Progettazione ed implementazione di un sistema di gestione dei near-miss secondo l'approccio Lean Management
3. Come utilizzare la conoscenza «latente» nelle organizzazioni per migliorare le performance del sistema di gestione della sicurezza
4. La valutazione dinamica dei rischi tramite la conoscenza estratta dai near-miss
5. Proposta di un metodo quantitativo per la classificazione dei near miss
6. Proposta di un modello «rapido» di classificazione dei near-miss

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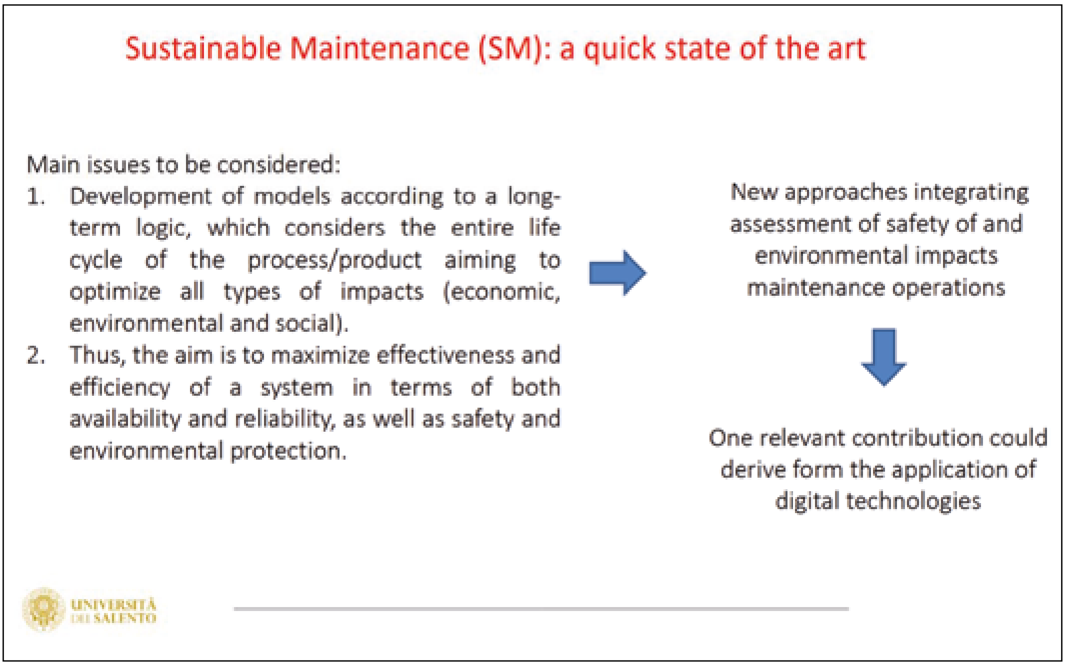
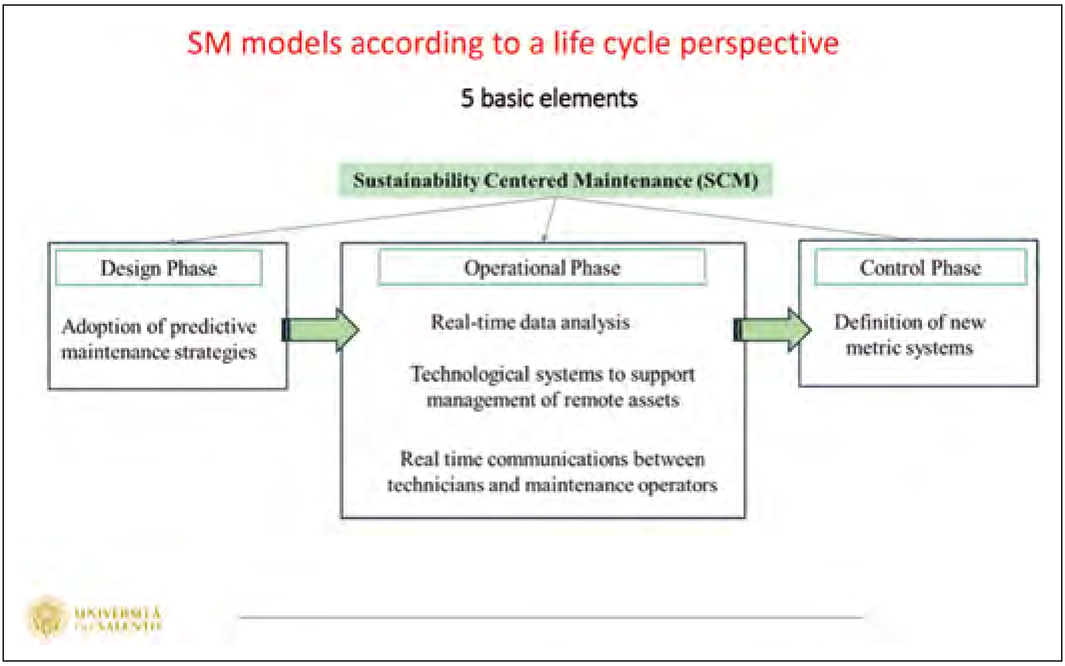

Sustainable Maintenance (SM): a quick state of the art
Main issues to be considered:
1. Development of models according to a long-term logic, which considers the entire life cycle of the process/product aiming to optimize all types of impacts (economic, environmental and social).
2. Thus, the aim is to maximize effectiveness and efficiency of a system in terms of both availability and reliability, as well as safety and environmental protection.
New approaches integrating assessment of safety of and environmental impacts maintenance operations
One relevant contribution could derive form the application of digital technologies


SM models according to a life cycle perspective
5 basic elements
Sustainability Centered Maintenance (SCM)
Design Phase
Adoption of predictive maintenance strategies
Operational Phase
Real-time data analysis
Technological systems to support management of remote assets
Real time communications between technicians and maintenance operators
Control Phase
Definition of new metric systems

A prototype development of SM model in industrial sector

- The proposed prototype tool– called KNOW4I - is a digital twin based model to support sustainable maintenance in manufacturing systems;
- The SM module is based on a tool for prognostic health management, which forecasts – based on real time data- both data for planning maintenance activities (fault occurrence as well as down time) and environmental impact (in terms of CO2 emissions) of the specific process

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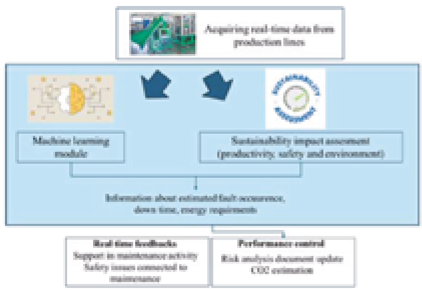
A prototype development of SM model in industrial sector

1. The prototype tool acquires information about the current condition of a specific equipment (e.g. automatic production lines) trough real time sensors:
2. Information regards both occurred faults or non-conformities as well as cycle time for producing an item, and energy required for the specific production activities.
3. Data are sent to the prognostic health management model in order to forecast reliability parameters to both way maintenance activities and energy consumption and to assess environmental impact.



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A test case example

- Data acquisition has been carried out on five similar assembly workstations produced and tested (before delivery to the final customer) in a mechanical company,
- Information regards occurred failures as well as non-conformities in one month.
- The total number of events observed is equal to 200: 6% of the sample have occurred in all five workstations, 79.5% of events was collected on a single station, 8.5% and 1.5% on 2 and 3 workstations respectively.
- Verifying effectiveness of different Machine Learning (ML) algorithms in the Prognostic Health Management (PHM) is the target of the test case.

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Sample data assesment

Event	Category type	Impact			Description
		Productivity	Environment	Safety	
1	Clamp failure	2	0	2	The pallet is present but has not been clamped, because the two terminals do not reach the required clamping height.
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Comparison of different ML models

1. Two main parameters to be estimated have been outlined, such as:
   - Parameter P1: it represents the frequency (defined as error occurrence) characterizing a specific fault can occur on a specific station;
   - Parameter P2: it represents the machine downtime.
2. Next, three types of ML algorithms have been selected: Support Vector Regression Model; Neural Network Regression Model; Random forest Regression Model.

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Comparison of different ML models

Mean Square Errors (MSE): it represents the average square error between the observed data values and the data values estimated by ML models. If the specific ML model is working as the best, this value is the lowest one.

o Mean Absolute Errors (MAE): it represents the distance (in absolute value) between the predicted estimated value and the actual one; also in this case, the most effective ML model is characterized by the lowest value.

o Pearson coefficient (R^2): it represents the coefficient of determination, i.e. the link between the variability of the data and the correctness of the adopted prediction model.

Adoptd ML model	Evaluated Metrics					
	MAE (test)	MAE (training)	MSE (test)	MSE (training)	Pearson's R^2 (test)	Pearson's R^2 (training)
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Random Forest Regression	7.10	5.790	63.529	55.307	0.898	0.931

Neural Network Regression model provides the best performance for the specific collected data sets

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Identifying the Future Skills Requirements of the Digital Maintenance era

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Abstract

The ongoing surge in the digitization of industry and the increasingly stringent sustainability requirements are reshaping the discipline of maintenance and its management. To meet the demands of these digital and sustainable trends, it is crucial to have a workforce equipped with the necessary skills. Achieving compliance requires anticipating changes in the skill set required for maintenance management. With this context conditions, Sidenor, with the support of the University of Deusto, analyses the most suitable skills for effectively implementing maintenance strategies, to afterwards develop customized didactic materials based on, among others, digital twin approaches.

1. Introduction

The rapid and exponential increase of differentiation, along with a continuously growing demand for digitization and virtualization, is causing a significant transformation in Asset Management. On a global scale, the industrial and service sectors have experienced significant changes in recent years, and this trend is expected to continue. Companies must have a well-designed strategy to effectively tackle upcoming technologies and their simulation methods, such as digital twins or augmented reality. A digital twin is a virtual representation of a physical object or system.

Developing a workforce with a diverse range of skills should be the focus to successfully execute the strategy and achieve the digital and virtual transformation.

More specific, the industrial sector has undergone significant transformation in recent years due to the increased use of virtualization, digital twins, and augmented reality (AR). Virtualization has become a fundamental technology that allows businesses to simplify operations, improve scalability, and optimize resource usage by abstracting physical infrastructure. Simultaneously, digital twins have transformed industrial processes

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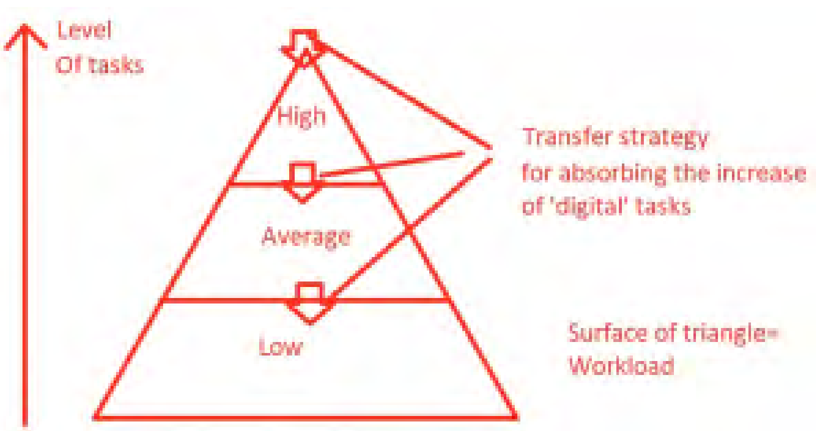
by creating virtual reproductions of actual assets in real-time, analysing new layouts or increasing productivity of existing ones. This enables predictive maintenance, optimization driven by simulation, and exceptional levels of efficiency. Augmented reality has moved beyond the world of entertainment and is now an emerging tool in multiple industries. It provides workers with immersive experiences that are filled with data, enhancing their talents and decision-making. These technologies are bringing about a new era of innovation, efficiency, and competitiveness [1]. Digital counterparts are seamlessly integrating with physical activities, resulting in unparalleled levels of production and value generation.

These two facts, technological advancements and increasing demands for environmental responsibility, are evolving the field of maintenance management to a new level. Thus, the industry necessitates a deep re-evaluation of the abilities necessary for adapting to this new scenario. To meet the requirements of a fast-evolving world, industries must prioritize the development of a skilled workforce that is proficient in the complexities of digitization and sustainability. To address this matter, it is necessary to take a proactive strategy to foresee changes in the skill sets that are necessary for effective maintenance management. This essay explores the core of this ever-changing environment, utilizing knowledge from specific sectors and interdisciplinary research efforts, and relevant literature.

In summary, anticipating changes and updating the skills of the current staff are essential for successfully achieving a transition. Previously, this transformation has occurred by transferring low-value work to roles with lower qualifications in the qualification chain. These duties constitute a substantial amount of the time that a mid-level Asset Management technician dedicates [2] (see figure 1).

Figure 1

Workload and difficulty level of tasks performed by Asset Management technicians



Source: https://eqvegan.eu/eqvegan-online-workshop-on-digital-skills-and-competencies-in-the-food-sector/ , visited Apr 30th, 2024, and adapted from Goti, 2024.

Put simply, it is not appropriate for highly skilled experts to engage in basic duties. Instead, these responsibilities should be delegated to operators with lesser levels of expertise. Only through this method will they have the opportunity to update and enhance their level of competence. According to Nakajima's Total Productive Maintenance [3], the transfer of lower-level duties like as cleaning, inspection, greasing, and basic adjustments has been a longstanding practice. To address the aforementioned requirements of digitalization and virtualization, it is necessary to make a visit for the purpose of transfer.

The major objective of this essay is to address a significant need in the field of maintenance management by recognizing new talents (specific skills required for these roles) that are emerging as a result of industrial evolution and sustainability requirements. As well, the aim is to select and develop the most appropriate materials to cover this skills gap using a train the trainers approach. To achieve this, the findings from prior research has been utilized.

Therefore, the article is structured in the following manner: In Section 2, the manuscript provides an overview of the research works and databases that were analyzed. Subsequently, Section 3 outlines the procedure and approach used to determine the most pertinent profiles. Section 4 proceeds by delineating the utmost crucial future capabilities that need to be cultivated for the selected profiles mentioned in Section 3, along with some samples of the pedagogic material developed within the framework of this research project, shown in Section 5. Section 6 serves to outline the primary closing remarks and future guidelines of this research.

2. **Related research**

2.1. *Projects*

The conducted research was supported by the ESSA project [4], which was established to build a comprehensive plan for a sustainable European Steel Skills Agenda led by the steel industry and coordinated efforts. In addition, we utilized data from the SPIRE-SAIS [5] -Skills Alliance for Industrial Symbiosis, a multi-sectoral EU project focused on energy efficiency (EE) and industrial symbiosis (IS), aimed at creating a sustainable process industry. Furthermore, we incorporated data from the EQVEGAN project [6], which pertains to the vegan food business. More lately, we employed another European Union initiative called SMeART —Making Europe's Small and Medium Enterprises (SMEs) smart— that aids in the digitalization of engineering SMEs [7]. In this moment, we are currently running a project called SUSTASKILLS [8], titled "Development of a roadmap for the implementation of skills related to industrial symbiosis and energy efficiency in order to achieve a sustainable process industry" that reinforces all experience and knowledge gained from previous project and continues to enhance the framework needed for industry to accomplish this change.

For these studies, we mostly relied on the ESCO [9] database (amongst other related databases), which was generated by the ESCO organization. ESCO stands for European

Multilingual Classification of Skills, Competences, Qualifications, and Occupations, and it was designed by the European Commission. This database is derived from the basic framework "International Standard Classification of Occupations" (ISCO-08) established by the International Labour Organization (ILO).

3. Profile selection and future skill definition process

As previously stated in Section 2.1, we relied on the ESCO database as our main source of data for choosing job profiles and their corresponding skill requirements [10]. To find job profiles directly associated with asset management, we initially established a list of keywords. Subsequently, we applied our historical expertise to filter and select the most pertinent and closely connected options. The roles that were chosen are as follows:

— (1) 3115.1.6 - industrial maintenance supervisor,
— (2) 2152.1.13 - predictive maintenance expert,
— (3) 2141.8 - maintenance and repair engineer, and
— (4) 1219.1.1 - facilities manager.

Furthermore, we have chosen three additional job profiles that are closely related to asset management. These profiles were picked based on our analysis of the projects and articles discussed in Chapter 2. The user's text has three occupation codes:

— (5) 2151.1 for electrical engineer,
— (6) 2144.1 for mechanical engineer, and
— (7) 1431.1.2 for performance production manager.

4. Definition of the skills and competences to be developed by the future profiles

After carefully choosing the most pertinent and illustrative job profiles associated with asset management, our subsequent task involved determining their shared requirements for future abilities. To achieve this objective, we thoroughly examined all the frameworks that were introduced in Chapter 2. The future skill requirements for asset management profiles have been established.

The abilities that have the largest gaps between the current and future levels of expertise are defined.

Active listening and adaptability are important skills that involve being receptive and responsive to others, as well as being able to adjust and thrive in changing circumstances.

Also following skills are considered important and we have been detected gaps that should be closed: Proficient in communication, Proficient in data analysis and modelling, Proficient in IT abilities and programming, Advanced literacy, Artificial Intelligence

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(AI), Augmented Reality, Automation, Basic numeracy and communication and Circular economy. Elaborate cognitive processing and analysis, Computerized Maintenance Management and Continuous Learning. Creativity, critical thinking, and decision making.

Expertise in cross-functional process management, Cultural empathy, Cybersecurity Data management refers to the process of organizing and controlling data in a secure manner to ensure its safe storage.

Enhancing the effectiveness of energy utilization, Ecological consciousness, Ethical comprehension, Information and Communication Technology,

Integrative thinking and behaviour, Internet of Things, Mixed Reality, Evaluation of potential opportunities, Subjective encounter, Predictive and proactive maintenance strategies and Problem solving (process of finding solutions to complex issues or challenges).

Process analysis and product life cycle impact evaluation. Proficiency in quantitative and statistical abilities, Resource reuse/recycling Risk management Robotics and sensor technologies.

Resource management that is focused on long-term sustainability.

Educating and instructing people, Collaborative teamwork, Utilization of modern communication technologies, Minimization of waste and effective waste management and Operate independently.

5. **Samples of the pedagogic material developed to train the trainers**

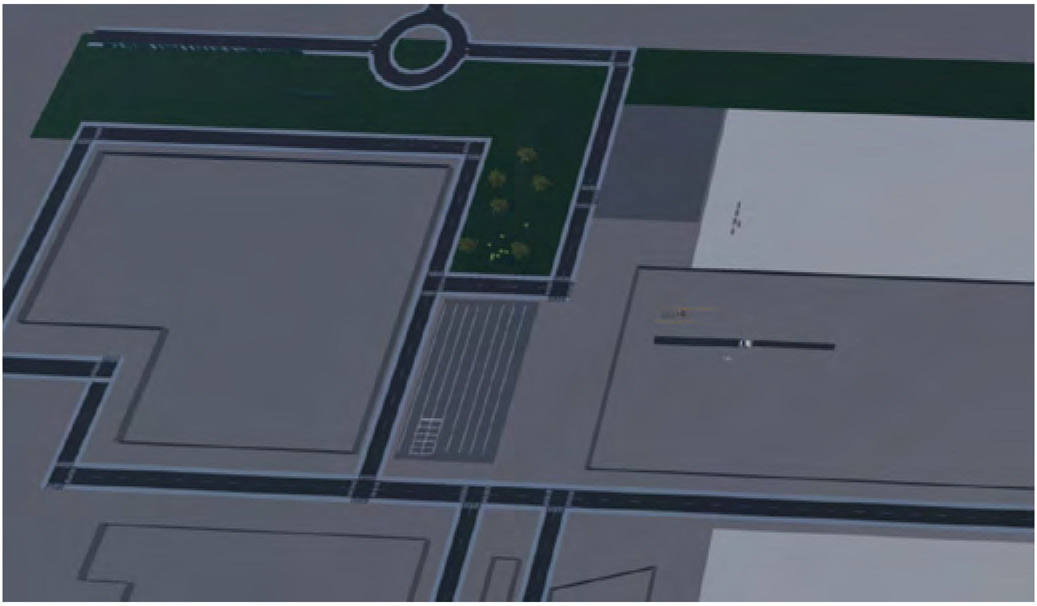
The university-industry collaboration established in this SUSTASKILL [8] project demands to generate material to train a bunch of technicians in very different areas of Sidenor. Part of the material generated can be concept based, but it is necessary to understand that a technician or operator should be able to make mistakes when producing or repairing, to notice the consequences of the failures they make. Thus, it is necessary as well to tackle virtual training. In this case, and as it can be seen in figure 2 and 3 several parts of the factory of Basauri have been modelled to develop training oriented to safety and manufacturing operations:

Figure 2

Sample Virtual Reality (VR) model of a loading dock of Sidenor Basauri

Figure 3

Sample Virtual Reality (VR) model of the transportation circuits of Sidenor Basauri



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It is worth noting that the 3D models developed until now have been obtained using the 4Prot gamification for learning software.

6. Conclusions

The implementation of smart technologies and new environment and sustainability related policies is causing considerable changes in various sectors. Consequently, industries require a workforce with diverse skills that can effectively tackle the difficulties arising from digital and environmental changes, while also leveraging them to improve asset management. The “reshaping” of skills is crucial due to a significant disparity between future skill requirements and existing levels of expertise. To establish a trained workforce, it is important to anticipate skill changes in the manufacturing industry and provide the necessary upskilling and reskilling opportunities to the current workforce. Thus, this publication was designed to ascertain the skill requirements for the most prominent job profiles related to asset management, and to show that it is possible to provide training even at situations when failures can occur, thanks to the use of VR. We are confident that our work can make a valuable contribution to future efforts aimed at developing more targeted training for asset management.

Acknowledgements

Work funded by project SUSTASKILLS: Development of a roadmap for the implementation of skills related to industrial symbiosis and energy efficiency to achieve a sustainable process industry. Grant Agreement No PUE_2023_1_0006. The sole responsibility for the issues treated in the present paper lies with the authors; the Commission is not responsible for any use that may be made of the information contained therein.

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Identifying the Future Skills Requirements of the Digital Maintenance era

1

Felix Bayón, Aitor Oyarbide[2], Aitor Goti[3], Tugce Akyazi[4]

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2,3 Aitor Goti and Aitor Oyarbide - Dept. of Mechanics, Design and Industrial Management, University of Deusto, Bilbao, Spain.
4 Tugce Akyazi – Deusto Business School, University of Deusto, Bilbao, Spain.

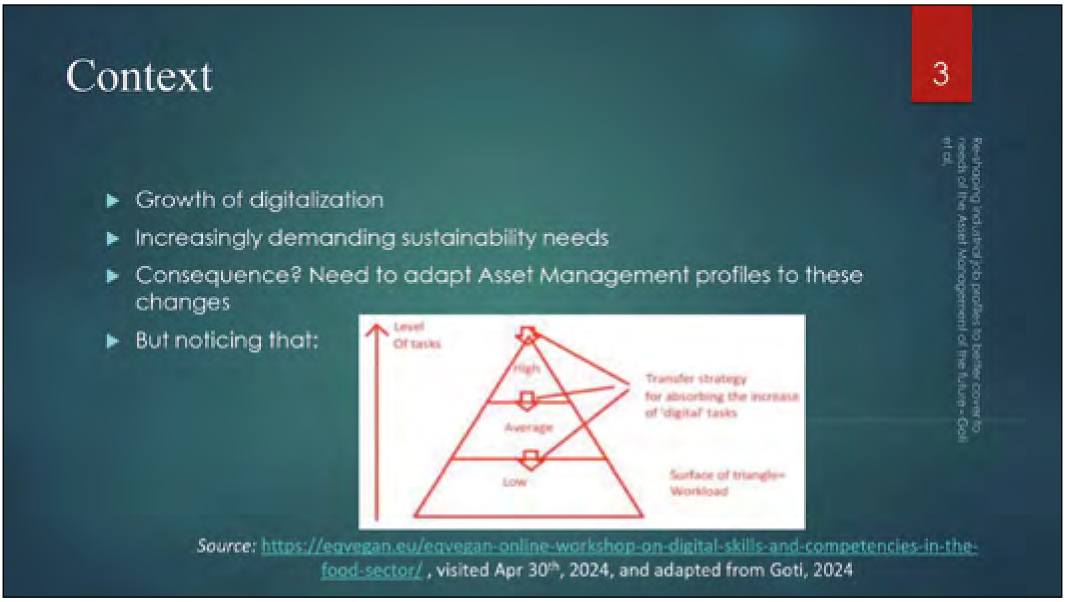
Correspondence: aitor.goti@deusto.es

Identifying the Future Skills Requirements of the Digital Maintenance era – Bayón et al

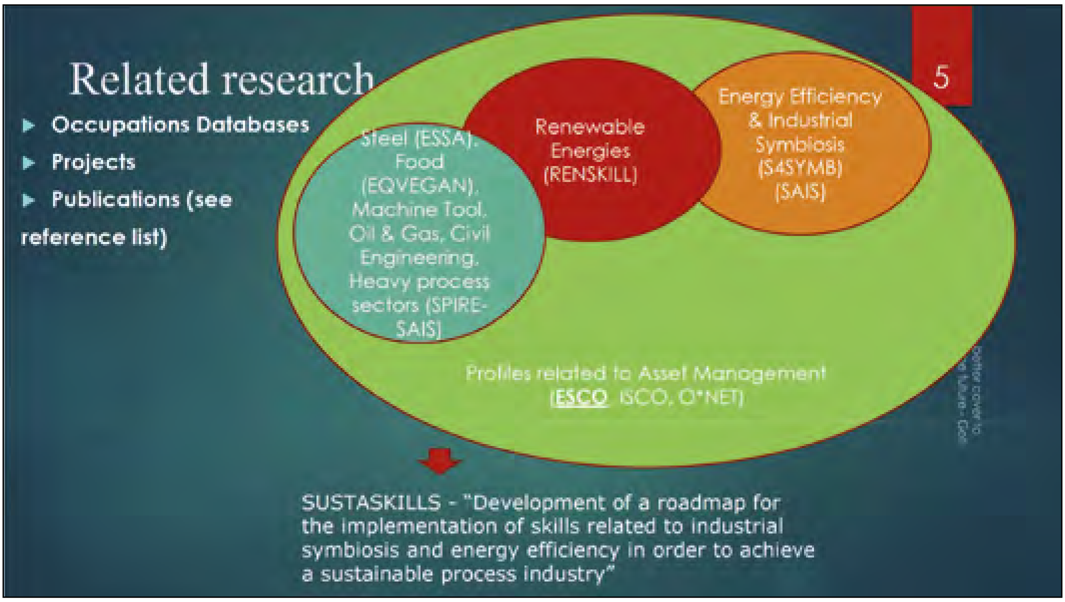
Table of contents

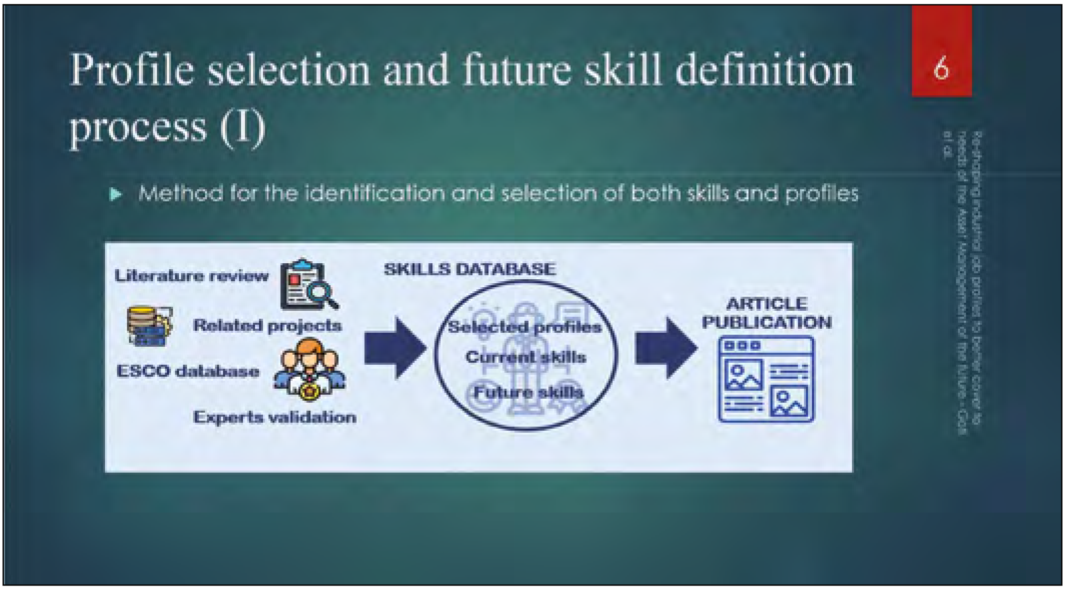
2

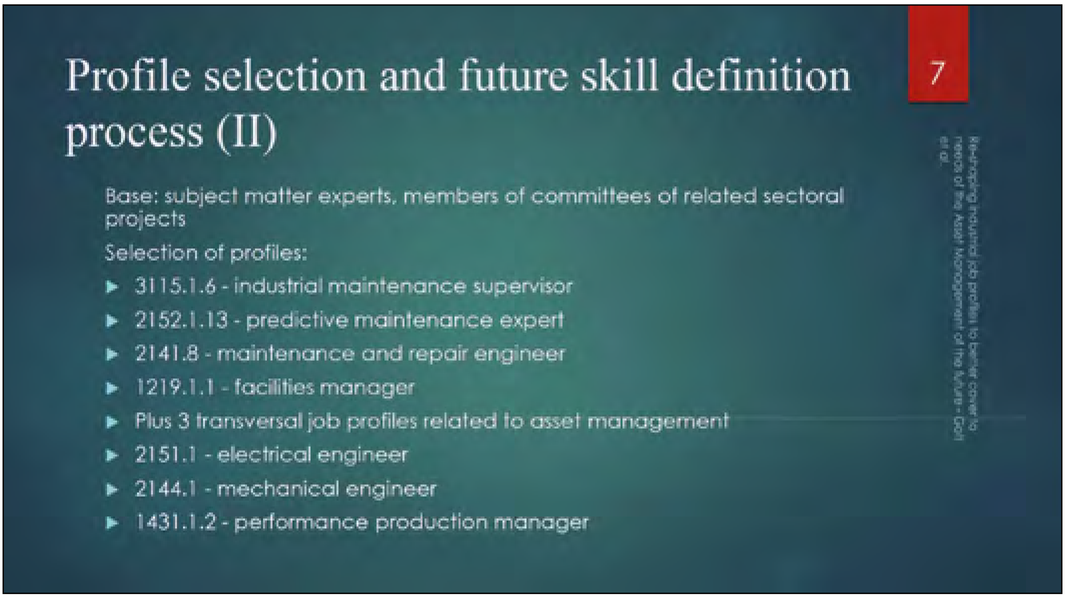
Re-shaping industrial job profiles to better cover to needs of the Asset Management of the future - Goti et al


Context
3
Reshaping industrial job profiles to better cover to needs of the Asset Management of the future - Goti et al.
Growth of digitalization
Increasingly demanding sustainability needs
Consequence? Need to adapt Asset Management profiles to these changes
But noticing that:
Level
Of tasks
High
Average
Low
Transfer strategy
for absorbing the increase
of 'digital' tasks
Surface of triangle=
Workload
Source: https://eqvegan.eu/eqvegan-online-workshop-on-digital-skills-and-competencies-in-the-food-sector/ , visited Apr 30th, 2024, and adapted from Goti, 2024

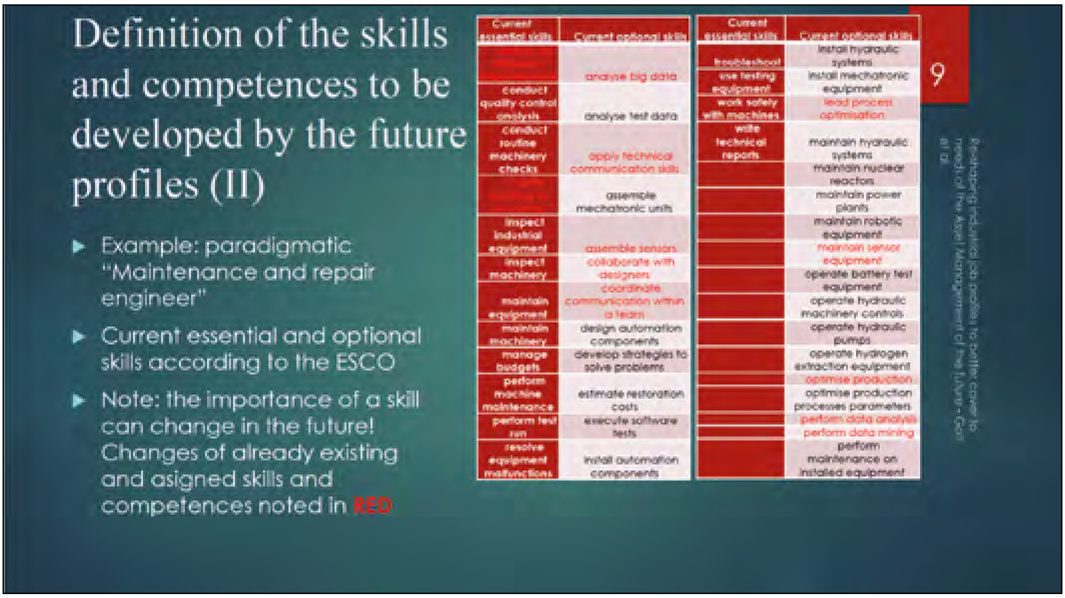

Aims
4
Reshaping industrial job profiles to better cover to needs of the Asset Management of the future - Goti et al.
to address a significant need in the field of maintenance management by recognizing new talents (specific skills required for these roles) that are emerging as a result of industrial evolution and sustainability requirements.
to select and develop the most appropriate materials to cover this skills gap using a train the trainers approach. To achieve this, the findings from prior research has been utilized.

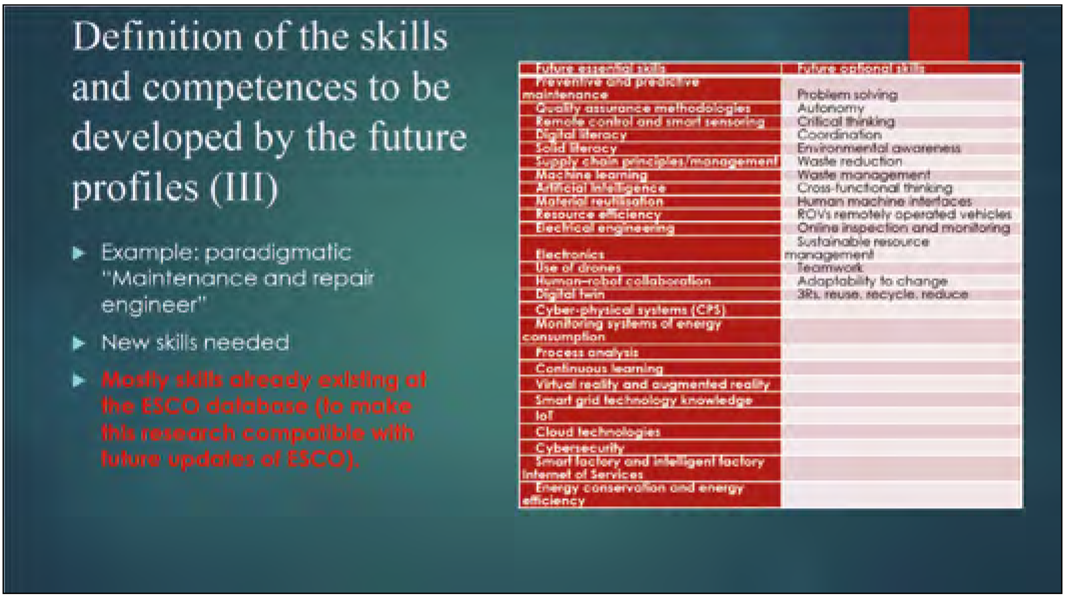

Related research
Occupations Databases
Projects
Publications (see reference list)
Steel (ESSA), Food (EQVEGAN), Machine Tool, Oil & Gas, Civil Engineering, Heavy process sectors (SPIRE-SAIS)
Renewable Energies (RENSKILL)
Energy Efficiency & Industrial Symbiosis (S4SYMB) (SAIS)
5
Profiles related to Asset Management (ESCO, ISCO, O*NET)
SUSTASKILLS - "Development of a roadmap for the implementation of skills related to industrial symbiosis and energy efficiency in order to achieve a sustainable process industry"

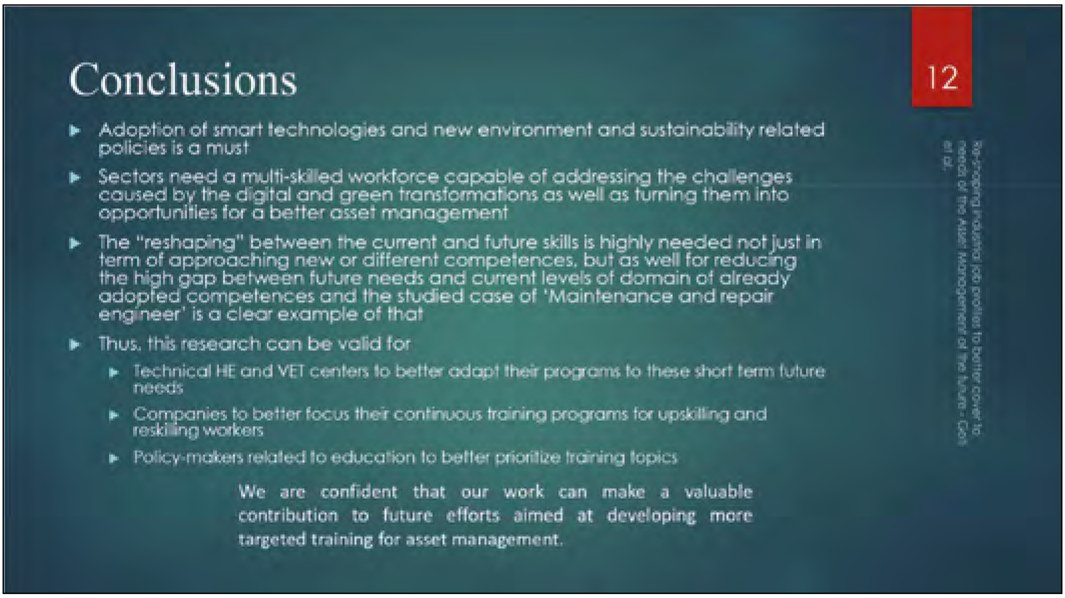

Profile selection and future skill definition process (I)
6
Method for the identification and selection of both skills and profiles
Literature review
Related projects
ESCO database
Experts validation
SKILLS DATABASE
Selected profiles
Current skills
Future skills
ARTICLE PUBLICATION


Profile selection and future skill definition process (II)
7
Base: subject matter experts, members of committees of related sectoral projects
Selection of profiles:
3115.1.6 - industrial maintenance supervisor
2152.1.13 - predictive maintenance expert
2141.8 - maintenance and repair engineer
1219.1.1 - facilities manager
Plus 3 transversal job profiles related to asset management
2151.1 - electrical engineer
2144.1 - mechanical engineer
1431.1.2 - performance production manager


Profile selection and future skill definition process (II)
8
Base: subject matter experts, members of committees of related sectoral projects
Selection of skills and competences*
Active listening, Adaptability and adapt to change, Advanced communication skills, Advanced data analysis and modelization, Advanced IT skills and programming, Advanced literacy, Artificial Intelligence (AI), Augmented Reality, Automation, Basic numeracy and communication, Circular economy, Complex information processing and interpretation, Computerized Maintenance Management, Continuous learning, Creativity, Critical thinking and decision making, Cross-functional process know-how, Cultural empathy, Cybersecurity, Data management-safe storage, Digital twin, Energy efficiency, Environmental awareness, Ethical understanding, ICT, Interdisciplinary thinking and acting, IoT, Mixed Reality, Opportunity assessment, Personal experience, Predictive and Proactive maintenance, Problem solving, Process analysis, Product life cycle impact assessment, Quantitative and statistical skills, Resource reuse/recycling, Risk management, Robotics, Sensors technology, Sustainable resource management, Teaching and training others, Team working, Use of digital communication tools, Waste reduction and waste management, Work autonomously.


Definition of the skills and competences to be developed by the future profiles (II)
Example: paradigmatic "Maintenance and repair engineer"
Current essential and optional skills according to the ESCO
Note: the importance of a skill can change in the future! Changes of already existing and asigned skills and competences noted in RED
Current essential skills
Current optional skills
analyse big data
conduct quality control analysis
analyse test data
conduct routine machinery checks
apply technical communication skills
assemble mechatronic units
inspect industrial equipment
assemble sensors
inspect machinery
collaborate with designers
maintain equipment
coordinate communication within a team
maintain machinery
design automation components
manage budgets
develop strategies to solve problems
perform machine maintenance
estimate restoration costs
perform test run
execute software tests
resolve equipment malfunctions
install automation components
Current essential skills
Current optional skills
troubleshoot
install hydraulic systems
use testing equipment
install mechatronic equipment
work safely with machines
lead process optimisation
write technical reports
maintain hydraulic systems
maintain nuclear reactors
maintain power plants
maintain robotic equipment
maintain sensor equipment
operate battery test equipment
operate hydraulic machinery controls
operate hydraulic pumps
operate hydrogen extraction equipment
optimise production
optimise production processes parameters
perform data analysis
perform data mining
perform maintenance on installed equipment
9


Definition of the skills and competences to be developed by the future profiles (III)
Example: paradigmatic "Maintenance and repair engineer"
New skills needed
Mostly skills already existing at the ESCO database (to make this research compatible with future updates of ESCO).
Future essential skills
Future optional skills
Preventive and predictive maintenance
Quality assurance methodologies
Remote control and smart sensoring
Digital literacy
Solid literacy
Supply chain principles/management
Machine learning
Artificial Intelligence
Material reutilisation
Resource efficiency
Electrical engineering
Electronics
Use of drones
Human–robot collaboration
Digital twin
Cyber-physical systems (CPS)
Monitoring systems of energy consumption
Process analysis
Continuous learning
Virtual reality and augmented reality
Smart grid technology knowledge
IoT
Cloud technologies
Cybersecurity
Smart factory and intelligent factory Internet of Services
Energy conservation and energy efficiency
Problem solving
Autonomy
Critical thinking
Coordination
Environmental awareness
Waste reduction
Waste management
Cross-functional thinking
Human machine interfaces
ROV's remotely operated vehicles
Online inspection and monitoring
Sustainable resource management
Teamwork
Adaptability to change
3Rs, reuse, recycle, reduce



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Industrial service – the red pill

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Ibon Iribarren
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Linqcase Industrial Solutions

Abstract

This work focuses on the concept of servitization, emphasizing the transformation of traditional business models to incorporate service-oriented solutions. It addresses the challenges entrepreneurs face when implementing new service offerings, particularly the common customer perceptions that services should be free or not worth the effort. This servitized RAMS oriented presentation outlines a structured approach for entrepreneurs to identify and articulate customer problems, propose effective solutions, and link their service offerings to these needs. By understanding the customer's perspective and effectively communicating the value of services, businesses can enhance customer satisfaction and drive revenue growth. The key take-away is the importance of thorough preparation and customer engagement in successfully transitioning to a service-based model.

1. Introduction

Industrial suppliers have increasingly sought to develop business models that capitalize on service-based activities rather than relying solely on machinery and hardware sales.

Although it's widely assumed that service-oriented models yield higher revenue, greater profitability, and foster stronger relationships with end users, many industrial equipment manufacturers continue to struggle with selling and implementing services at customers' premises. The authors suggest that this challenge may stem from specific misconceptions about how to develop a service business model.

One common misstep is a limited understanding of how to fuel the sales funnel effectively. Rather than filling the funnel through targeted market research and prospecting, many organizations focus primarily on the development of new value propositions based on their own (supply-side) assumptions. This approach often leads to significant development costs before genuine interest from target markets is assessed, and —possibly— confirmed.

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Secondly, many industrial suppliers become fixated on the possibilities created by Industry 4.0, connectivity, and Artificial Intelligence, which drives an exhaustive search for data. Yet, the benefits of acquiring such data can be uncertain. As a result, discussions between end users and equipment manufacturers frequently revolve around data ownership, when instead, equipment providers should concentrate on strategies for monetizing the data that can be made available.

To enhance the competitiveness of both customer plants and equipment manufacturers, the authors propose that the latter prioritize service packages that deliver measurable performance improvements for equipment in use, irrespective of data ownership or usage. They also recommend sticking to a straightforward sales funnel process to identify and address support needs within customer plants, creating opportunities to capitalize on industrial service sales.

Service: **the red pill**

How to make industrial service **a reality**

Bart Kamp
Ibon Iribarren

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Before we get started…

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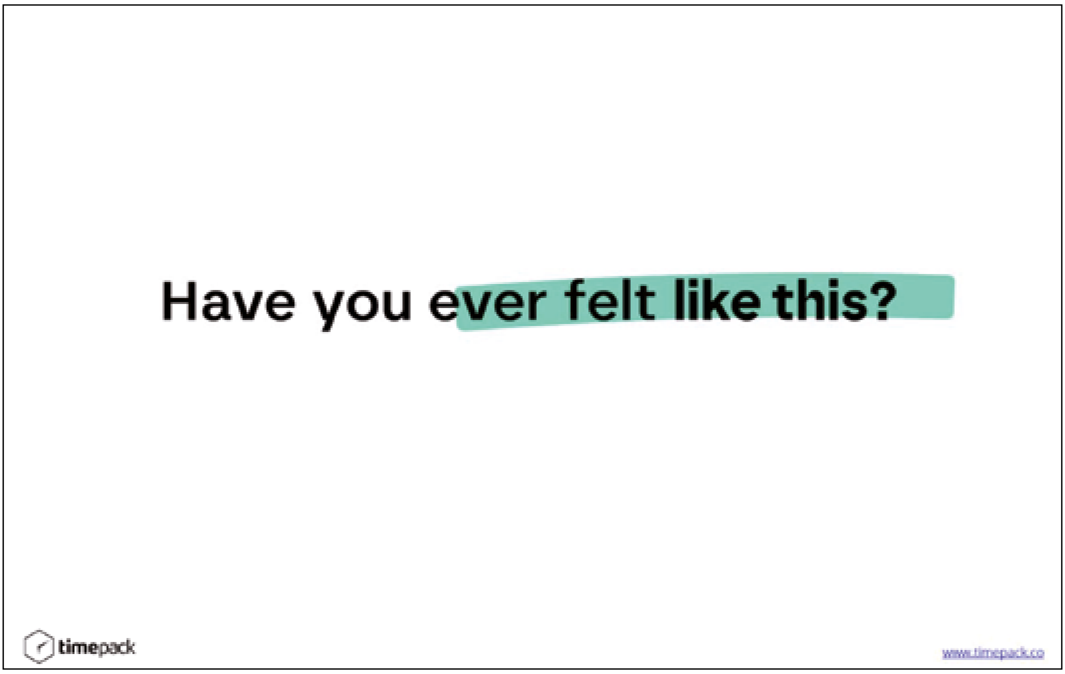
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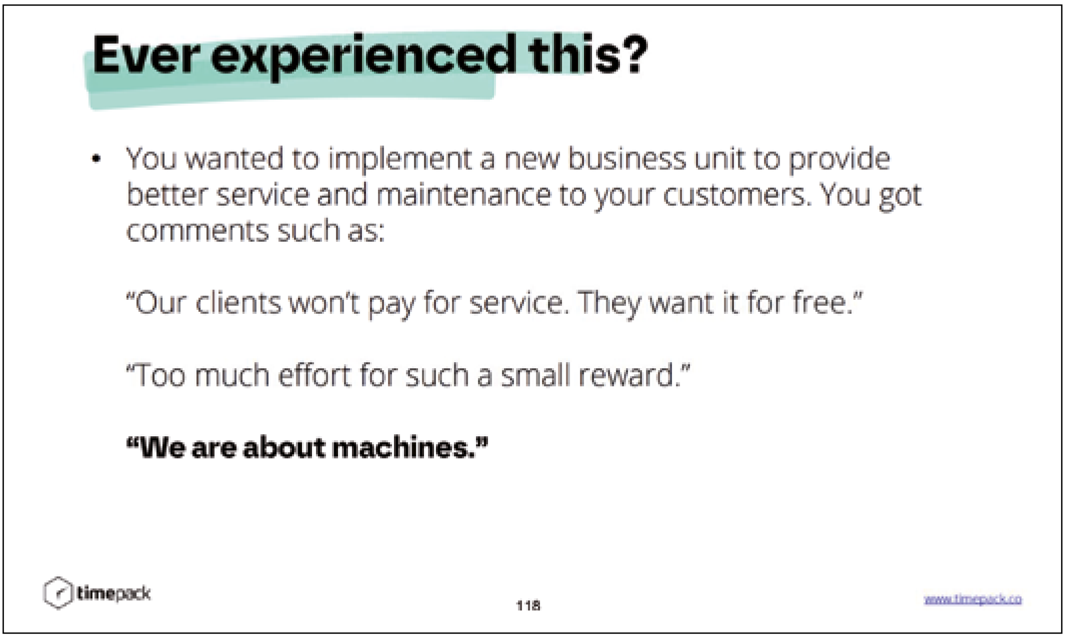
Ever experienced this?
• You wanted to implement a new business unit to provide better service and maintenance to your customers. You got comments such as:
"Our clients won't pay for service. They want it for free."
"Too much effort for such a small reward."
"We are about machines."
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Ever experienced this?

- You tried selling a data box to your customers to capture critical data such as spindle bearing temperature, vibration, etc.
- Customers refused to buy.
- Then you tried implementing the device for free.
- **And stumbled upon the dreaded...**

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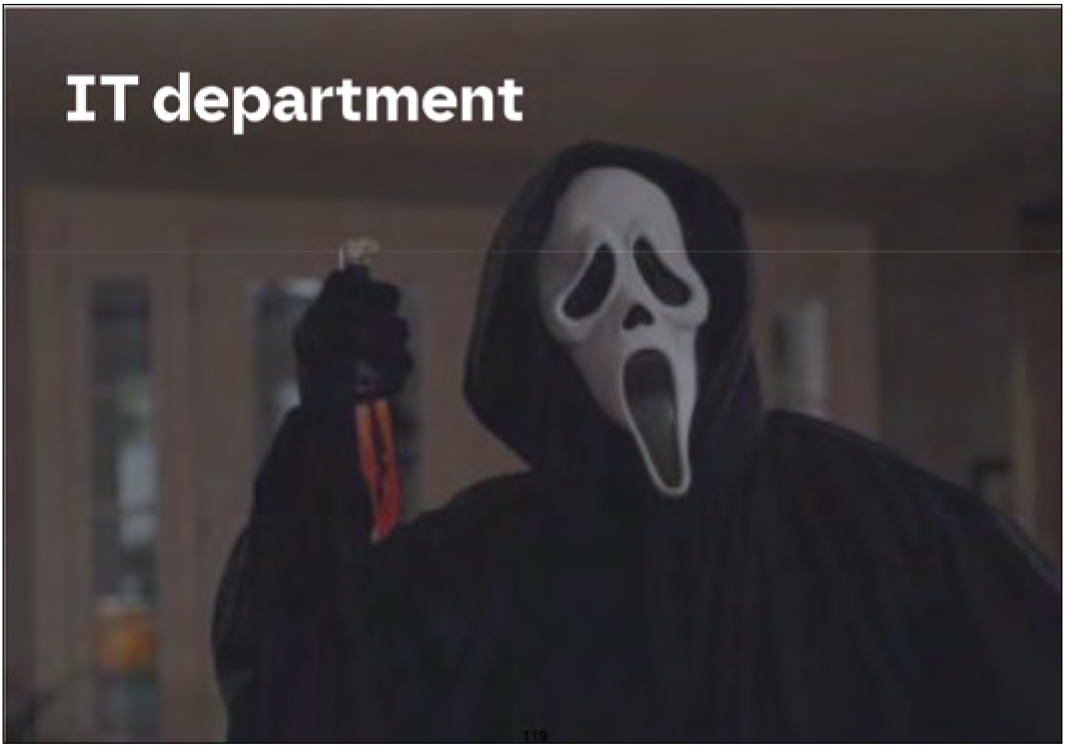

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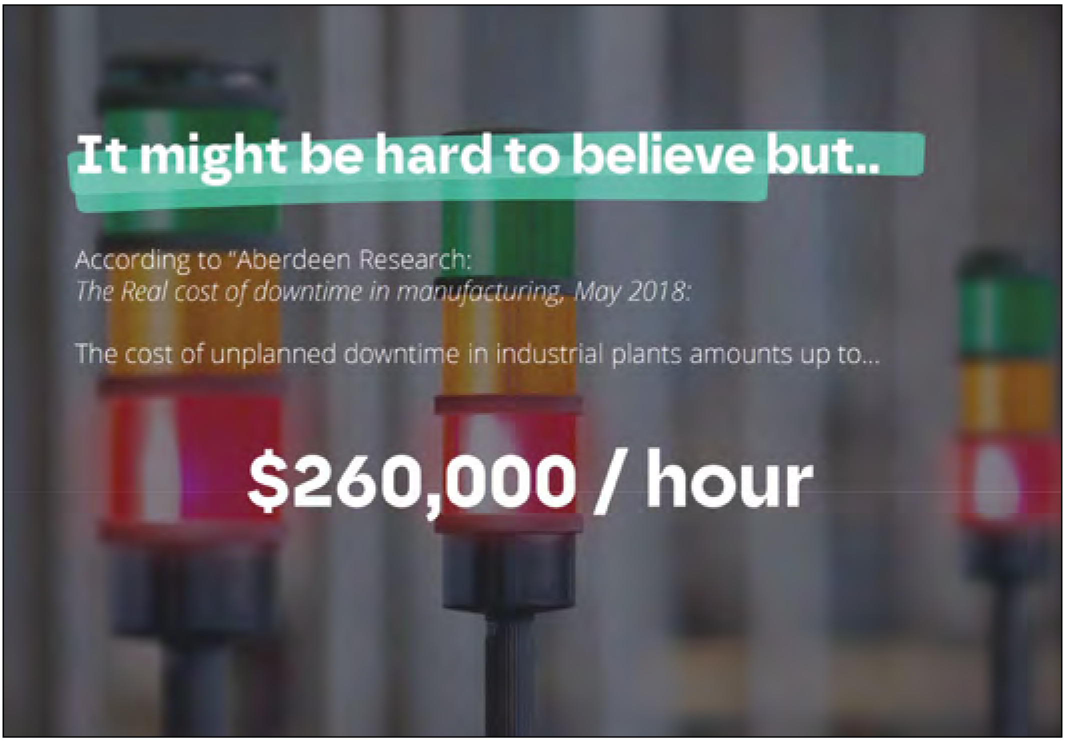
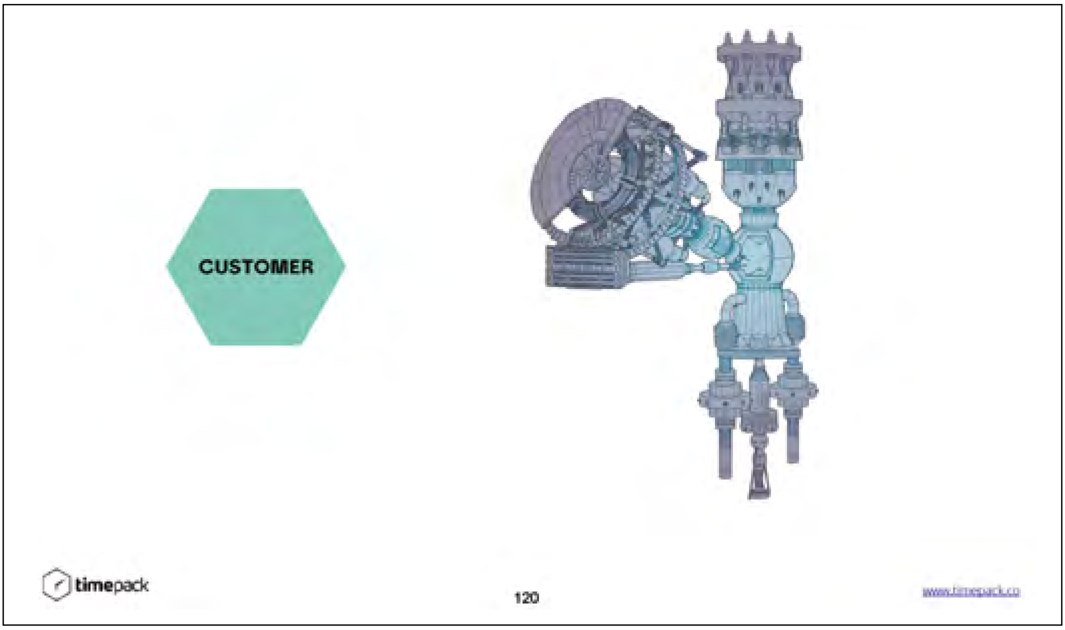

It might be hard to believe but..
According to "Aberdeen Research:
The Real cost of downtime in manufacturing, May 2018:
The cost of unplanned downtime in industrial plants amounts up to...
$260,000 / hour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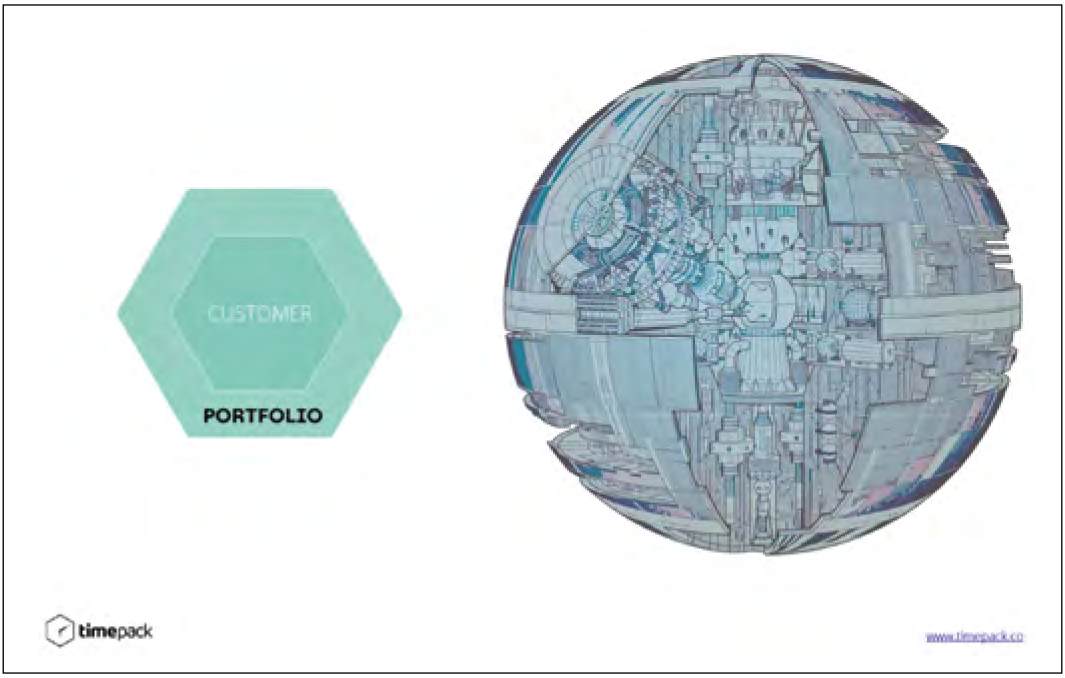

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Reasons why
you may fail
to sell service
#1
Too focused on
PRODUCT
Service
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Reasons why
you may fail
to sell service
#2
Too focused on
DATA


Reasons why you may fail to sell service
#3
Not grasping your BUSINESS MODEL
Customer knowledge
Full
Partial
MULTICHANNEL
PLATFORM
SUPPLIER
MODULAR PROVIDER
Value chain
Ecosystem
Transversal business
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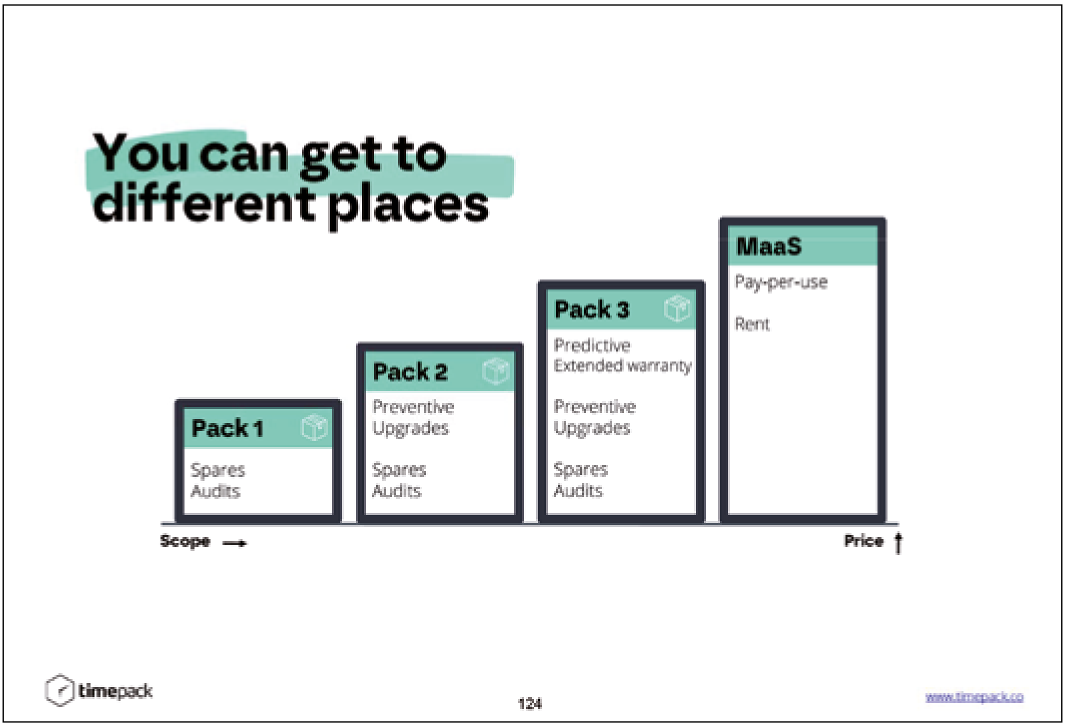
You can get to different places
Pack 1
Spares
Audits
Pack 2
Preventive
Upgrades
Spares
Audits
Pack 3
Predictive
Extended warranty
Preventive
Upgrades
Spares
Audits
MaaS
Pay-per-use
Rent
Scope
Price
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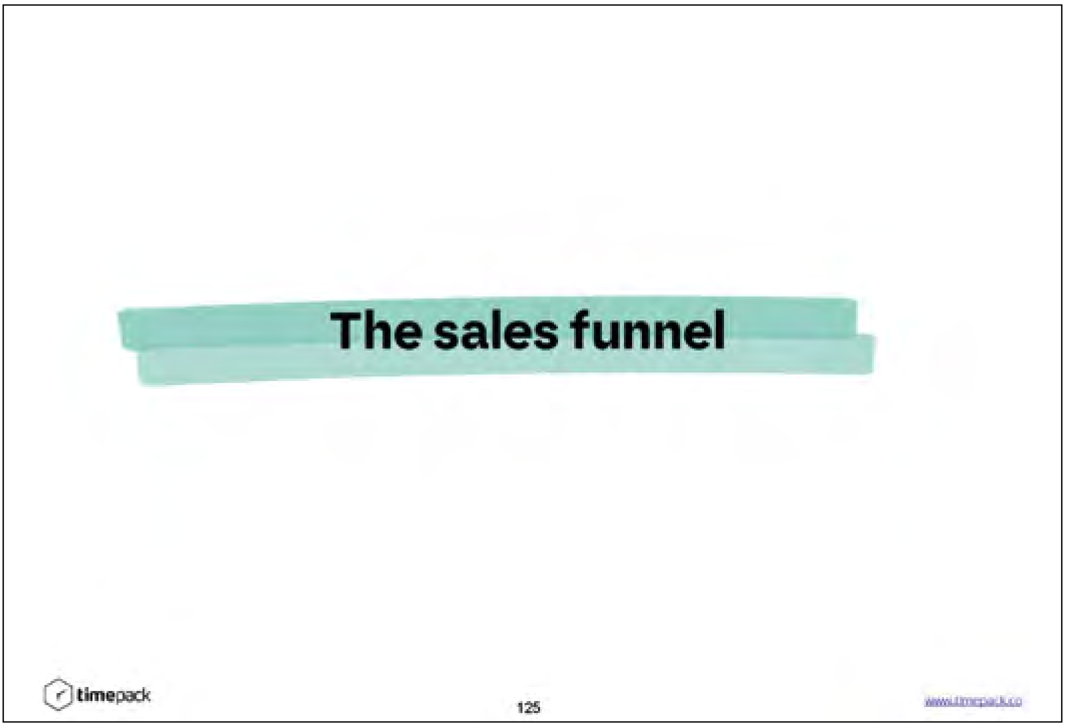

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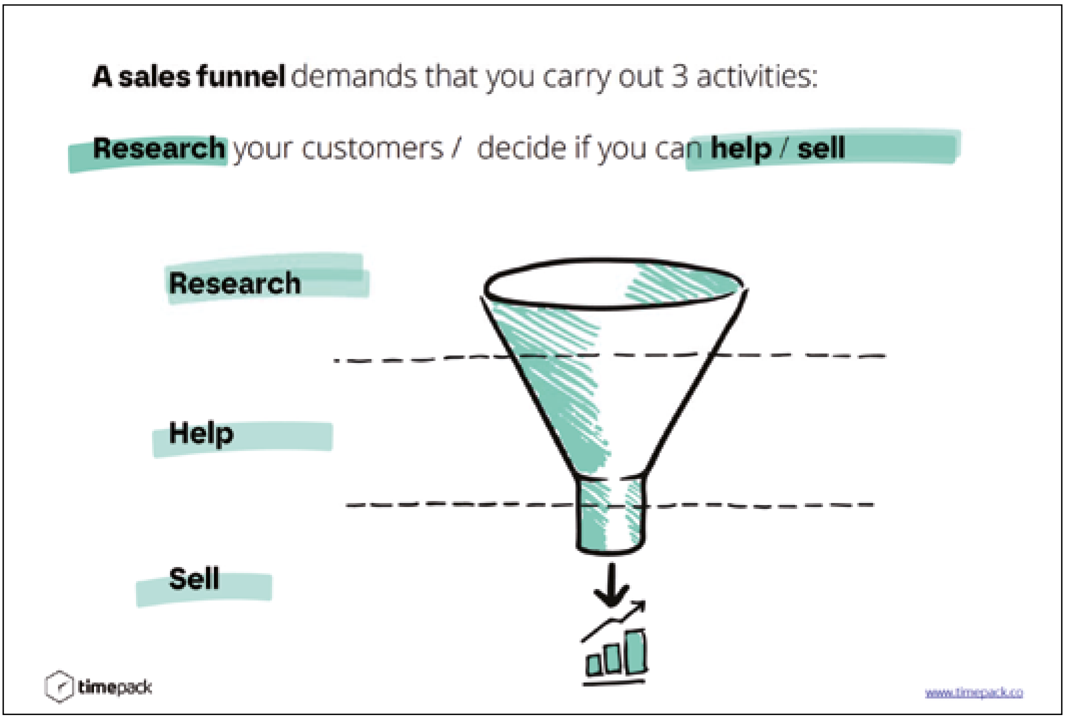

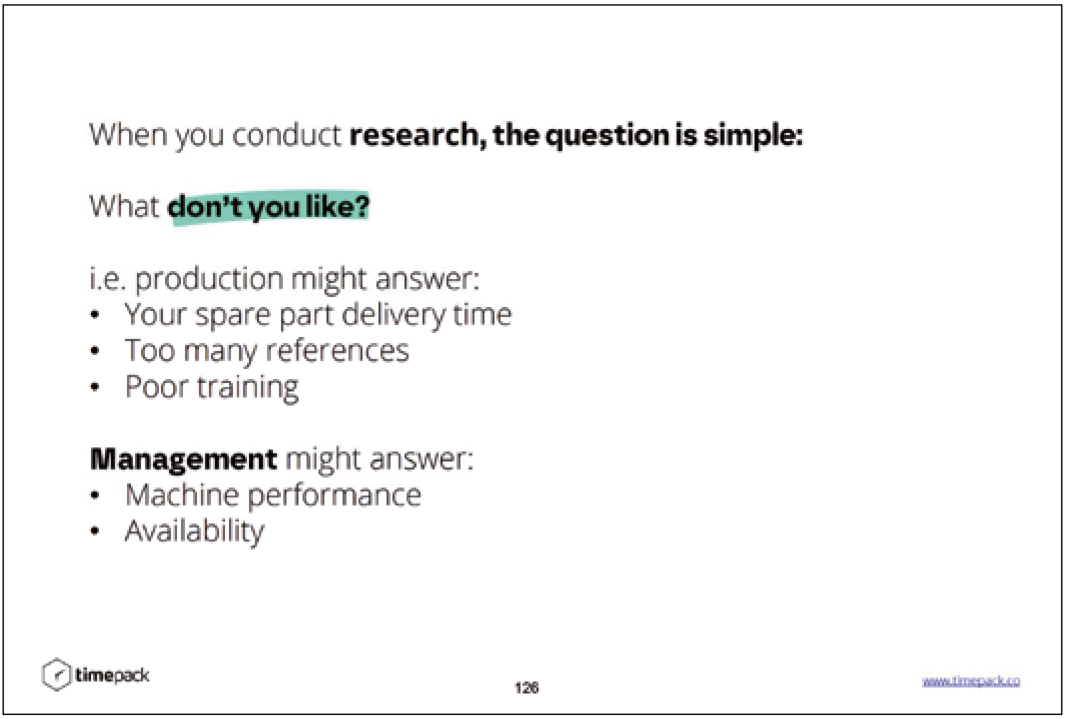

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Before you sell, decide and convince your customer that **you can help:**

- What is the problem?
- What is the bigger problem?
- What is the solution?

This feeback is priceless to improve the next generation of equipment.

(And it offers the chance to sell very simple service products)

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At one point, you will present your product.

If you conducted the previous phase properly, you will be able to link this product to the desired solution / to the problem the client wishes to solve.

i.e. "you had a chip issue within the machine working unit. This new front guarding allows you to virtually eliminate the chip evacuation problem".

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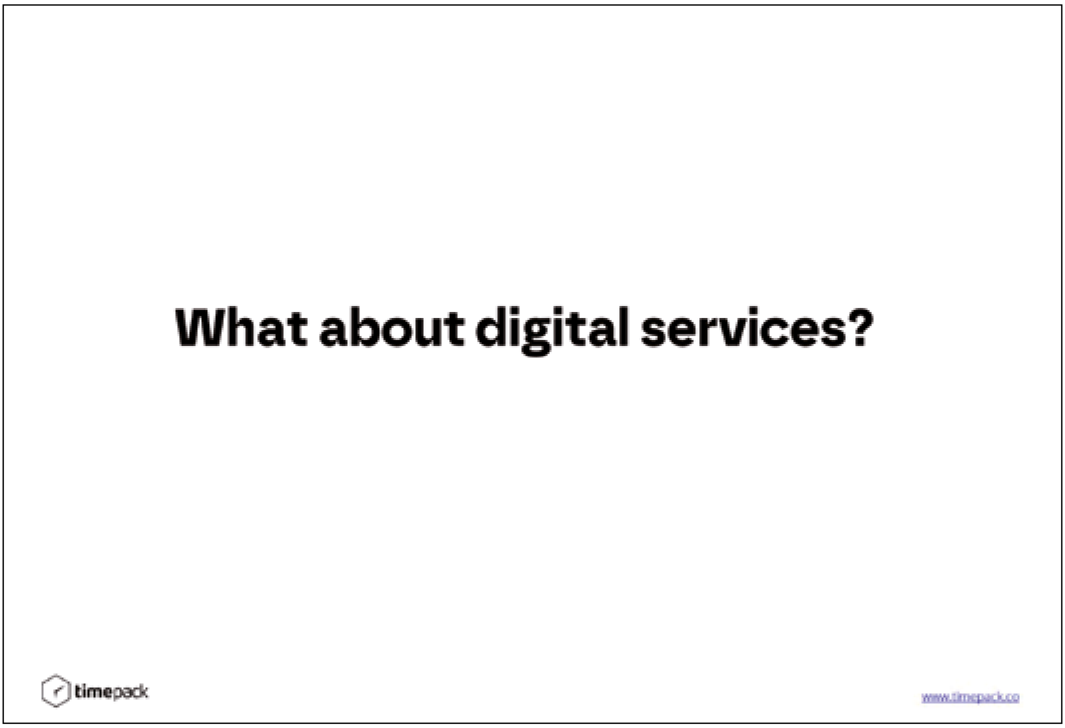
What about digital services?
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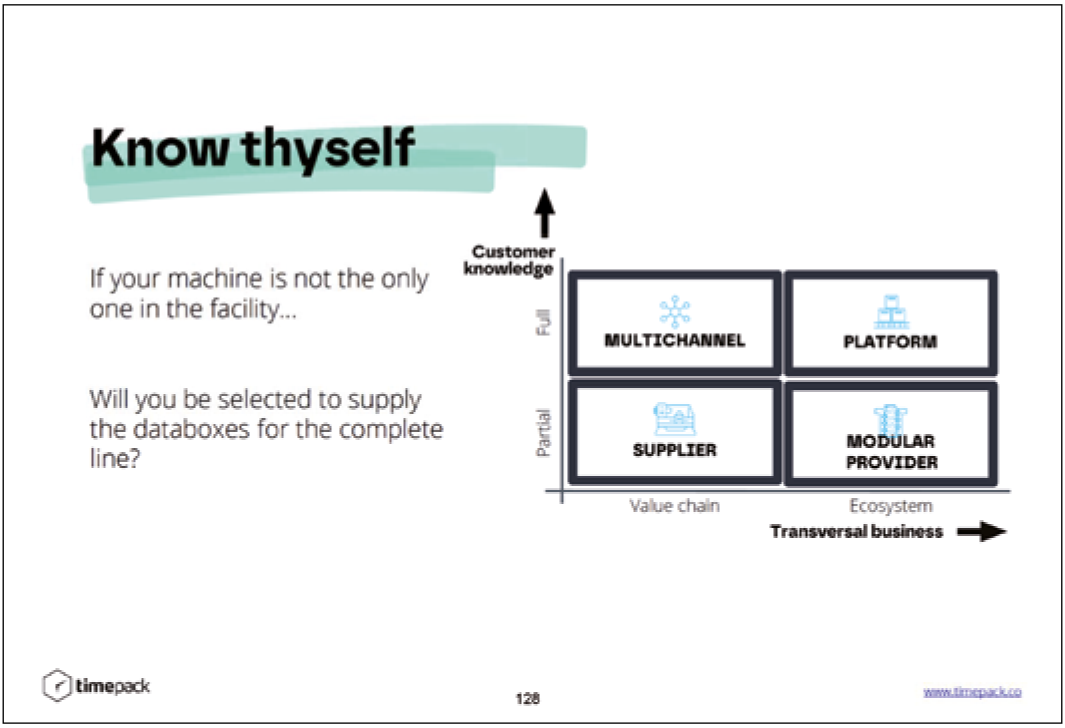
Know thyself
If your machine is not the only one in the facility...
Will you be selected to supply the databoxes for the complete line?
Customer knowledge
Full
Partial
MULTICHANNEL
PLATFORM
SUPPLIER
MODULAR PROVIDER
Value chain
Ecosystem
Transversal business
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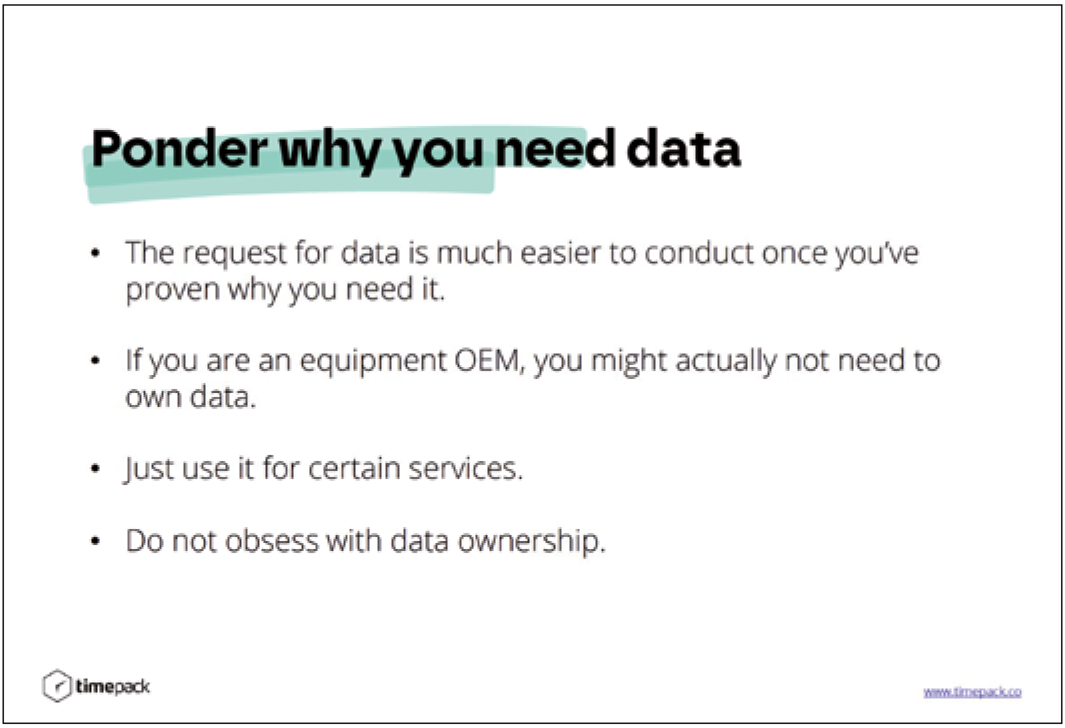
Ponder why you need data
• The request for data is much easier to conduct once you've proven why you need it.
• If you are an equipment OEM, you might actually not need to own data.
• Just use it for certain services.
• Do not obsess with data ownership.
timepack
www.timepack.co

Smart factory maintenance: building a predictive model of pathogen contamination during the food fabrication process

Sébastien Delmotte[1], Alexandre Feugier[2], Jean-Alain Brossier[2], Florent Arrignon[1]

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[2] Royal Canin, 650 Avenue de la Petite Camargue, F-30470 Aimargues, France

Abstract

One of the major aims of food safety is to prevent pathogens (mostly bacteria, e.g. Salmonella enterica sp.) to transmit to final products during the food fabrication process. Detection of contamination is thus of crucial importance at every stage of the process. The sanitation (maintenance) is both preventive and performed at a given frequency or corrective when a contamination is detected. Optimization of sanitation faces two main issues: (i) the apparent random occurrence of contamination due to multiple sources and inherent to complexity biological processes; (ii) the delay between sampling and results of microbiological analysis (1 to 2 days), which implies to remove or to recall a part of the production once a contamination is detected. This can lead to major financial loss. Therefore, prediction of contamination is fundamental to optimize prevention and to reduce the costs of a contamination and is a main driver of the factory management. To this aim, we have firstly analysed the daily data of salmonella contamination from 5 factories in the world over 8 years. For each factory, the sampling points covered all the different functional zones from raw materials storage to palletization of final product. After data cleaning and processing of descriptive statistics, we modelled contamination using survival analysis and transposing basic reliability concepts in calculating the Mean Time between Contaminations (MTBC). A Weibull distribution (2 parameters) was retained among several models as the best fit to data. The reliability diagram was obtained and we characterized the functioning durations without contamination at the scales of functional zones and factories. These results were used to: (i) compare the different zones inside factories and to compare factories to each other; (ii) optimize the frequencies of maintenance. Such indicators can be used to assess the maintenance efficiency over time. Finally, we built for one factory an artificial neural network (multilayer perceptron) to predict the occurrence of a contamination in the final product knowing the contaminations in the different zones occurring the previous week or the previous day and we implemented it into a dedicated visualization software displaying the factory plan, the contamination points and the final predictions. This software can be connected to the real-time measures of contamination. It constates a first step to the digital twin of the factory dedicated to risk management. management.

1. Introduction

In the context of climate change, enhancing productivity while ensuring the safety and sustainability of food supply chains has become increasingly complex. In the

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European food and beverage industry, there were 4,837 recall events reported in 2023, marking a 7% increase from the previous year. Bacterial contamination is the second leading cause of these recalls (Sedgwick, 2024). Financially, the average cost of each recall is estimated at $10 million, as reported by a Deloitte study for the Food Marketing Institute and the Grocery Manufacturers Association (GMA, Deloitte, 2010). This figure only accounts for direct recall costs and excludes indirect losses, such as those related to reputational damage. Additionally, many contaminated products are destroyed at the factory stage, representing not only a significant financial loss for companies but also a serious concern for resource sustainability. Among various biological risks, Salmonella and Escherichia coli are predominant (Uyttendaele *et al.,* 2015). The US Centers for Disease Control and Prevention (CDC) estimates that 95% of Salmonella infections in the population are food-related (Fatica and Schneider, 2011). These bacteria contributed to 5,700 to 10,200 cases of foodborne illness in the US and France in the last decade of the 20th century (Fung *et al.,* 2018).

Modern food supply chains are globally extensive, meaning that contamination of end products can have multifaceted causes, such as pre-contaminated raw materials, contaminated water used in processing, or external contamination of machinery by agents or resident bacteria at the facility. To address these issues, the US Department of Agriculture, Food Safety and Inspection Service introduced the Pathogen Reduction Hazard Analysis and Critical Control Point (PR-HACCP) Rule (US Department of Agriculture, Food Safety and Inspection Service, 1996 in Williams *et al.,* 2020). In the meat and poultry sectors, a noticeable reduction in contaminations has been observed since the implementation of this rule. However, anomalies persist and causal explanations remain elusive, largely due to the intricate nature of contamination processes (Williams *et al.,* 2020). Predictive modeling and quantitative risk assessment serve as crucial strategies for managing pathogen contamination (Vikram *et al.,* 2024). Various mathematical models have been developed to describe and predict the survival of Salmonella under different heat conditions, the probabilities of contamination during transport, throughout the supply chain, and the likelihood of illness from consuming contaminated food based on Salmonella concentration (Rajan *et al.,* 2016). These models range from kinetic and probabilistic to empirical and mechanistic (Stavropoulou & Bezirtzoglou, 2019; Vikram *et al.,* 2024).

This study, initiated in 2021 using historical data, aimed to develop and test complementary modelling approaches for contamination at the plant level. Through this approach, we have provided insights for optimizing data collection and cleaning processes and have begun integrating the food safety dimension into the digital twin of the supply and production chain.

2. **Data description**

The study is based on data collected from five factories distributed worldwide. Of these, four recorded daily data from 2016 to 2019, while the fifth gathered data from 2013 to 2020. A lot of measurement points were sampled across the factory and on very different supports: raw materials, ground, stairs, ramps, production lines elements, critical points of the fabrication chain, final products, packagings... Originally, these data were not collected for modelling purposes but for real-time microbiological monitoring. Consequently, variations can be observed in the number of measurement points and their frequency over different periods. Additionally, since the factories operate independently, measurement protocols are not standardized. Therefore, an initial effort to standardize the data was undertaken. After a data cleansing process and the removal of incomplete measurement points (more than 5% of missing data), between 31 to 138 measurement points are available. These points are grouped into zones: overall (Global), raw materials, materials in the process of cooking, cooked materials, and final product. Descriptive statistics and trend analysis (positive autocorrelations) have been conducted on an annual, monthly, and weekly basis. No temporal trends nor cycles were detected at the scales of the year to the scale of the study period, but peaks of contamination can suddenly appear.

For confidentiality reasons, the locations of the factories, the different intra-factory zones, and measurement points are anonymized. Similarly, the scales of contamination rates could not be disclosed.

3. **Characterization of contamination rates**

3.1. *Modelling approach based on reliability assessment*

By applying reliability engineering methods (Signoret, Leroy, 2021) and survival statistics, the main characteristics of contaminations can be identified. The first step involves creating a dataset for each zone, which records the number of days since the last contamination at each measurement point. The day counter is reset whenever a contamination occurs. To characterize the actual contamination regime of each zone inside each factory, it was decided not to reset the day count following (i) scheduled preventive sanitations, for which frequency and methods may vary from one factory to another; (ii) daily cleanings of the facilities. Indeed, in some zones, preventive sanitations are not sufficient to eliminate resident colonies, and contamination can reappear shortly after, necessitating further intervention. Thus, the contamination characteristics derived from our calculations reflect the actual contamination regime and the effectiveness of the existing preventive measures.

The uncertainties related to missing data (less than 5%) are evaluated through Monte Carlo simulation: missing values are replaced with positive or negative values, using the calculated contamination frequency distribution of the corresponding zone. This process is repeated 1,000 times for each zone, and all subsequent calculations are performed at each iteration to derive average or median parameters and confidence intervals. For each set of values:

— Weibull, Log-normal, Normal, and Exponential distributions are fitted, and the quality of their fit assessed graphically (Probability plots). The two-parameter Weibull distribution (noted 2P) has consistently proven to be the most suitable due to its greater flexibility (figure 1).

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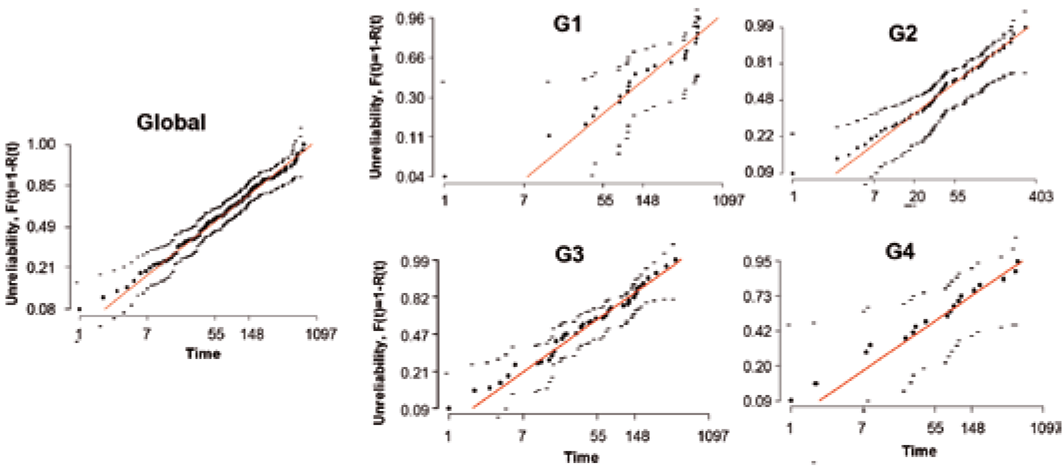
Figure 1

Example of adjustment of a 2P-Weibull distribution on contamination measures in the different zones of a factory



— The main characteristics of contamination are calculated: mean time between contamination (MTBC) and quartiles of operating durations before contamination.
— curves of instantaneous contamination rate over time and reliability probability (non-contamination) as a function of operating duration are produced.

This data processing process was applied at the scales of the year and of the study period for each factory.

3.2. *Results*

As illustrated in figure 2, the reliability function is directly established from the fit of the 2P-Weibull distribution for each zone within a factory and for each factory as a whole. This function allows for characterizing the contamination regime of each zone and enables comparisons both within a factory and between different factories. A simple indicator, denoted as $t_{0.5}$ and defined as $\Pr(T > t_{0.5}) = 0.5$, facilitates these comparison: it represents the minimal time the system can operates without contamination with a probability of 0.5 (in other words, the system has one chance on two to operate without contamination during more than $t_{0.5}$ and one chance on two to operate during less than $t_{0.5}$). Another indicator facilitating comparisons that can be directly calculated using the reliability function has been named MTBC (Mean Time Between Contaminations), in reference to MTBF in reliability (Mean Time Between Failures): it represents the average time between two contaminations in a zone or a factory. These indicators also aid in identifying severe malfunctions to search for the sources of contamination, in adjusting the frequencies of preventive sanitations and measurement frequencies to optimize effort and resource allocation across factories and zones within the factories.

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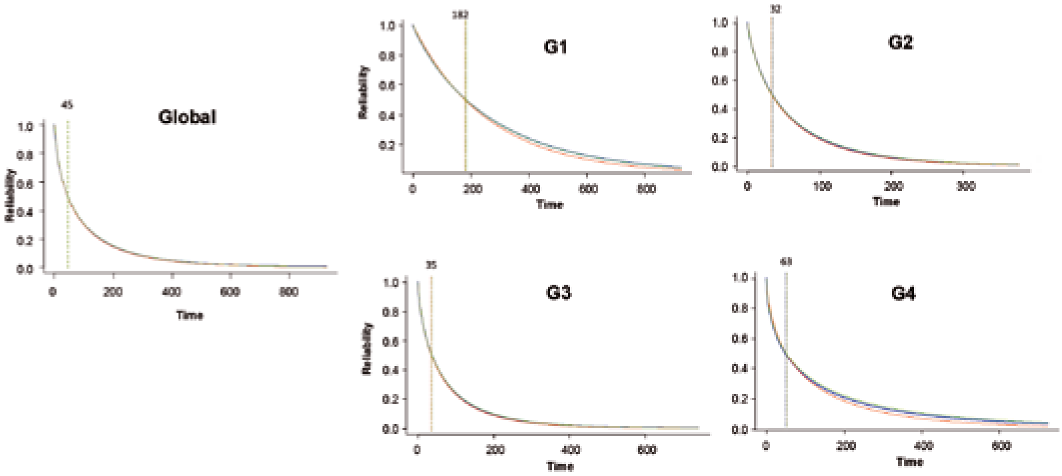
Figure 2

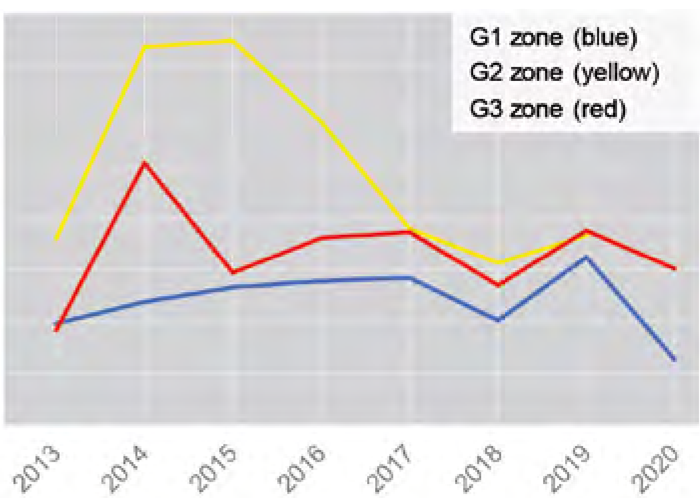
Example of adjustment of a 2P-Weibull distribution on contamination measures in the different zones of a factory. The blue curve represents the average function calculated over the Monte Carlo repetitions, and the red and green ones represent the IC95. The average time $t_{0.5}$ associated to a probability of functioning without contamination equal to 0.5 is represented by the vertical line



These indicators can be used to assess temporal evolution of the contamination rates as illustrated in figure 3. In that, these indicators are good KPI to, manage food safety. It requires to adjust the model to the annual scale.

Figure 3

Example of temporal evolution of MTBC

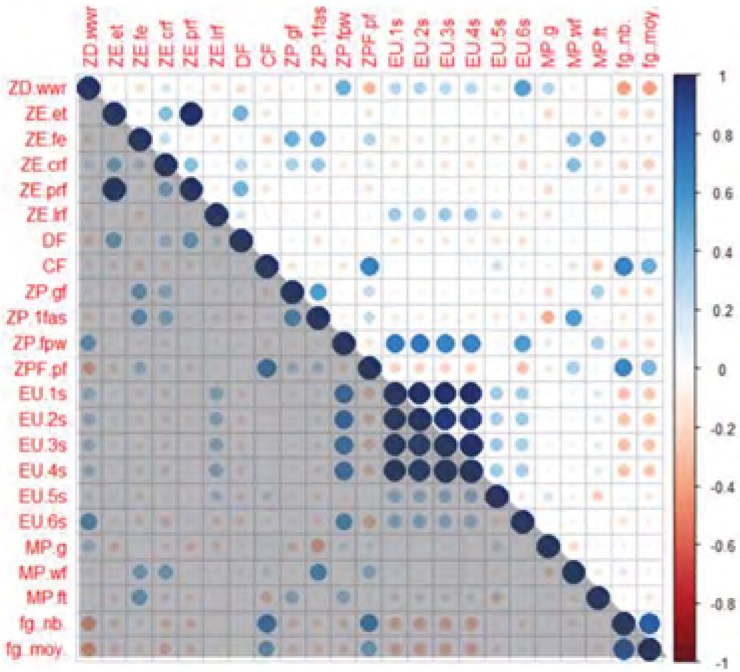


4. Predictive modelling of final product contamination

The causal relationships between the contamination of an element or area of the factory and that of the finished product (or another area) are not necessarily unidirectional, and the evidence of a statistical relationship between different measurements does not necessarily mean that there is a causal relationship of contamination. This leads to the following working hypotheses: (i) Contamination of one element (denoted 1) may be associated with contamination of another element (1), because it is the direct cause or consequence of the contamination or because they are both related to the same other element or event. The statistical relationship "contamination x positively correlated to contamination y" (1 = >1) may therefore valid in reality, although it does not systematically imply a functional or a causal relationship; (ii) the absence of contamination of one element (denoted 0) cannot be the cause of contamination of another element (1). The absence of the bacteria in one place cannot be the cause of its presence in another place. In fact, the statistical relationship "contamination x negatively correlated to contamination y" (0 = >1 or 1 = >0) does not make sense in reality. It is quite possible to find 0/1 or 1/0 associations in the dataset, which, recurring, produce a statistical relationship of negative correlation that does not make functional sense in terms of causality, and such a rule cannot be used in a predictive model. The interpretation and use of the results of the statistical work of this study, for modelling and prediction purposes, is based on these assumptions.

Figure 4

Rank correlation (Spearman) matrix between points of measurement in a factory. Only blue points make sense in terms of causal relationships



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As an illustration, figure 4 Shows the Spearman correlation between points of measure in a factory. Some, negative correlations appears to be moderately strong but it doesn't makes sense in terms of causality as explained before. At the opposite, positive correlations can be interpreted in terms of causality, especially when it corresponds to spatial patches as in figure 5. Such correlations were used to optimize the effort of measures.

4.1. *Model development*

The objective of predictive modelling is to predict the contamination of the final product from contamination measurements at different points in the plant. In order to make it an operational and usable model, it is necessary to take into account the time taken to acquire the results of the measurements (2 days): predicting the contamination of the final product one day from the measurements made on the same day would therefore be of no interest, it is necessary to introduce a time lag between the date of measurement of the predictor and the date concerning the prediction of the contamination of the final product. In this case, monthly predictions with a monthly lag, weekly predictions with a one-week lag and daily predictions with a lag of 2 to 6 days were tested. The weekly prediction with a one-week lag was chosen for its best performance.

As a first step, two models were tested on data from one factory to predict the presence or absence of contamination of the final product: a logistic regression model and a simple multilayers perceptron were adjusted. Neural network was designed with one hidden layer and a softmax output layer. Due to a high number of measurement points that can be correlated, input variables were selected previously to model fitting to keep it parsimonious.

Models were adjusted at the monthly, weekly and daily scales, but only the daily scale is presented because it represents the most interesting scale of prediction for operations. Additionally, instead of predicting the occurrence of contamination, daily rates of contamination (number of positive/number of samples) were modelled but the results were not sufficiently accurate.

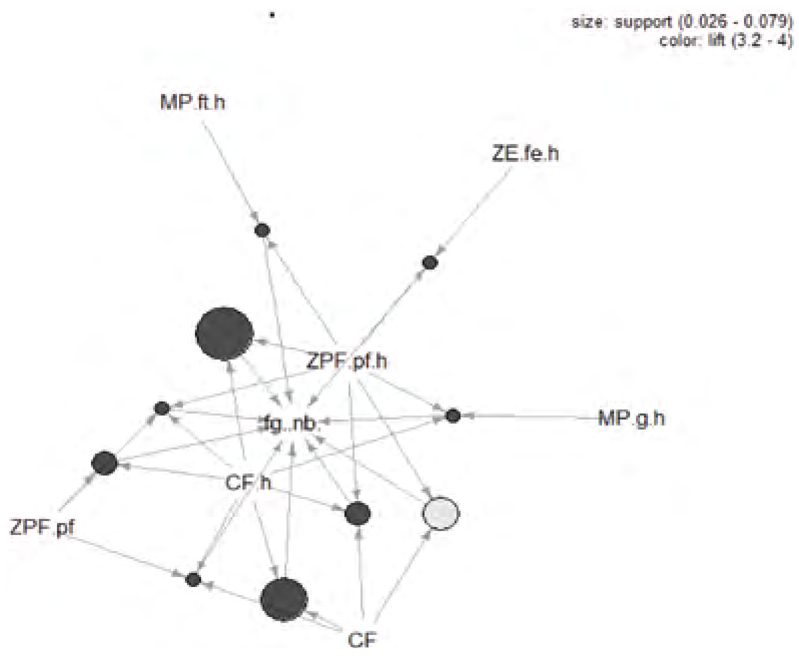
4.1.1. INPUT VARIABLES SELECTION

As explained in the previous paragraph, a negative correlation between measurements at two points cannot have functional significance in reality. Moreover, due to a high number of measurement points that can be correlated, input variables were selected previously to model fitting.

The first selection method is the "Apriori" method (Agrawal *et al.,* 1994). It is used for learning association rules in large data ensembles. Here, it was conducted to determine if there were co-occurrences of positive measurements of variables associated with contamination of the final product. This algorithm leads to rules of the type {var1 = 1, var2 = 1} => {PF.fg = 1}. To qualify the validity of the rule, several indicators are associated with it: (i) the support, which corresponds to the frequency of occurrence of the association of all variables in the rule across all rows of the dataset; (ii) the confidence, which is the ratio of the support to the number of occurrences of the association of the "antecedent" elements of the rule. This confidence can be assimilated to a probability of obtaining the result when the antecedents are combined; (iii) the lift, which indicates the improvement provided by a rule compared to a random response. If it is equal to 1, there is no relationship between the antecedents and the outcome of the rule, and the higher it is, the stronger the dependence between the two. The calculations were processed using R packages "arules" and "arulesviz". The calculated association rules were filtered to only keep the rules leading to a contamination of the final product with a confidence greater than 0.8, leading to the 10 rules represented in figure 5.

Figure 5

Association rules leading to a positive measure for the final product.
All the rules have a confidence level greater than 0.8



The set of variables retained as input variables through the application of the Apriori method was consolidated and complemented by applying the PLS-DA method (Partial Least Squares Discriminant Analysis, Barker *et al.*, 2003) on the same dataset (R package "Caret"). This method is traditionally used for classification and regression.

Its implementation in R facilitates variable selection as well as regularization. Ultimately, 7 input variables were selected.

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4.1.2. Training and validation

Once the input variables were selected, model training was conducted using 10-Folds cross-validation. For the neural network, a factorial design was used to adjust the hyperparameters, including the number of neurons in the hidden layer. Given the low contamination rates of the final product, stratification of the 10-Folds was implemented to ensure that each fold presented a representative contamination rate. The AUC associated with the ROC curve was calculated to rank the results from different hyperparameter configurations. Finally, for the neural network, the top 10 models from factorial fine-tuning were selected to form an ensemble model (the final score corresponds to the average of the scores from the top 10 models). The Youden's index was chosen as the decision threshold for contamination.

4.2. *Results*

While the neural network model significantly outperforms logistic regression on monthly and weekly scales, it shows similar validation performance to logistic regression at daily scale: both models achieved an AUC of 0.88 and 0.87 respectively, with a specificity of 0.85 and a sensitivity of 0.83, indicative of strong performance. These similar performances are not surprising given the substantial effort in selecting input variables, which were reduced to a small number. The selection through association rules for positives, confined to very high confidence levels, enabled the identification of robust relationships between certain measurement points and the final product. Beyond the predictive aspect, this allows for a deeper investigation into the causes of these contaminations in the final product.

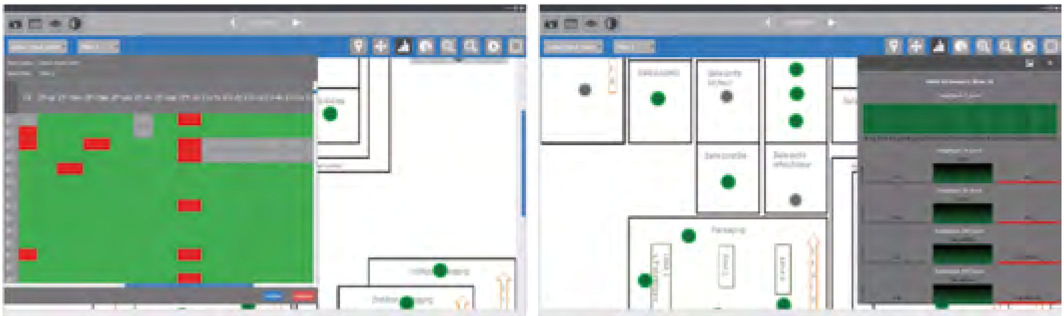
4.3. *Software*

Ultimately, this initial predictive approach to contamination at the plant level led to the implementation of a straightforward software tool (figure 6) that enables the following after uploading a factory layout and measurement points:

— Visualization of contamination values (0/1) derived from measurements.
— Visualization of the predicted contamination status of the final product (0/1) by the two models.
— Visualization of the historical data and statistical summary of contaminations for a selected point directly on the screen.

Figure 6

Screenshots of the software graphical user interface



5. Conclusion

This study, based on a multifaceted modeling approach to contamination at the factory level, should be considered as the foundational element of a digital twin that incorporates food safety aspects, which are crucial in the agri-food sector. The direct applications and insights derived from this are manifold.

Regarding the data, daily measurements extended across all factory zones are a valuable resource for modeling. However, constraints in modeling have led to information loss during data cleaning. Although factories worldwide are designed on the same model, the contamination measurements obtained show variability in both the number of measurement points and the frequency of these measurements. Standardizing measurements specifically for modeling would enable the generalization of the predictive approach to all factories, including those not included in the initial study. Moreover, enriching the datasets with information related to the supply chain of raw materials, environmental conditions at measurement points (temperature, humidity…), and the factories environments (weather...) would enhance understanding of contamination determinants and improve the predictive capabilities of the models.

Regarding the modeling itself, the initial layer of statistical processing (spatial and temporal correlations) directly optimized measurement efforts by eliminating highly correlated measurement points within the same spatial patch.

On the one hand, probabilistic modeling, rather than simple measurement tracking, has the advantage of generalizing measurements through statistical distributions from which certain characteristics of contamination can be calculated. The modeling step involving survival analysis and the development of reliability models has facilitated the creation of indicators based on the probabilities of operating time before contamination (or between contaminations) by zones in factories and at the global level of each factory. These indicators are generalizable and transferable to all factories with multiple applications: characterization of contaminations by zones, identification of zones and periods of increased vigilance, optimization of preventive sanitation, intra- and interfactory comparisons, temporal evolutions and detection of changes in the contamination. They can be easily updated based on new data. Finally, they could be defined at a finer scale than factory zones, at critical points of the production chain, for example. Their integration into a digital twin is promising as it would enable the production of reliability simulations.

On the other hand, the predictive modeling, based on a relatively simple approach in this study, demonstrated excellent performance after a significant reduction of input variables through a selection process based on simple assumptions about causality relationships of microbiological contamination. To date, it has only been applied to a single factory but could be generalized. However, the models constructed here focus only on predicting the final product and do not address contaminations in different factory zones, the representation of underlying contamination mechanisms, or the biological processes involved in contaminations.

Future modeling developments should consider:

— Modeling the flows of materials, personnel, or other physical or biological vectors within factories. Indeed, part of the contaminations arises from the movement of contaminated supports, whether on the production line or in its environments. A multi-agent system (MAS) approach would integrate these flows as well as contamination and decontamination events and all intervention events that could create contamination channels (for example, a maintenance operation on the production line). This type of model also has the capacity to integrate multiple scales, from fine-scale bacterial colony growth to the flows of personnel and material on a global scale. An agent-based approach, already implemented by Zoellner *et al.* (2019), would primarily aim to test contamination scenarios to improve practices and identify the most influential determinants in contaminations. This approach could integrate measurements, reliability models, scientific knowledge from the literature, expertise, and empirical knowledge from various industrial domains associated with;

— Building predictive models using Graph Neural Networks (GNN) (Kipt and Welling, 2017; Wu *et al.,* 2019) possibly combined with a recurrent neural network (RNN) as Long Short Term Memory (LSTM) model (Yu *et al.,* 2019, Wu *et al.,* 2020). A GNN architecture embeds the network structure of the system, with nodes and edges linking them, associated with feature vectors. The GNN is based on a function of message passing that updates a node’s features using information from its neighbors. They capture global and local dependencies within the system and handle any type of graph. In the present case, a factory can be represented as a graph linking different measurement points considering physical links and flows, and can thus be modeled by a GNN. RNN models are neural networks geared towards time series prediction, considering the entire history of measurements. Roughly, LSTM is a particular RNN which weights measures according to its distance in the past. This aspect is fundamental for contamination prediction as it must perform it based on measurements acquired before the contamination date. Since the determinants of contamination are both spatial and temporal, a dynamic GNN is particularly well-suited to the issue of contamination within factories. This approach would have a purely predictive objective and could be limited by the quantity and quality of the data on which it entirely relies.

Regardless of the modeling choices, it will be essential to keep the models up-to-date to account for structural changes that alter the characteristics of contaminations: changes in practices in terms of preventive or corrective maintenance, as well as structural modifications of production lines, equipment changes, supplier changes, or even climate changes may render models based on previous data inadequate. The challenge will thus be to optimally capture the structural aspects of contaminations and distinguish them from situational aspects. For this, the Global Risk Analysis (GRA, Desroches *et al.,* 2016) is particularly well-suited.

Finally, a digital twin integrating food safety, making models useful at an operational level, would have several objectives: (i) real-time spatialized visualization of contaminations through the direct integration of the results of microbiological analyses; (ii) real-time optimization of preventive and corrective sanitation operations based on contamination models. In this context, integrating reliability models of production line and its maintenance would optimize production downtime; (iii) detection of deviations from requirements and predictions indicating potentially abnormal operation; (iv) simulation of contamination scenarios.

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64th ESReDA Seminar: digital maintenance in the digital twin era
Smart factory maintenance: building a predictive model of pathogen contamination during the food fabrication process
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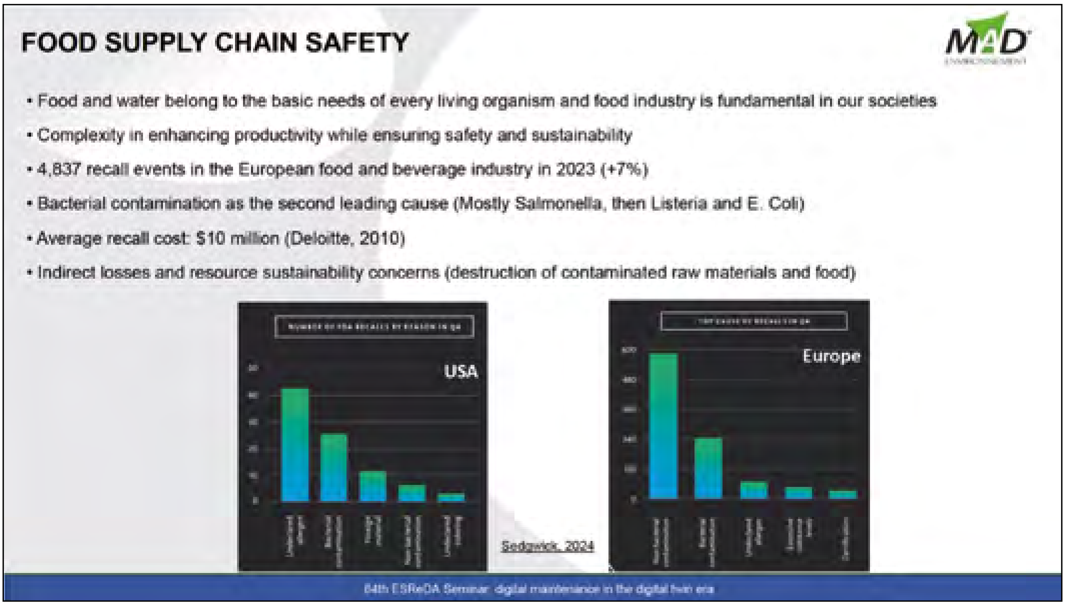
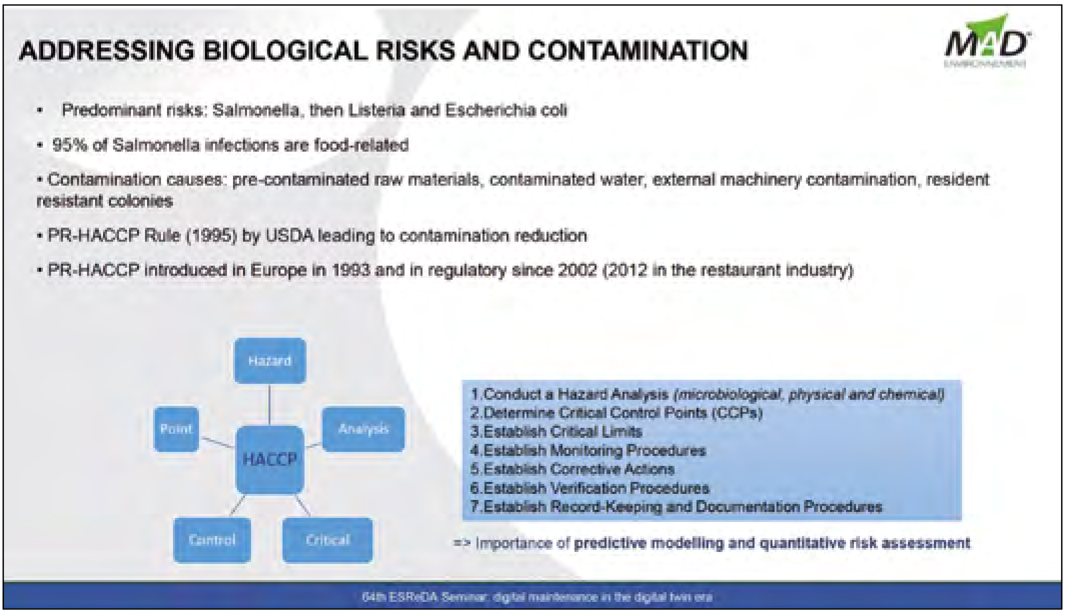
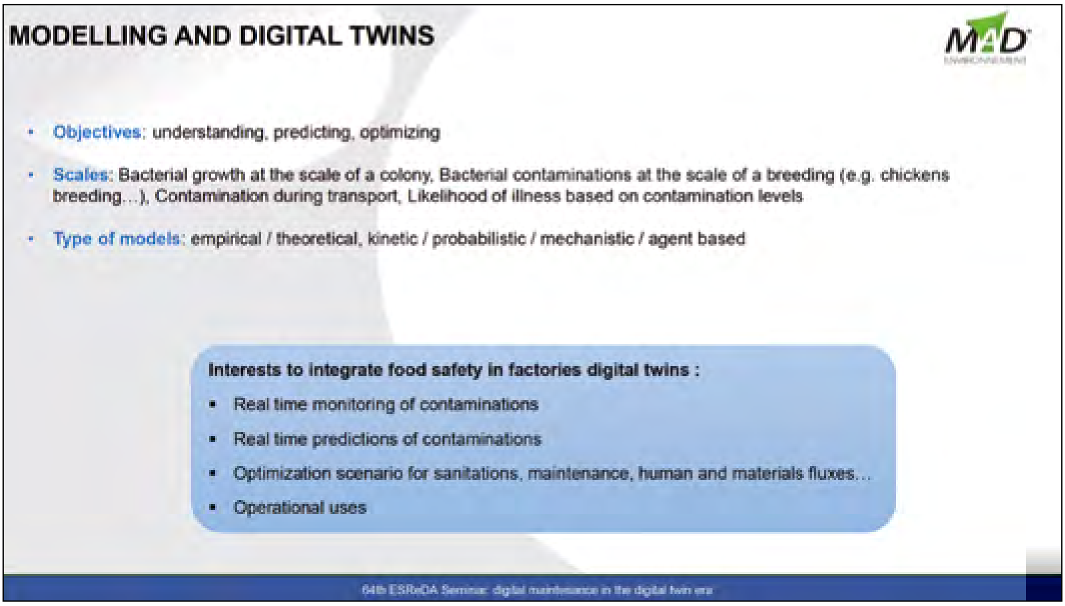
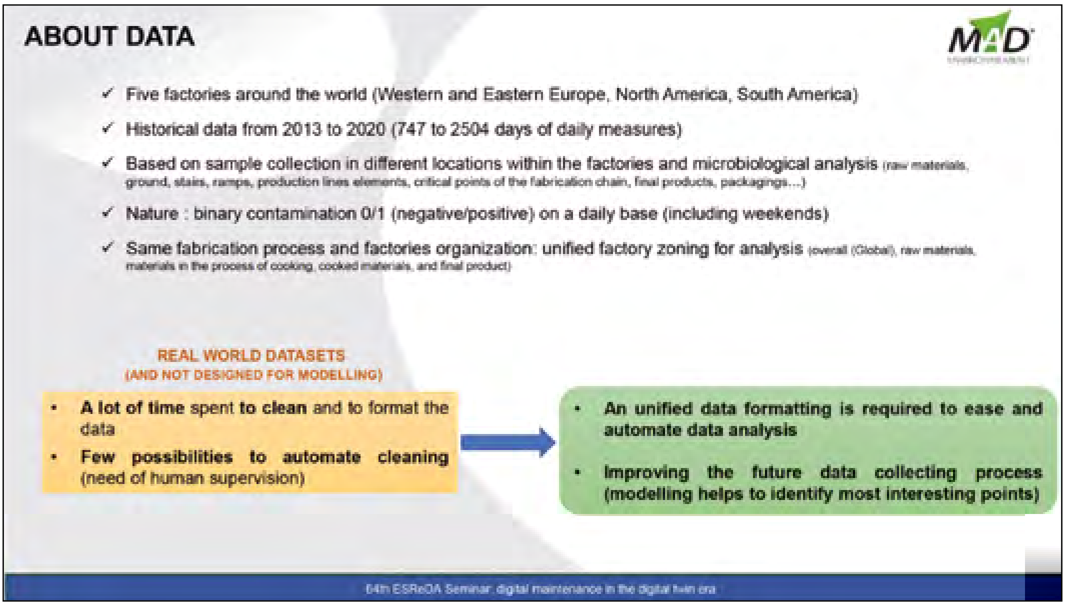
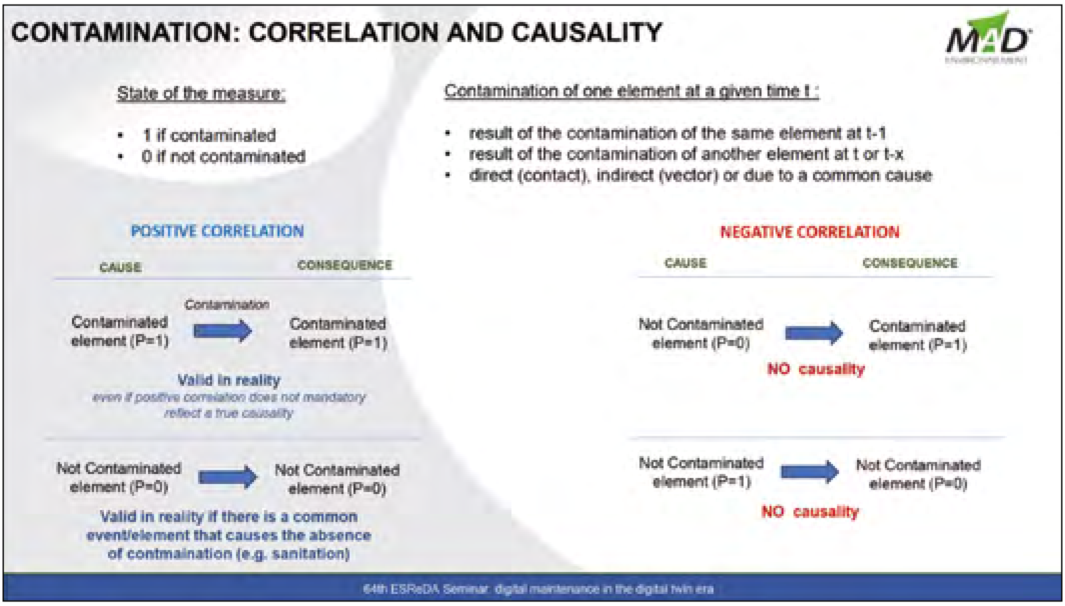

FOOD SUPPLY CHAIN SAFETY
• Food and water belong to the basic needs of every living organism and food industry is fundamental in our societies
• Complexity in enhancing productivity while ensuring safety and sustainability
• 4,837 recall events in the European food and beverage industry in 2023 (+7%)
• Bacterial contamination as the second leading cause (Mostly Salmonella, then Listeria and E. Coli)
• Average recall cost: $10 million (Deloitte, 2010)
• Indirect losses and resource sustainability concerns (destruction of contaminated raw materials and food)
USA
Europe
Sedgwick, 2024
64th ESReDA Seminar: digital maintenance in the digital twin era


ADDRESSING BIOLOGICAL RISKS AND CONTAMINATION
MAD
• Predominant risks: Salmonella, then Listeria and Escherichia coli
• 95% of Salmonella infections are food-related
• Contamination causes: pre-contaminated raw materials, contaminated water, external machinery contamination, resident resistant colonies
• PR-HACCP Rule (1995) by USDA leading to contamination reduction
• PR-HACCP introduced in Europe in 1993 and in regulatory since 2002 (2012 in the restaurant industry)
Hazard
Point
HACCP
Analysis
Control
Critical
1.Conduct a Hazard Analysis (microbiological, physical and chemical)
2.Determine Critical Control Points (CCPs)
3.Establish Critical Limits
4.Establish Monitoring Procedures
5.Establish Corrective Actions
6.Establish Verification Procedures
7.Establish Record-Keeping and Documentation Procedures
=> Importance of predictive modelling and quantitative risk assessment
64th ESReDA Seminar: digital maintenance in the digital twin era


MODELLING AND DIGITAL TWINS
MAD
• Objectives: understanding, predicting, optimizing
• Scales: Bacterial growth at the scale of a colony, Bacterial contaminations at the scale of a breeding (e.g. chickens breeding…), Contamination during transport, Likelihood of illness based on contamination levels
• Type of models: empirical / theoretical, kinetic / probabilistic / mechanistic / agent based
Interests to integrate food safety in factories digital twins :
• Real time monitoring of contaminations
• Real time predictions of contaminations
• Optimization scenario for sanitations, maintenance, human and materials fluxes…
• Operational uses
64th ESReDA Seminar: digital maintenance in the digital twin era





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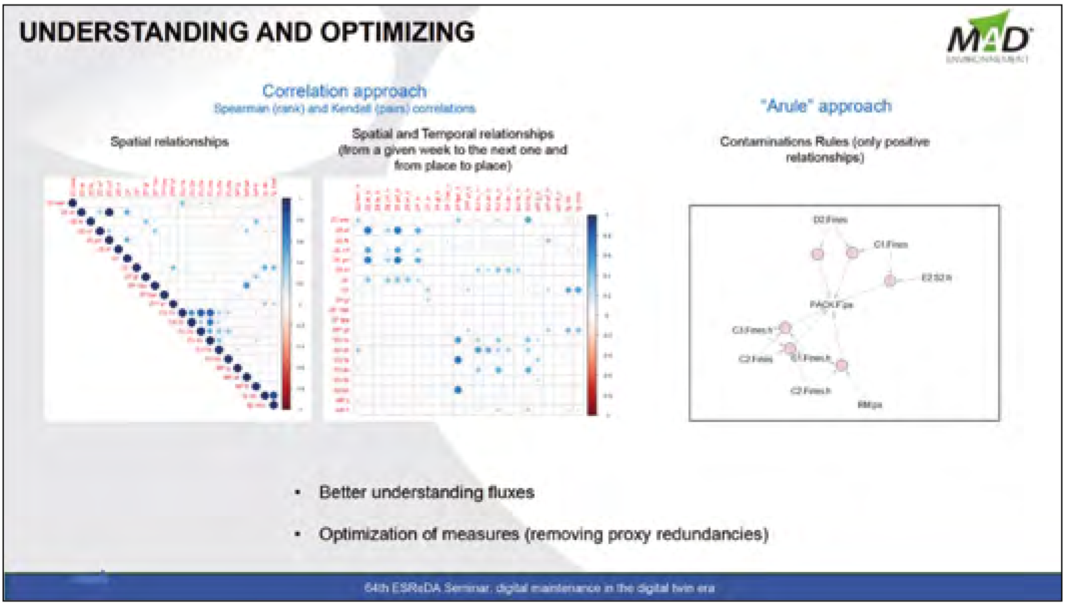

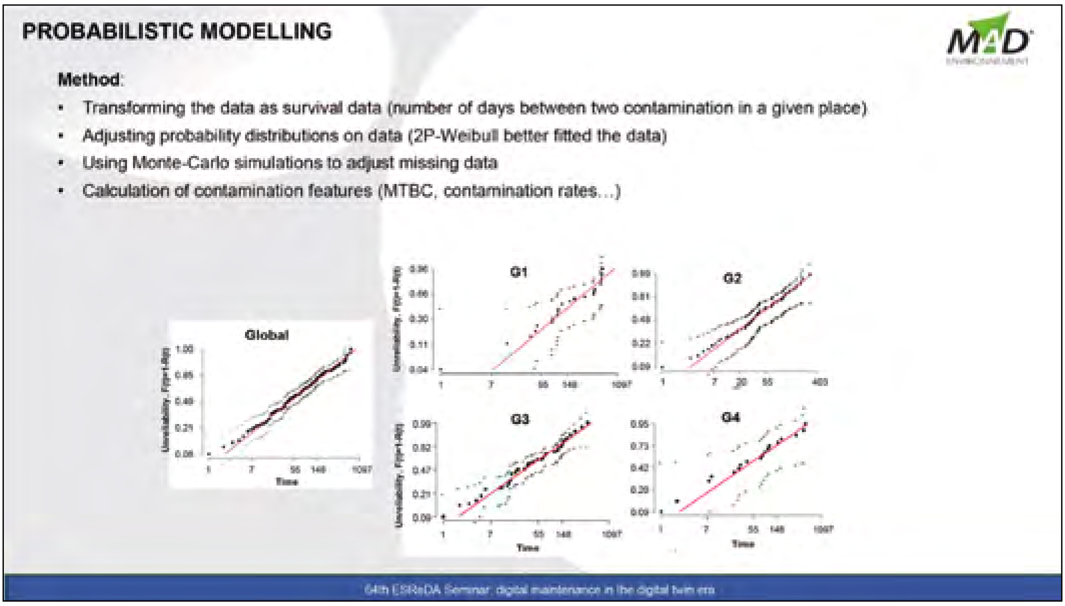

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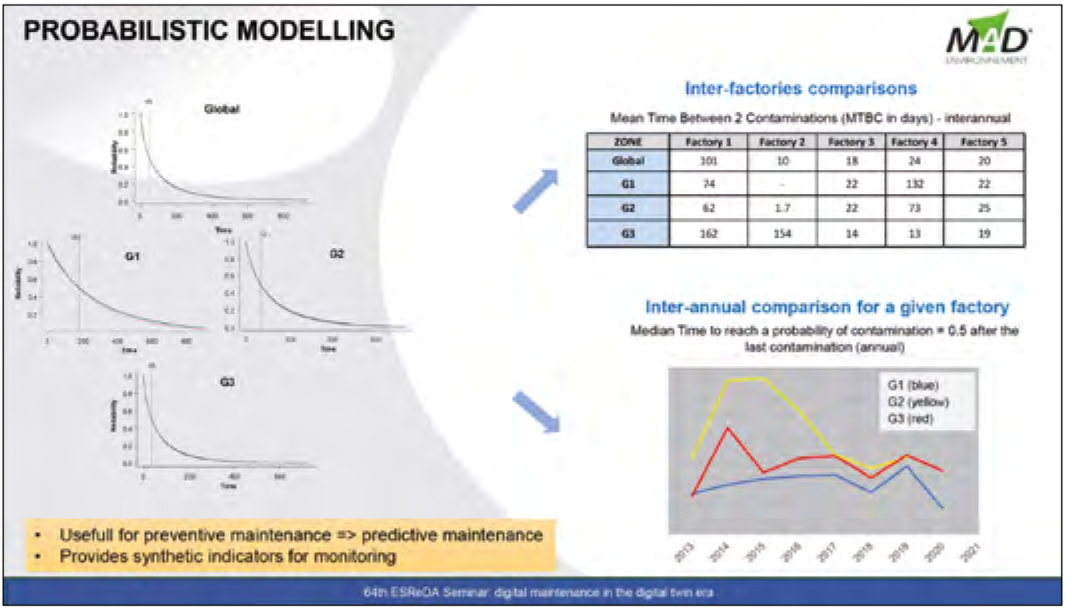
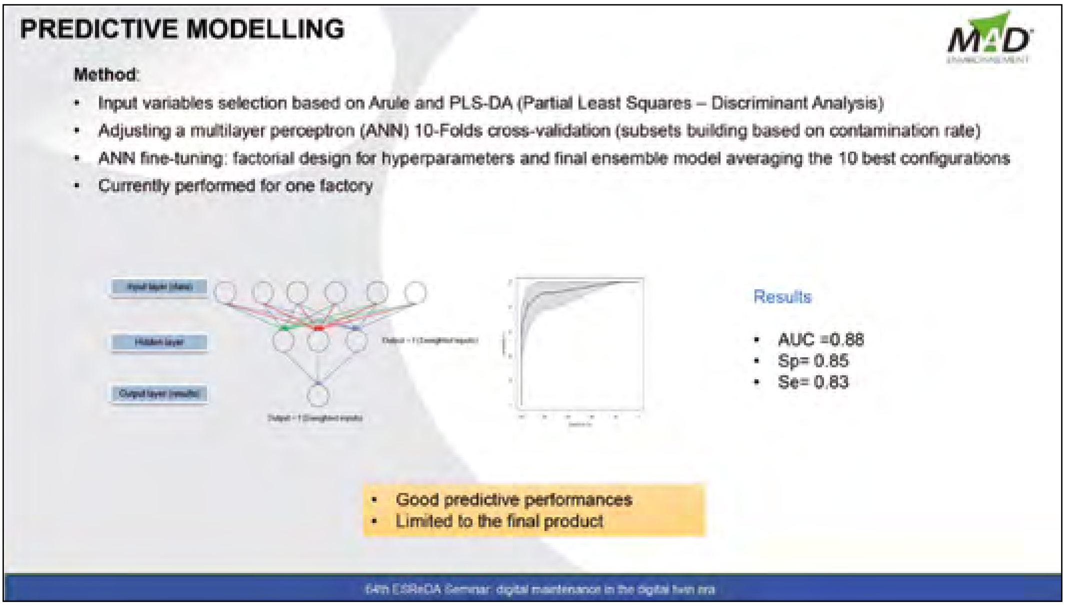


ZONE	Factory 1	Factory 2	Factory 3	Factory 4	Factory 5
Global	101	10	18	24	20
G1	74	-	22	132	22
G2	62	1.7	22	73	25
G3	162	154	14	13	19



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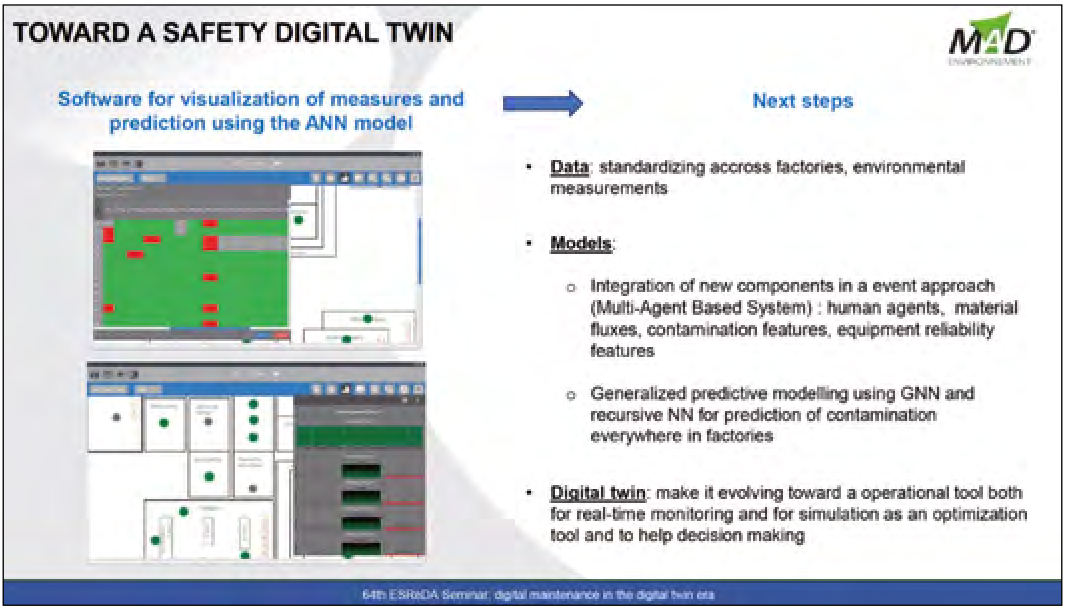
TOWARD A SAFETY DIGITAL TWIN
Software for visualization of measures and prediction using the ANN model
Next steps
• Data: standardizing accross factories, environmental measurements
• Models:
o Integration of new components in a event approach (Multi-Agent Based System) : human agents, material fluxes, contamination features, equipment reliability features
o Generalized predictive modelling using GNN and recursive NN for prediction of contamination everywhere in factories
• Digital twin: make it evolving toward a operational tool both for real-time monitoring and for simulation as an optimization tool and to help decision making
64th ESReDA Seminar: digital maintenance in the digital twin era

AI-Powered Models: Catalysts for Digital Twin Advancements in Operations & Maintenance

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Abstract

A strategy for the development of accurate yet dynamic and time-evolving engineering models is presented in this work. These models are deemed the backbone of the Digital Twins (DTs), representing the core intelligence that empowers them to fulfil their objectives across different domains and industries. Models form the dynamic heart that allows diagnostics and damage assessment, predictive maintenance, and overall operational enhancement, with data, analytics and visualization serving as enablers of the models' efficacy.

Artificial intelligence (AI)-based models and specifically, physics-informed neural networks (PINNs,) emerge as an optimal model architecture owing to their ability to integrate the learning capacity and high performance of data-driven models such as neural networks (NNs), while incorporating the physics theory and constraints into the learning process. This integration effectively captures complex physical behaviours, thereby enhancing model precision and interpretability.

The challenge related to deploying a suitable model architecture and gathering sufficient data in quality and quantity to accurately perform its training is overcome in the present research. A model-assisted training approach is employed, capitalizing on generative models which assume a pivotal role in training the predictive models tailored to handle the DT functions.

1. Introduction

In the realm of the Digital Twin (DT) and the Operations and Maintenance (O&M) landscape, the integration of engineering knowledge and the increasingly growing potential of technology synergistically converge, culminating in a framework equipped to steer asset management throughout its entire lifecycle, maximizing its capacities. What was originally conceived as an Asset Administration Shell (AAS) is undergoing a transformation into a fully-fledged DT. This evolution is driven by the incorporation of cutting-edge technologies such as the Internet of Things (IoT) and

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edge/fog computing, bolstered by the prowess of artificial intelligence (AI) and data analytics as key enablers for incorporating multidimensional engineering knowledge through the models.

In this work, emphasis is given to AI-model based system engineering (MBSE) as a key component of the DT [1]. The models are built upon a hybrid approach, grounded in a physics-informed (PI) data-driven strategy founded on neural networks (NN).

Model-assisted training involves leveraging one or more pre-existing models to aid in the training of another model. In the context of this research, this technique integrates *generative* models to support the deploying and training of the *predictive* models serving the DT. This paradigm extends traditional training techniques, providing pragmatic solutions to challenges, notably those related to data constraints in diverse domains. It probes particularly advantageous in scenarios characterized by limited or noisy data, such as those encountered in O&M.

This paper proposes a case study to illustrate this approach, featuring a scaled 6-storey metal tower subjected to lateral forces leading to reduced bolt stiffness, consequently impacting its O&M. A structural integrity analysis of the system identifies strategic locations for executing a discrete data monitoring strategy. The raw data, which is time-independent yet bearing meaningful physical significance, is ready for ingestion at edge computing into the DT models. This process will effectively showcase the real-time structural health and the damage if present.

2. Models related to Operations&Maintenance

Operations asset management employs data to optimize resource utilization, enhance efficiency, reduce costs, and maximize benefits by strategically managing both tangible and intangible assets. At the same time *maintenance management*, targeting only tangible assets, aims to reduce downtime, minimize failure risks, and ensure reliability through maintenance practices. Although both consider different aspects, effective maintenance is essential for successful operations asset management.

Maintenance protocols include corrective and preventive approaches, with preventive maintenance encompassing predefined, condition-based, and predictive techniques. Early *damage detection* and *diagnostics* are crucial for proactive intervention, preventing minor issues from becoming major failures.

DT models for O&M focus on damage assessment using sensors, data analytics, and modelling to monitor asset health and detect early signs of damage. Rytter's Hierarchy [2] evaluates the degree of knowledge about a damaged condition across four levels: Level 1 (Damage detection), Level 2 (Damage location), Level 3 (Damage extent), and Level 4 (Damage prediction).

2.1. *AI-architecture of the models*

The proposed architecture of the models is grounded in PINNs and tailored to suit the specific task that each of the models has to perform within the DT. The infusion of physics into the NN models expands its capacity for generalization, enabling the introduction of *what-if* scenarios while ensuring they remain within the engineering domain, thus preserving explicability. Furthermore, PI data-driven models serve as efficient surrogates [3], facilitating a fast and accurate response, and dynamically adapting to changes in both external and internal conditions.

This transformative process empowers the DT to autonomously make real-time decisions, seamlessly adapt to evolving environments, and continually optimize the performance of its physical counterpart, all in a secure and controlled environment. Within this context, not only can potential damage be anticipated, enabling predictive maintenance, but it can also be autonomously corrected by the proactive strategies of prescriptive maintenance, which anticipate the optimal moment for the best action.

In the present O&M context, the models are tasked with undertaking the following primary functions:

— Generation: to mimic the system's behaviour and provide the predictive models with a substantial volume of high-quality labelled data, reducing their risk of overfitting and bias, and achieving improved performance and scalability.
— Prediction: encompassing both classification and regression tasks. Classification detects damage employing discrete class labels (damaged/undamaged) for a simple binary classification, and to locate the damage at a specific point of the system (multiclass classification with damaged/undamaged labels in every predefined location). Regression, on the other hand, forecasts the extent of the damage based on the reduction of the material's parameter values and the remaining useful life (RUL) of the system.

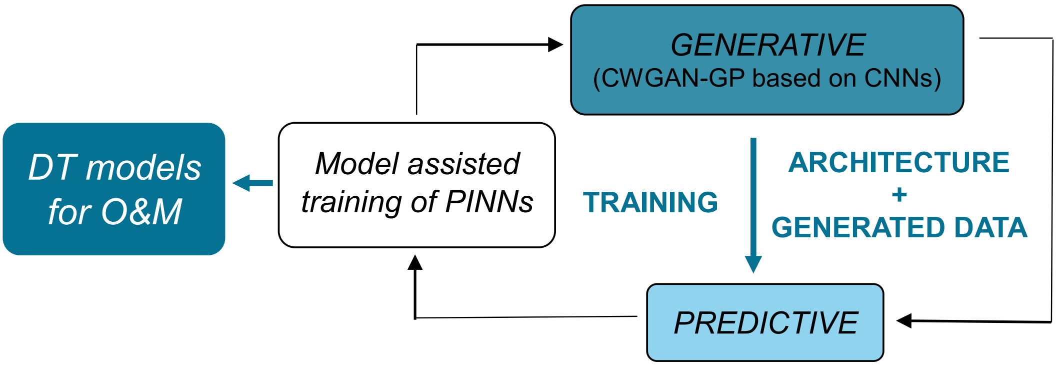
Depending on the problem and the nature of the data involved, the architecture of the models will be selected. In the present work, Convolutional Neural Networks (CNNs) were preferred for detecting spatial features, Feedforward Neural Networks (FNNs) for establishing complex relationships between inputs and outputs, and Generative Adversarial Networks (GANs) for data generation.

2.2. *Model-assisted training*

Model-assisted training emerges as a novel trend in design, streamlining the development and training of accurate predictive models based on a pre-existing architecture and relevant data of sufficient quantity and quality. During the initial stages of predictive modelling, the steep learning curve and the significant demand for data and knowledge required pose considerable challenges to implementation. It is in this context that model-assisted training plays a crucial role, furnishing both the model's framework and the requisite data for precise model training.

Figure 1

Model-assisted training strategy for DT models in O&M



In this research, the generative model plays a pivotal role by providing the training data, thereby facilitating the training of the predictive models and enhancing its training process and resilience. Moreover, the transfer of architectural knowledge from the generative model to the predictive model is leveraged to enhance its performance (Figure 1).

2.3. *Generative models*

The generative model is the model which will serve the DT predictive models in the model-assisted training strategy, acting as a digital representation of the asset. This is achieved by generating quality data similar to the real-world observations of the system, being the generative models regarded as mirror models that generate virtual counterparts of the assets [4].

This generative model is part of a Generative Adversarial Network (GAN) [5], where a discriminant model is simultaneously trained. The generative model generates synthetic data samples, while the discriminant model learns to distinguish between real and synthetic samples. Through adversarial training, the generative model improves its ability to generate realistic data, while the discriminant model enhances its capability to differentiate between real and synthetic data, leading to the refinement of both models. Within the context of damage diagnostics, GANs are the preferred generative method due to their probed capability of encapsulating damage characteristics using a combination of categorical (i.e., labels) and continuous variables (i.e., numerical data values), providing significant benefits [6].

Due to its demonstrated training stability [7] and good performance [8], the selected variant of GAN for this research is the conditional Wasserstein generative adversarial network with gradient penalty (CWGAN-GP), enabling class balance and context awareness in the generated data [9].

2.4. *Predictive models*

In the context of a DT dedicated to O&M of assets, predictive models primarily focus on the critical task of damage assessment, as an essential step for the implementation of maintenance policies. As previously outlined, a robust damage evaluation requires the deployment of a series of models capable of addressing the four levels of the damage assessment hierarchy proposed by Rytter [2]: Level 1 (damage detection), Level 2 (damage location), Level 3 (damage extent) and Level 4 (damage prediction), with each model dedicated to a specific level.

To develop these tasks, a binary classifier is employed for damage detection in the first level, followed by a multiclass classifier for damage location at the second level. Subsequently, regressors are constructed for the third and fourth levels of assessment. These models are PINN models, inheriting the architecture of the generative model and being trained with its generated data.

3. **Dynamic and time-evolving model capability**

In a DT, models are required to adapt and evolve over time to accurately represent the behaviour of the physical system facing changing conditions such as different operating scenarios, environmental factors, or damage and degradation of the assets being modelled.

In this context, the Bayesian method provides a principled way to incorporate new data, prior knowledge, and uncertainty into the model updating process. Specifically, the Bayesian *inverse problem* [10] refers to the process of inferring model parameters or states from observed data.

This way, the dynamic and time-evolving features of the DT models can be realized through iterative cycles of model updating, where new data is aggregated to refine the model [11]. Furthermore, Bayesian methods enable the incorporation of uncertainty quantification into the model updating process. By representing uncertainty in model parameters or states, DTs can provide not only point estimates but also probabilistic predictions, along with credible intervals.

Not only the Bayesian method can help the DT models evolve, but also generative models can adapt to changing conditions over time, allowing DT models to be updated dynamically. As new data becomes available, generative models can be retrained or fine-tuned to capture any shifts or new trends in the underlying data distribution, ensuring that the DT models remain accurate and up-to-date.

4. Models integration into the DT workflow

Petri nets [12] are proposed for coordinating DT components and especially to streamline the integration of models into the DT workflow. By delineating the flow of data and actions, Petri nets ensure that the models are properly interconnected and aligned for the DT to achieve its intended functionality and objectives [13].

Petri nets are a graphical and mathematical framework providing a formalism for representing interactions and dependencies between the different components and processes within the DT. They consist of two main elements: places (representing states or conditions) and transitions (representing events or actions). Arcs connect places and transitions, denoting the flow of tokens (symbolizing resources, data, or control) between them. This representation enables the modelling of distributed and concurrent processes, synchronization, and resource allocation, capturing the dynamic behaviour of the system and consequently, of its DT.

5. Case study

This section introduces a case study to illustrate the methodology previously outlined. The computational tools utilized are entirely open-source and Python-compatible [14], leveraging resources established by the author [13].

The case study implementation consists of a six-storey 1.5m-high steel frame structure and its corresponding DT as shown in Figure 2, receiving discrete displacement and force measurements through sensors. The structure is exposed to variable lateral forces and experiences damage as a result of the gradual loosening of its bolts, quantified as time of damage (denoted as t, time since the damage began). Wireless IoT sensors employing ultrasonic methods were utilized to record the displacements of individual storeys (expressed as *d1, d2, d3, d4 d5, d6*), while an IoT digital transducer was employed to measure the force (named F), both supplying the monitoring data. The virtual twin is computationally simulated using a numerical model based on Finite Elements (FE) developed in Openseespy [15] providing physics-informed data about the system.

Supplied with both monitoring and physics-informed data, the generative model generates the required data, ensuring both quality and quantity for precise training of the predictive models, which also inherit its architecture. This way, the generative model enables the model-assisted training of the predictive models. The data generated guarantees class balance through the categorical condition introduced, with labels of damaged/undamaged indicating the health state of the asset globally for level 1: damage detection, and locally for level 2: damage location. Levels 3 and 4 correspond respectively to the quantification of the damage extent and the prediction of the RUL, both directly calculated through the predicted time of damage t.

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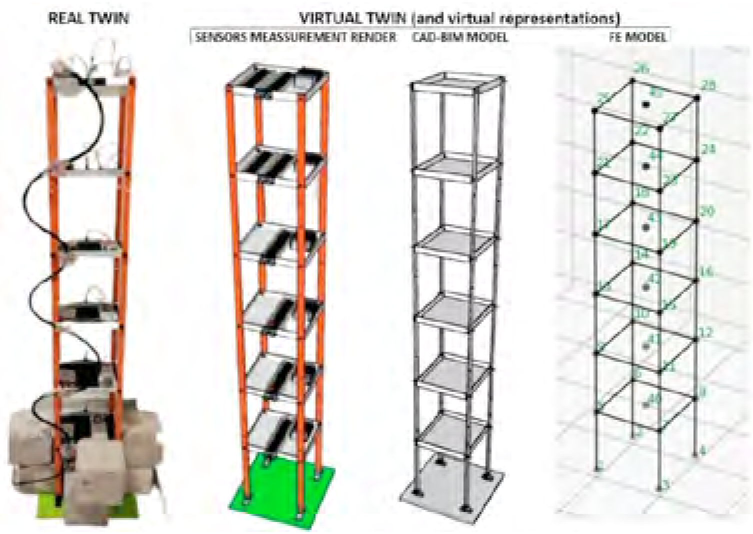
Figure 2

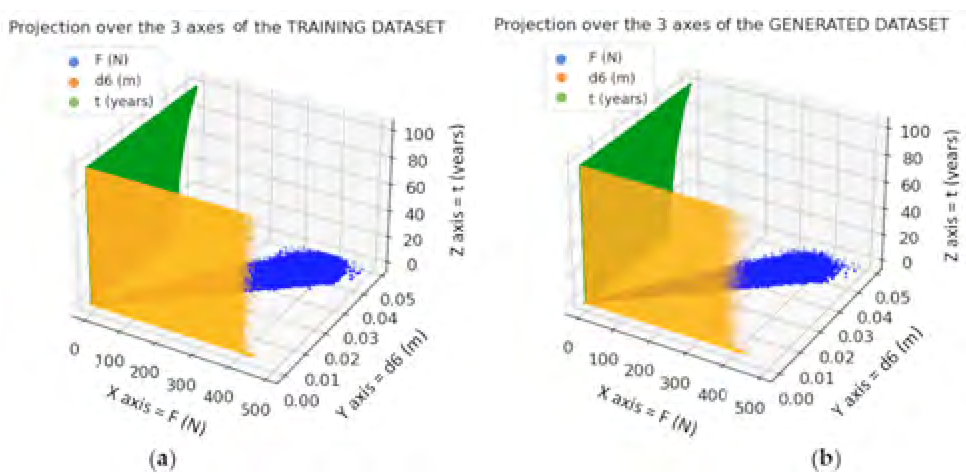
Case study: the DT of a steel tower.



The outcomes of the data generation utilizing the proposed CNN-based CWGAN-GP approach are illustrated in Figure 3, showcasing the real and the generated values corresponding to the force (F), the displacement on the 6th floor (d6) and the time of damage (t). The visual outcomes reveal that the generated results closely resemble the real values, exhibiting a sense of originality.

Figure 3

3-D visual comparison of the data generated: (a) training dataset-real values, and (b) generated dataset.



To demonstrate the effectiveness of the model-assisted training strategy, a comparison is shown in the following images (Figures 4, 5, 6 and 7) between the damage assessment DT models trained using the classic approach and the same models trained with the generated dataset following the model-assisted strategy. The classic approach consists of producing data from numerical simulations through FE analysis with added statistically generated noise.

Figure 4

Normalized confusion matrix results corresponding to level 1: damage detection, performed by the binary classifier model. The results corresponding to the model trained with the generative data (b) surpassed those obtained through the classic training approach (a)

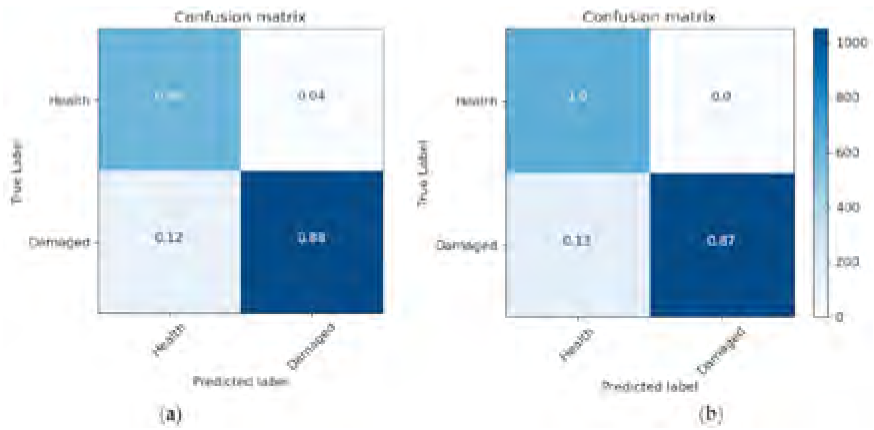


Figure 5

Normalized confusion matrix results corresponding to level 2: damage location, performed by the multiclass classifier model. Again the generative approach (b) outperformed the classical method (a).

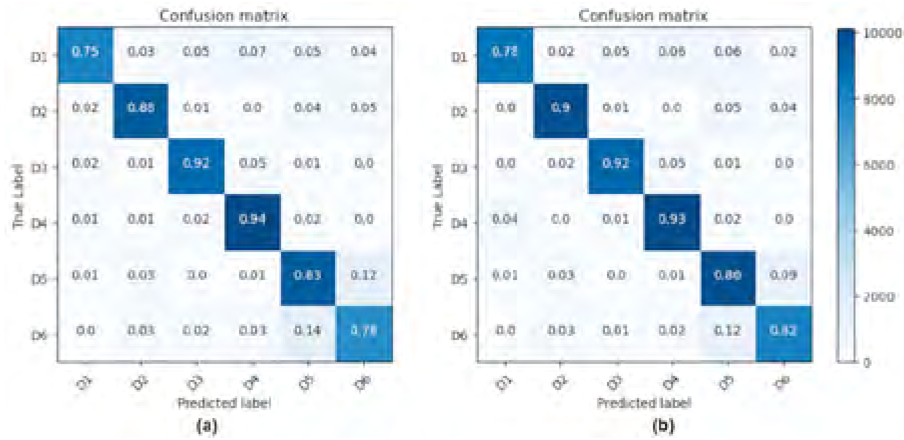


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Figure 6

At level 3 of damage quantification, the learning approximation of the regressor model predicting the time of damage *t* differs between the two approaches, with the generative procedure (b) demonstrating a wider exploration of the space of possible solutions compared to the classic method (a). Once *t* is predicted, the *structural damage index* (SDI) can be calculated to quantify the damage.

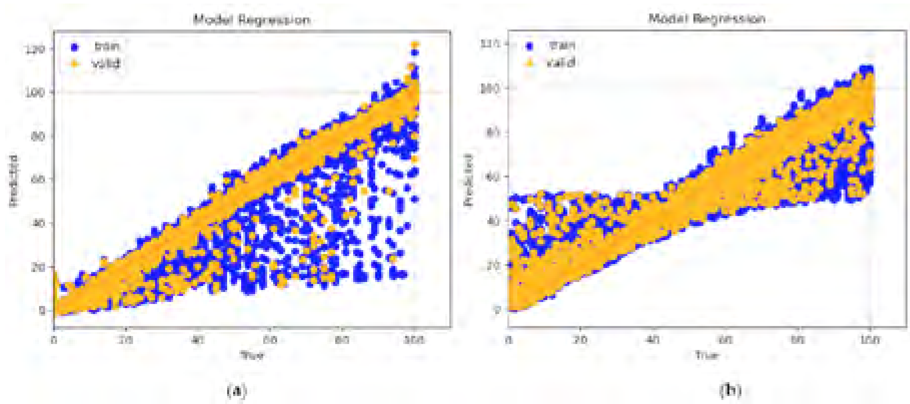
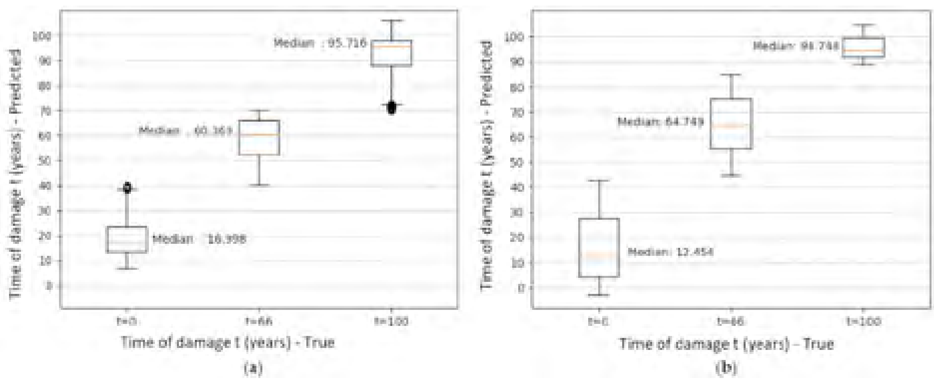


Figure 7

At level 4, the RUL is forecasted as the difference between the time of damage *t* and the useful life of the asset (UL). The results from the regressor model show more accurate values for the predicted median and quartiles in the three scenarios tested (t=0 years for the healthy state, t=66 years for medium damaged and t=100 years for fully damaged) using the generative procedure (b) compared to the classic method (a), while also avoiding outliers.



6. Conclusions

In this work, a model-assisted training strategy has been developed to leverage models serving a DT in the O&M of assets, illustrated through a case study. The proposed strategy demonstrates significant improvements in training efficiency and

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model performance compared to traditional approaches. By generating synthetic data and incorporating it into the training process along with the architectural inheritance of the PINN models, the model-assisted approach enhances the robustness and accuracy of the DT models, particularly in damage detection, quantification, and prediction tasks. The results show that the models trained with the generative data surpass those trained with conventional methods, providing more accurate predictions and a better exploration of the solution space. Furthermore, the dynamic and time-evolving features of the DT models have been incorporated through the Bayesian framework and the Petri Net modelling, ensuring a comprehensive representation of asset behaviour over time and a high-performance model integration into the DT workflow.

Future work will focus on further refining the generative processes and exploring their application to a broader range of assets and operational conditions.

Acknowledgements

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The code for the models is available upon request.

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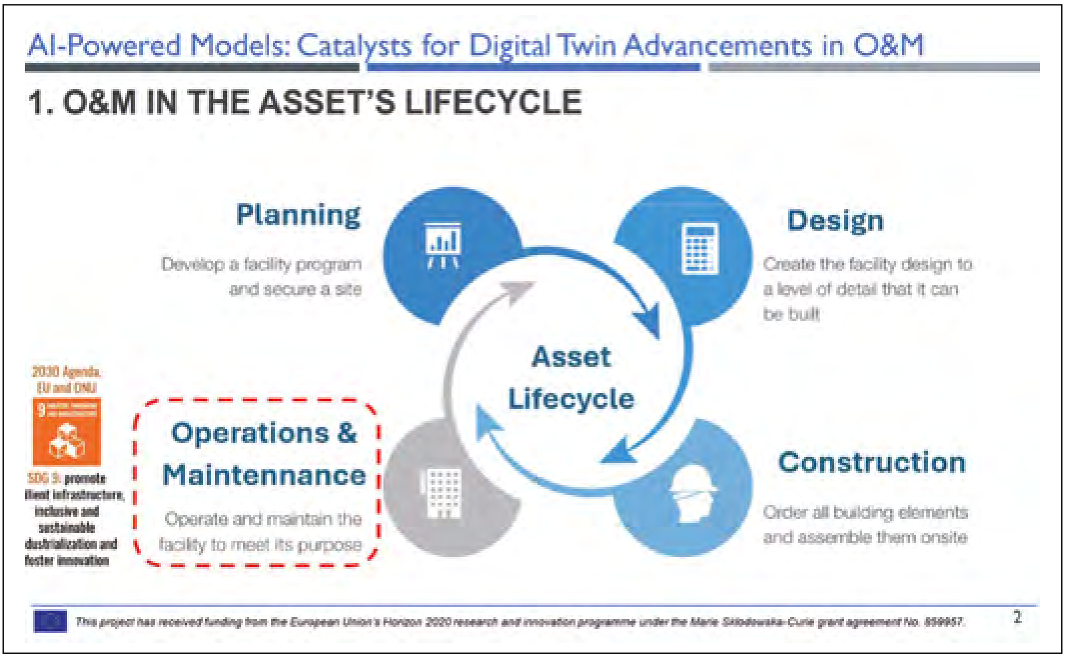

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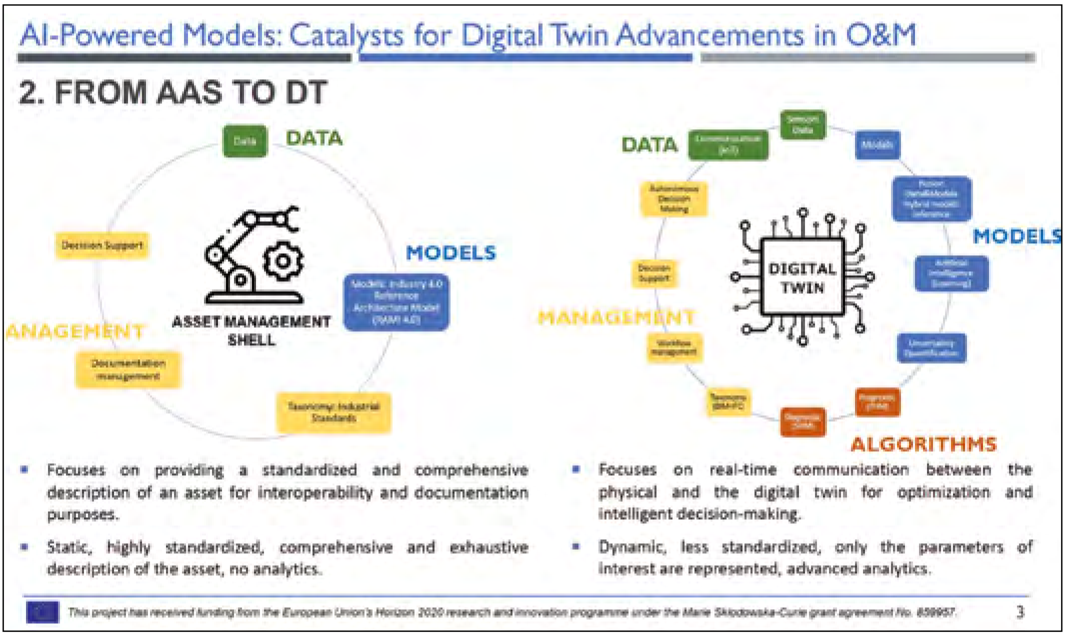

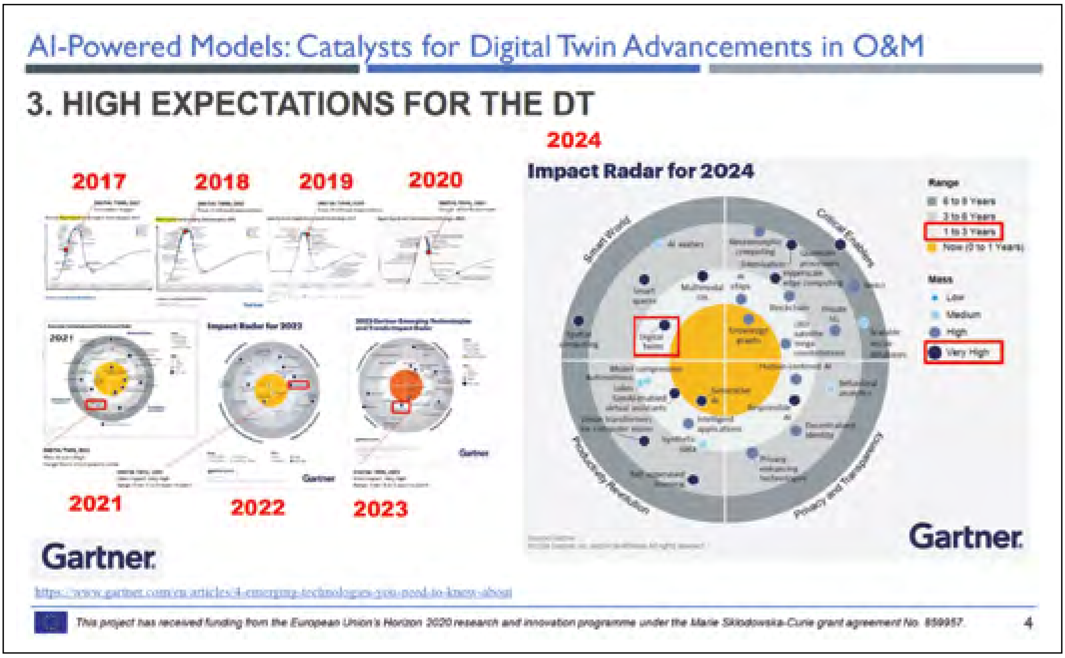

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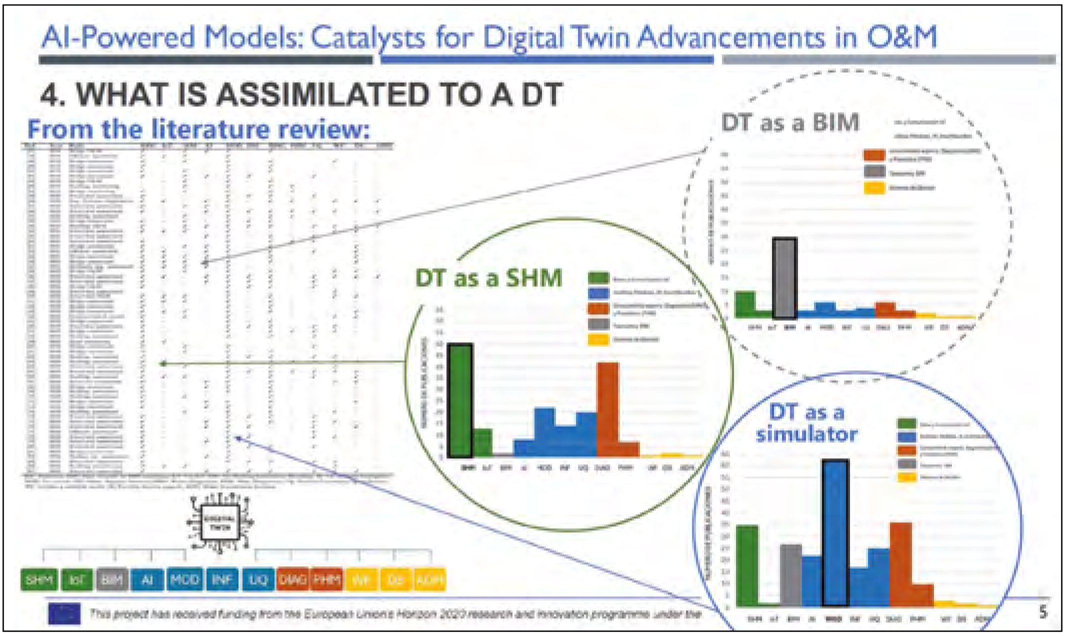
AI-Powered Models: Catalysts for Digital Twin Advancements in O&M
4. WHAT IS ASSIMILATED TO A DT
From the literature review:
DT as a BIM
DT as a SHM
DT as a simulator
DIGITAL TWIN
SHM
IoT
BIM
AI
MOD
INF
UQ
DIAG
PHM
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the
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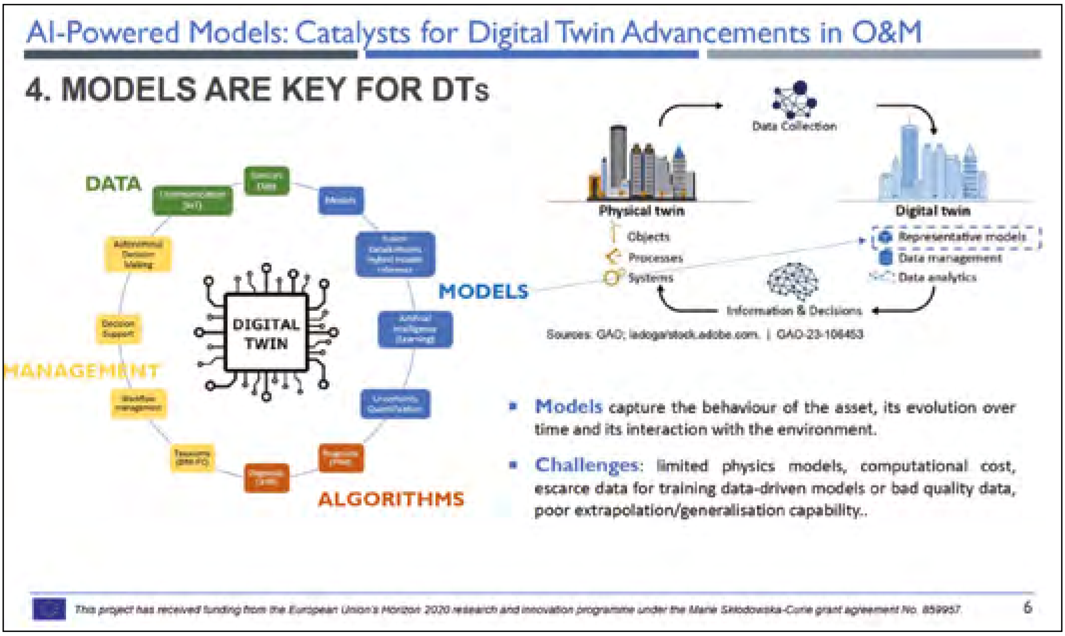
AI-Powered Models: Catalysts for Digital Twin Advancements in O&M
4. MODELS ARE KEY FOR DTs
DATA
MODELS
MANAGEMENT
ALGORITHMS
DIGITAL TWIN
Data Collection
Physical twin
Objects
Processes
Systems
Digital twin
Representative models
Data management
Data analytics
Information & Decisions
Sources: GAO; ladoga/stock.adobe.com. | GAO-23-106453
Models capture the behaviour of the asset, its evolution over time and its interaction with the environment.
Challenges: limited physics models, computational cost, escarce data for training data-driven models or bad quality data, poor extrapolation/generalisation capability..
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
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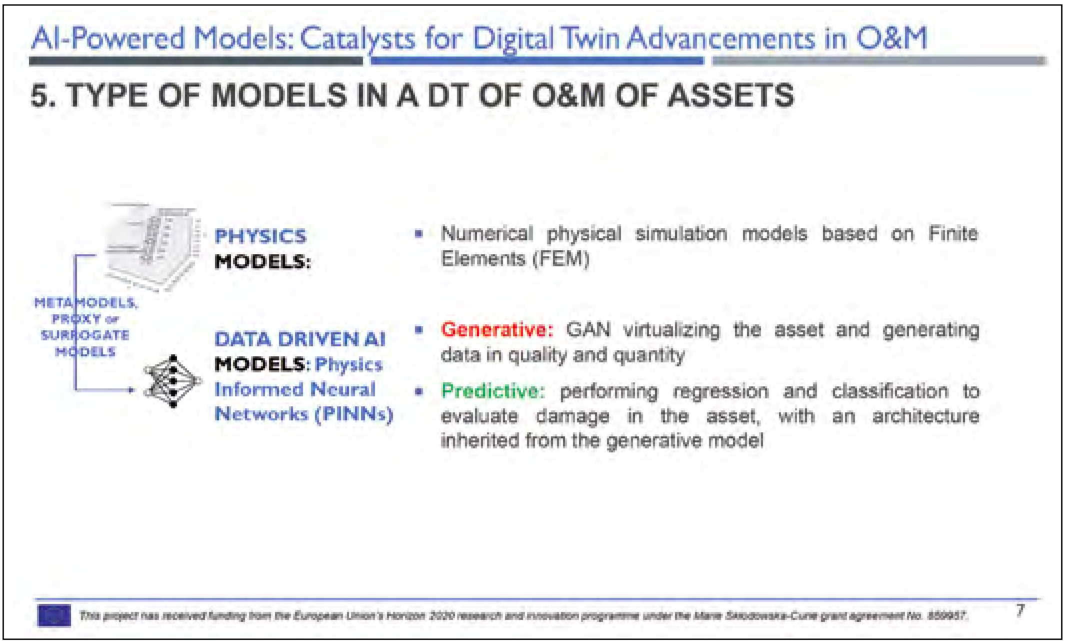

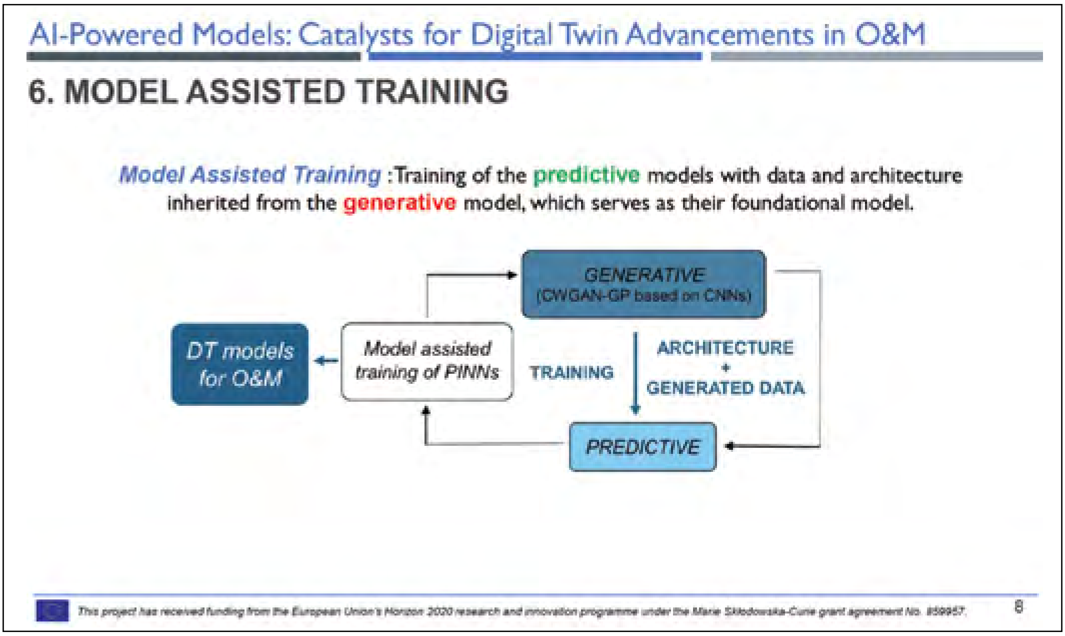

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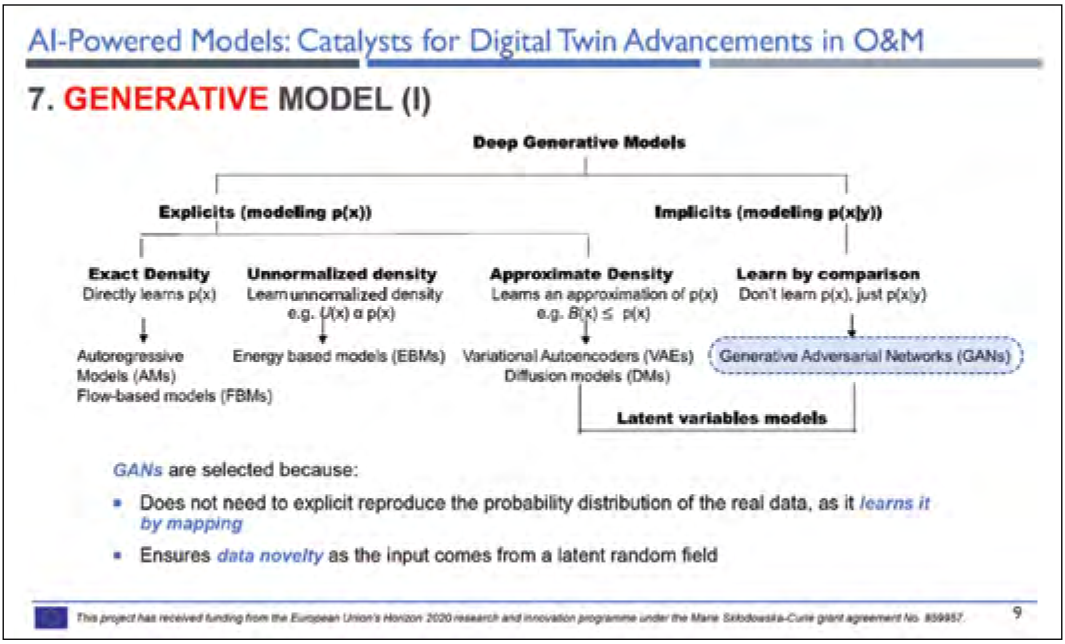
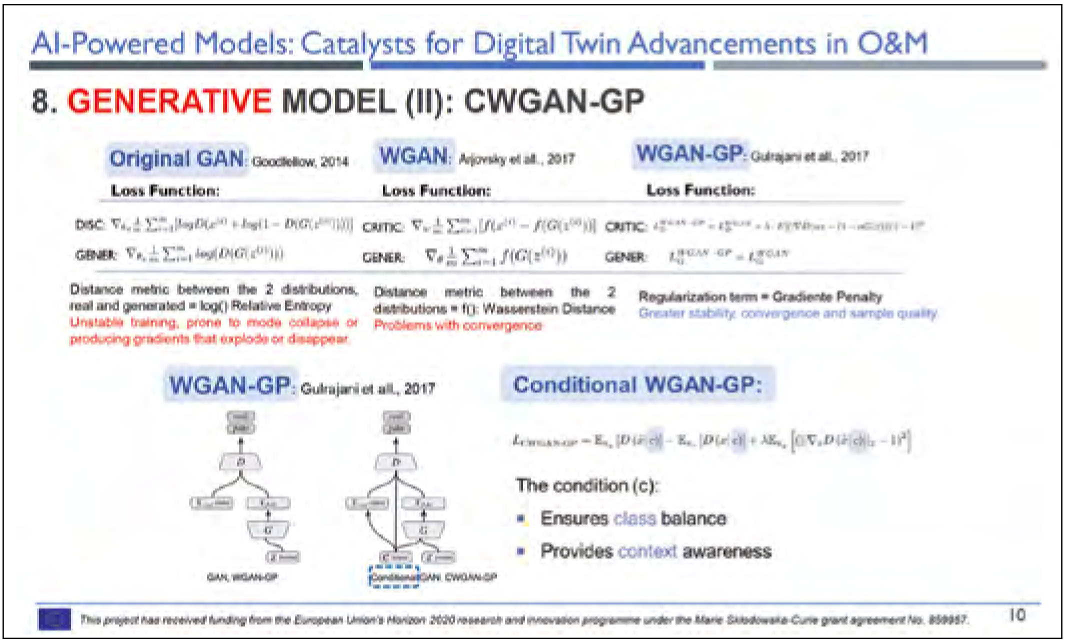

AI-Powered Models: Catalysts for Digital Twin Advancements in O&M
7. GENERATIVE MODEL (I)
Deep Generative Models
Explicits (modeling p(x))
Implicits (modeling p(x|y))
Exact Density
Directly learns p(x)
Unnormalized density
Learn unnormalized density
e.g. U(x) α p(x)
Approximate Density
Learns an approximation of p(x)
e.g. B(x) ≤ p(x)
Learn by comparison
Don't learn p(x), just p(x|y)
Autoregressive Models (AMs)
Flow-based models (FBMs)
Energy based models (EBMs)
Variational Autoencoders (VAEs)
Diffusion models (DMs)
Generative Adversarial Networks (GANs)
Latent variables models
GANs are selected because:
Does not need to explicit reproduce the probability distribution of the real data, as it learns it by mapping
Ensures data novelty as the input comes from a latent random field
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
9


AI-Powered Models: Catalysts for Digital Twin Advancements in O&M
8. GENERATIVE MODEL (II): CWGAN-GP
Original GAN: Goodfellow, 2014
WGAN: Arjovsky et all., 2017
WGAN-GP: Gulrajani et all., 2017
Loss Function:
Loss Function:
Loss Function:
DISC:
CRITIC:
CRITIC:
GENER:
GENER:
GENER:
Distance metric between the 2 distributions, real and generated = log() Relative Entropy
Unstable training, prone to mode collapse or producing gradients that explode or disappear
Distance metric between the 2 distributions = f(): Wasserstein Distance
Problems with convergence
Regularization term = Gradiente Penalty
Greater stability, convergence and sample quality
WGAN-GP: Gulrajani et all., 2017
Conditional WGAN-GP:
GAN, WGAN-GP
Conditional GAN, CWGAN-GP
The condition (c):
Ensures class balance
Provides context awareness
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
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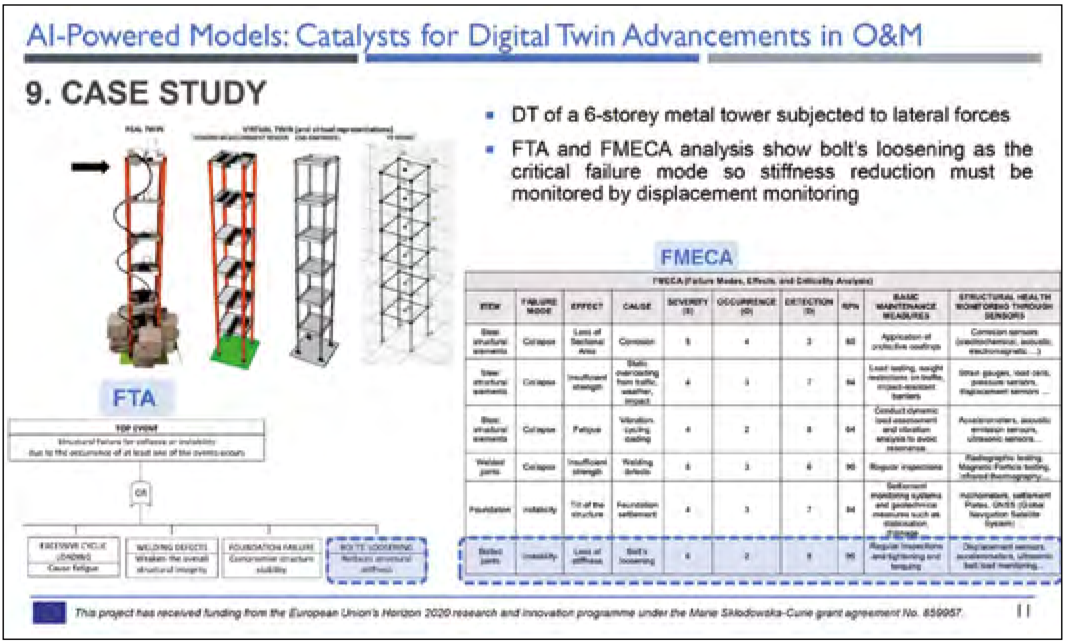

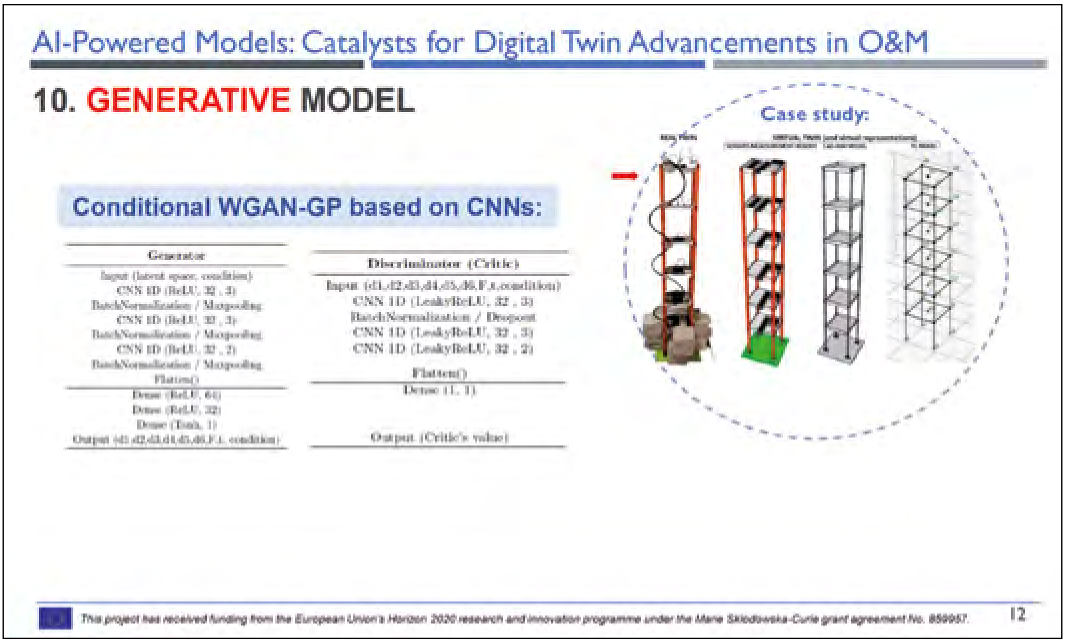

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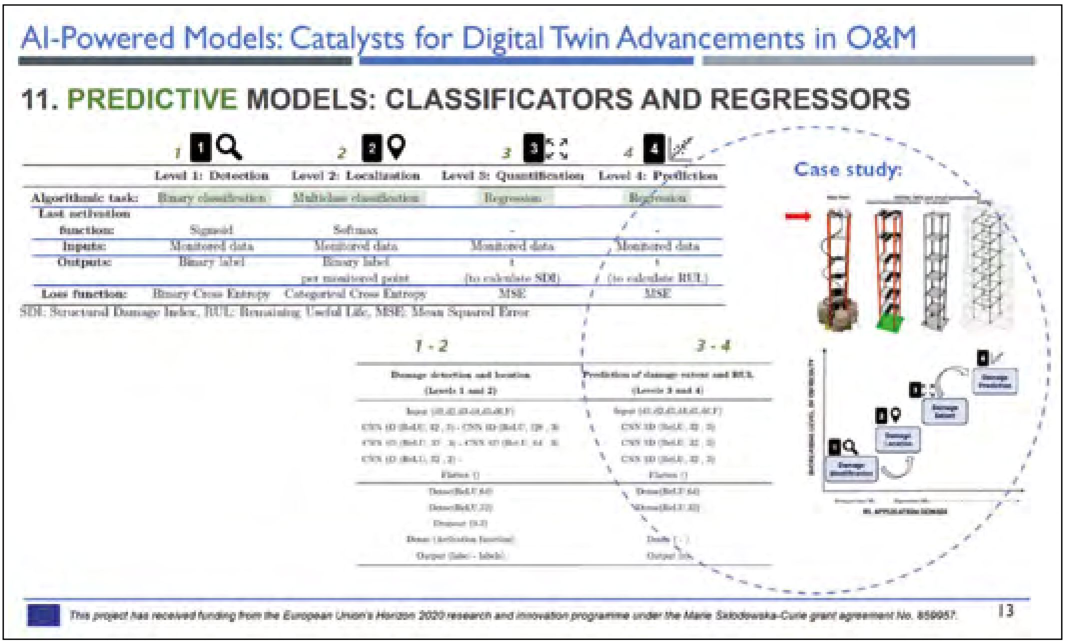

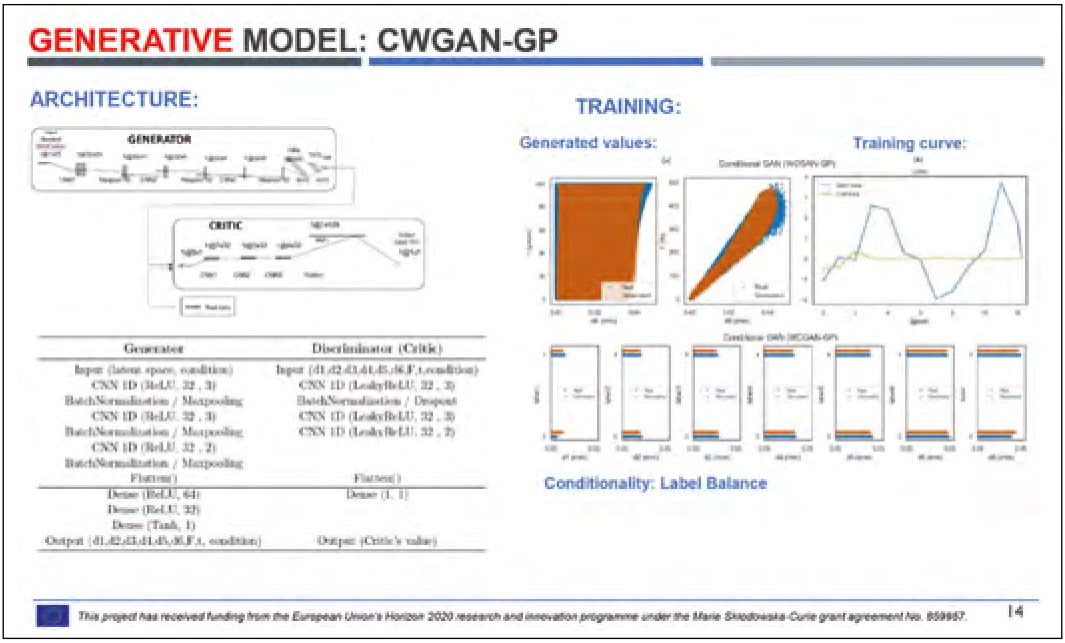

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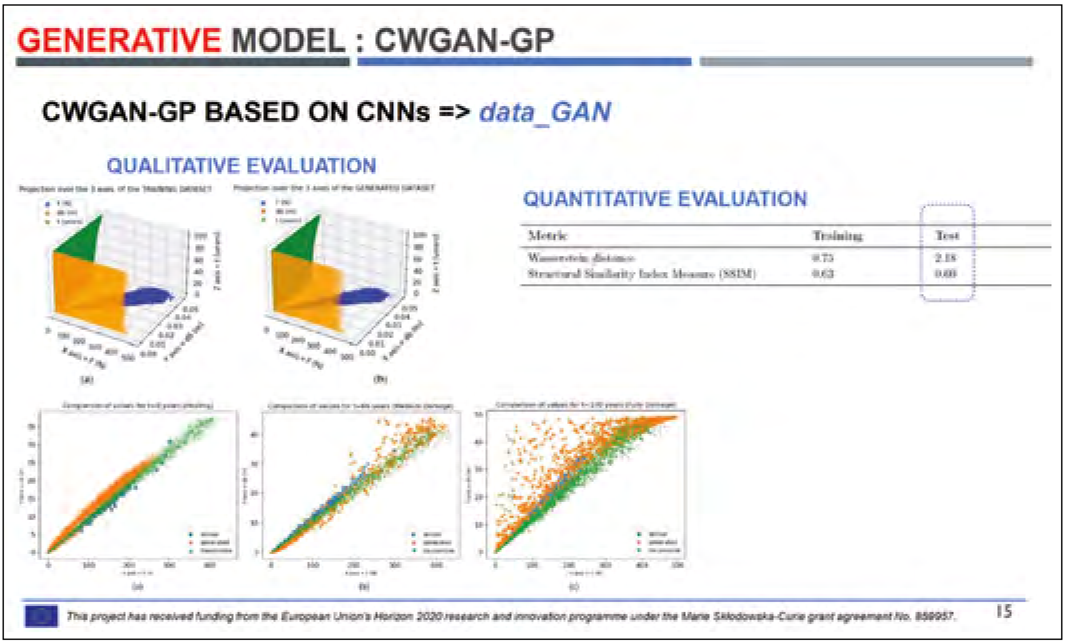
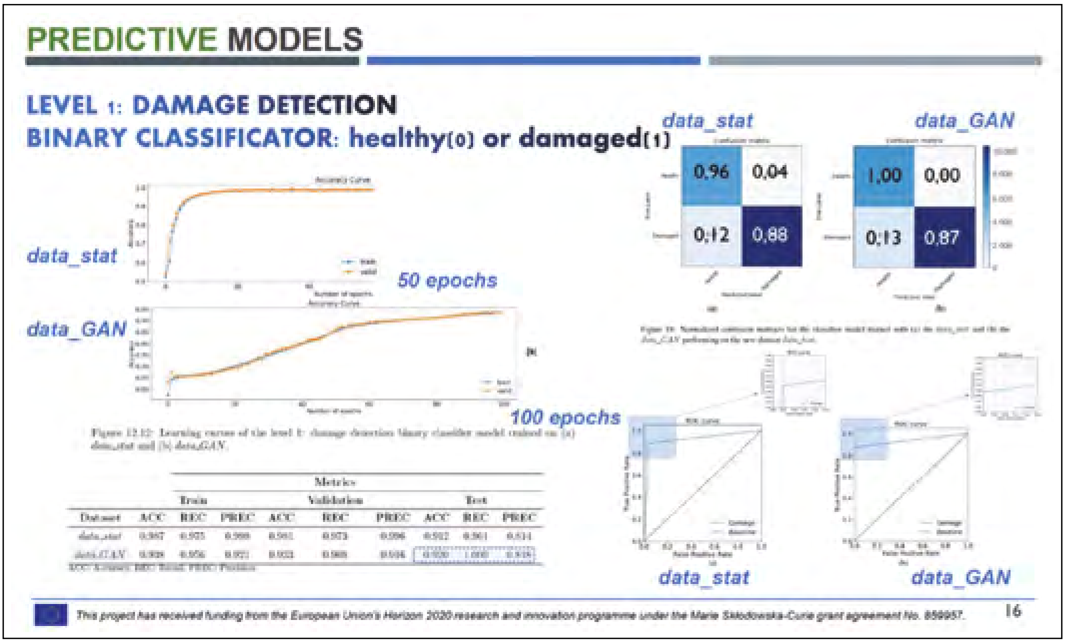
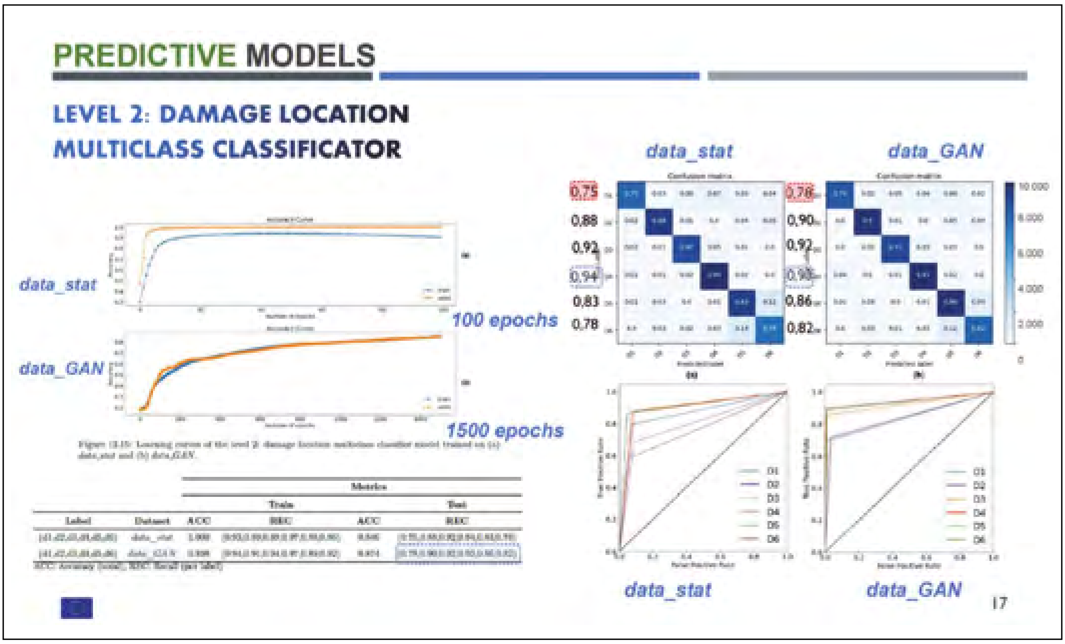
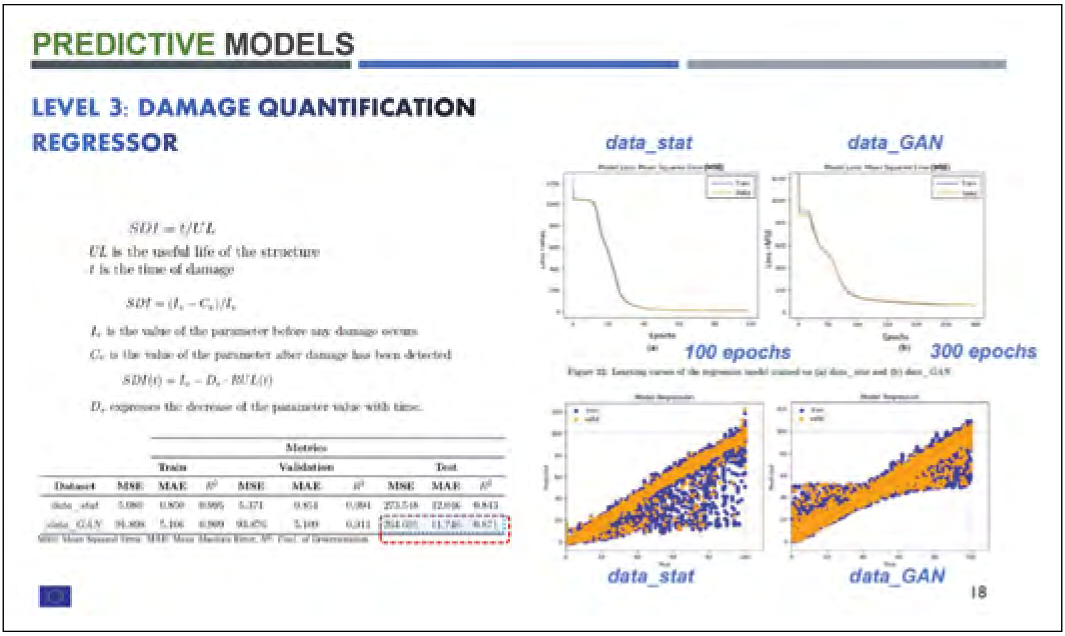

GENERATIVE MODEL : CWGAN-GP
CWGAN-GP BASED ON CNNs => data_GAN
QUALITATIVE EVALUATION
QUANTITATIVE EVALUATION
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
15

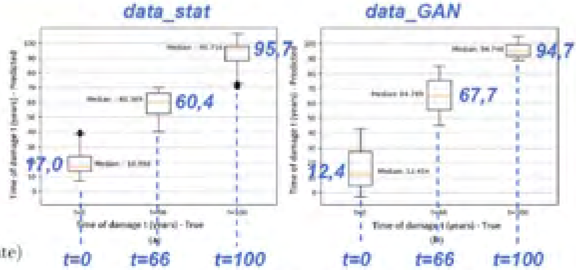

PREDICTIVE MODELS
LEVEL 1: DAMAGE DETECTION
BINARY CLASSIFICATOR: healthy(0) or damaged(1)
data_stat
data_GAN
50 epochs
100 epochs
0,96
0,04
0,12
0,88
1,00
0,00
0,13
0,87
data_stat
data_GAN
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
16


PREDICTIVE MODELS
LEVEL 2: DAMAGE LOCATION
MULTICLASS CLASSIFICATOR
data_stat
data_GAN
100 epochs
1500 epochs
data_stat
data_GAN
0,75
0,88
0,92
0,94
0,83
0,78
0,78
0,90
0,92
0,98
0,86
0,82
data_stat
data_GAN
17


PREDICTIVE MODELS
LEVEL 3: DAMAGE QUANTIFICATION
REGRESSOR
SDI = t/UL
UL is the useful life of the structure
t is the time of damage
I_v is the value of the parameter before any damage occurs
C_v is the value of the parameter after damage has been detected
D_v expresses the decrease of the parameter value with time.
data_stat
data_GAN
100 epochs
300 epochs
data_stat
data_GAN
18

PREDICTIVE MODELS

LEVEL 4: DAMAGE PREDICTION REGRESSOR



$$RUL(years) = 100 - t_i$$

t_i is the predicted time of damage at a discrete time i, expressed in years

$$F = K(t) \cdot d$$
$$K(t) = \alpha \cdot t$$
$$\alpha = 1 - 0,006 \cdot t$$

t = 0 (healthy state)
t = 66 years (mediumdamage state)
t = 100 years (fully damaged state)

	Properties of the predicted values distributions							
Dataset for the training:	t (years)	Median	Q1	Q3	IQR	MIN	MAX	OUT
data_stat	0	16.999	12.796	25.334	12.565	12.768	39.850	7
	66	60.369	52.137	65.475	13.338	40.045	69.938	0
	100	95.716	86.804	97.919	11.115	70.001	105.859	5
data_GAN	0	12.453	4.458	27.684	23.226	-2.838	62.813	0
	66	67.749	56.841	78.809	21.968	45.051	89.942	0
	100	94.748	92.894	101.481	8.587	90.034	109.225	0

Q1: Percentile 25%, Q3: Percentile 25%, IQR: interquartile range, MIN: Minimum value, MAX: Maximum value, OUT: Outliers

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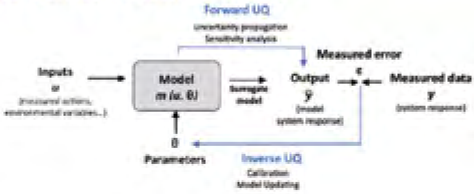
12. TIME EVOLVING CAPABILITY OF THE MODELS

BAYESIAN FRAMEWORK



$$p(\theta|y, \mathcal{M}) = \frac{p(y|\theta, \mathcal{M}) \cdot p(\theta|\mathcal{M})}{p(y|\mathcal{M})} \propto p(y|\theta, \mathcal{M}) \cdot p(\theta|\mathcal{M})$$

	Forward Problem	Inverse Problem
Objective	Predict system output $\hat{y}$ quantifying the uncertainty by $p(\hat{y}\|u, \theta)$	Estimate parameters $\hat{\theta}$ quantifying the uncertainty by $p(\hat{\theta}\|y, u)$
Inputs	System inputs u, model parameters θ	System inputs u, Observed data y, model class $\mathcal{M}$
Outputs	System response predictions $\hat{y} = m(u, \theta)$ and likelihood distribution $p(\hat{y}\|u, \theta)$	Inferred model parameters $\hat{\theta}$ and posterior distribution $p(\hat{\theta}\|y, u)$

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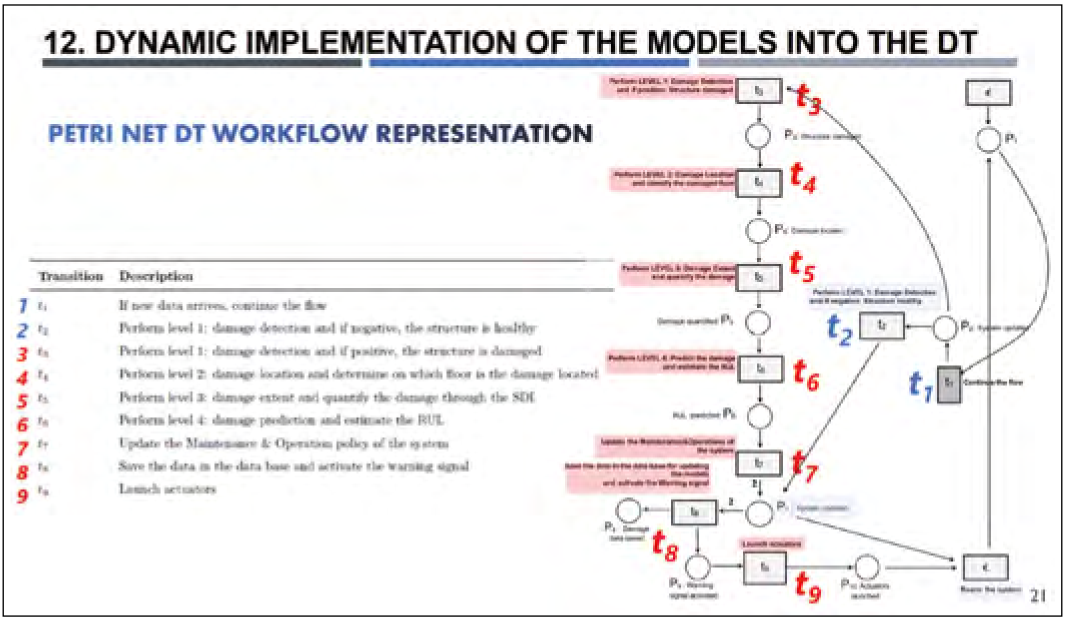
12. DYNAMIC IMPLEMENTATION OF THE MODELS INTO THE DT
PETRI NET DT WORKFLOW REPRESENTATION
Transition Description
1 t_1 If new data arrives, continue the flow
2 t_2 Perform level 1: damage detection and if negative, the structure is healthy
3 t_3 Perform level 1: damage detection and if positive, the structure is damaged
4 t_4 Perform level 2: damage location and determine on which floor is the damage located
5 t_5 Perform level 3: damage extent and quantify the damage through the SDI
6 t_6 Perform level 4: damage prediction and estimate the RUL
7 t_7 Update the Maintenance & Operation policy of the system
8 t_8 Save the data in the data base and activate the warning signal
9 t_9 Launch actuators
t_1
t_2
t_3
t_4
t_5
t_6
t_7
t_8
t_9
21


DIGITAL TWIN
DaSCI
Instituto Andaluz Interuniversitario en Data Science and Computational Intelligence
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UNIVERSIDAD DE GRANADA
THANKS FOR YOUR ATTENTION
CONTACT:
mmegia@ugr.es
https://h2020-enhanceitn.eu/
https://github.com/mmmmaria/Digital-twin.git
ENHAnCE
HORIZON 2020
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.
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Simulation on reliability analysis of linear consecutive *K*-out-of-*n*:*G* systems for Weibull parameter estimation with incomplete failure data

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Abstract

The area of Reliability, as well as the new area of Digital Twin (DT), is faced with the need to bring its theoretical or virtual model closer to real models. For this, it needs to determine the best statistical distribution and its parameters to approximate and tune the real model as best as possible using real data, which is often censored or incomplete data. In this way, it becomes possible to simulate the estimated useful life of equipment, systems and components virtually.

This article develops an algorithm for simulating the estimation of Weibull parameters for consecutive *K*-out-of-*n* systems that exist in many modern systems, such as oil pipeline systems, computer ring networks, telecommunications, etc.

The article develops the complex and coherent systems theory and the respective reliability models. With a new and original approach, algorithms were designed with a simulation that generated random and censored data (right-censored and type I data). The case studies of linear consecutive *K*-out-of-*n* systems were developed to validate the algorithms *K*-out-of-*n*:*G*. A set of simulations was designed with the variation of the different parameters of the reliability models to compare, tune and optimize the estimation of parameters and the simulation of these complex systems.

One relevant result shows that the more censored data in the sample, the more significant the bias and the error about the true value. Increasing the parameter *β* (shape factor) proportionally increases the bias.

One of the relevant results shows that the more censored data in the sample, the greater the bias and error about the true value. Increasing the parameter *β* (shape factor) proportionally increases the bias.

1. Introduction

The current era of 4.0 industry and digital transformation is characterized by the use of advanced technologies that allow means for monitoring and predicting the performance of assets and processes (1), which enables the review of the maintenance programs and contributes to the reduced asset management costs, ease of maintenance, more safety and business risk mitigation.

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The subject of reliability and simulation of systems and the structural relationship between a system and its components is very important in the field of reliability. A comprehensive discussion of reliability theory can be found in (2) and in (3). Reliability Block Diagrams (RBD) can be defined as a network of blocks describing the system's function with logical connections of components needed to produce a specified system function. (2) presents an exhaustive description of the theory of RBD and, more recently (4). If the system has more than one function, each function must be considered individually, and different diagrams need to be made for each system function. The system is fixed in one moment of time; the present state of the system is assumed to depend only on the current states of the components. The connection through a block, in RBD, means that the component is functioning.

A Reliability Block Diagram is developed in terms of functions. Usually not have an account for safety and auxiliary functions and components used to protect equipment, people or the environment. Reliability Block Diagrams can be used for repairable and non-repairable systems or components. In the survival analysis and reliability field, there are several situations in which equipment, components, and units are lost or taken from the study while they are still working. The data censored may occur in control situations, as in life-testing and preassigned time or actual operations, and to make a predictive analysis of failures on time, with systems with vast numbers of sensors and monitoring lots of parameters; in this case, using reliability models containing censored data is fundamental. (5) refers to the fact that, in practice, life test data are almost always time-censored or type I because the study defines the time at which the test will end. Several methods and techniques have been proposed over the past decades for analyzing different types of reliable data. Most of them refer to complete data. However, evaluating highly censored reliability data has not been widely studied. (6) presented an excellent work on this topic. In the beginning, few of the studies used simulation tools, but over time, simulation in the reliability field increased, most of them to estimation parameters.

Many articles use the percentage of data censored (% C) to compare and analyze the model and study simulations, like in (7), (8) and (9). The use and application of data censored in the field of reliability can be seen in (10). The type of distribution used in this study is typically used in the reliability field. Understanding and developing a systematic method to build an accurate simulation model in the presence of censored data is essential, giving more accuracy and precision to the simulation process in the reliability field (11) and (6).

2. State of art: systems, reliability and censored data

A system composed of n components will be classified as a system of order n. The components are to be numbered consecutively from 1 to n. Let $C = \{c_1, c_2, ..., c_n\}$ be the set of all components, where c_i is the i^{th} component, and n is the number of components in the system. Let x_i be the state of component c_i the system can be in one and only one of two states that are either functioning or failed. To indicate the state of the i^{th} component a binary indicator variable x_i to component i is assigned:

$$x_i = \begin{cases} 1, \text{if component } i \text{ is functioning,} \\ 0, \text{if component } i \text{ is a failed.} \end{cases} \tag{1}$$

for $i = 1, ..., n$, where n is the number of the components in the system. The number of components n in the system is called the order of the system. The joint performance of all components in the system can be indicated by vector $X = (x^1, x^2, ..., x^n)$ called a state vector. Similarly, the binary variable ϕ indicates the state of the system:

Similarly, the binary variable ϕ indicates the state of the system:

$$\phi_i = \begin{cases} 1, \text{if system } i \text{ is functioning,} \\ 0, \text{if system } i \text{ is a failed.} \end{cases} \tag{2}$$

The state of system is determined completely by the states of the components, so that may write:

$$\phi = \phi(x), \quad \text{where} \quad x = (x_1, ..., x_n).$$

The function $\varphi(x)$, is called the structure-function of the system. A knowledge of the structure-function is equivalent to an understanding of the structure of the system.

2.1. *Definition of* k-*out-of*-n *structure*

A system function, if and only if at least k of the n components is working, is called a k-out-of-n structure-function.

$$\phi(x) = \prod_{i=1}^{n} x_i \quad \text{for} \quad k = n \tag{3}$$

for $1 \leq k \leq n$, every choice of k out of the n x's appears exactly. A parallel structure is a 1-out-of-n structure and a series structure is an n-out-of-n structure.

2.2. *Right data censored*

The data is considered complete when the exact time of each system failure is known. In many cases, the data contain uncertainties, i.e., when the failure occurred is unknown. The data containing such uncertainty as when the event occurred are regarded as incomplete or partial. Incomplete data can be classified as censored or truncated (12).

From the theoretical point of view, censoring may not be the most efficient way to conduct an experience, but due to time, cost, or practical things, it's so frequent that researchers have had to find ways to deal with it.

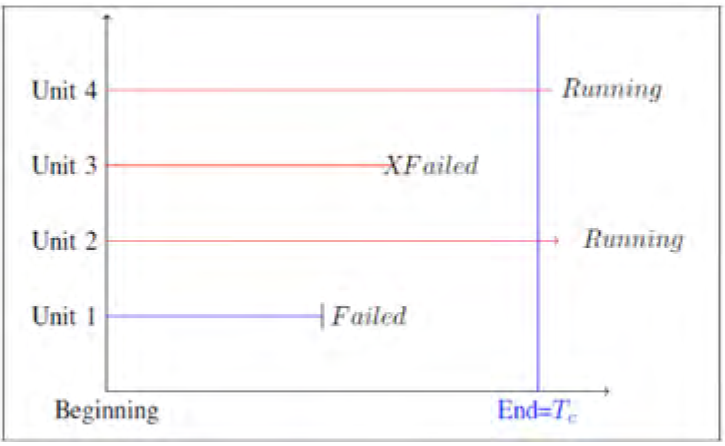
Characterizing the censoring mechanisms is essential to analyze the data and the phenomena in the study. Such a report can be based on several elements: the status of the entity observed, the study's span, the system's dynamic in the study, and the times of start and finish of the observations. Censoring mechanisms can also be characterized based on when and how the time to finish the study is defined. One of the most common types of censored data that may arise in real cases is type-I right censored data.

In type-I right censored data, all units of a system are observed up to the date of completion of the study. For this censorship scheme, the time each unit is under observation is fixed, while the number of units that fail (uncensored observations) is random. In this type of censoring, the stopping time (t_c) is defined or pre-established, and the number of failures observed during the analysis period is random. It ends the experiment and stops monitoring all the entities at some pre-specified time t_c, independent of the event of interest. The Weibull distribution is the most popular statistical distribution in reliability engineering (13). It can be used to fit many life distributions, and it has a significant advantage in the reliability field by changing the parameters to adjust perfectly to the reliability data.

Type I censoring occurs when the experiments are run only for a fixed duration t_c; the lifetimes are known for those whose lifetimes are $t_i \leq t_c$, as it's possible to see in fig. 1.

Figure 1

Fixed type I right censored



The difference between type I and type II is that in type I censoring, the number of observed lifetimes is a random variable, and in type II, the number of observed events is fixed.

2.3. *Linear Consecutive* k-*out-of*-n *systems*

Consecutive K-out-of-n systems can be categorized into consecutive k-out-of-n:G and consecutive k-out-of-n:F systems. A Consecutive k-out-of-n:G system is an n component system that functions whenever at least k consecutive components are functioning. A consecutive k-out-of-n:F is an n component system that fails whenever at least k consecutive component are failed. Such system can either be a linear system, where all components are arranged linearly, or be a circular system, where all components are arranged circularly. The consecutive K-out-of-n:F system was introduced by (14) and explain the relevance of such a system to telecommunication and oil pipeline systems. The application to street light systems and microwave tower systems are discussed by (15). The structure and reliability functions for both systems follow the notion and development made by (16).

The minimal-path representation is used to find the structure function of the linear consecutive k-out-of-n:G system, where $2 \leq k \leq n$. The number of minimal-path vectors for this system is equal to $n - k + 1$ possibilities for placing the K consecutive 1's on n possible locations. So, the set of minimal-path vectors for linear consecutive k-out-of-n:G systems is:

$$\phi_i = \{Z_i\}_{i=1}^{n-k+1} = \{(1_k, 1_{n-k})(0, 1_k, 0_{n-k-1}), \ldots, (0_{n-k}, 1_k)\} \tag{4}$$

where 0_j is the j-dimensional zero vector (0, 0, ..., 0) and 1_j is the j-dimensional unit vector (1, 1, ..., 1).

(16) define that based on the minimal-path vector representation the structure function of a linear consecutive k-out-of n:G system for $n > k$, can be obtained recursively by using state of the system:

$$\phi(x,n,k) = \phi(x,n-1,k) + (1-\phi(x,n-1,k)) \prod_{j=n-k+1}^{n} x_j \tag{5}$$

The structure function (x, n, k), for $n = k$, is simply $\prod_{j=1}^{n} x_j$, which is the structure function of the well-known series system.

2.4. *Reliability functions of linear consecutive* k-*out-of*-n:G *systems*

The reliability of a system is the probability that is structure function $\phi(x, n, k)$ equals 1, which, since ϕ is an indicator variable, equals its expectation:

$$R(P, n, k) = P(\phi(x, n, k) = 1) = E(\phi(x, n, k)) \tag{6}$$

For a system with independent components, R may be found, simply, by replacing x by p in the "reduced" structure function ϕ. The reliability function of linear consecutive

k-out-of-n:G systems when all components are independent and $n > k$ is obtainable recursively by:

$$R_G(p,n,k) = R_G(x,n-1,k) + \left(1 - R_G(x,n-k-1,k)\right) q_{n-k} \prod_{j=n-k+1}^{n} p_j \tag{7}$$

To compute system reliability, especially for a large system, equation 5 can be used directly to produce algorithm. The algorithm should begin with reading and checking the input n; k and p_j such that $1 \leq k \leq n$ and $2 \leq p_j \leq n$. The next step is to compute $R_G(p,k,k)\prod_{j=1}^{n} p_j$, and the last step is to compute $R_G(P, n, k)$ using 5.

2.5. *Simulation of linear consecutive* k*-out-of-*n

To compute a simulation of Monte Carlo linear consecutive k-out-of-n, using Weibull distribution the follow algorithm is developed:

— Step 1. Define the function of the structure of linear consecutive k-out-of-n system.
— Step 2. Calculate the time to censoring - t_c with the parameters of distribution choose.
— Step 3. Generate t_i from random distribution function.
— Step 4. Compare the time t_i with Tc to each component and give $x_i = 0$ if are above or $x_i = 1$ below the t_c.
— Step 5. With x_i and structure function calculate if the system are working or not.
— Step 6. Repeat for M times (the dimension of the cycle simulation).
— Step 7. Calculate the reliability: the number of times that the system are working for the number of samples M.

3. **Case study - linear consecutive 2-out-of-5:*G* system**

Consider the linear consecutive 2-out-of-5:G system. This system is working when at least two consecutive components are functioning. Here $k = 2$ and $n = 5$. Using the equation 5 the structure function of this system is:

$$\begin{aligned}
\phi(x,5,2) &= \phi(x,4,2) + \left(1 - \phi(x,2,2)(1-x_3)\right)\prod_{j=4}^{5} x_j \\
&= x_1x_2 + (1-x_1)x_2x_3 + (1-x_2)x_3x_4 + (1-x_1x_2)(1-x_3)x_4x_5 \\
&\quad (1 - x_1x_2 + x_2x_3 + x_3x_4 - x_1x_2x_3 - x_3x_3x_4)x_4x_5 \\
&= x_1x_2 + x_2x_3 + x_3x_4 + x_4x_5 - x_1x_2x_3 - x_2x_3x_4 \\
&\quad -x_3x_4x_5 - x_1x_2x_4x_5 + x_1x_2x_3x_4x_5
\end{aligned} \tag{8}$$

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The program has been written in *R* language and the software is the *R* Studio, and in the beginning it's define the function structure and simulations and then applied the loop "for" to made the cycle and the reliability calculation. The structure function of the system in the program is define by a function with the name *str fun*.

Algorithm 1. *Simulation of linear consecutive* k-*out-of*-n:G

```
bet=beta[j]
tcm=0;fiab=0;tcm1=0
for (k in 1:4){
    cen <- ceni[k]
    tc <- scx1*(-log(cen))^(1/shx1)
    for (i in 1:length(mi)){
    m=mi[i]
    rest=simul_fun(m)
    fiab[i]=rest/m
    }
    tcm=cbind(tcm,fiab)
    cens=censtr[k]
    bi=bstr[k]
}
tcm1=tcm[,-1]
bi=bstr[j]
```

The simulation of linear consecutive 2-out-of-5:*G* to all components used the same Weibull parameters; the shape parameter β have the values 0,5; 1; 1,5 and 2; the scale parameter is η = 10, for all components and simulations. The simulation is made for different number of samples to verified the impact of the number of samples for each simulation. Another interest characteristic is to simulate reliability with different censored data, in this case it's used 5%,10%, 20% and 30%.

Table 1

Simulation 2-out-of-5:*G*, Weibull (;%C; *n*), = 10 M = 100

	$C_{5\%}$				$C_{10\%}$				$C_{20\%}$				$C_{30\%}$			
Sample	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2
10	1	1	0.90	0.70	1	1	0.90	0.80	1	1	0.90	0.90	1	1	1	1
100	0.95	0.95	0.83	0.83	0.99	0.99	0.93	0.86	1	1	0.97	0.87	1	1	0.98	0.88
500	0.96	0.91	0.90	0.81	1	0.98	0.94	0.88	1	1	0.97	0.90	1	1	0.99	0.92
1.000	0.96	0.92	0.89	0.84	1	0.99	0.94	0.85	1	1	0.98	0.88	1	1	1	0.92
2.000	0.95	0.93	0.88	0.82	1	0.99	0.94	0.87	1	1	0.98	0.90	1	1	1	0.92

4. Conclusions

The results are explicit in the table 1 and from the analysis of the table, it's possible to see that with the increase of the sample number the value of reliability stabilized at a certain value. With the increase of the shape factor, the value of reliability decreases, not so much, but can appoint the exponential shape as the most favourable state to have a higher value of reliability. The reliability decreases smoothly with the increase of censored data. One possible explanation is that with the increase of censorship, the system is not so stable and the faults are a little more and have more impact on reliability. Test with other parameters and also make a comparative test with different parameters for each component will be recommend.

Acknowledgements

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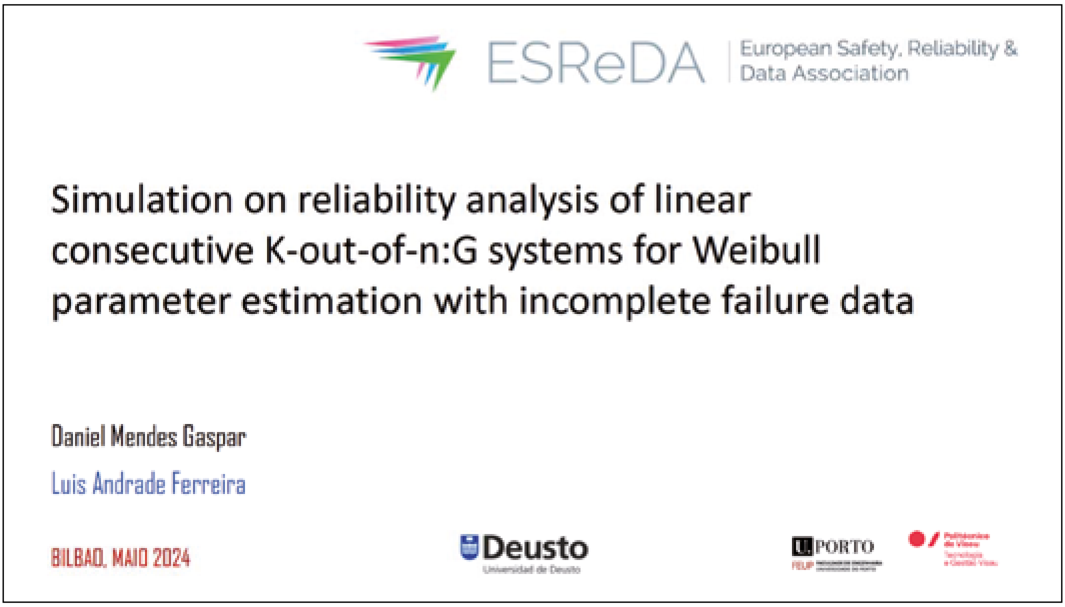

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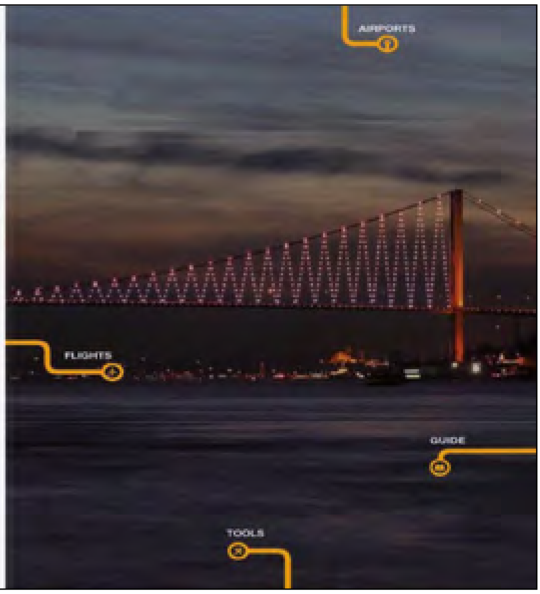
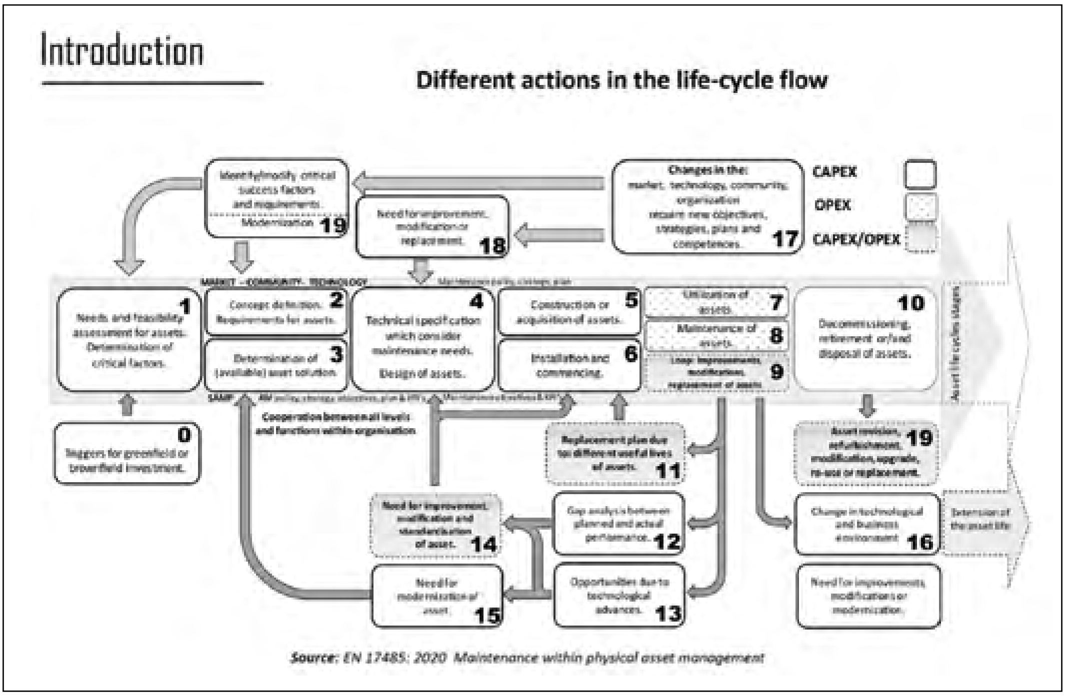
01

Introduction

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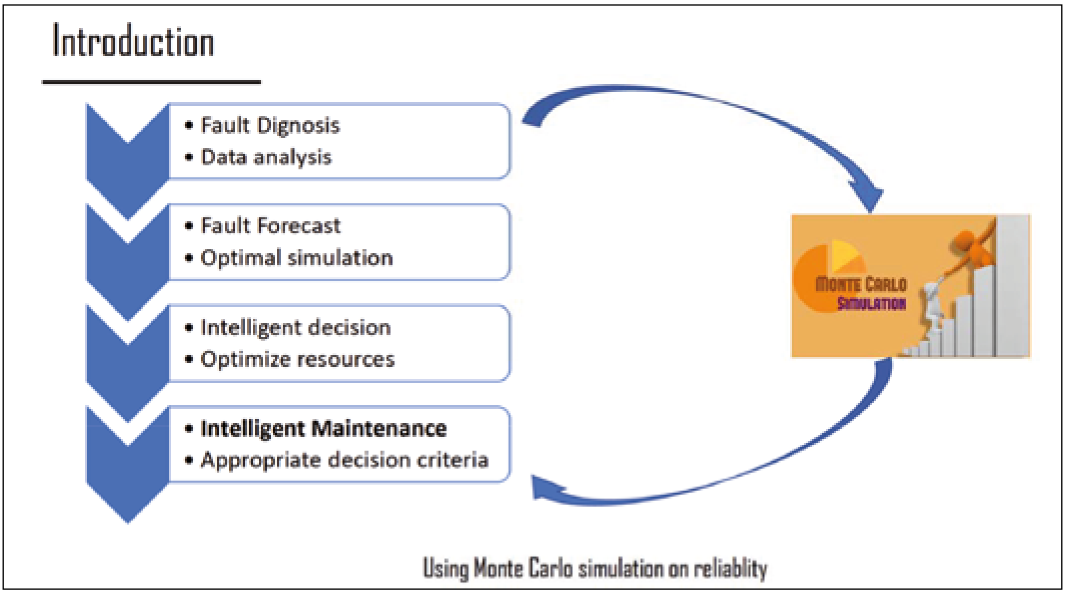
Different actions in the life-cycle flow
CAPEX
OPEX
CAPEX/OPEX
Source: EN 17485: 2020 Maintenance within physical asset management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• Fault Dignosis
• Data analysis
• Fault Forecast
• Optimal simulation
• Intelligent decision
• Optimize resources
• Intelligent Maintenance
• Appropriate decision criteria
Monte Carlo Simulation
Using Monte Carlo simulation on reliablity

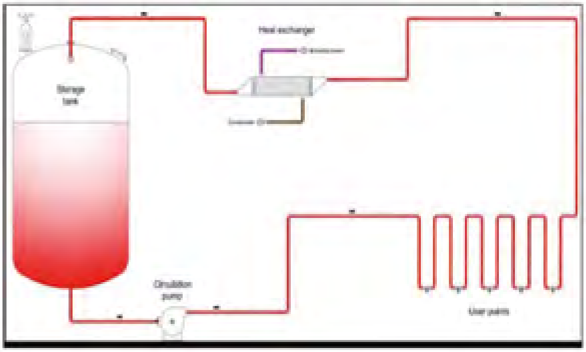
Introduction

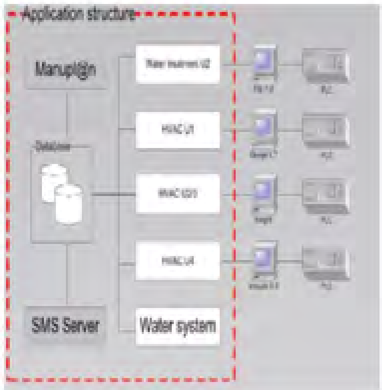
Introduction

Water for Injection (WFI) – This is a water of the highest chemical purity, perfectly sterile, since its main use is the preparation of injectable solutions
The pharmaceutical water distribution system is usually organized in form of a circulation loop, assuring turbulent water motion in the pipes 24 hours a day and 7 days a week

Introduction

WFI loop must remain among **75°C and 90 °C** to conserve the physicochemical and microbiological characteristics of the water.





Introduction

WFI loop

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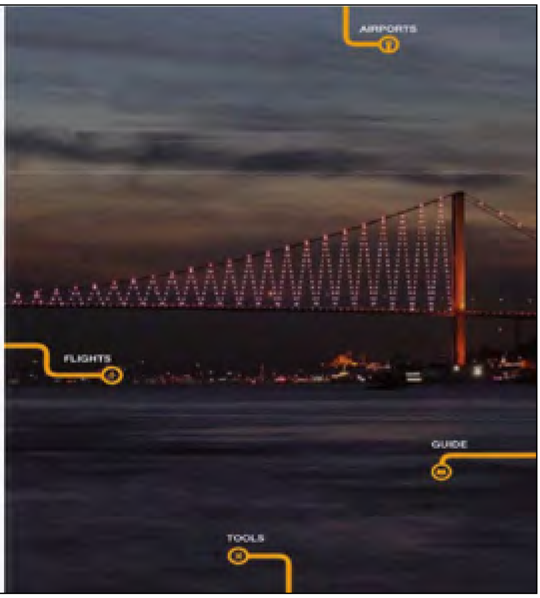
02

Reliability of systems



The Reliability of systems

The state of the ith component (binary indicator)

$$x_i = \begin{cases} 1, & \text{if component i is functioning,} \\ 0, & \text{if component i is failed.} \end{cases}$$

the state of the system

$$\phi_i = \begin{cases} 1, & \text{if system i is functioning,} \\ 0, & \text{if system i is failed.} \end{cases} \qquad \phi = \phi(x), \quad \text{where} \quad x = (x_1, \ldots, x_n).$$

The function $\phi(x)$, is called the structure-function of the system.

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Definition of k-out-of-n structure

A system function, if and only if at least k of the n components is working, is called a k-out-of-n structure-function

$$\phi(x) = \prod_{i=1}^{n} x_i \quad for \quad k = n$$

for $1 \le k \le n$, every choice of k out of the n x's appears exactly.
A parallel structure is a 1-out-of-n structure and a series structure is an n-out-of-n structure.

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Linear Consecutive k-out-of-n systems

A Consecutive k-out-of-n:G system is an n component system that functions whenever at least k consecutive components are functioning.

A consecutive k-out-of-n:F is an n component system that fails whenever at least k consecutive component are failed.

Such system can either be a linear system, where all components are arranged linearly, or be a circular system, where all components are arranged circularly

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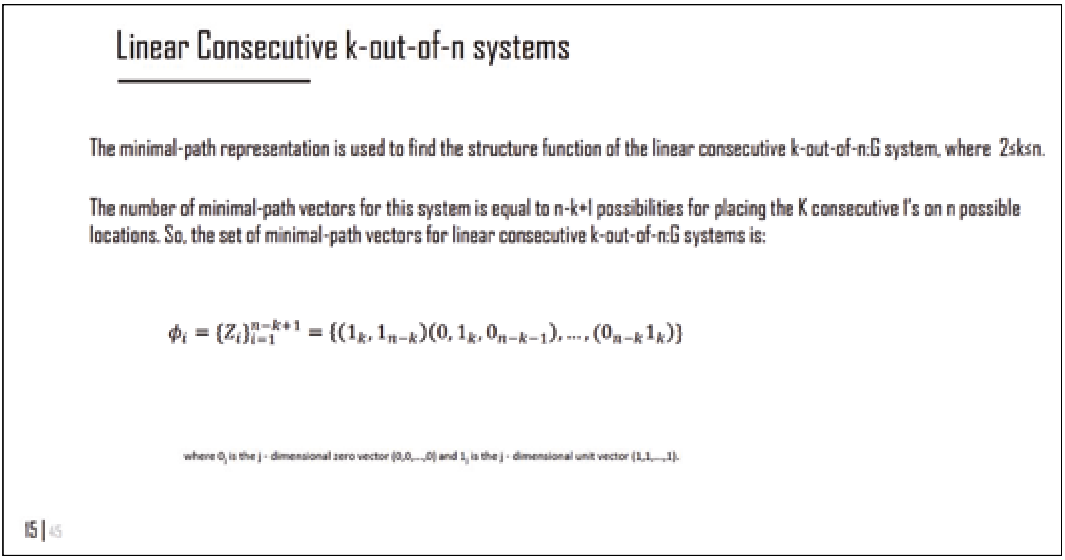

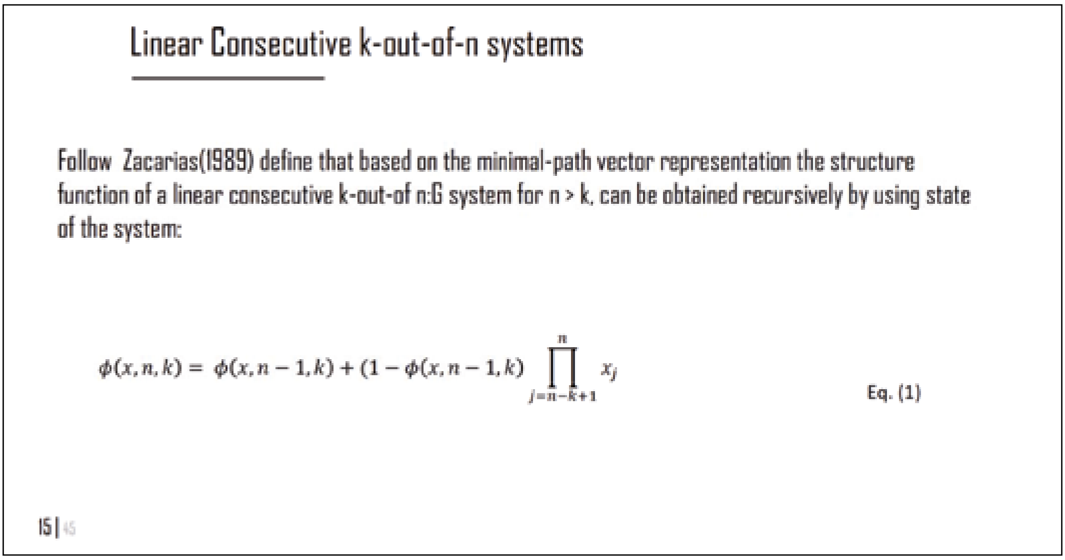

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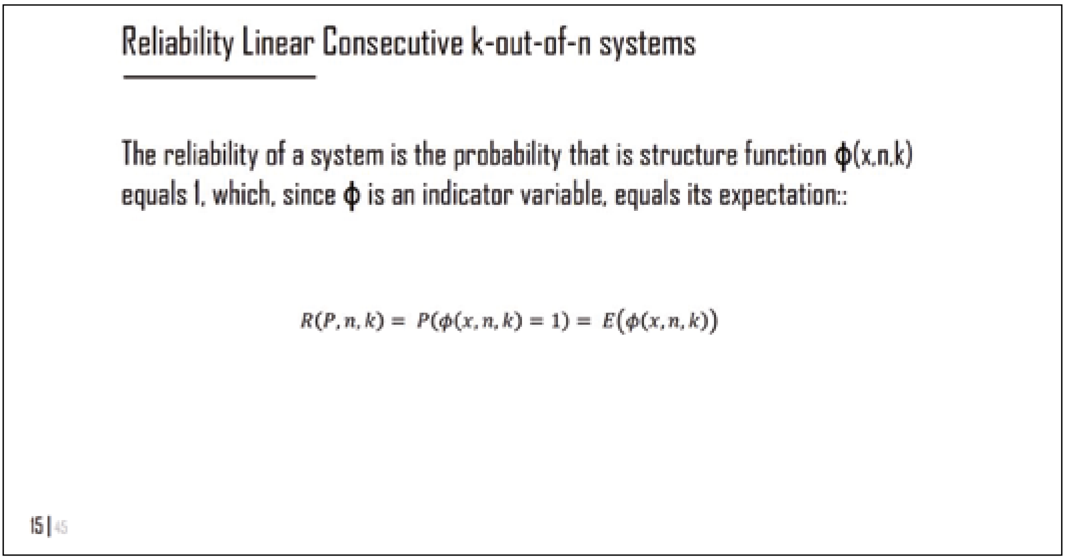

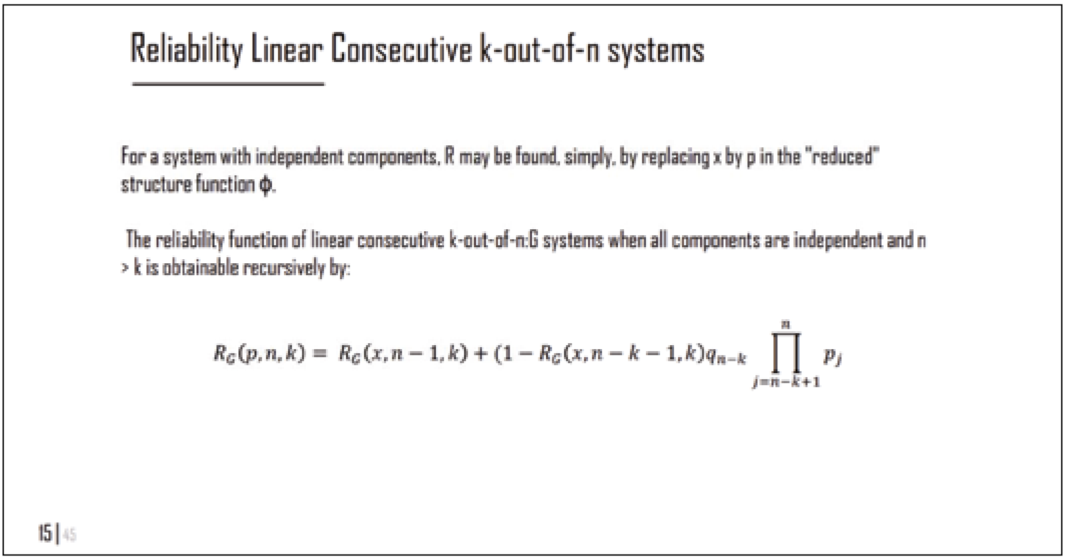

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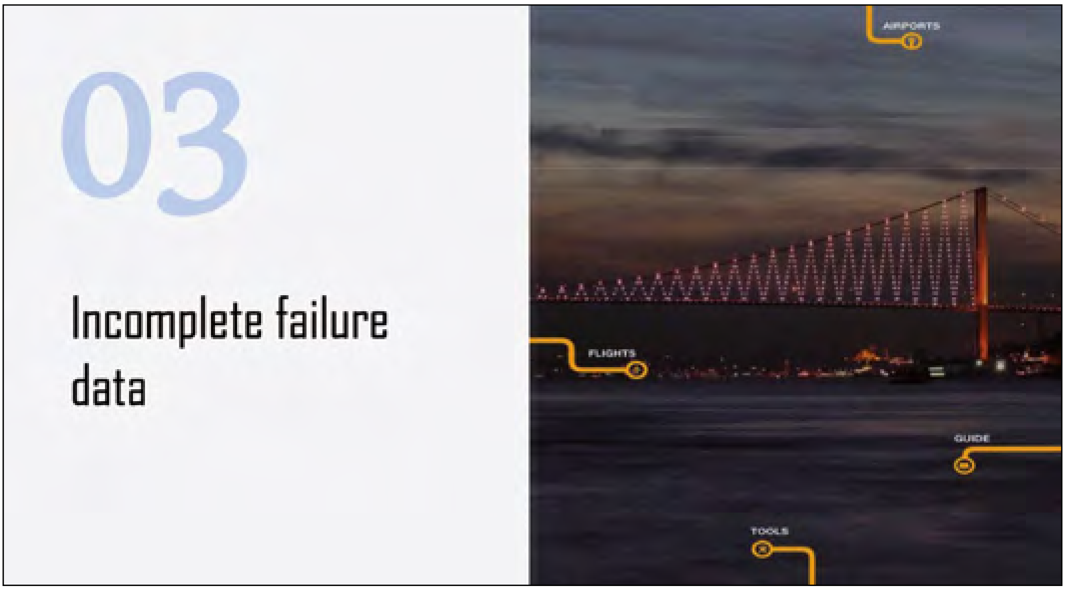
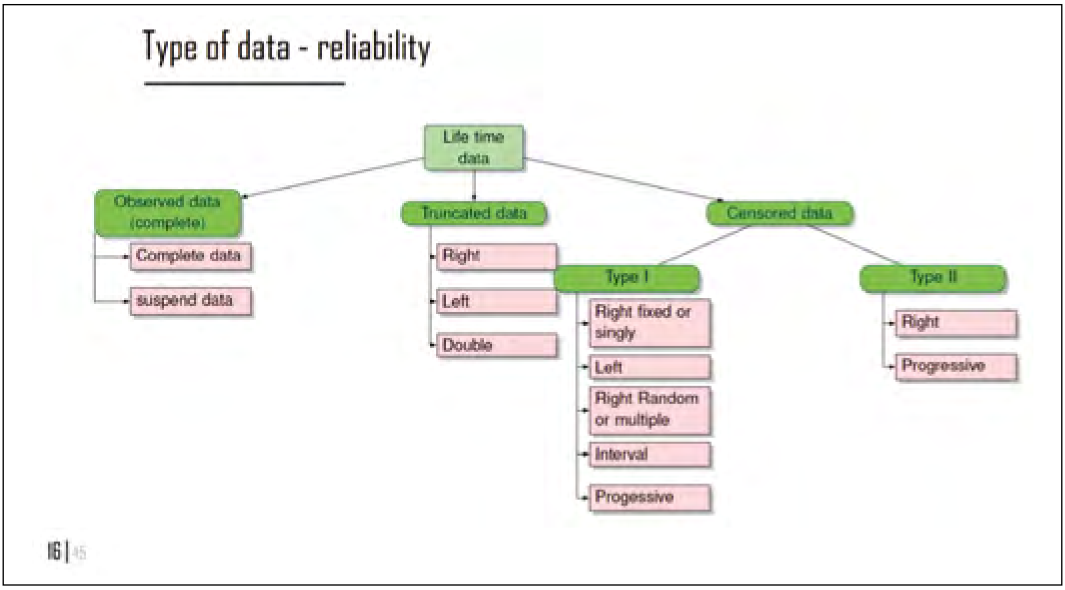
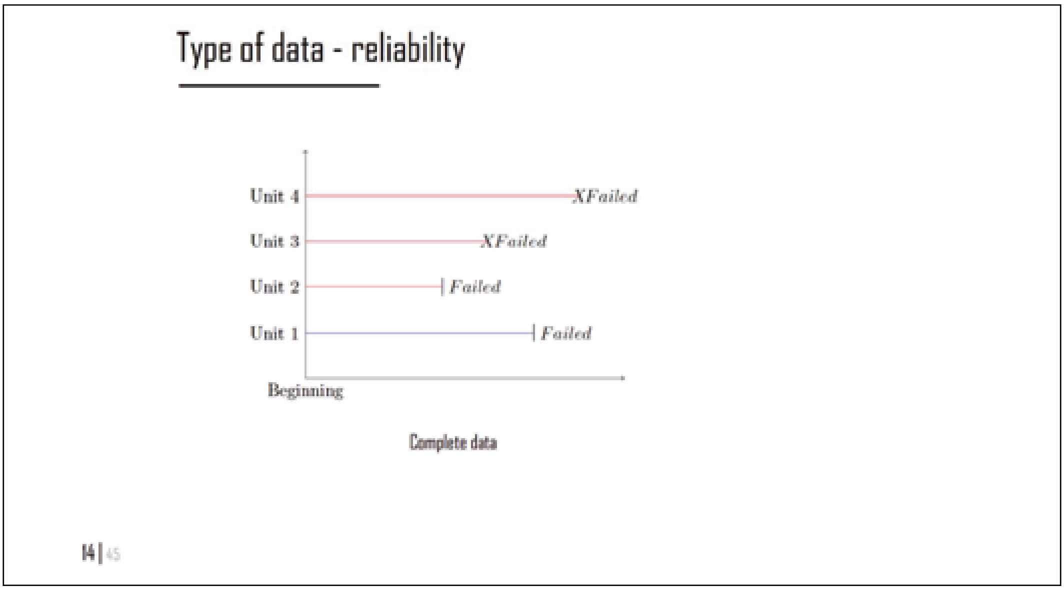
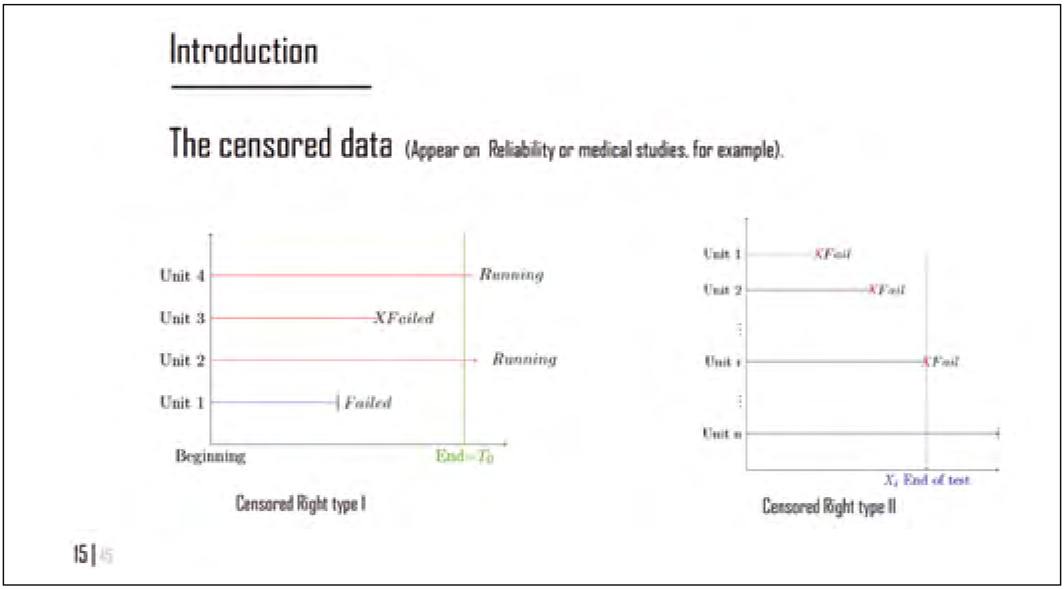
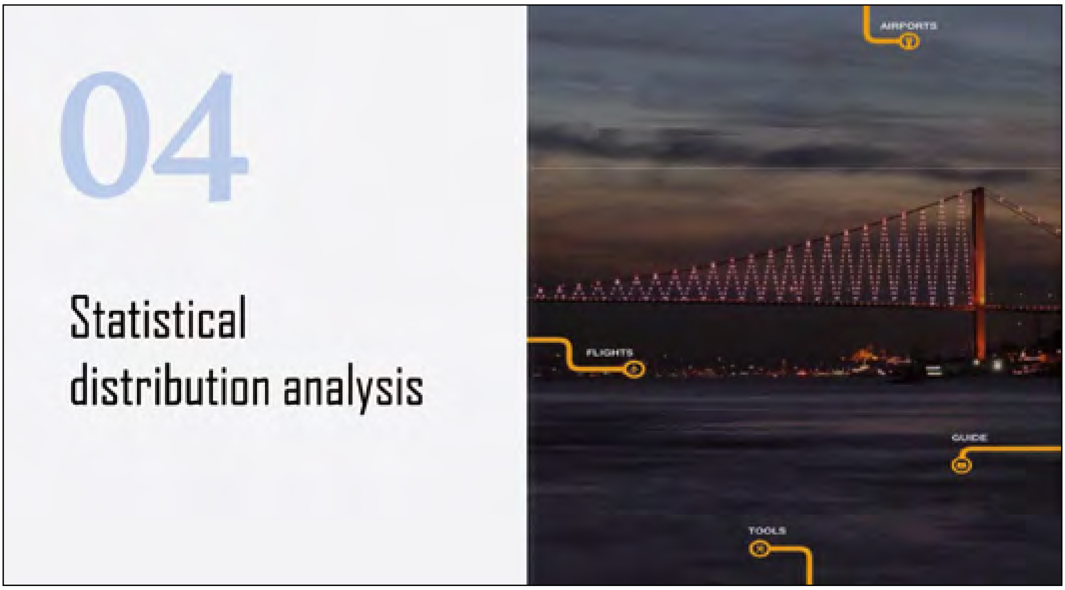
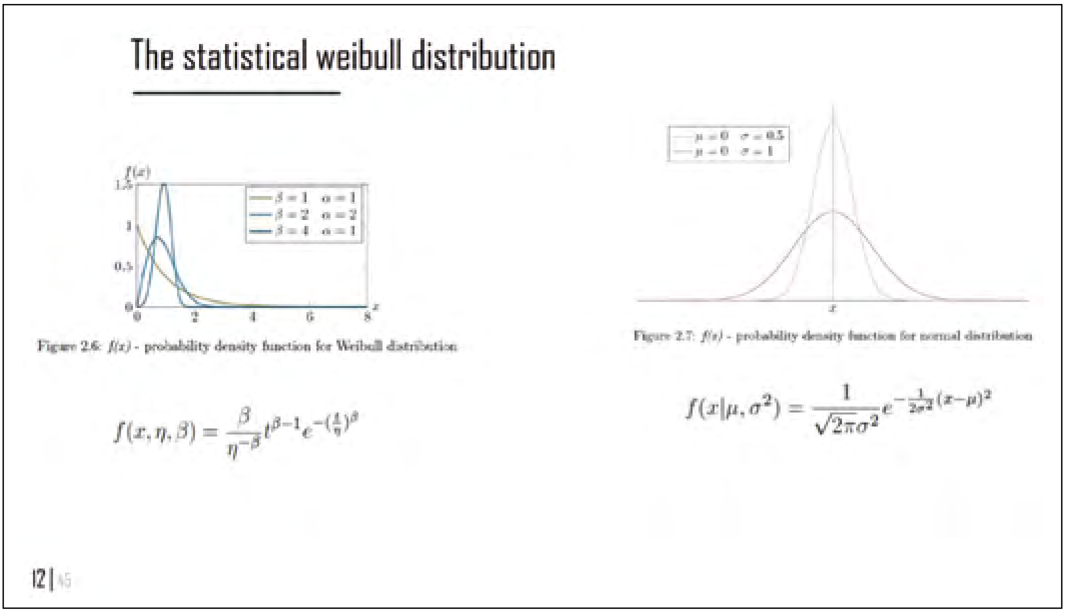

03
Incomplete failure data
AIRPORTS
FLIGHTS
GUIDE
TOOLS


Type of data - reliability
Life time data
Observed data (complete)
Complete data
suspend data
Truncated data
Right
Left
Double
Censored data
Type I
Right fixed or singly
Left
Right Random or multiple
Interval
Progessive
Type II
Right
Progressive
16 | 45


Type of data - reliability
Unit 4
XFailed
Unit 3
XFailed
Unit 2
Failed
Unit 1
Failed
Beginning
Complete data
14 | 45


Introduction
The censored data (Appear on Reliability or medical studies, for example).
Unit 4
Running
Unit 3
XFailed
Unit 2
Running
Unit 1
Failed
Beginning
End=T0
Censored Right type I
Unit 1
XFail
Unit 2
XFail
Unit r
XFail
Unit n
Xr End of test
Censored Right type II
15 | 45





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General formulation of censored data

$$L(\theta; x, \delta) = \prod_{d \in D} f(x_d) \prod_{r \in R} S(x_r) \prod_{l \in L} S(x_r)[1 - S(x_l)] \prod_{i \in I} [S(U_i) - S(V_i)]$$

Where D is the set of death times, R is the set of right censored times. L is the set of left censored observations, I is the set of interval censored observations

Complete data MLE Weibull:

$$L(\eta, \beta) = \left(\frac{\beta}{\eta^\beta}\right)^n \prod_{i=1}^{n} \left[t_i^{\beta-1} \exp\left(-\left(\frac{t_i}{\eta}\right)^\beta\right)\right]$$

The log-likelihood can be written as:

$$\ln L(\eta, \beta) = n \ln \beta - n\beta \ln \eta + (\beta - 1) \sum_{i=1}^{n} \ln t_i - \sum_{i=1}^{n} \left(\frac{t_i}{\eta}\right)^\beta$$

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Right censored type I MLE Weibull

$$L(\eta, \beta) = \prod_{i=1}^{n} \left\{ \frac{\beta}{\eta} \left(\frac{t_i}{\eta}\right)^{\beta-1} \exp\left(-\left(\frac{t_i}{\eta}\right)^\beta\right)\right\}^{\delta_i} \left\{ \exp\left(\left(-\frac{t_i}{\eta}\right)^\beta\right)\right\}^{1-\delta_i}$$

The log-likelihood can be written as:

$$\ln L(\eta, \beta) = r \ln \beta - r\beta \ln \eta + (\beta - 1) \sum_{i=1}^{n} (\delta_i \ln t_i) - \sum_{i=1}^{n} \left(\frac{t_i}{\eta}\right)^\beta$$

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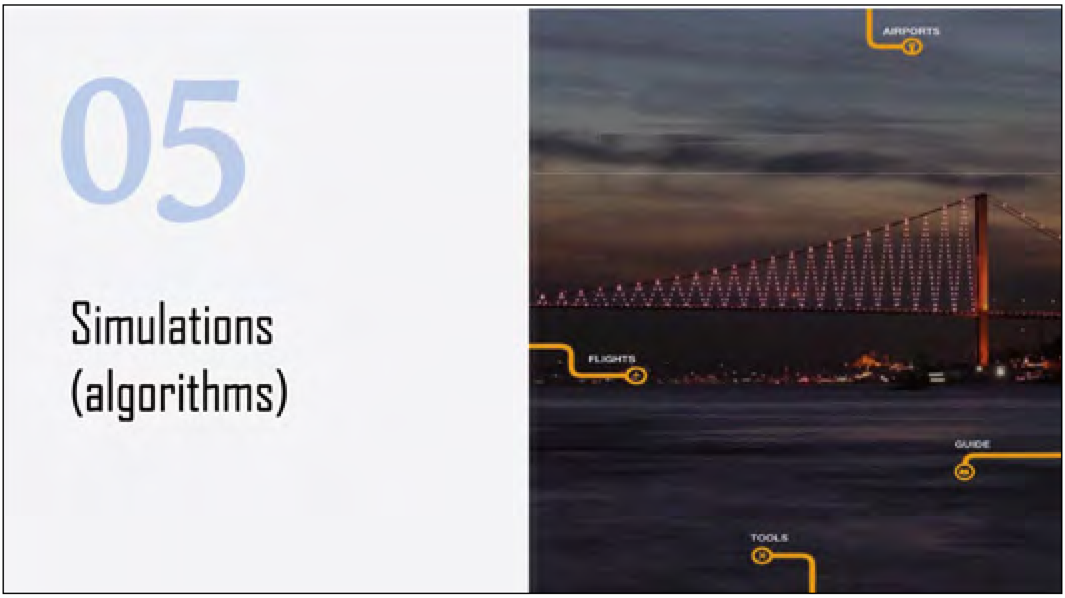
05
Simulations (algorithms)
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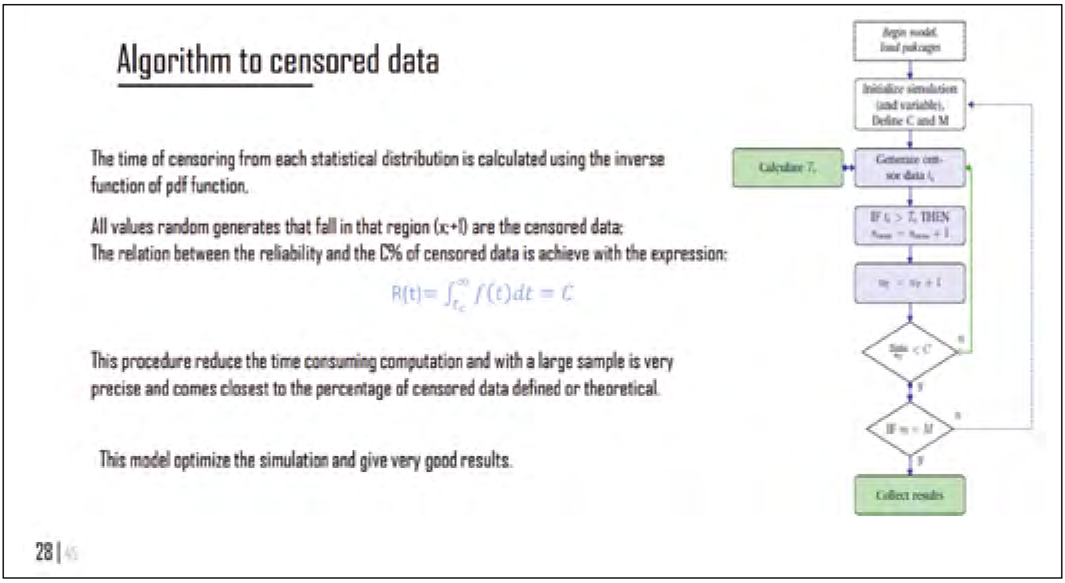
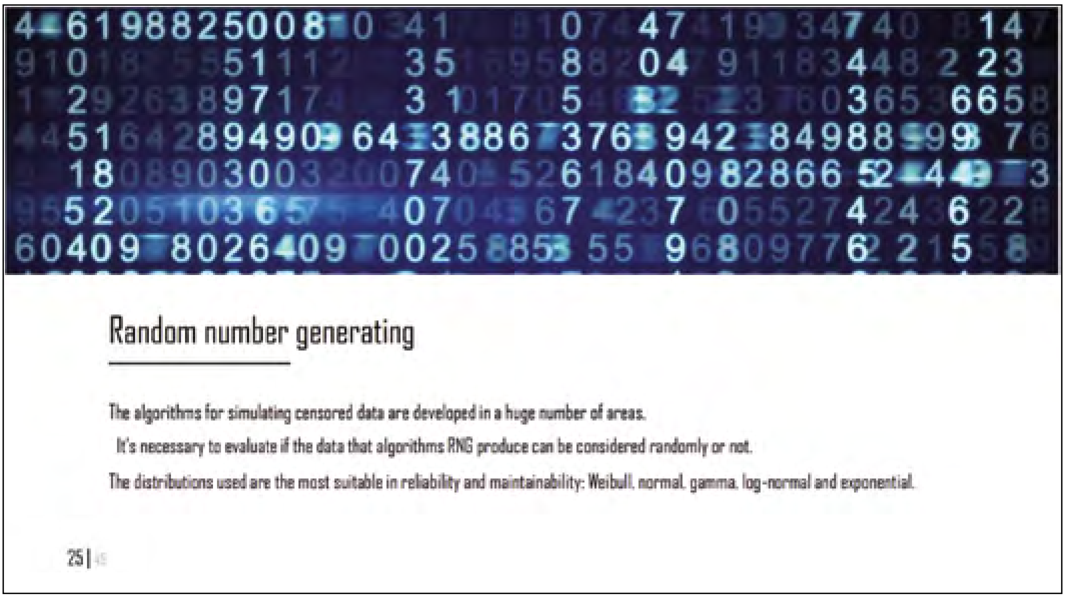

Algorithm to censored data
The time of censoring from each statistical distribution is calculated using the inverse function of pdf function.
All values random generates that fall in that region (x;+I) are the censored data;
The relation between the reliability and the C% of censored data is achieve with the expression:
$R(t) = \int_{t_c}^{\infty} f(t)dt = C$
This procedure reduce the time consuming computation and with a large sample is very precise and comes closest to the percentage of censored data defined or theoretical.
This model optimize the simulation and give very good results.
Initialize simulation (and variable), Define C and M
Collect results
28 | 45


Random number generating
The algorithms for simulating censored data are developed in a huge number of areas.
It's necessary to evaluate if the data that algorithms RNG produce can be considered randomly or not.
The distributions used are the most suitable in reliability and maintainability: Weibull, normal, gamma, log-normal and exponential.
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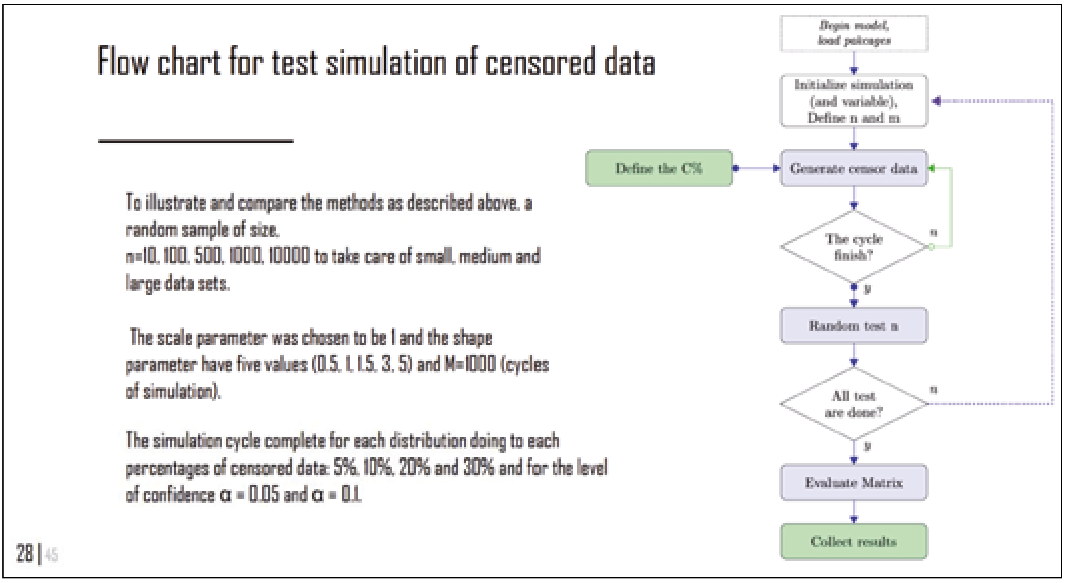
Flow chart for test simulation of censored data
To illustrate and compare the methods as described above, a random sample of size.
n=10, 100, 500, 1000, 10000 to take care of small, medium and large data sets.
The scale parameter was chosen to be 1 and the shape parameter have five values (0.5, 1, 1.5, 3, 5) and M=1000 (cycles of simulation).
The simulation cycle complete for each distribution doing to each percentages of censored data: 5%, 10%, 20% and 30% and for the level of confidence α = 0.05 and α = 0.1.
Begin model,
Initialize simulation (and variable), Define n and m
Define the C%
Generate censor data
The cycle finish?
n
y
Random test n
All test are done?
n
y
Evaluate Matrix
Collect results
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Test for randomness

Kolmogorov-Smirnov Test is the two-level test is to compare the empirical distribution of these U_j's to the uniform distribution, via a goodness-of-fit (GOF)

The **Wald–Wolfowitz** runs test (or simply runs test), is a non-parametric statistical test that can be used to test the hypothesis that the elements of the sequence are mutually independent

The non-parametric **Mann-Kendall test** is commonly employed to detect monotonic trends in series of random or reliability data.

The **turning point test** for randomness is used to determine if the peaks and troughs (or turning points) of a serial data set (time-series) is independent of the order of the observations.

The **runs test – up and down** examines the arrangement of the numbers in a sequence to test the hypothesis of independence.

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Reliability Linear Consecutive k-out-of-n systems

To compute system reliability, especially for a large system, equation 5 can be used directly to produce algorithm.

The algorithm should begin with reading and checking the input n; k and p_i such that $1 \leq k \leq n$ and $2 \leq p_j \leq n$.

The next step is to compute $R_G(p,k,k)\prod_{j=1}^{n} p_j$, and the last step is to compute $R_G(p,n,k)$ using 5.

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Simulation of linear consecutive k-out-of-n

To compute a simulation of Monte Carlo linear consecutive k-out-of-n, using Weibull distribution the follow algorithm is developed::

Step 1: Define the function of the structure of linear consecutive *k-out-of-n* system;

Step 2: Calculate the time to censoring - t_c with the parameters of distribution choose;

Step 3: Generate t_i from random distribution function;

Step 4: Compare the time ti with Tc to each component and give $x_i = 0$ if are above or $x_i = 1$ below the t_c ;

Step 5: With x_i and structure function calculate if the system are working or not;

Step 6: Repeat for M times (the dimension of the cycle simulation);

Step 7: Calculate the reliability: the number of times that the system are working for the number of samples M.

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linear consecutive 2-out-of-5:G Algorithm

The program has been written in R language and the software is the R Studio, and in the beginning it's define the function structure and simulations and then applied the loop "for" to made the cycle and the reliability calculation.

```
bet<-beta[j]
tcm<-0;fiab<-0;tcm1<-0
for (k in 1:4){
    cen <- ceni[k]
    tc <- scxi*(-log(cen))^(1/shx1)
    for (i in 1:length(mi)){
    m<-mi[i]
    rest<-simul_fun(m)
    fiab[i]<-rest/m
    }
    tcm<-cbind(tcm,fiab)
    cena<-cenatr[k]
    bi<-batr[k]
}
tcm1<-tcm[,-1]
bi<-batr[j]
```

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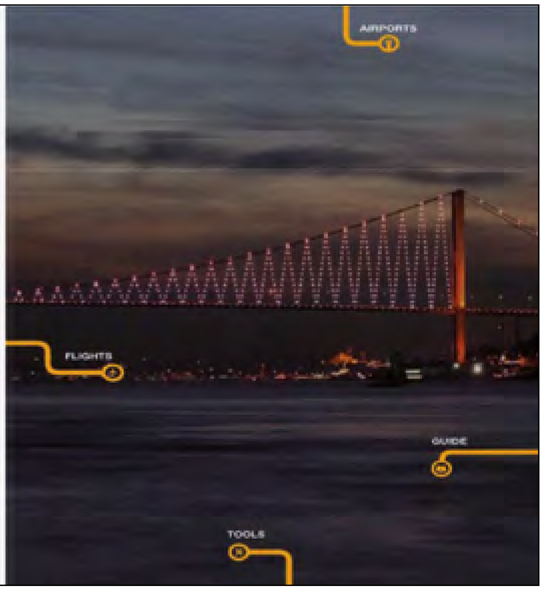
06

Simulation Results



linear consecutive 2-out-of-5:G system

This system is working when at least two consecutive components are functioning. Here k = 2 and n = 5. Using the equation I the structure function of this system is::

$$\phi(x,5,2) = \phi(x,4,2) + (1 - \phi(x,2,2)(1 - x_3)\prod_{j=4}^{5} x_j$$
$$= x_1x_2 + (1 - x_1)x_2x_3 + (1 - x_2)x_3x_4 + (1 - x_1x_2)(1 - x_3)x_4x_5$$
$$(1 - x_1x_2 + x_2x_3 + x_3x_4 - x_1x_2x_3 - x_3x_3x_4)x_4x_5$$
$$= x_1x_2 + x_2x_3 + x_3x_4 + x_4x_5 - x_1x_2x_3 - x_2x_3x_4$$
$$-x_3x_4x_5 - x_1x_2x_4x_5 + x_1x_2x_3x_4x_5$$

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linear consecutive 2-out-of-5:G system

The simulation of linear consecutive 2-out-of-5:G to all components used the same Weibull parameters: the shape parameter β have the values 0.5;1;1.5 and 2 ; the scale parameter is η = 10. for all components and simulations

	$C_{5\%}$				$C_{10\%}$				$C_{20\%}$				$C_{30\%}$			
Sample	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2
10	1	1	0.9	0.7	1	1	0.9	0.8	1	1	0.9	0.9	1	1	1	1
100	0.95	0.95	0.83	0.83	0.99	0.99	0.93	0.86	1	1	0.97	0.87	1	1	0.98	0.88
500	0.96	0.91	0.9	0.81	1	0.98	0.94	0.88	1	1	0.97	0.9	1	1	0.99	0.92
1000	0.96	0.92	0.89	0.84	1	0.99	0.94	0.85	1	1	0.98	0.88	1	1	1	0.92
2000	0.95	0.93	0.88	0.82	1	0.99	0.94	0.87	1	1	0.98	0.9	1	1	1	0.92

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linear consecutive 2-out-of-5:F system

This system is failed when at least two consecutive components are failed. Here k = 2 and n = 5.. the structure function of this system is:

$$
\begin{aligned}
\psi(x,5,2) &= \prod_{i=1}^{4}(1-\prod_{j=i}^{i+1}(1-x_j)) \\
&= (1-(1-x_1)(1-x_2))(1-(1-x_2)(1-x_3) \\
&\quad (1-(1-x_3)(1-x_4))(1-(1-x_4)(1-x_5) \\
&= x_2x_4 + x_1x_3x_4 + x_1x_3x_5 + x_2x_3x_5 - x_1x_2x_3x_4 - \\
&\quad x_1x_3x_4x_5 - x_1x_2x_3x_5 - x_2x_3x_4x_5 - x_1x_2x_3x_4x_5.
\end{aligned}
$$

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linear consecutive 2-out-of-5:F system

The simulation of linear consecutive 2-out-of-5:F to all components used the same Weibull parameters; the shape parameter β have the values 0,5;1;1,5 and 2 ; the scale parameter is η = 10, for all components and simulations

	$C_{5\%}$				$C_{10\%}$				$C_{20\%}$				$C_{30\%}$			
Sample	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2	$\beta_{0.5}$	β_1	$\beta_{1.5}$	β_2
10	1	0.8	0.7	0.5	1	1	0.7	0.5	1	1	1	0.8	1	1	1	1
100	0.89	0.8	0.79	0.63	0.98	0.98	0.86	0.71	1	0.99	0.97	0.78	1	1	1	0.81
500	0.91	0.87	0.74	0.65	0.98	0.98	0.87	0.71	1	1	0.95	0.77	1	1	0.99	0.8
1000	0.88	0.85	0.76	0.67	0.99	0.96	0.86	0.74	1	1	0.94	0.77	1	1	0.98	0.83
2000	0.9	0.84	0.75	0.68	0.99	0.96	0.88	0.7	1	0.99	0.94	0.79	1	1	0.98	0.82

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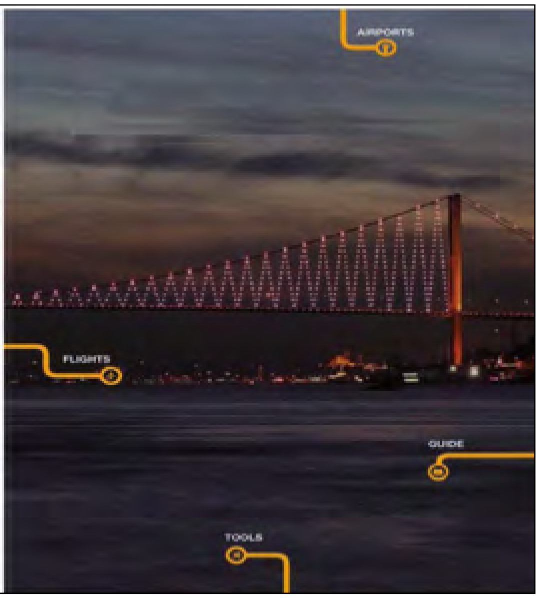
07

Conclusions



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Conclusions

The results are explicit in the table I and II. From the analysis of the table, it's possible to see that with the increase of the sample number the value of reliability stabilized at a certain value.

With the increase of the shape factor, the value of reliability decreases, not so much, but can appoint the exponential shape as the most favourable state to have a higher value of reliability.

The reliability decreases smoothly with the increase of censored data. One possible explanation is that with the increase of censorship, the system is not so stable and the faults are a little more and have more impact on reliability.

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Conclusions

_This research work was used to develop reliability model simulation algorithms for complex equipment/systems, when the data collection is faced with censored data.

_The algorithms are innovative and their development was done in three different software: Python, Matlab and R.

_A methodology of analysis (hypothesis tests) and validation with an evaluation matrix is proposed to test the i.i.d. data of RNG of censored data.

_The majority of simulation studies reported in the literature are not providing sufficient details of simulation random generator data.

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_There are influence of parameters of distribution or the parameters of model simulations in the randomness of data generation.

_Modifications of the simulation process, such as altering the number of simulations or other parameters are possible, but this modifications can be a time-consuming processing.

_The hypothesis test to apply to the specific generator censored data must be selected very carefully in order to have good results and to optimize the simulation time.

To final conclusion, we hope our work permit to generate some more discussion and attention to the algorithms that simulate data censored, and give some tools and results to made the simulations and the studies more accuracy and optimized...

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Future Work

Compare four distribution: - exponential, weibull, gamma and log-normal, in which we can see the different behaviour when we change the scale parameters and have the same %C percentage of censored data.

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Pioneering Precision: Unsupervised K-means Clustering and Attention-CNN-1D for Railway Corrugation Estimation

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Abstract

This study introduces a deep learning approach for estimating corrugation in railway systems by Attention-based One-Dimensional Convolutional Neural Networks (Attention-CNN-1D) coupled with Unsupervised K-means clustering using acceleration in longitudinal and vertical directions. The model's performance is examined in a 1:10 scale vehicle running at two forward velocities: 0.5 and 1.00 m/s. In addition, the newly developed model's ability to train with one velocity and test at another was analyzed. The findings indicated that the model performed accurately across different velocities and combinations. The study shows that unsupervised K-means- Attention-CNN-1D can potentially improve corrugation estimation. This can lead to more reliable and efficient maintenance and repair of railways.

1. Introduction

Corrugation is a common issue that occurs in the contact areas of rails, causing wave-like pattern damage [1]. This defect leads to significant damage to both the vehicle and track components [2]. Researchers usually categorize corrugations into different classes, such as normal and abnormal or based on their physical characteristics, such as the wavelength or frequency of occurrence. Numerous attempts have been made since 1895 to estimate corrugation through laboratory experiments, field tests, and analytical and numerical models, as documented in various studies [2, 3]. The

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most accurate estimation of corrugation largely depends on conducting field tests and laboratory experiments to establish the governing equations and hypotheses. Railway engineering has been greatly impacted by utilizing computers and numerical and analytical approaches. This has led to solutions to previously challenging problems. Consequently, researchers proposed new theories and numerical models by integrating laboratory or field tests with computer technology to estimate the corrugation accurately. According to Xie (2022) [4], some methods are time-consuming, expensive, and sensitive to simplifications and boundary conditions. To overcome these weaknesses, Artificial Intelligence models (AI) provide a suitable alternative to civil and mechanical engineering problems due to their ability to handle complex, non-linear systems efficiently. Notably, in the case of railway corrugation, few studies have been carried out to estimate this defect using One-dimensional Convolutional Neural Networks (CNN-1D) and other Deep Learning (DL) such as Long Short-Term Memory (LSTM) models [4, 5]. Despite the success of these studies in estimating railway corrugation, there are still many gaps in research when it comes to estimating the properties of corrugation, such as wavelength and depth. Direct estimation with only acceleration variables is one such gap.

It is important to determine the roles of acceleration in different directions and estimate corrugation geometry's properties. This paper aims to address the following objectives:

- Develop an Attention-based-One-Dimensional Convolutional Neural Network (Attention-CNN-1D) model to accurately estimate corrugation at different forward velocities without any information on the track type (straight or curved line) and the contact surface between the vehicle-track systems in inner and outer rails.
- Determine how to estimate corrugation using variables commonly found in railway systems.
- How well could the model be trained at one velocity and tested at another?

2. **Material and Methods**

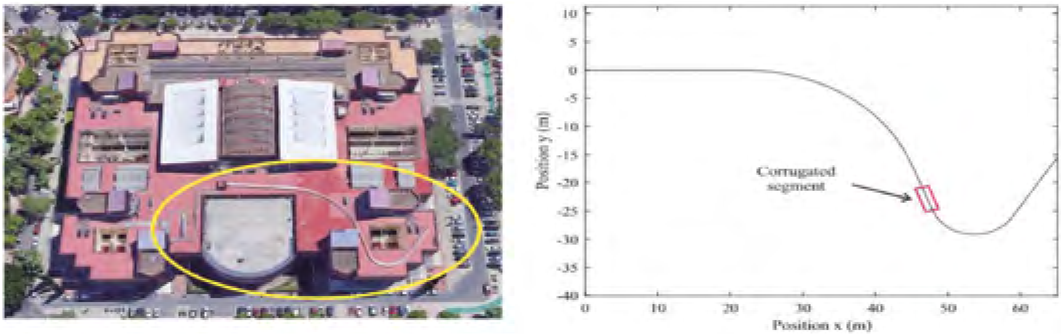
This section outlines the methodology that we used to conduct our research.

2.1. *Description of laboratory set-up*

To gather experimental data, the University of Seville's railway research group built a 1:10 scale track prototype featuring a 90-meter-long track and an instrumented vehicle. The experiments were conducted on a 5-inch-wide-scale track on the School of Engineering's roof. During the laboratory experiments, data on acceleration in longitudinal (A_x) and vertical (A_z) directions, as well as corrugation, were gathered at forward velocities of 0.5 m/s and 1.00 m/s. Figure 1 shows an aerial photo and a schematic plan view of the track centre line.

Figure 1

Plan view of the scaled track: aerial photograph (a) and scheme of the track centre line (b)



The table below presents a tabulated range of data gathered at different forward velocities.

Table 1

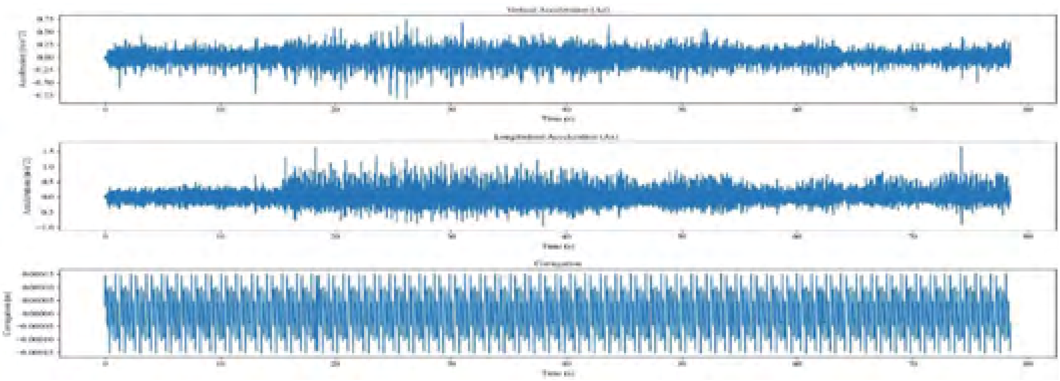
The range of gathered data during the laboratory experiments

Forward Velocity m/s	Longitudinal Acceleration (Ax) (m/s^2)	Vertical Acceleration (A_z) (m/s^2)	Corrugation (meter)	Number of Datapoints
0.50	–0.955-1.665	–0.955-0.7470	–0.00015-0.00015	39260
1.00	–2.918-3.336	–2.173-2.0612	–0.00015-0.00015	19043

Figure 2 shows a graphical representation of gathered data, their distributions, and characteristics.

Figure 2

Graphical representation of gathered data at forward velocity 0.5 m/s



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In the following section, we discuss how we implement the gathered data using the developed approach.

2.2. K*-means-Attention-CNN-1D Model for Corrugation Estimation*

In this study, after gathering the datasets at different forward velocities, they were analyzed using the unsupervised *K*-means clustering method, which helped detect patterns and natural grouping in the data points without prior knowledge of their labels or classes. Based on this analysis, each data point was assigned a label. These labels, along with A_z and A_x, were then utilized as input parameters to estimate corrugation. The task of estimating is carried out by a DL model named Attention-based One-Dimensional Convolutional Neural Network (Attention-CNN-1D).

CNN-1D is a well-known DL model designed to address the challenges of time series regression. In this study, CNN-1D, integrated with attention mechanisms, operates by dynamically weighting input parameters to find relations between inputs and outputs. This approach uses convolutional layers to detect hierarchical features from the input data, followed by attention mechanisms focusing on significant features while eliminating irrelevant ones. This process allows the network to focus on helpful information and aims to enhance performance in sequence modelling, where temporal dependencies are crucial.

CNN-1D's fundamental core is the convolutional layer, which utilizes kernels to find patterns in the data. Like other DL models, CNN-1D uses an activation function to map complex relationships between inputs and outputs by non-linear transformations. Different activation functions exist, such as sigmoid rectified linear unit (ReLU). In this study, Exponential Linear Units (ELU) were used as activation functions, and this activation function performs better in the learning process. Readers can find detailed information about other hyperparameters, such as padding, strides, kernel size and kernel regularizer, in [5]. During this investigation, we employed 8 convolutional layers, and the attention layers were added between each pair of CNN-1D layers. Detailed information about model architecture is tabulated in table 2.

Table 2

Detailed information on hyperparameter types and their values

No	Hyper-Parameters	Range of Values/Types	No	Hyper-Parameters	Range of Values/Types
1	Number of Kernels	5-100	7	Learning Rate	ReduceLROnPlateau
2	Kernel size	2-4	8	Kernel-regularizer	l1(0.1)
3	Stride	1	9	Padding	Same
4	Epochs-Patience level	50-5	10	Activation	Elu
5	Train-Validation-Test Ratios	47.3%, 20%, 32.7%	11	Optimization	Adam
6	Sliding Window	(Size:500) - Overlap	12	Loss function	Huber

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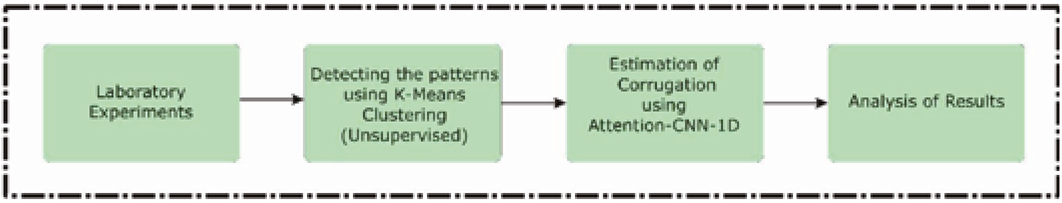
After identifying the best model structure and tuning the hyperparameters, we evaluated the model at different forward velocities. Furthermore, the datasets were combined to identify how well the model could be trained at one velocity and tested at another, such as training at 0.5 m/s and testing at 1.00 m/s. The process of estimation of corrugation in this study is visualized in figure 3.

Figure 3

Process of estimation of railway corrugation using *K*-means-Attention-CNN-1D



The following section will discuss the results that have been obtained.

3. **Results and Discussion**

This section summarizes the main findings of this study. To investigate the capability of the proposed approach to estimating the corrugation, three performance metrics (Mean Squared Error (MSE), Mean Absolute Error (MAE) and Correlation Determination (R2)) were used for the model's evaluation. The results of the developed approach in the training and test stages were tabulated in table 3. At forward velocity 0.5 m/s, the *K*-means-Attention-CNN-1D model has an MSE of 1.016 E-10, MAE of 5.823E-6, and R^2 of 0.983 in the training stage. In the test stage, this model generated results with performance metrics of MSE of 3.296 E-10, MAE of 1.281E-5, and R^2 of 0.945. At forward velocity 1.00 m/s, During training, the model exhibited a high R^2 value of 0.971, indicating a solid fit for the data. It also had a low MSE of 1.708 E-10 and an MAE of 8.075E-6, reflecting accurate predictions and minimal deviation. In the testing stage, while the R^2 decreased slightly to 0.85, the model still showed reliable predictive capability, as evidenced by an MAE of 2.333E-5 and MSE of 9.160E-10, suggesting accurate predictions and relatively low deviation between predicted and observed values. Finally, the datasets from different forward velocities were combined to explore the possibilities of training with one velocity and testing with another. To do this, the model trained with a velocity of 0.5 m/s and tested it with a velocity of 1.00 m/s. During the training stage, the model showed high accuracy with an R^2 value of 0.975, an MSE of 1.458 E-10, and an MAE of 6.870 E-6. In the test stage, the model obtained satisfactory results with an R^2 of 0.678, an MSE of 1.951 E-9, and an MAE of 3.507 E-5.

Table 3

The performance metrics of *K*-means-Attention-CNN-1D in both the training and test stages

Forward Velocity (m/s)	MSE (meter)	MAE (meter)	R^2
Train stage			
0.5	1.016E-10	5.823E-6	0.983
1.00	1.708E-10	8.075E-6	0.971
0.5-1.00	1.458E-10	6.870E-6	0.975
Test stage			
Forward Velocity (m/s)	MSE (meter)	MAE (meter)	R^2
0.5	3.296E-10	1.281E-5	0.945
1.00	9.160E-10	2.333E-5	0.850
0.5-1.00	1.951E-9	3.507E-5	0.678

The line charts in figures 4a, 4b, and 4c visualize the generated results for velocities 0.5 m/s, 1.0 m/s, and their combinations. These figures show two lines: blue and red. The blue line represents the predicted values, while the red represents the observed values. The *K*-means-Attention-CNN-1D model performed satisfactorily across all forward velocities and combinations of velocities.

Figure 4.a

Test results at $V = 0.50$ m/s in time interval $t = 64$ s and $t = 77.5$ s

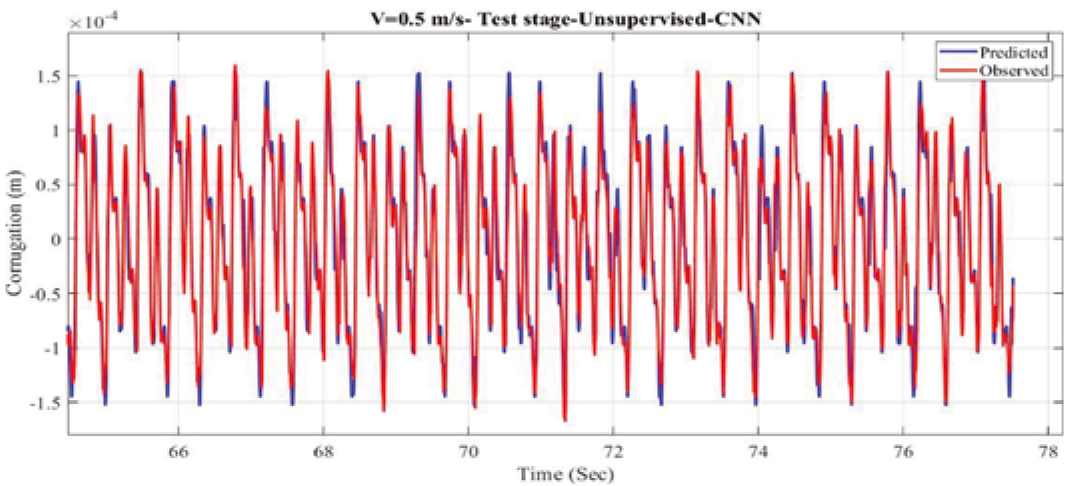


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Figure 4.b

Test results at $V = 1$ m/s in time interval $t = 34$ s and $t = 37.5$ s

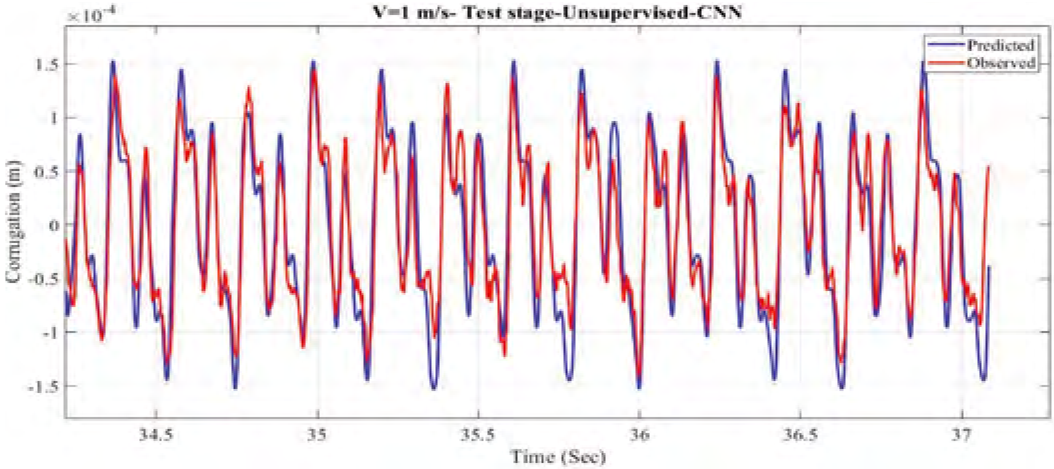
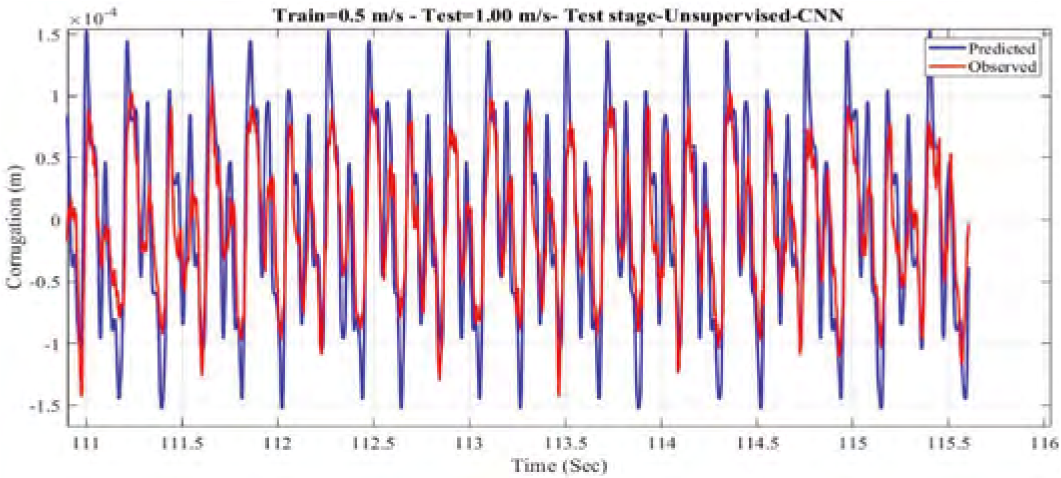


Figure 4.c

Test results at $V = 1$ m/s, Trained by 0.5 m/s,in time interval $t = 111$ s and $t = 115.5$ s



The results mentioned above confirm the capability of the *K*-means-Attention-CNN-1D model for estimating corrugation in different forward velocities, which can be applied to the field and real data in the industry in the next steps.

4. **Conclusion**

This paper has developed a hybrid *K*-means-Attention based-One-Dimensional Convolutional Neural Networks (*K*-means-Attention-CNN-1D) model to estimate railway corrugation at different forward velocities and their combinations. The laboratory data at different forward velocities were gathered to achieve this goal. The acceleration in vertical (A_z) and longitudinal (A_x) directions were collected for forward velocities 0.5 and 1 m/s, and used as input to estimate the corrugation. Firstly, the data were entered into *K*-means clustering to find natural grouping and patterns within the data. The label for each data point was obtained, and the labels were added to inputs to feed the Attention-CNN-1D model and estimate the target. During the training stage, the R^2 metric showed values of 0.983, 0.971, and 0.975 at forward velocities of 0.5 m/s, 1.00 m/s, and in the combined training scenario with 0.5 m/s, and testing with 1.00 m/s. In the test stage, this metric exhibited values of 0.945, 0.850, and 0.678 at forward velocities of 0.5 m/s, 1.00 m/s, and in the combined scenario of training with 0.5 m/s, and testing with 1.00 m/s. The results revealed that the developed approach successfully estimated corrugation at different forward velocities and their combination in training and test stages.

Acknowledgement

This work has been developed within the framework of the project Geminhi (Digital model for Intelligent Maintenance based on Hybrid prognostics models), (Grant US-1381456, founded by Junta de Andalucía, Andalucía FEDER 2014-2020) and the AMADIT Project (PID2022-137748OB-C32), funded by MCIN/AEI/10.13039/501100011033/FEDER, EU.

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[2] Grassie, S.L. Rail corrugation: characteristics, causes, and treatments. Proceedings of the Institution of Mechanical Engineers, Part F: *Journal of Rail and Rapid Transit,* 2009 Nov 1;223(6):581-96.

[3] Liu, Q.Y, Zhang, B., Zhou, Z.R. An experimental study of rail corrugation. *Wear,* 2003 Aug 1;255(7-12):1121-6.

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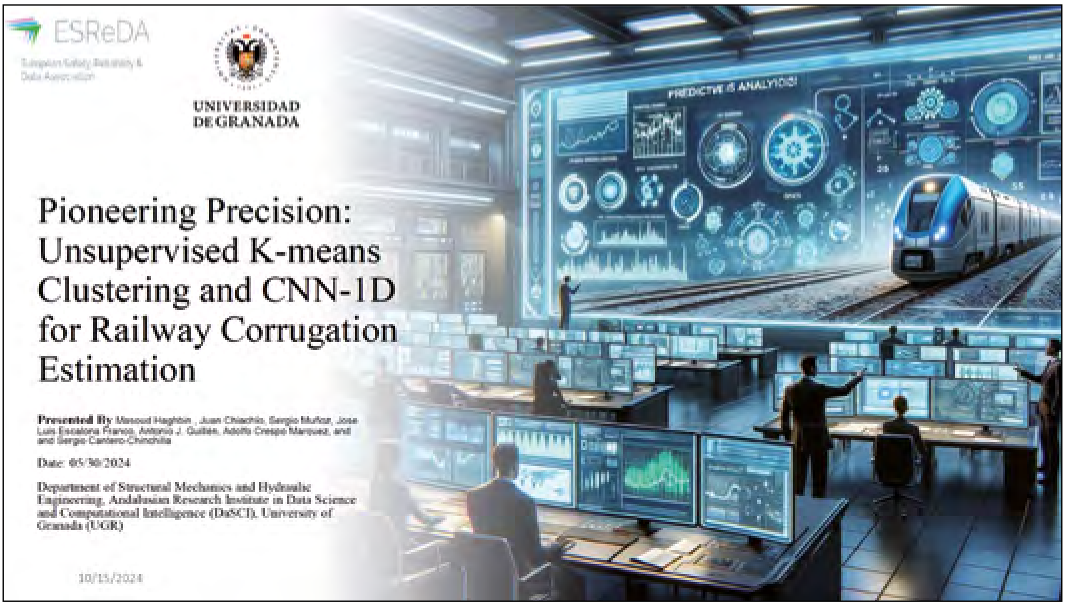
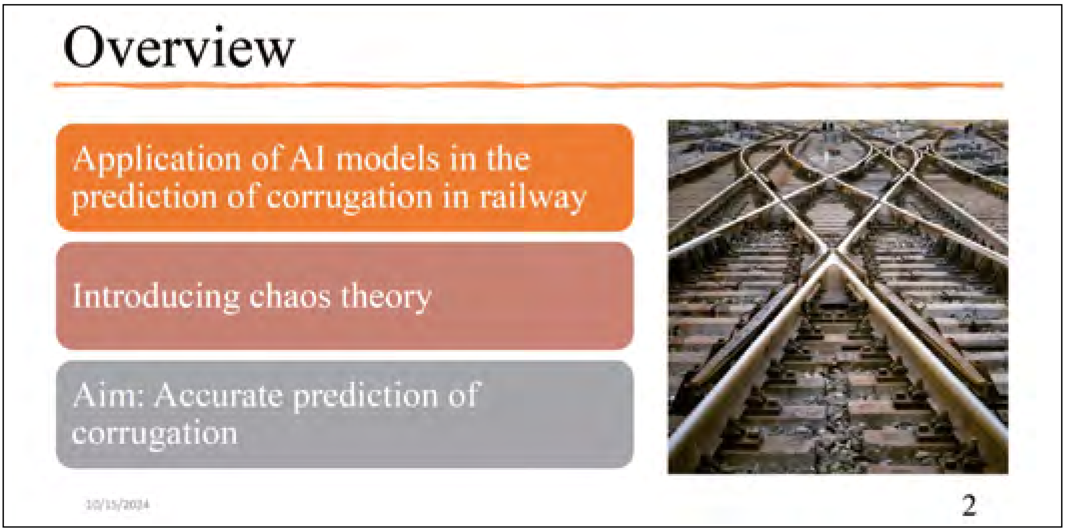
[5] Xie, Q., Tao, G., Lo, S.M., Yang, X., Wen, Z. A data-driven convolutional regression scheme for on-board and quantitative detection of rail corrugation roughness. *Wear,* 2023 Jul 15;524:204770.


ESReDA
UNIVERSIDAD DE GRANADA
Pioneering Precision: Unsupervised K-means Clustering and CNN-1D for Railway Corrugation Estimation
Presented By Masoud Haghbin , Juan Chiachío, Sergio Muñoz, Jose Luis Escalona Franco, Antonio J. Guillén, Adolfo Crespo Marquez, and and Sergio Cantero-Chinchilla
Date: 05/30/2024
Department of Structural Mechanics and Hydraulic Engineering, Andalusian Research Institute in Data Science and Computational Intelligence (DaSCI), University of Granada (UGR)
10/15/2024
PREDICTIVE IS ANALYTICS


Overview
Application of AI models in the prediction of corrugation in railway
Introducing chaos theory
Aim: Accurate prediction of corrugation
10/15/2024
2

Overview of Railway Corrugation

- Railway corrugation refers to the wave-like deformations formed on the surface of rail tracks. These deformations typically occur due to the dynamic interaction between the train wheels and the rail surface.

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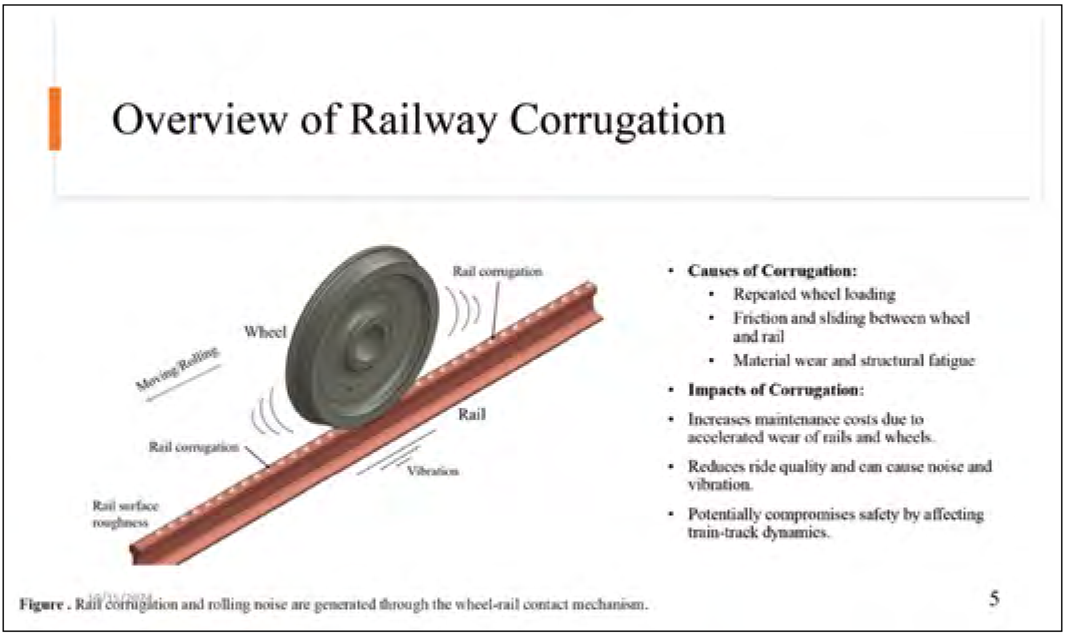
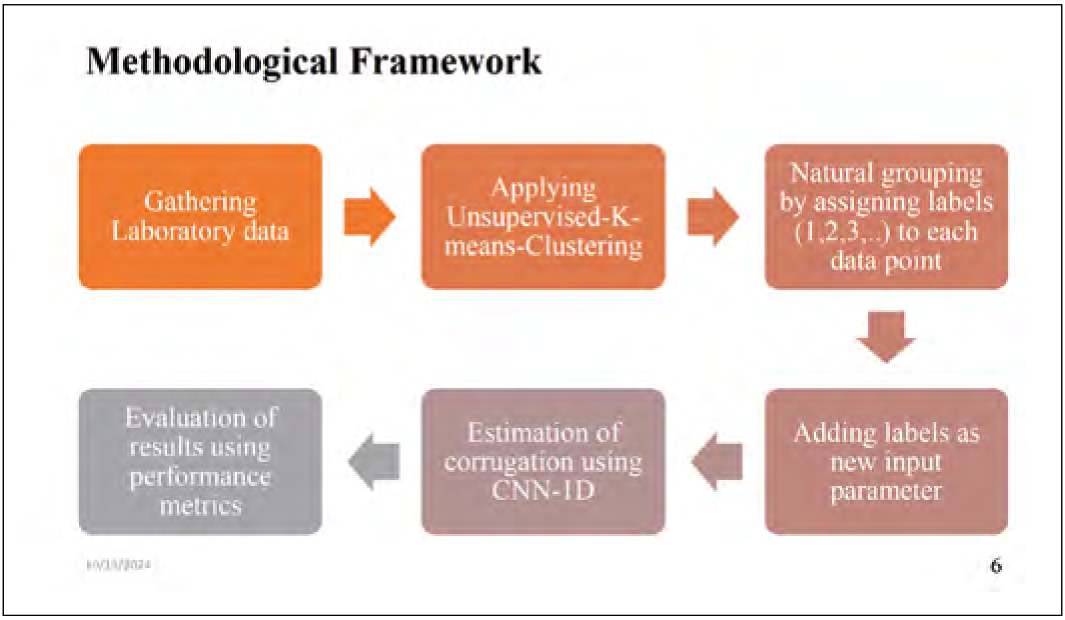
The New Frontier in Railway Damage Analysis

- **Importance of Railway Damage Estimation:**
  - **Ensuring Safety:** Early damage detection reduces the risk of accidents and enhances passenger safety.
  - **Cost-Effective Maintenance:** Timely maintenance based on accurate damage analysis can significantly reduce repair costs.
  - **Operational Efficiency:** Advanced estimation techniques lead to more efficient maintenance scheduling and fewer service disruptions.

4





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Gathered Data and Input Parameters for Predictive Models

10/15/2024 7

Generating Corrugation: Laboratory Experiment

Figure 1:Plan view of the scaled track: aerial photograph

Figure 2:Designed corrugation

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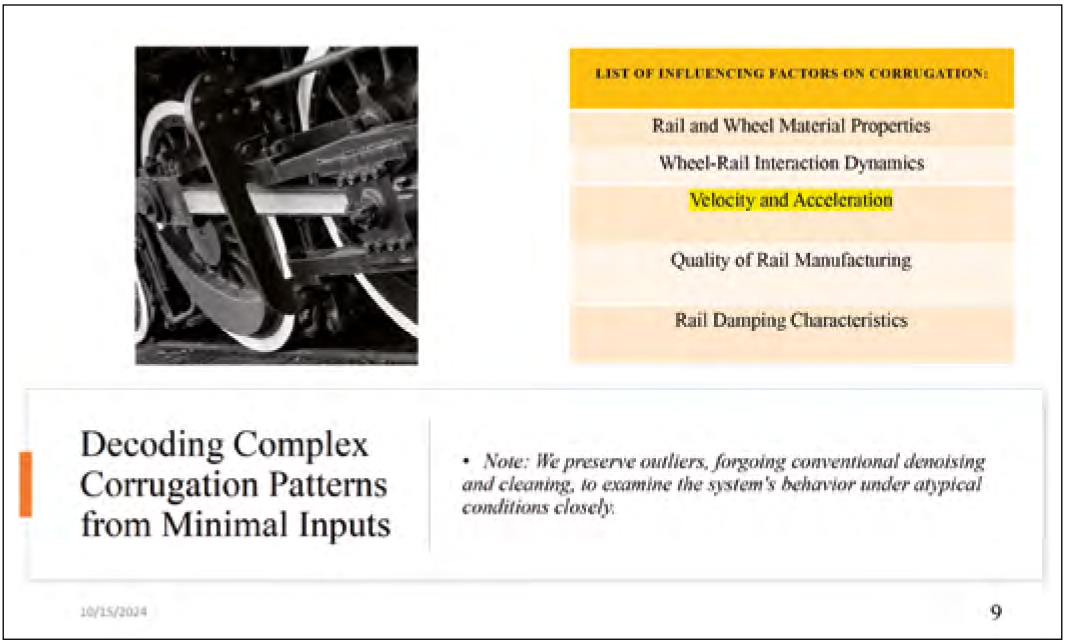
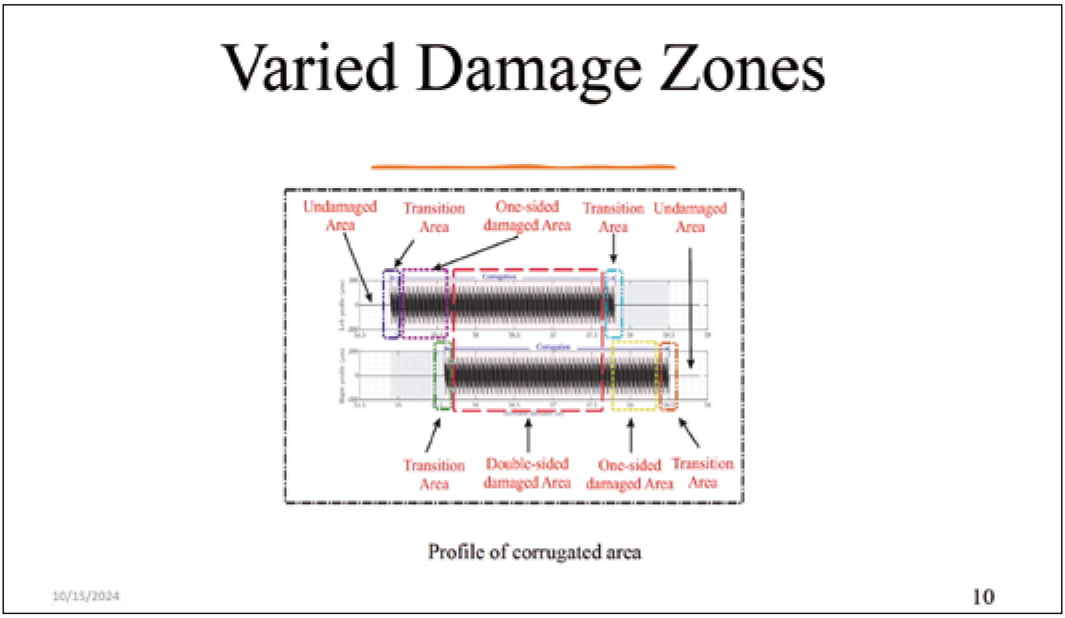
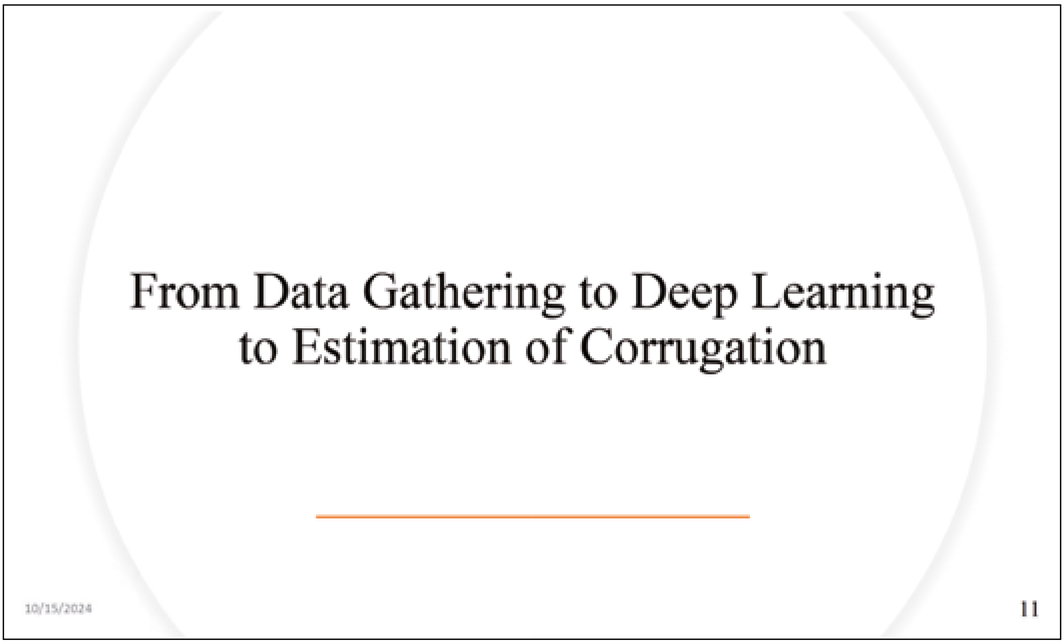
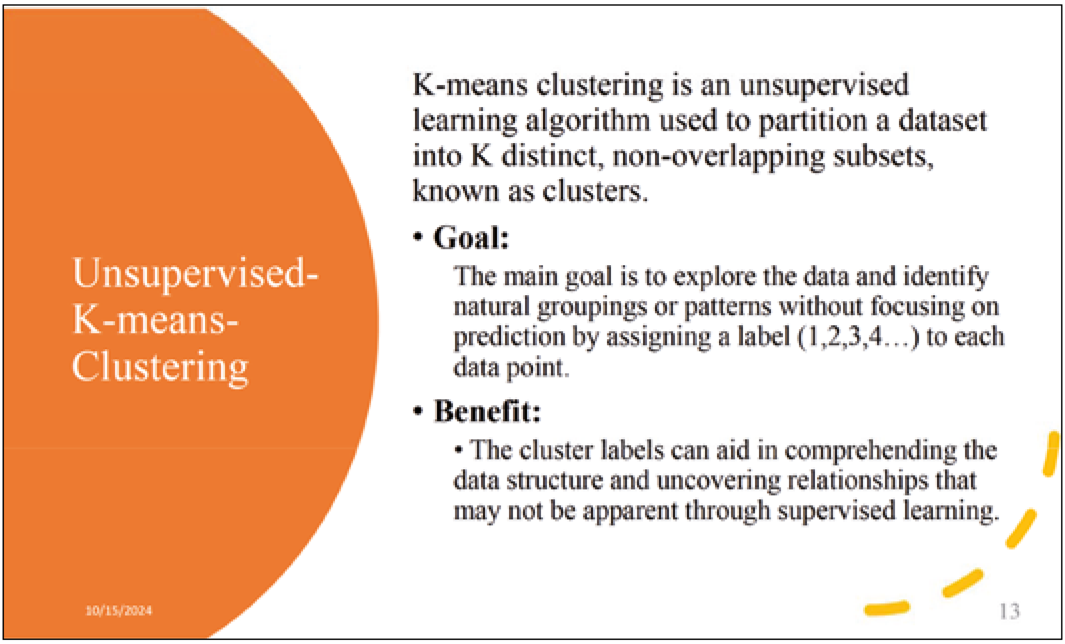
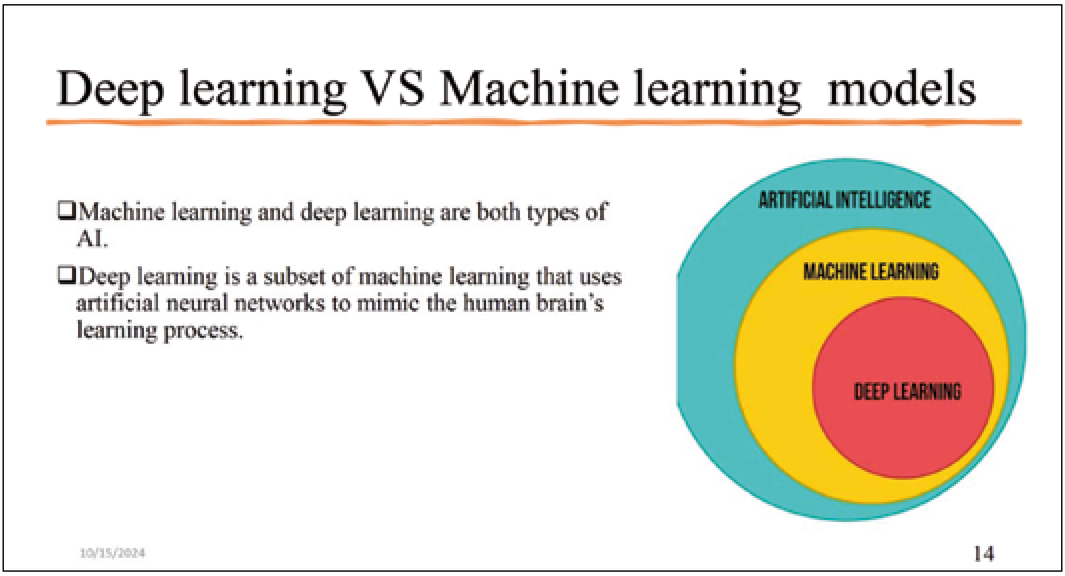

LIST OF INFLUENCING FACTORS ON CORRUGATION:
Rail and Wheel Material Properties
Wheel-Rail Interaction Dynamics
Velocity and Acceleration
Quality of Rail Manufacturing
Rail Damping Characteristics
Decoding Complex Corrugation Patterns from Minimal Inputs
• Note: We preserve outliers, forgoing conventional denoising and cleaning, to examine the system's behavior under atypical conditions closely.
10/15/2024
9


Varied Damage Zones
Undamaged Area
Transition Area
One-sided damaged Area
Transition Area
Undamaged Area
Transition Area
Double-sided damaged Area
One-sided damaged Area
Transition Area
Profile of corrugated area
10/15/2024
10


From Data Gathering to Deep Learning to Estimation of Corrugation
10/15/2024
11


What path has been taken so far?
1
Finding appropriate preprocess approaches
•Does the dataset need pre-processing? If yes, what strategies can be applied?
2
Finding the best input combinations
• Do we need to lag the input parameters before feeding the models?
• What is the best combination of input parameters?
3
Finding the best Machine learning models
• Can Machine Learning models estimate corrugation accurately? If No, What other strategies can be applied?
4
Finding the best Neural Networks based model
• What types of Neural Networks can estimate corrugation?
10/15/2024
12





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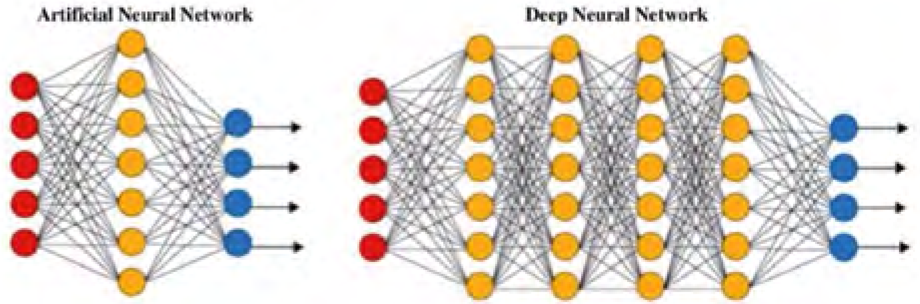

What are the main differences between classical neural networks and deep learning models?

- A classical neural network comprises an input layer, a hidden layer, and an output layer. On the other hand, deep learning includes several hidden layers of neural networks that perform complex operations on massive amounts of structured and unstructured data.

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Convolutional Neural Networks-1D

Yann Le Cunn introduced the concept of Convolutional Neural networks, called CNN, in 1998 with its paper "Gradient-based learning applied to document recognition".

However, It took 14 years to become a popular method for solving various problems.

CNN is a network that is able to detect patterns and make sense of them

CNN is commonly utilized for image recognition, video analysis, natural language processing, anomaly detection, and time series forecasting.

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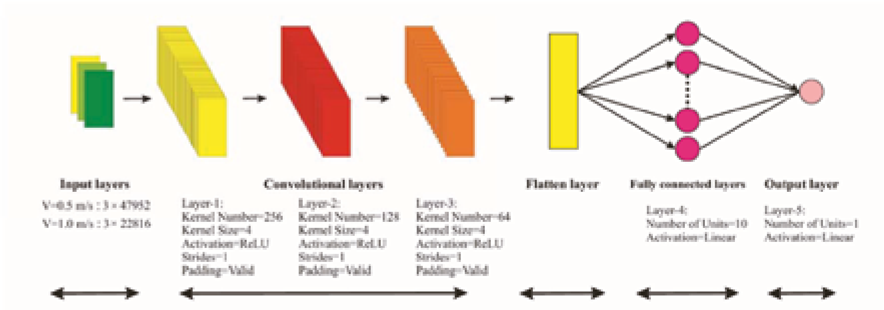


CNN architecture

- A convolutional neural network consists of an input, hidden, and output layer. In a convolutional neural network, the hidden layers include layers that perform convolutions.

10/15/2024 **17**

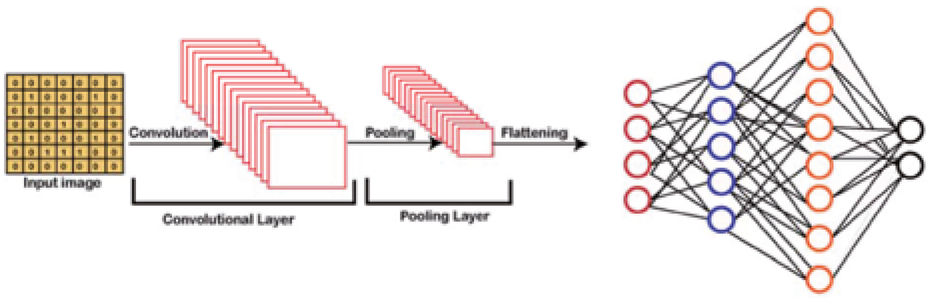
Convolutional Layers:
It convolves the image or tabular data using filters to detect data patterns. These filters are what we are teaching during the Training. The network learns filter values automatically to detect important features to the right output.

10/15/2024 **18**

Activation layer:

The activation layer is the non-linear transformation over the input signals. This transformed output feeds the next layer of neurons as inputs.

10/15/2024 **19**



Fully connected layer

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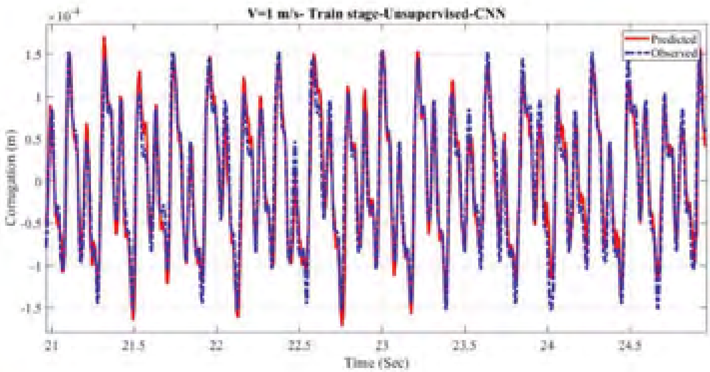
Input parameters

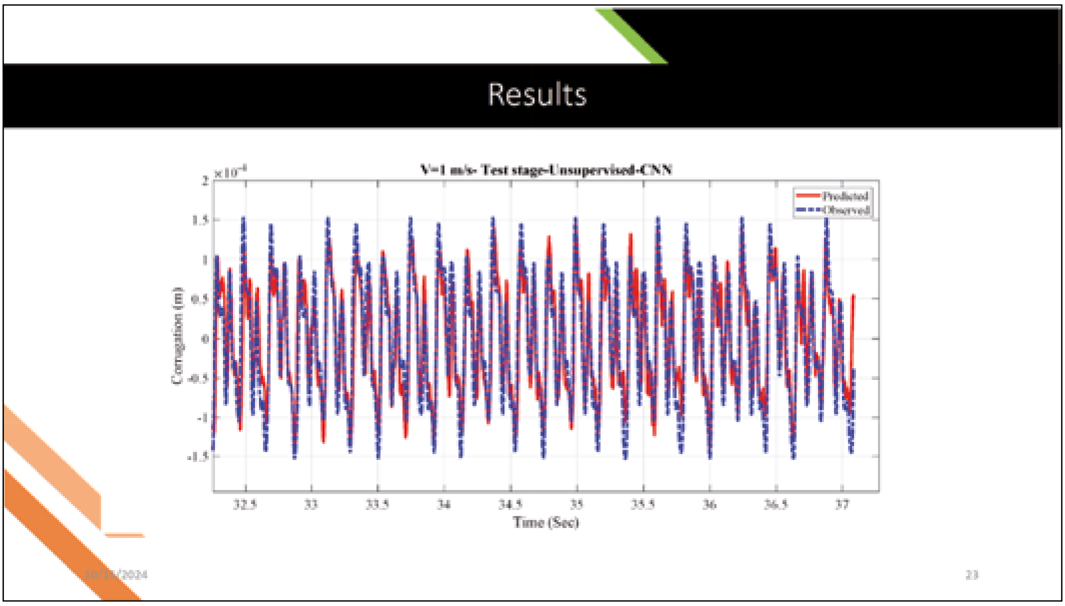
V (m/s)	Inputs	Number of data points	Train %	Validation %	Test %
0.5	Forward velocity+ Acceleration in x and Z directions + Label	47952	60	20	20
1.00	Forward velocity+ Acceleration in x and Z directions + Label	22816	20	20	20

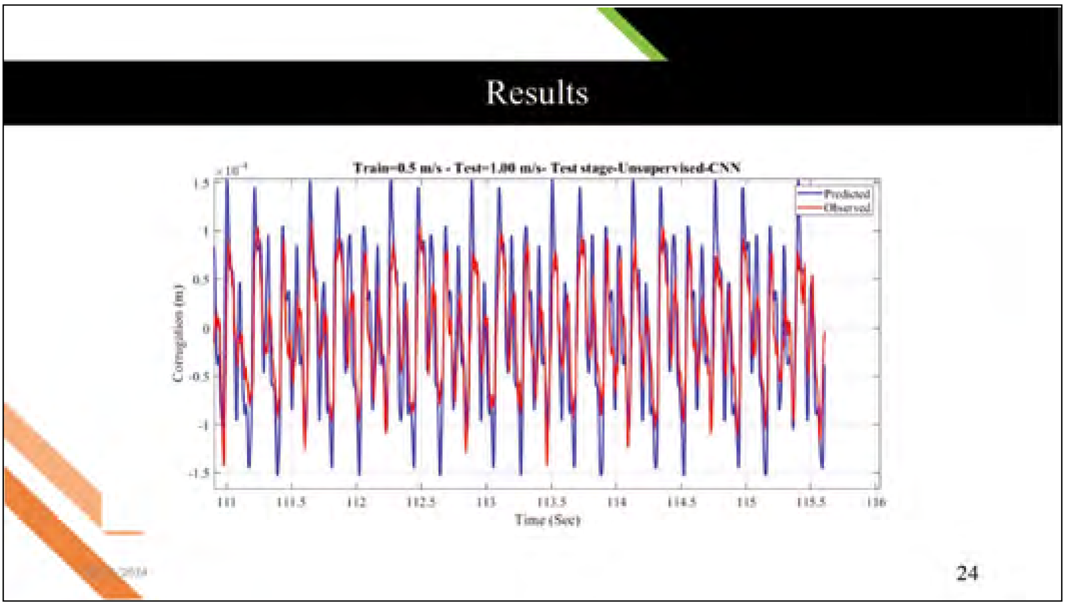
21

Results



22


Results
V=1 m/s- Test stage-Unsupervised-CNN
Predicted
Observed
Corrugation (m)
Time (Sec)
23


Results
Train=0.5 m/s - Test=1.00 m/s- Test stage-Unsupervised-CNN
Predicted
Observed
Corrugation (m)
Time (Sec)
24

Performance metrics

Train stage			
Forward Velocity $(\frac{m}{s})$	MSE (meter)	MAE (meter)	R^2
0.5	1.016E-10	5.823E-6	0.983
1.00	1.708E-10	8.075E-6	0.971
0.5-1.00	1.458E-10	6.870E-6	0.975
Test stage			
Forward Velocity $(\frac{m}{s})$	MSE (meter)	MAE (meter)	R^2
0.5	3.296E-10	1.281E-5	0.945
1.00	9.160E-10	2.333E-5	0.850
0.5-1.00	1.951E-9	3.507E-5	0.678

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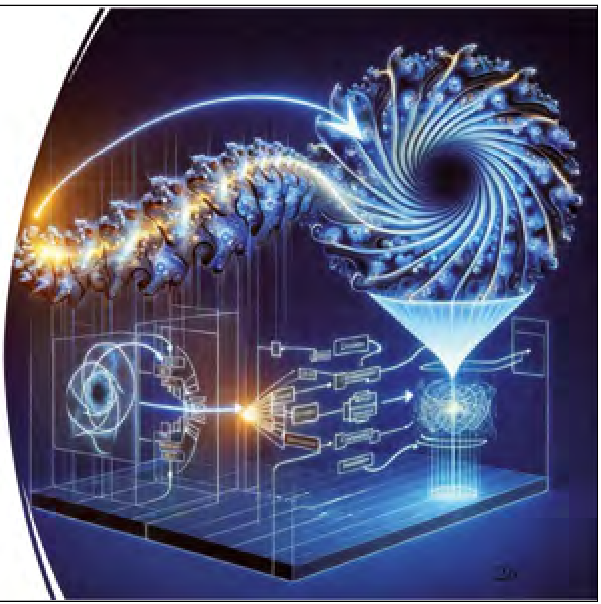
Attractors: Mapping the Dynamics of Railway Systems



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Chaos Theory

- Chaos theory is a branch of mathematics that studies complex systems whose behavior is highly sensitive to slight changes in conditions.
- This sensitivity is popularly referred to as the "butterfly effect." In the context of railway systems, chaos theory can provide insights into the unpredictable and complex nature of railway damage prediction in railway systems.

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How can we apply the chaos theory in train system?

- **Non-Linear Interaction:** For instance, the accumulation of minor stresses in a rail track may suddenly lead to a major fracture.
- **Fractal Analysis and Self-Similarity:** For example, microscopic cracks in metal components can resemble larger-scale structural failures. By applying fractal analysis, early signs of damage that might be overlooked can be detected.

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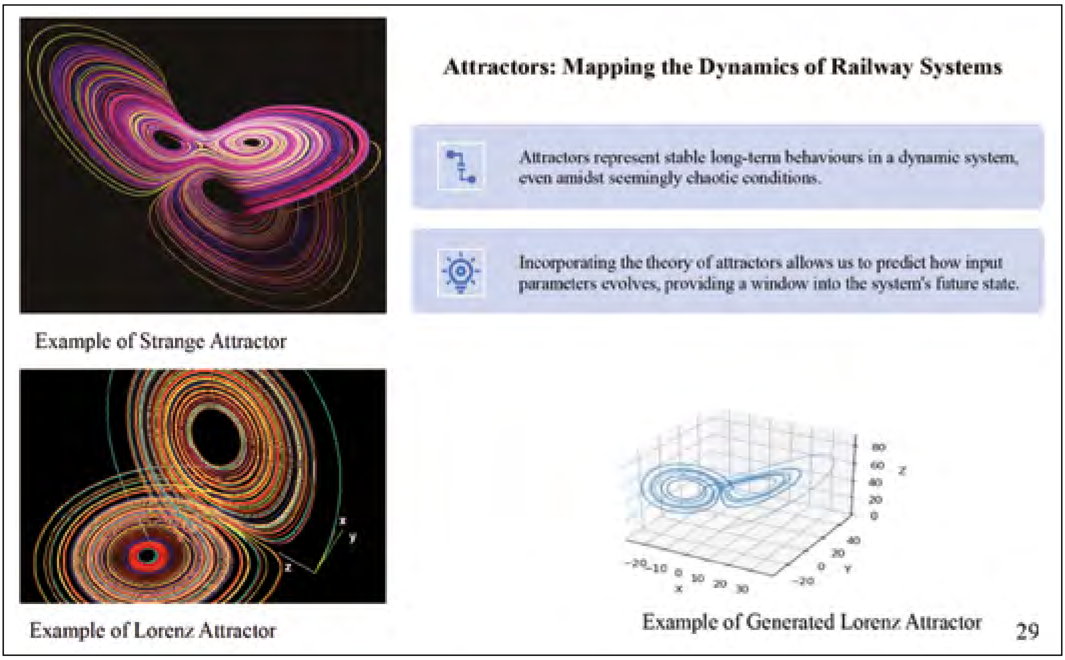
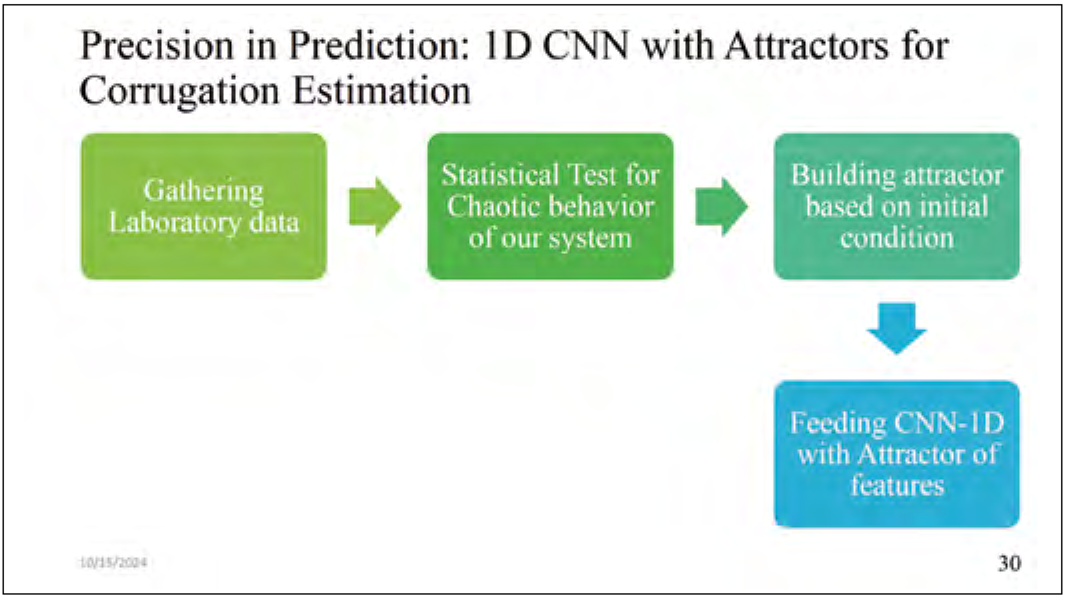
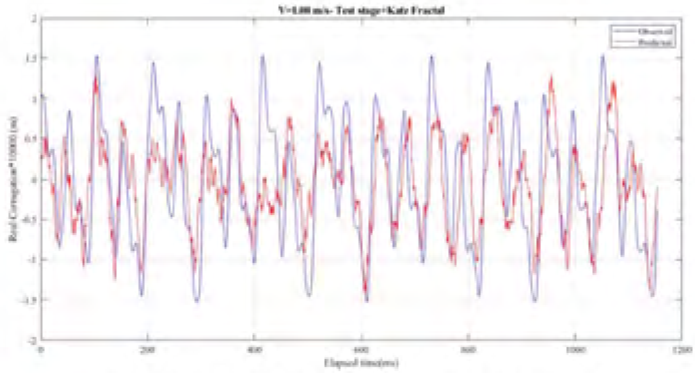
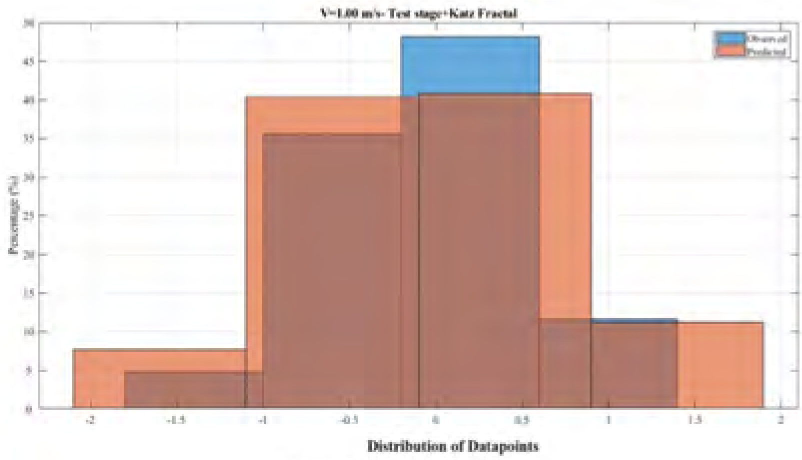

Attractors: Mapping the Dynamics of Railway Systems
Attractors represent stable long-term behaviours in a dynamic system, even amidst seemingly chaotic conditions.
Incorporating the theory of attractors allows us to predict how input parameters evolves, providing a window into the system's future state.
Example of Strange Attractor
Example of Lorenz Attractor
Example of Generated Lorenz Attractor
29


Precision in Prediction: 1D CNN with Attractors for Corrugation Estimation
Gathering Laboratory data
Statistical Test for Chaotic behavior of our system
Building attractor based on initial condition
Feeding CNN-1D with Attractor of features
10/15/2024
30



Initial Generated Results using Katz fractal and Lorenz attractor

31



Histogram of generated results

32

Conclusion

- Applying K-means clustering and assigning labels to each data point makes the dataset easier to handle and could potentially improve the deep learning model's performance.
- Using unsupervised K-means reduces the complexity of the dataset by summarising groups of similar data points with a single label. This can improve the model's ability to differentiate between different groups of data points.
- Integration of deep learning model and unsupervised k-means clustering could help to predict corrugation in different velocities.

Suggestions for Future Work:

- It's essential to analyze the clusters and understand their characteristics.
- Cluster labels might not be easily interpretable, making it harder to understand the model's decisions. Adding explainability methods is essential to increase interpretability.
- Exploration of Physics-Informed Neural Networks
- Creating customized attractors for railway-track interaction.

10/15/2024

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Thanks for your attention!

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DaSCI

Instituto Andaluz Interuniversitario en Data Science and Computational Intelligence

10/15/2024 36

Impact of Digitalization on Physical Asset Management

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Head of Maintenance Management & Analysis-Enagas

Abstract

Digitalization is one of the main drivers of investment and growth in the maintenance sector. There are many potential benefits, and there is no doubt that it is a competitive factor that will differentiate itself in the coming years. For this reason, any business development currently takes on the concept of "digital native," as technological integration and process efficiency are considered from the very beginning.

However, the transformation process for a traditional business is not always so simple. First, investment volumes remain very high. Despite the fact that some technology is becoming increasingly affordable, it still requires a significant investment. The cybersecurity risk, especially when it comes to critical infrastructure, is also significant. And many of the efficiencies achieved in processes result in freeing up human resource time, which cannot always be amortized. This raises the question: How can we face an inevitable digitalization process when profitability is not purely economic?

The goal is to be able to incorporate technology in a reasonable manner, incorporating it into the current business logic, but with an eye toward an increasingly uncertain future. This work shares the main pillars on which Enagas is focusing its digital transformation process and the main impacts expected in the specific field of asset management.

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Why is difficult to achieve the impact of digitization on physical asset management
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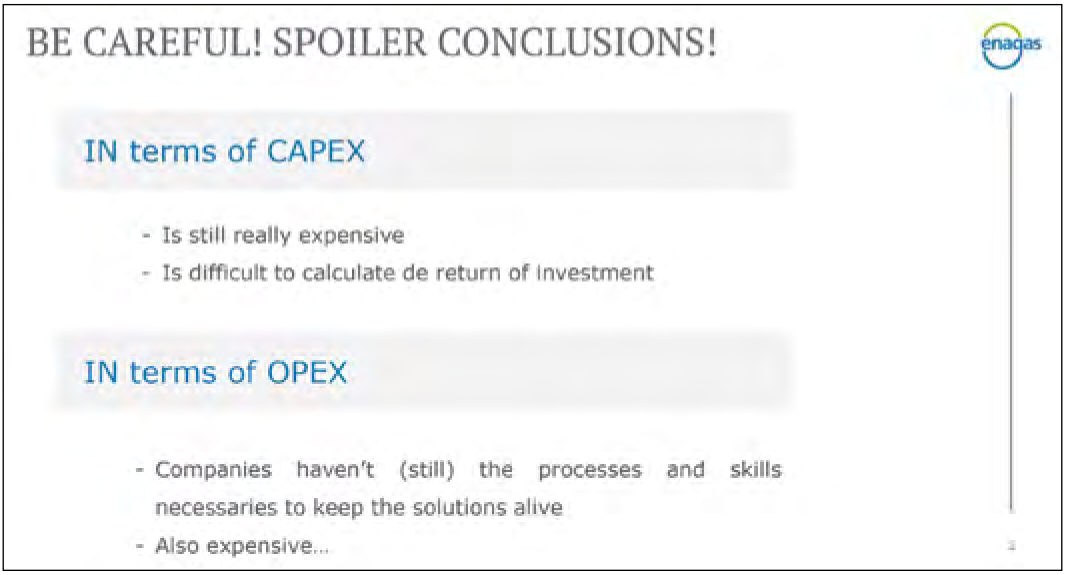
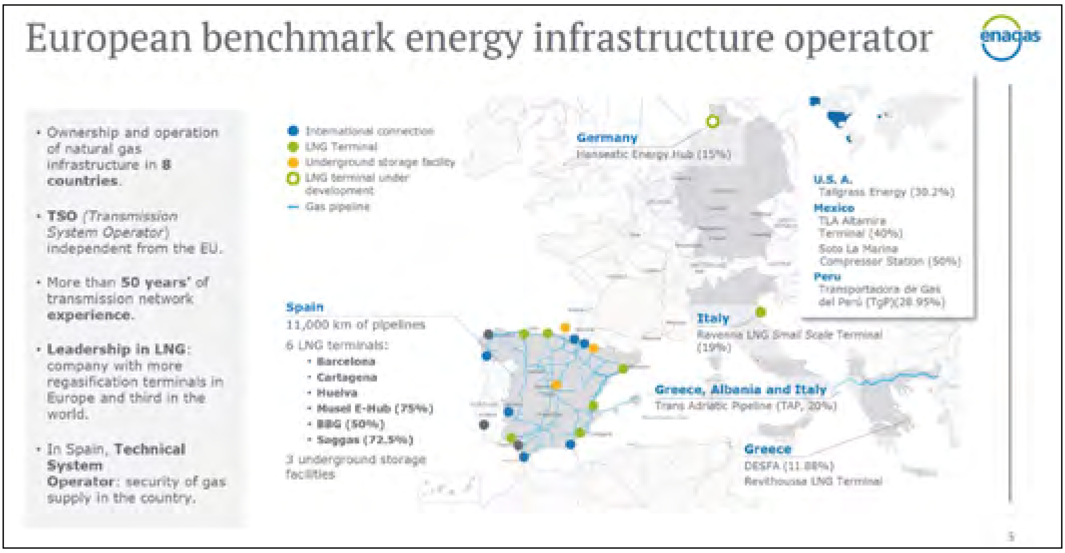
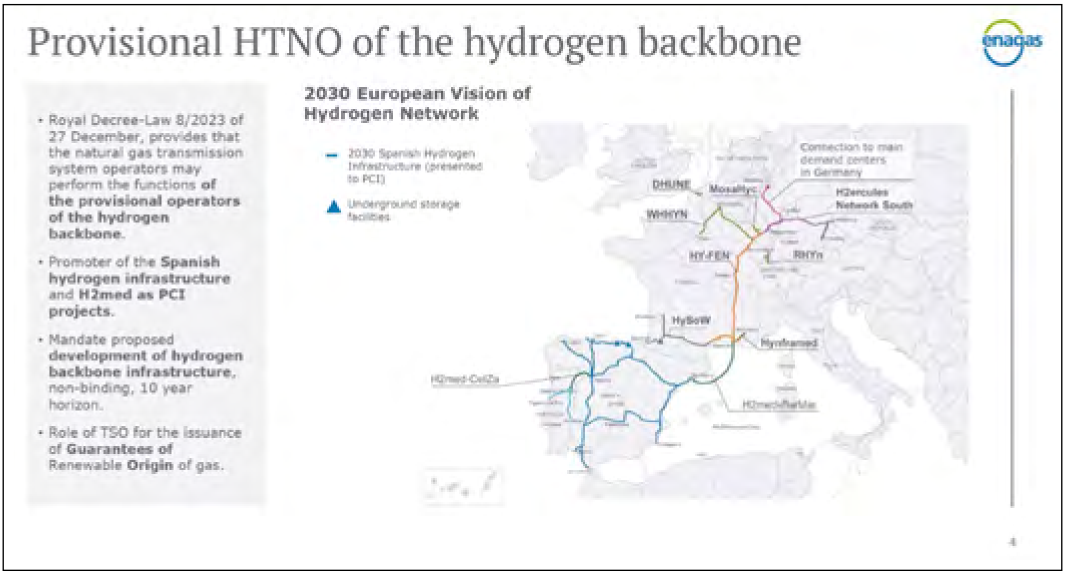

BE CAREFUL! SPOILER CONCLUSIONS!
enagas
IN terms of CAPEX
- Is still really expensive
- Is difficult to calculate de return of investment
IN terms of OPEX
- Companies haven't (still) the processes and skills necessaries to keep the solutions alive
- Also expensive...





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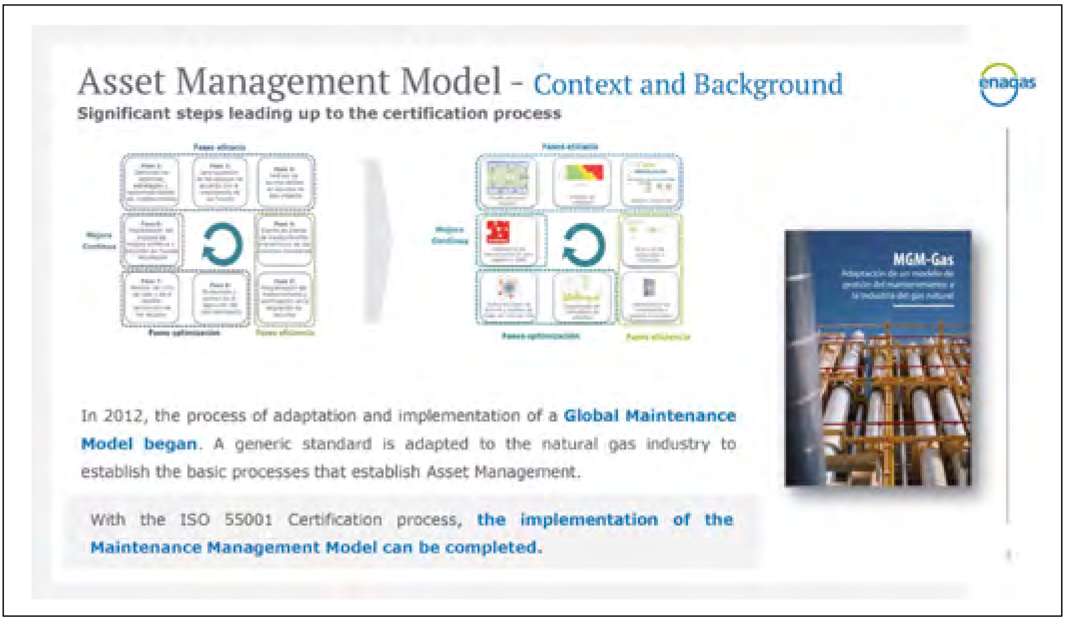
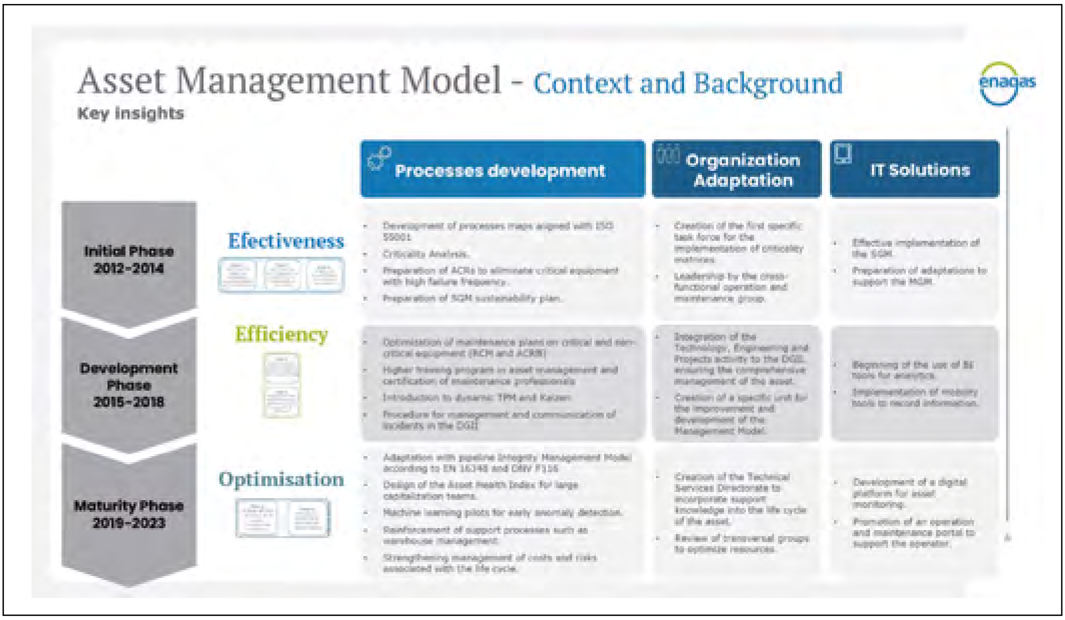
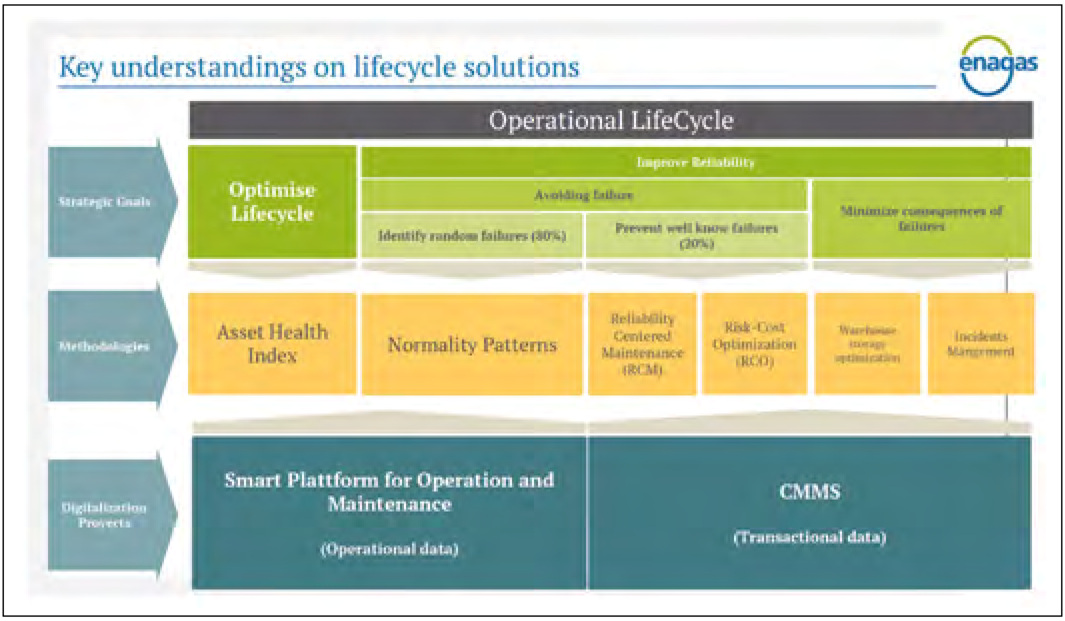


Asset Management Model - Context and Background
Significant steps leading up to the certification process
enagas
MGM-Gas
In 2012, the process of adaptation and implementation of a Global Maintenance Model began. A generic standard is adapted to the natural gas industry to establish the basic processes that establish Asset Management.
With the ISO 55001 Certification process, the implementation of the Maintenance Management Model can be completed.



Asset Management Model - Context and Background
Key insights
enagas
Processes development
Organization Adaptation
IT Solutions
Initial Phase 2012-2014
Development Phase 2015-2018
Maturity Phase 2019-2023
Efectiveness
Efficiency
Optimisation
Development of processes maps aligned with ISO 55001
Criticality Analysis.
Preparation of SGM sustainability plan.
Creation of the first specific task force for the implementation of criticality matrixes.
Leadership by the cross-functional operation and maintenance group.
Effective implementation of the SGM.
Preparation of adaptations to support the MGM.
Optimization of maintenance plans on critical and non-critical equipment (RCM and ACRB)
Higher training program in asset management and certification of maintenance professionals
Introduction to dynamic TPM and Kaizen
Procedure for management and communication of incidents in the DGI
Integration of the Technology, Engineering and Projects activity to the DGI, ensuring the comprehensive management of the asset.
Creation of a specific unit for the improvement and development of the Management Model.
Beginning of the use of BI tools for analytics.
Implementation of mobility tools to record information.
Adaptation with pipeline Integrity Management Model according to EN 16348 and DNV F116
Design of the Asset Health Index for large capitalization teams.
Machine learning pilots for early anomaly detection.
Reinforcement of support processes such as warehouse management.
Strengthening management of costs and risks associated with the life cycle.
Creation of the Technical Services Directorate to incorporate support knowledge into the life cycle of the asset.
Review of transversal groups to optimize resources.
Development of a digital platform for asset monitoring.
Promotion of an operation and maintenance portal to support the operator.


Key understandings on lifecycle solutions
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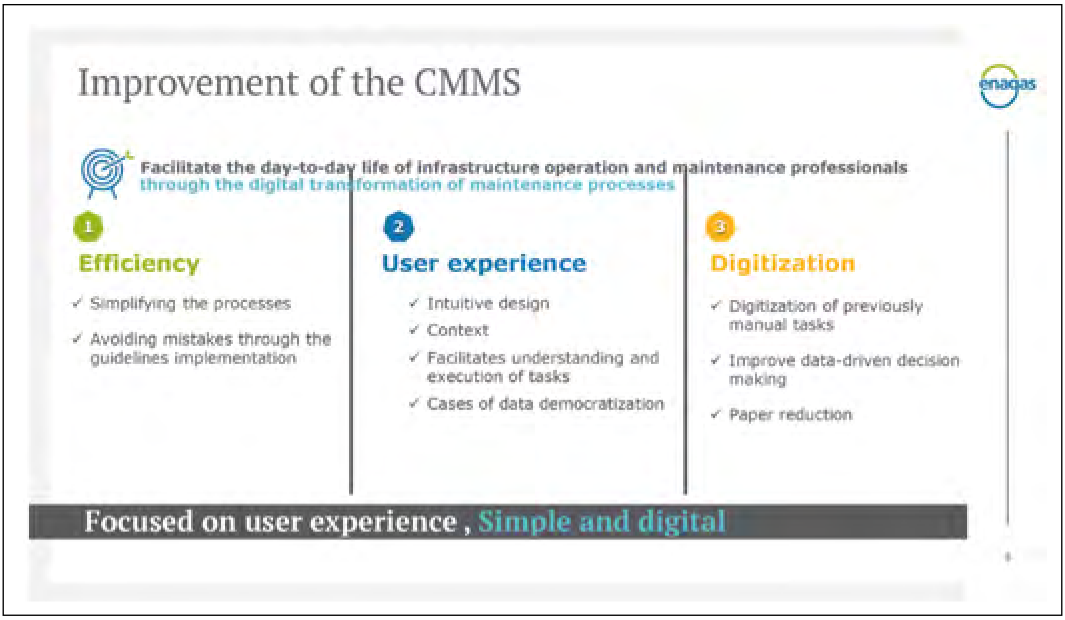
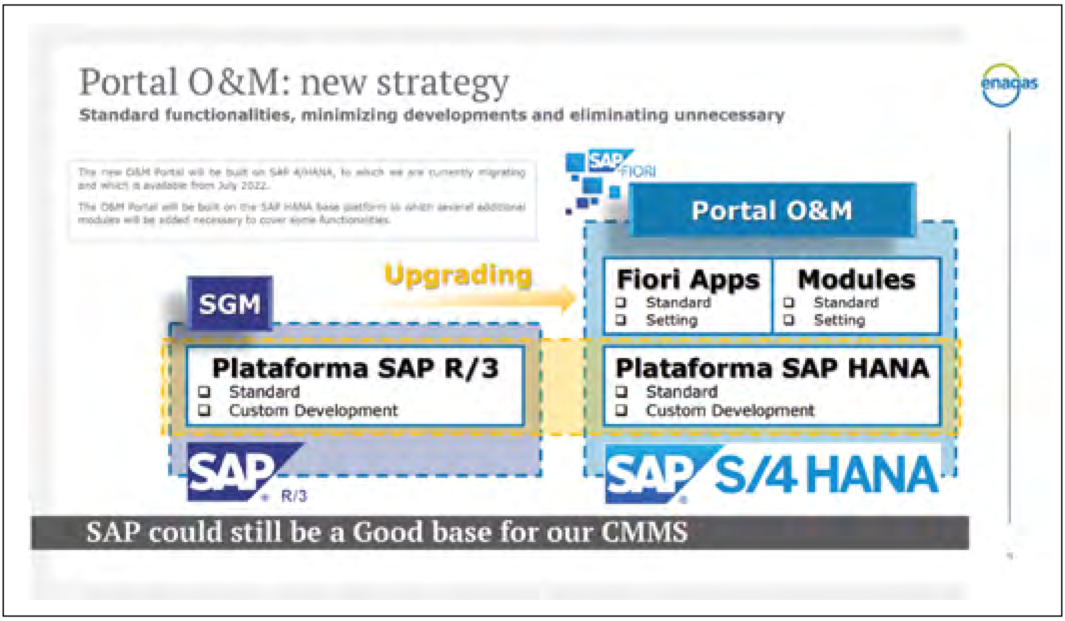
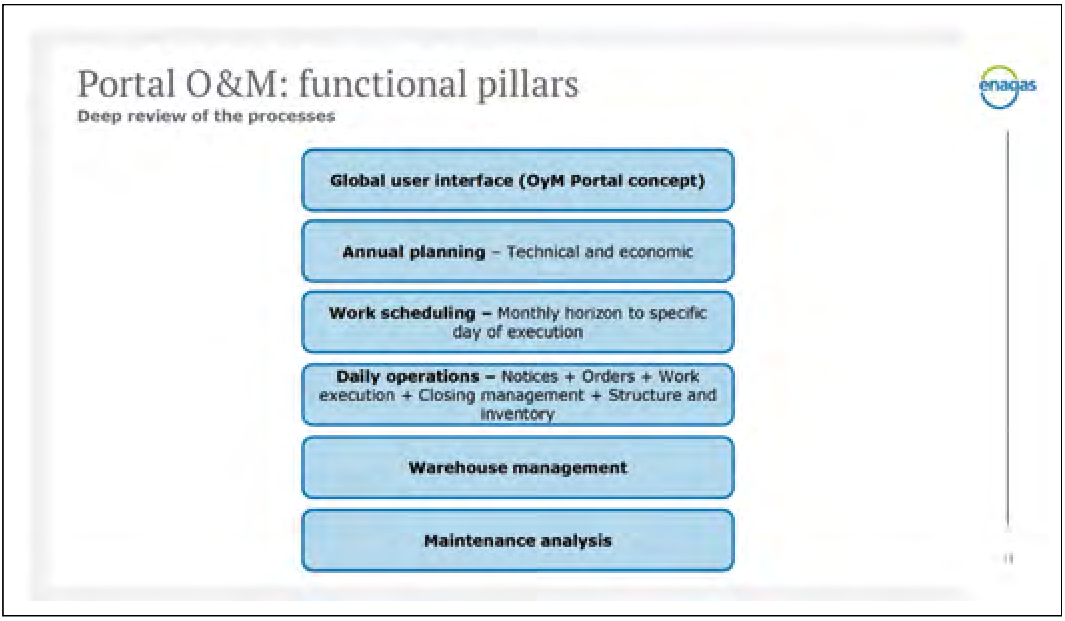
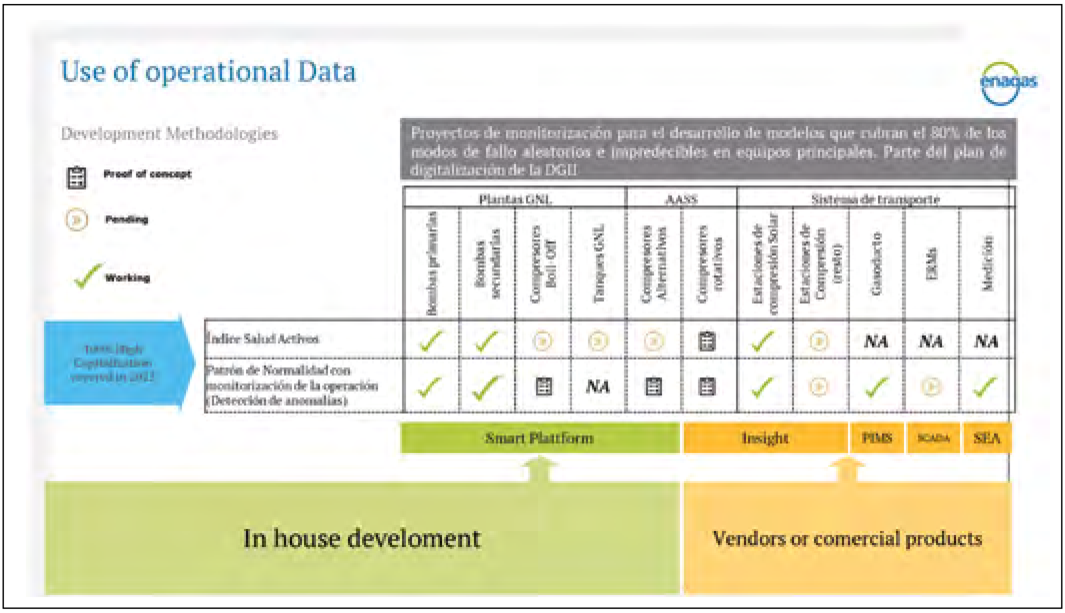
Operational LifeCycle
Strategic Goals
Optimise Lifecycle
Improve Reliability
Avoiding failure
Identify random failures (80%)
Prevent well know failures (20%)
Minimize consequences of failures
Methodologies
Asset Health Index
Normality Patterns
Reliability Centered Maintenance (RCM)
Risk-Cost Optimization (RCO)
Incidents Mangement
Digitalization Projects
Smart Plattform for Operation and Maintenance
(Operational data)
CMMS
(Transactional data)

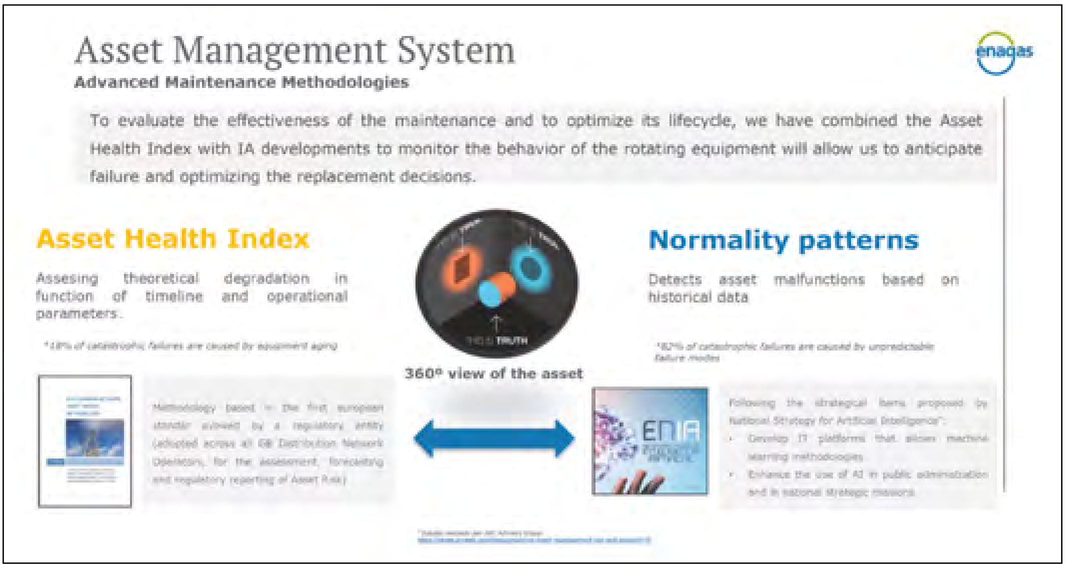

Improvement of the CMMS
enagas
Facilitate the day-to-day life of infrastructure operation and maintenance professionals through the digital transformation of maintenance processes
1
Efficiency
✓ Simplifying the processes
✓ Avoiding mistakes through the guidelines implementation
2
User experience
✓ Intuitive design
✓ Context
✓ Facilitates understanding and execution of tasks
✓ Cases of data democratization
3
Digitization
✓ Digitization of previously manual tasks
✓ Improve data-driven decision making
✓ Paper reduction
Focused on user experience , Simple and digital

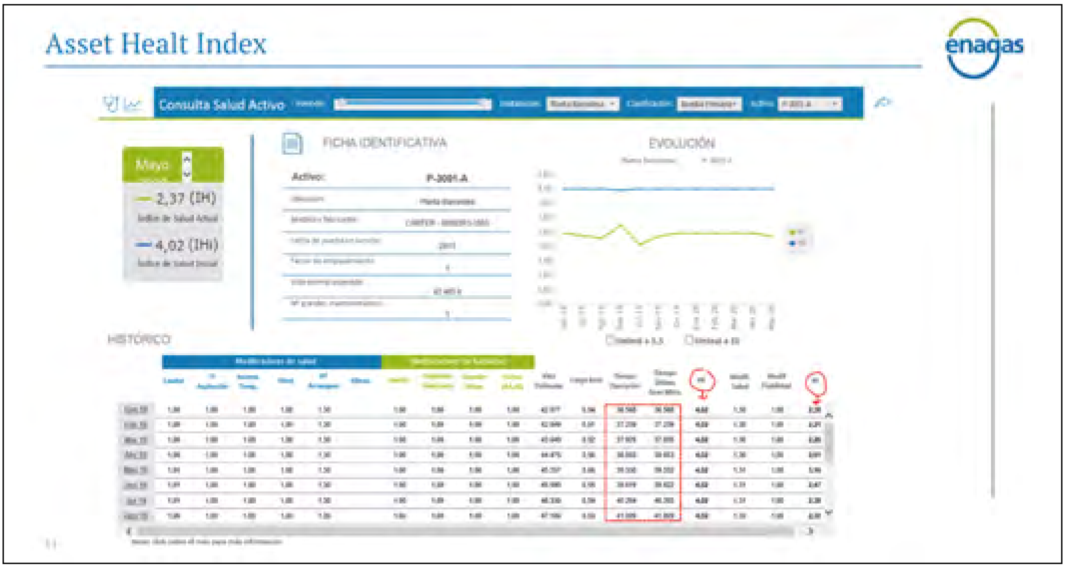

Portal O&M: new strategy
Standard functionalities, minimizing developments and eliminating unnecessary
The new O&M Portal will be built on SAP 4/HANA, to which we are currently migrating and which is available from July 2022.
The O&M Portal will be built on the SAP HANA base platform to which several additional modules will be added necessary to cover some functionalities.
enagas
SAP FIORI
Portal O&M
Fiori Apps
Standard
Setting
Modules
Standard
Setting
Upgrading
SGM
Plataforma SAP R/3
Standard
Custom Development
Plataforma SAP HANA
Standard
Custom Development
SAP R/3
SAP S/4 HANA
SAP could still be a Good base for our CMMS


Portal O&M: nuevo strategy
Clean Core Strategy
Clean Core is a methodology, strategy or recommendation for extension of SAP systems:
Completely separate extensions to the SAP standard
Access SAP business objects only through stable and well-defined interfaces
Clean Core Benefits:
Reduces TCO and improves upgrade times: reduces testing efforts for key users and development team efforts
Incorporate the innovation provided by SAP in less time
The extensions you make can be reused when making future updates
enagas
Classic view
Custom performance
Procesos back
No clean core
Greater maintenance effort
Complexity Upgrades and Innovation
Integration difficulty
SAP BTP
(SAP Business Technology Platform)
Development, integration, automation and analysis platform
clean core
Simplify Upgrades
Ease of Innovation and Integration
LowCode - NoCode
Automation of processes and tasks
Less maintenance
Cloud services licenses
Novel (reskilling)
New Modules
New SAP modules and tools that provide new functionality as standard
clean core
Standard functionality
Implementation agility
Version update
Additional licenses (cloud: 3 years)


Portal O&M: functional pillars
Deep review of the processes
Global user interface (OyM Portal concept)
Annual planning – Technical and economic
Work scheduling – Monthly horizon to specific day of execution
Daily operations – Notices + Orders + Work execution + Closing management + Structure and inventory
Warehouse management
Maintenance analysis


Use of operational Data
Development Methodologies
Proof of concept
Pending
Working
Proyectos de monitorización para el desarrollo de modelos que cubran el 80% de los modos de fallo aleatorios e impredecibles en equipos principales. Parte del plan de digitalización de la DGII
Plantas GNL
AASS
Sistema de transporte
Bombas primarias
Bombas secundarias
Compresores Boil-Off
Tanques GNL
Compresores Alternativos
Compresores rotativos
Estaciones de compresión Solar
Estaciones de Compresión (resto)
Gasoducto
ERMs
Medición
Índice Salud Activos
NA
NA
NA
Patrón de Normalidad con monitorización de la operación (Detección de anomalías)
NA
Smart Plattform
Insight
PIMS
SCADA
SEA
In house develoment
Vendors or comercial products





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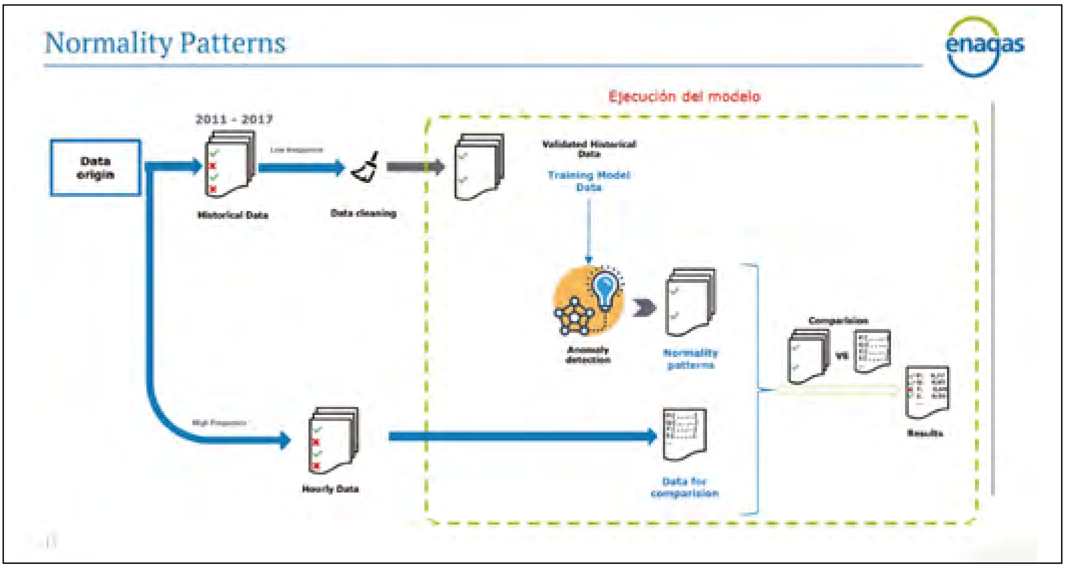
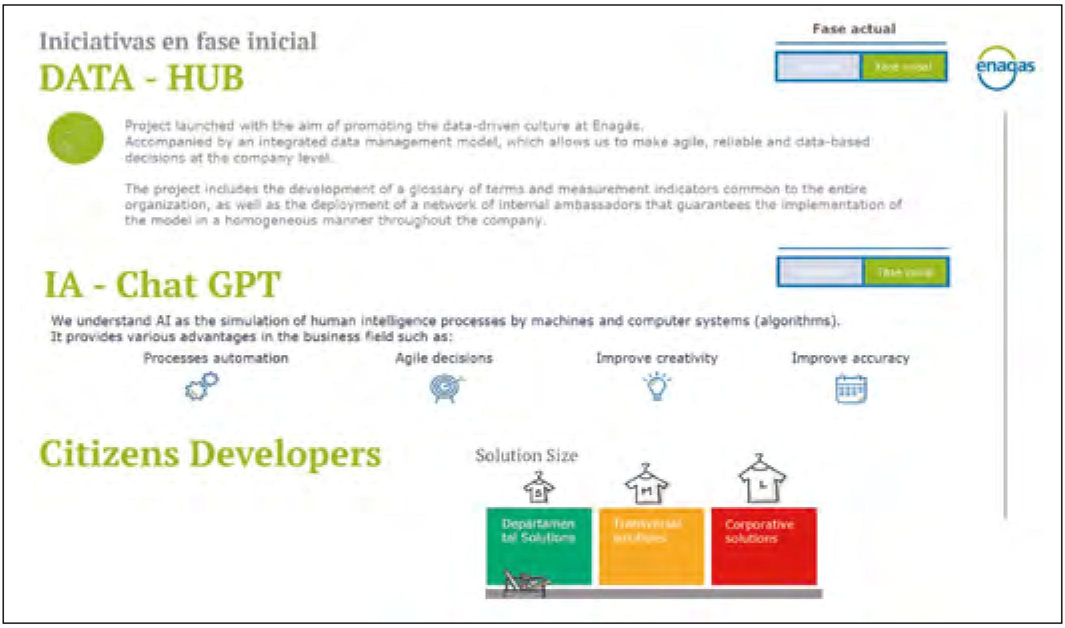
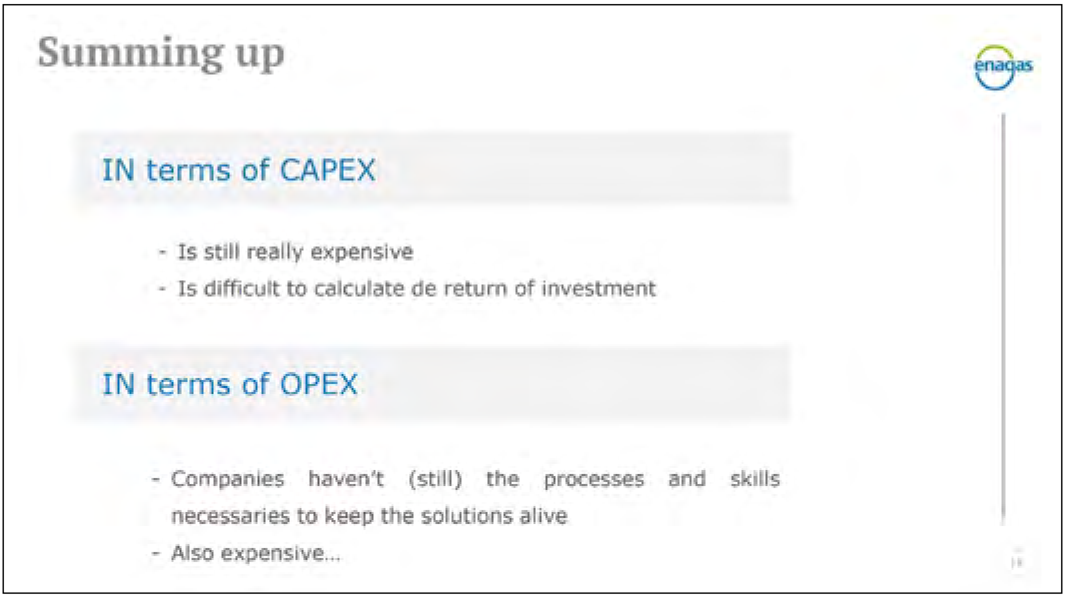

Normality Patterns
Ejecución del modelo
2011 - 2017
Data origin
Historical Data
Data cleaning
Validated Historical Data
Training Model Data
Anomaly detection
Normality patterns
Comparision
vs
Results
Hourly Data
Data for comparision


MicroStrategy – Análisis de una señal operacional
Resumen por Activo - GA-114-D
Score
Thershold
Score
Evolución anomalías
Ratio A =
Nº Anomalías
100 HF


Fase actual
Iniciativas en fase inicial
DATA - HUB
Project launched with the aim of promoting the data-driven culture at Enagás.
Accompanied by an integrated data management model, which allows us to make agile, reliable and data-based decisions at the company level.
The project includes the development of a glossary of terms and measurement indicators common to the entire organization, as well as the deployment of a network of internal ambassadors that guarantees the implementation of the model in a homogeneous manner throughout the company.
IA - Chat GPT
We understand AI as the simulation of human intelligence processes by machines and computer systems (algorithms).
It provides various advantages in the business field such as:
Processes automation
Agile decisions
Improve creativity
Improve accuracy
Citizens Developers
Solution Size
S
M
L
Departamental Solutions
Transversal solutions
Corporative solutions


Summing up
IN terms of CAPEX
- Is still really expensive
- Is difficult to calculate de return of investment
IN terms of OPEX
- Companies haven't (still) the processes and skills necessaries to keep the solutions alive
- Also expensive...

A Petri net-based Digital Twin development for managing wind turbine blade maintenance

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[2] Resilience Engineering Research Group, Faculty of Engineering, University of Nottingham (UK)
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Abstract

In this study, an application of Digital Twin concept is explored to foster intelligent maintenance strategies and enhance the reliability of wind turbines amidst their rapid industry growth. It introduces a Petri net-based model that integrates condition monitoring (CM) and predictive maintenance processes for managing wind turbine blade assets effectively. The process begins with simulating blade degradation scenarios, followed by the inclusion of a condition monitoring system that consistently identifies the state of a blade, considering both potential underestimations and overestimations of the actual state. Based on these identified states, engineers can select appropriate maintenance strategies. By introducing Petri Net (PN) modules, our model provides detailed predictions of the health of wind turbine blades under various asset management strategies. The proposed Digital Twin model offers a means to extend the lifespan of a blade in a cost-effective way.

1. Introduction

The application of digital twin technologies has the potential to revolutionize maintenance strategies by enhancing reliability and reducing maintenance costs amidst the rapid growth of wind energy [1-2]. Owing to their flexibility and applicability for simulating dynamic processes, PNs are used to construct a digital twin of wind turbine blade maintenance management, providing decision makers with a realistic representation of degradation processes, monitoring process with reliability consideration and maintenance actions. Section 2 introduces the proposed methodology. Section 3 outlines results and conclusions of this research.

2. Methodology

PNs are directed, bipartite, graphical and mathematical modelling tools. They can represent the structure of a system as a network of places, transitions, and arcs which

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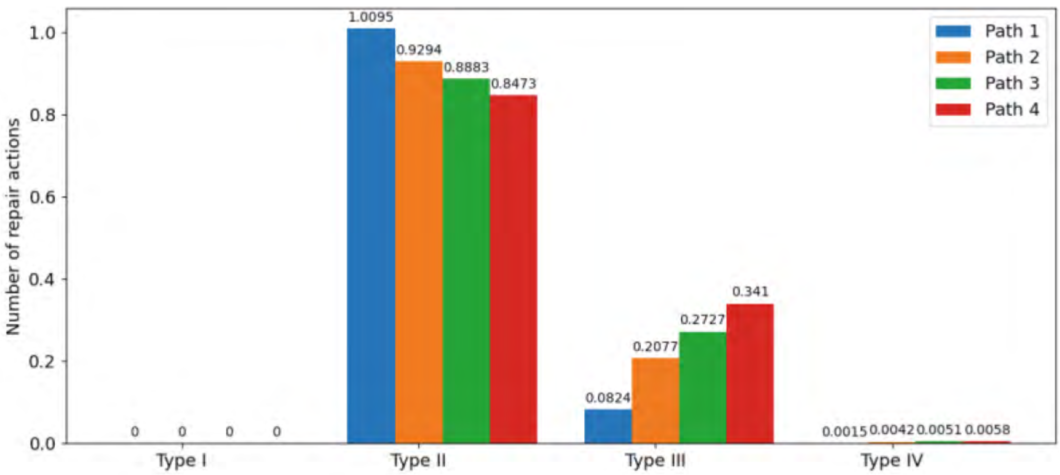
describe the flow between conditions and events [3]. The digital twin model consists of three modules: a degradation module, a CM module and a maintenance module. Stochastic distributions are used to simulate the degradation process of different types of defects in the degradation module. The CM module continuously tracks the state, considering both potential underestimations and overestimations based on provided monitoring accuracies [4]. The monitoring accuracy of the CM system gradually deteriorates over time due to an increasing probability of sensor failures. Within the maintenance module, engineers grade defects based on size, subsequently determining a repair strategy. The specific repair operation required is determined by the defect's severity, categorized in ascending order of severity from Type I to Type IV.

3. Results and conclusions

Blade condition state updates occur in real-time, enabling condition-based maintenance decisions through the proposed modules to predict maintenance strategies and system lifecycle. The simulation results, shown in fig. 1, examine the impact of monitoring system failure rates on repair actions. Monitoring system failure rates vary across four defined paths, with failure rates escalating from Path 1 to Path 4. It is observed that with accelerated aging, the number of Type II repair actions decreases, whereas for Type III and Type IV the number of repairs increase. This trend suggests that monitoring systems with higher failure rates are prone to make false state identification, hindering timely notifications to engineers and leading to maintenance delays.

Figure 1

Average number of different repair actions under different monitoring accuracy paths



In summary, this study develops a PN-based digital twin maintenance management model tailored to wind turbine blades, which incorporates the condition CM process and its reliability. Future research will focus on integrating real-time data from the physical structure to update the model, thereby enhancing its accuracy in identifying the actual condition state of the blade.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 859957.

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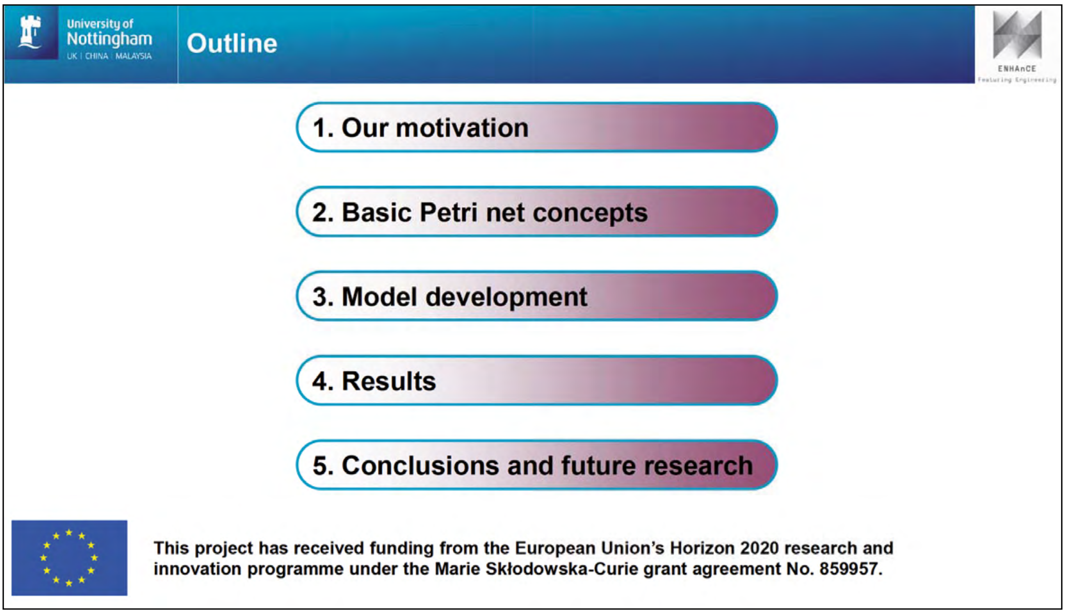
[2] Errandonea, I., Beltrán, S., & Arrizabalaga, S. (2020). Digital Twin for maintenance: A literature review. *Computers in Industry,* 123, 103316.

[3] Murata, T. (1989). Petri nets: Properties, analysis and applications. *Proceedings of the IEEE,* 77(4), 541-580.

[4] Wu, W., Cantero-Chinchilla, S., Prescott, D., Remenyte-Prescott, R., Chiachío, M. A general approach to assessing SHM reliability considering sensor failures. *Reliability Engineering & System Safety* (under review), 2023.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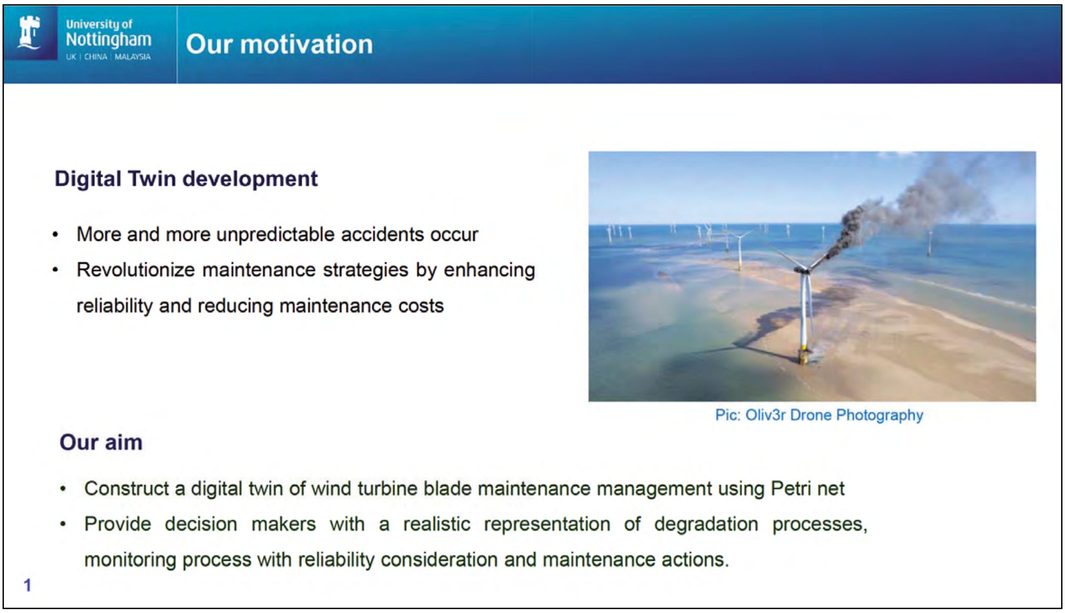
UK | CHINA | MALAYSIA
Outline
ENHAnCE
1. Our motivation
2. Basic Petri net concepts
3. Model development
4. Results
5. Conclusions and future research
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 859957.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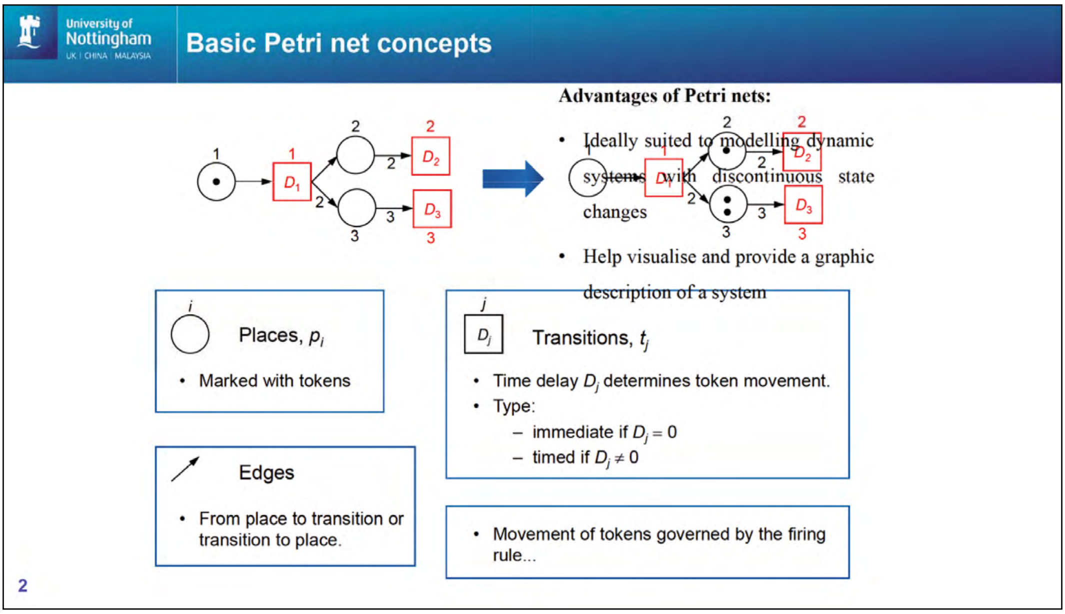
Our motivation
Digital Twin development
• More and more unpredictable accidents occur
• Revolutionize maintenance strategies by enhancing reliability and reducing maintenance costs
Pic: Oliv3r Drone Photography
Our aim
• Construct a digital twin of wind turbine blade maintenance management using Petri net
• Provide decision makers with a realistic representation of degradation processes, monitoring process with reliability consideration and maintenance actions.
1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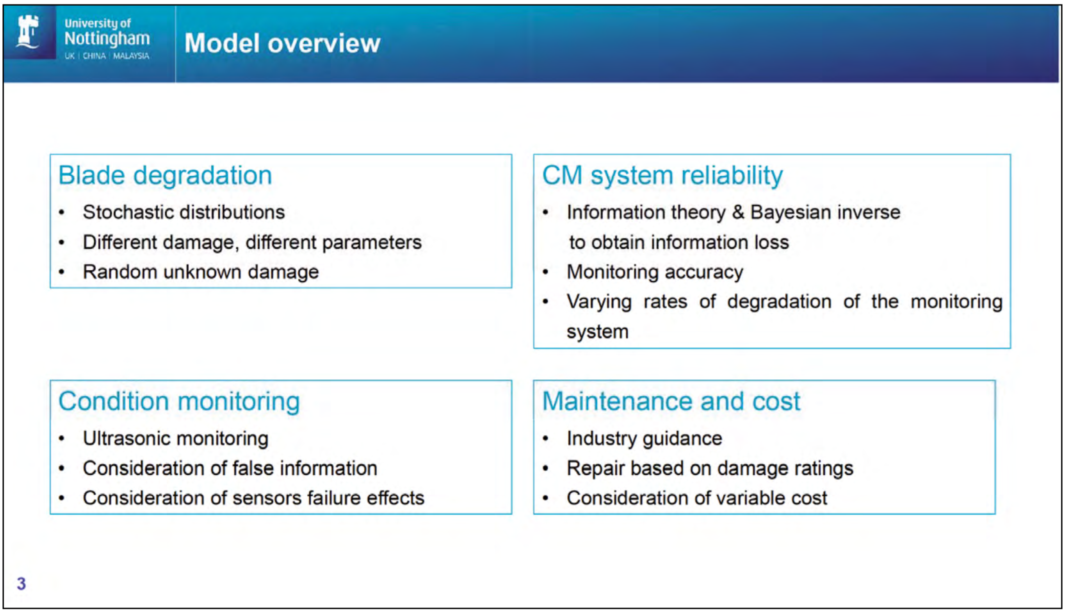
Basic Petri net concepts
Advantages of Petri nets:
• Ideally suited to modelling dynamic systems with discontinuous state changes
• Help visualise and provide a graphic description of a system
Places, p_i
• Marked with tokens
Transitions, t_j
• Time delay D_j determines token movement.
• Type:
– immediate if $D_j = 0$
– timed if $D_j \neq 0$
Edges
• From place to transition or transition to place.
• Movement of tokens governed by the firing rule...
2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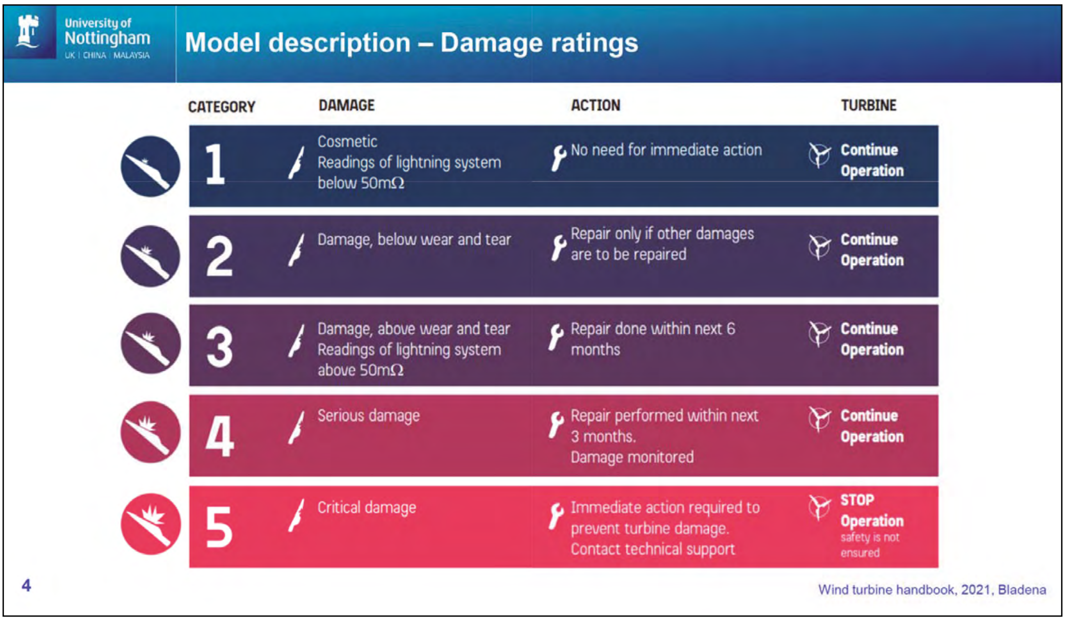
Model overview
Blade degradation
• Stochastic distributions
• Different damage, different parameters
• Random unknown damage
CM system reliability
• Information theory & Bayesian inverse to obtain information loss
• Monitoring accuracy
• Varying rates of degradation of the monitoring system
Condition monitoring
• Ultrasonic monitoring
• Consideration of false information
• Consideration of sensors failure effects
Maintenance and cost
• Industry guidance
• Repair based on damage ratings
• Consideration of variable cost
3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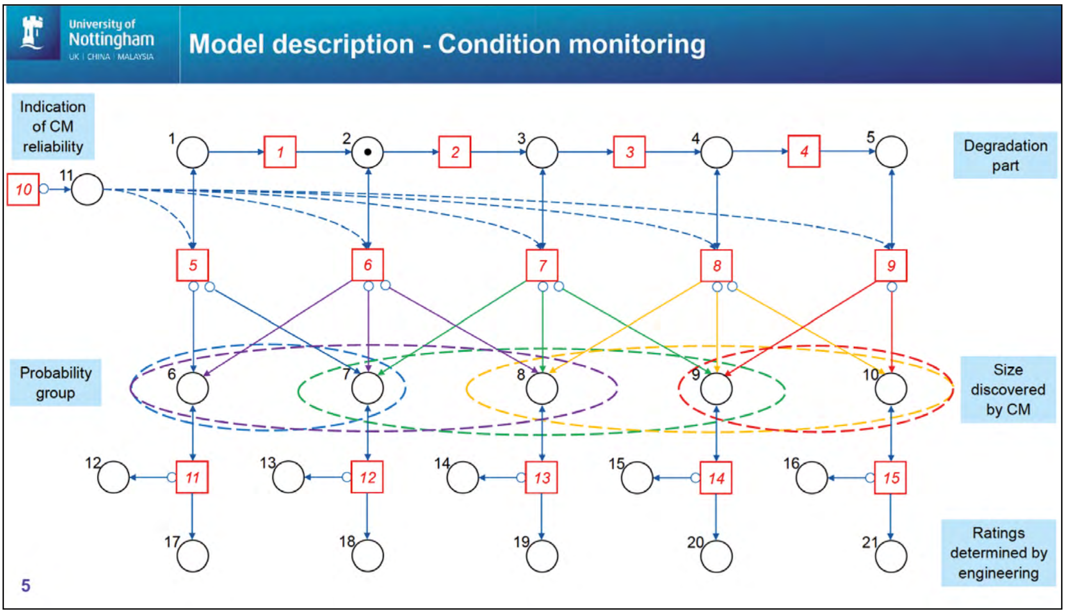
Model description – Damage ratings
CATEGORY
DAMAGE
ACTION
TURBINE
1
Cosmetic
Readings of lightning system below 50mΩ
No need for immediate action
Continue Operation
2
Damage, below wear and tear
Repair only if other damages are to be repaired
Continue Operation
3
Damage, above wear and tear
Readings of lightning system above 50mΩ
Repair done within next 6 months
Continue Operation
4
Serious damage
Repair performed within next 3 months.
Damage monitored
Continue Operation
5
Critical damage
Immediate action required to prevent turbine damage.
Contact technical support
STOP Operation
safety is not ensured
4
Wind turbine handbook, 2021, Bladena


University of Nottingham
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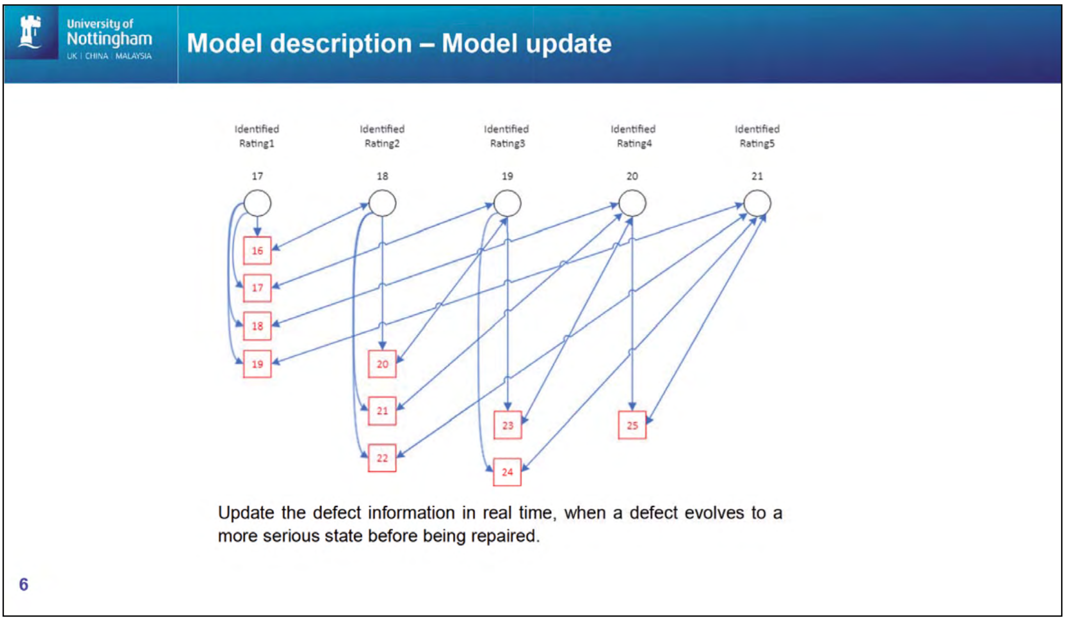
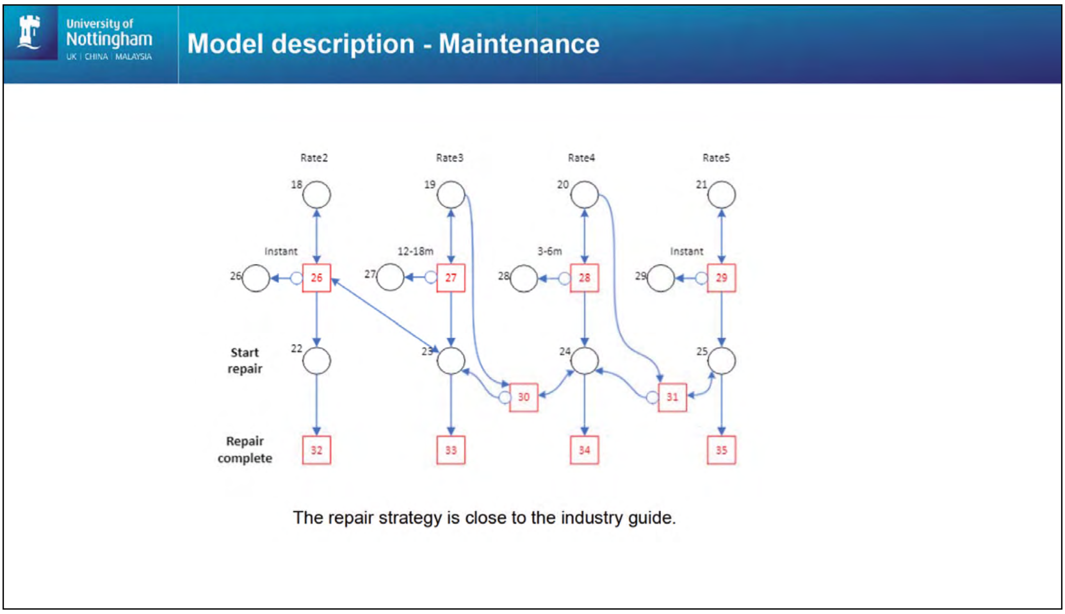
Model description - Condition monitoring
Indication of CM reliability
Degradation part
Probability group
Size discovered by CM
Ratings determined by engineering
5





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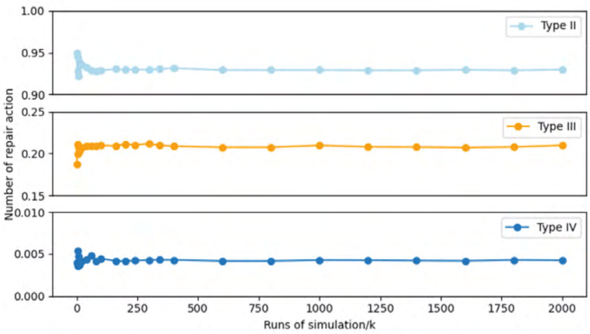
How do we analyse the model?



Converge routines in terms of the number of repair actions

- Bespoke research software has been developed in Python.
- Monte Carlo simulation is used to analyse the PNs.
- Convergence has been reached in terms of the number of different repair actions reaching a constant or stable value.

8

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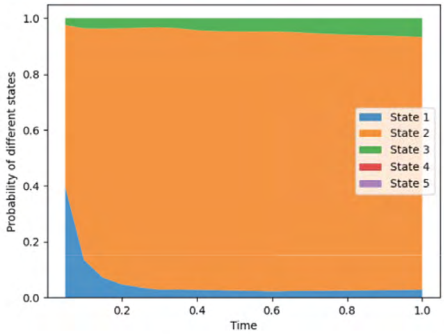
Results

C1: probability distribution of state discovery over time



- State the probability of the reporting and misreporting history with the CM system.
- Why CM monitoring system is wrong?

9

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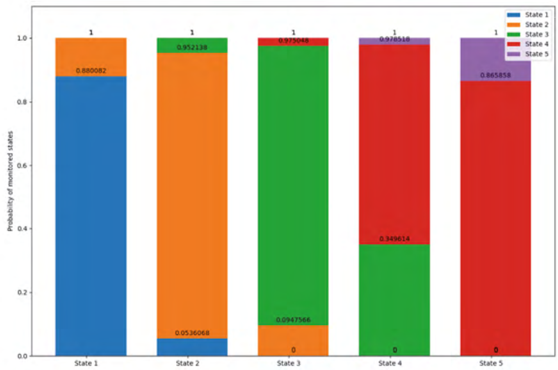
Results

C2: probability distribution of state discovery on average



The overall monitoring accuracy for different states, which shows probability distribution of state discovery on average.

10

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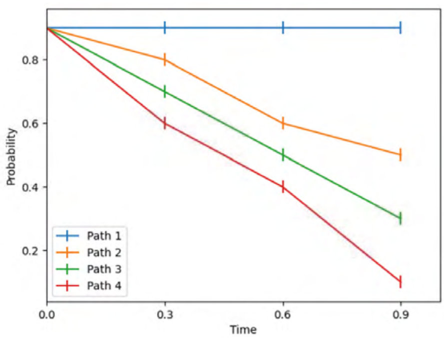
Results – Input about the monitoring system reliability



Level 1 indicates a perfect monitoring system. The monitoring system's failure rate increases from Level 2 to Level 4.

11

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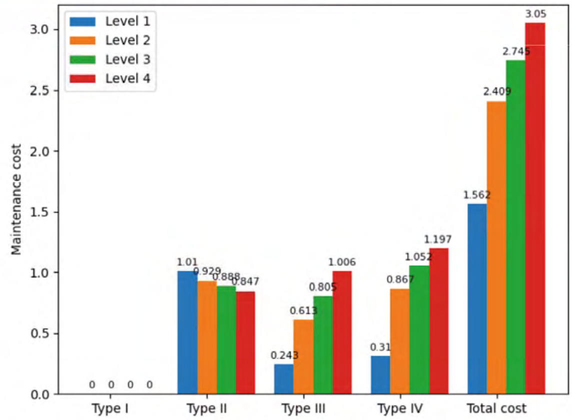
What can we get from the model?

C3: Cost under variable monitoring system's failure rates



12 Emphasises the importance of the CM system reliability on system performance and lifecycle cost.

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Conclusions and future research

Conclusions:

- Develops a PN-based digital twin maintenance management model tailored to wind turbine blades, which incorporates the condition CM process and its reliability
- Can predict the state discovery over time for wind turbine blade
- Can predict the CM reliability over time

Future research:

- Future research will focus on integrating real-time data from the physical structure to update the model, thereby enhancing its accuracy in identifying the actual condition state of the blade.

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EngageMate: Advancing Classroom Interaction with an Intelligent IoT Assistant driven by the Digital Twin Concept

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Abstract

The rapid evolution of educational technologies brings the Internet of Things (IoT) to the forefront as a transformative force, poised to reshape conventional teaching and learning methods through its network of interconnected devices and systems. This paper introduces an innovative IoT device enhanced by digital twin technology, aimed at improving teaching efficacy by enabling interactions with virtual replicas of physical objects for immersive, real-time learning simulations. The device goes beyond typical educational tools by monitoring classroom environmental conditions and assessing student engagement, supported by a web platform for educators to evaluate their teaching performances. A practical application involving two university teachers demonstrated the device's potential to significantly improve teaching strategies and student engagement, though it also revealed challenges in integrating such technologies into educational settings. These findings emphasize the need for ongoing research and development to overcome barriers and fully exploit IoT and digital twin technologies in education, thus facilitating a more interactive, effective, and personalized learning environment.

1. Introduction

In the rapidly evolving landscape of education, the Internet of Things (IoT) emerges as a transformative force, promising to redefine traditional teaching and learning paradigms through its interconnected devices and systems network. Integrating IoT into educational settings heralds a significant milestone in the journey towards more interactive, personalized, and accessible teaching and learning experiences for students of all ages, including those in higher education. Despite the potential, the body of literature exploring the full capabilities of IoT in education remains relatively underdeveloped, highlighting the need for novel proposals to enrich the academic discourse within the research community. This paper draws over two important concepts, engagement, and comfort. It introduces an innovative IoT device designed to enhance

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teaching performance through the application of digital twin technology. By leveraging the concept of digital twins, this device offers a groundbreaking approach to education, enabling teachers and students to interact with virtual replicas of physical objects. This interaction enriches the learning experience with immersive, real-time simulations, providing a hands-on understanding of complex subjects.

The proposed IoT device goes beyond traditional educational tools by measuring environmental conditions within the classroom and sending alerts to teachers, thus optimizing the learning environment. Furthermore, it includes features to gauge student engagement and comfort, and offers a web platform where educators can review and reflect on their daily teaching performance to increase students uptake and engagement. A practical application of the IoT-digital twin approach was conducted in a university setting with two different teachers to assess its impact. The study provided valuable insights into the device's effectiveness, revealing its potential to significantly enhance both teaching strategies and student engagement. However, it also identified limitations and challenges, sparking a discussion on the integration of emerging technologies in education. The findings from this study contribute to the ongoing exploration of how IoT and digital twins can be harnessed to enrich the educational landscape. They underscore the necessity for continued research and development in this area, aiming to overcome current barriers and fully realize the potential of these technologies in creating a more engaging, effective, and personalized learning experience. Through such innovations, the future of education can be shaped to better meet the diverse needs of students and educators alike, paving the way for a more informed, interactive, and inspired educational environment.

2. **State of the Art**

As presented in the introduction section, the reviewed literature draws over to underpinning concepts: engagement and comfort.

2.1. *Engagement*

Student engagement in the classroom is a multifaceted parameter involving at least three dimensions [1]: behavioural (associated with participation), cognitive (associated with mental performance) and emotional (associated with positive or negative reactions to different stimuli). Given the wide range of parameters it covers, engagement can be considered a good indicator of the quality of students' learning process and their personal development in the classroom [2, 3, 4]. This has prompted research into what methods and objectively measurable parameters can and should be taken into account when quantifying the level of student engagement [5]. Typically, this work revolves around observation of students and their natural performance in the classroom [2]: how many times they raise their hands, how many times they interact with peers, what position they hold on the chair, what they have on the table, how much they yawn, how many interactions they have with devices outside the teaching context (e.g., mobile phones), how much work they have handed in, what grades they have received, how much they have received, how many times they have been given a grade, how many times they have been given a grade, how many times they have been given a grade, how many times they have been given a grade, how many times they have been given a grade. Traditionally, this quantification of the level of student engagement is usually done subconsciously in a more or less informal way, and also depends on the experience and skills of the teacher.

Thus, engagement can be seen as one of the (multiple) connecting links between teacher and learners in the learning process [6]. Paradoxically, most of the studies that have been carried out to date look at this link in only one direction: from the learners to the teacher. However, it seems that teacher engagement in the classroom can also have a significant impact on the learning process of students [7]. In this case, it is evident that the aforementioned dimensions (behavioural, cognitive and emotional) cannot be directly and fully applied to quantify teacher engagement while delivering a classroom session [8].

2.2. *Comfort*

Typically, enhancing comfort in indoor environments aims to make individuals more relaxed within building interiors. Consequently, various methods to assess indoor conditions have been developed, such as the ANSI/ASHRAE Standard 55 [9] and the ISO 7730 [10]. In efforts to achieve a comfortable indoor atmosphere, numerous research projects have explored different approaches to evaluate comfort in educational spaces, offering recommendations to ensure classrooms are comfortable and establishing guidelines to maintain suitable conditions [11]. Commonly examined factors include thermal conditions [12], humidity levels [13], visual comfort, which involves appropriate lighting [14], acoustics [15], and air quality [16]. Additionally, some researchers have investigated the influence of design elements such as equipment availability or the spatial layout, which can evoke positive emotional responses [17]. Simultaneously, numerous studies have examined how indoor environmental conditions affect student performance and learning quality. For instance, Montiel *et al.* [18] discussed how inadequate acoustics or external noise disrupts learning and teaching activities. Likewise, factors like temperature and humidity significantly influence comfort levels. On this topic, Jiang *et al.* [19] discovered that optimal learning occurs when thermal comfort is balanced, while Fisk [20] reviewed ventilation issues in schools and their effects on student health and performance. This research highlights potential health issues arising from inadequate comfort measures, noting that high humidity can lead to increased fatigue and respiratory infections [21], and poor lighting may contribute to myopia [22]. Additionally, the COVID Emergency has prompted increased focus on air quality and its health implications [23]. However, a review of this research indicates that while these studies primarily focus on understanding educational comfort and its outcomes, there has been less emphasis on exploring students' subjective perceptions of the indoor environment in classrooms compared to ideal objective conditions. Nonetheless, Frabsson *et al.* [24] suggest that deeper understanding of the relationship between these subjective and objective factors could lead to more precise standards for designing indoor environments.

3. Technological framework

To assess indoor comfort, a custom-designed weather station has been employed to monitor the environmental conditions within the classroom. The starting point of this IoT tool was previously introduced by the authors in a former article [25]. This station is equipped with sensors to measure noise (in decibels dB), temperature (in Celsius degrees ºC), humidity (as a percentage %), luminosity (in lux), and air quality (CO_2 concentration in parts per million ppm). Constructed using the Wio Terminal platform from Seed Studio, this prototype (referenced in fig. 1) displays sensor readings on its built-in screen.

Figure 1

Smart IoT device to monitor the classroom activities and environment

Additionally, it wirelessly transmits data using the MQTT protocol for real-time analysis to a cloud server that manages both the environmental monitoring system and data collection. This server archives the indoor monitoring data for subsequent analysis and showcases them on a web-based dashboard. The IoT devices also allows to track the lecture performance where the teacher will have to define the values according to his class, i.e. he will have to choose the type of class (lecture, interactive, exercises, laboratory...), the number of students, the time of the day (morning, afternoon...), the day of the week (Monday, Tuesday...) or the breaks he/she is doing during the lecture.

To measure the engagement of students, the platform is inherited form a previous work of the authors [5]. The starting point was the systematic identification of a set of measurable digital characteristics that arise from the use of the inherent sensors (camera, microphone, and keyboard) in videoconferencing environments. This data is used to calculate the level of student engagement, and an analytical model is devised for its quantification. Ultimately, a system based on web technologies captures and monitors the digital characteristics, and through the repeated calculation of the analytical model is able to obtain the evolution of the level of engagement to make it (exclusively) available to the teacher. This information facilitates the deployment of adaptive teaching methodologies in synchronous virtual environments, reducing the difficulties presented by this type of environment compared to traditional face-to-face teaching models. The ten most relevant properties and dimensions of engagement are presented below.

Table 1

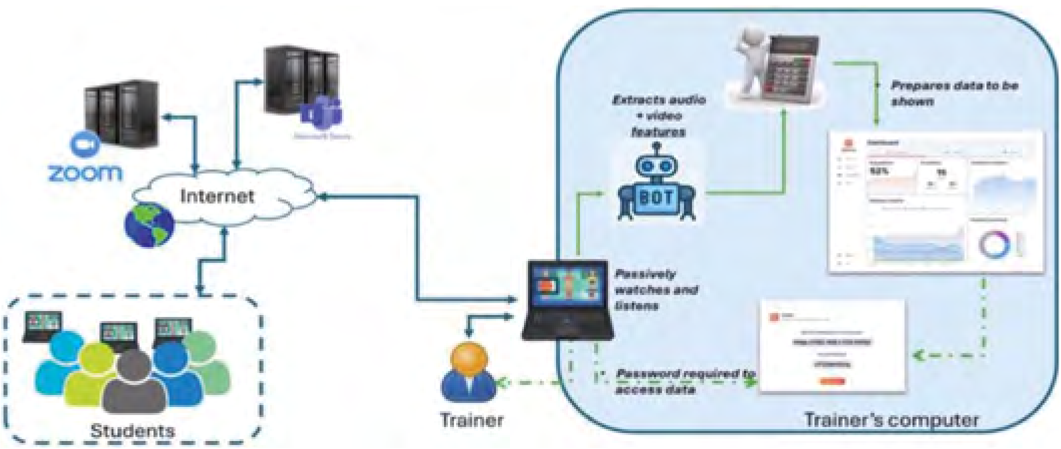
Characteristics of engagement

Digital Category (CD)	(*Engagement* dimension) Description
Assistance	(Behavioural / Emotional) Characteristics associated with the number of participants in the session and their variations.
Camera use	(Behavioural / Emotional) Camera status events and their variations.
Voice interactions	(Behavioural) Details (duration, number) concerning voice interventions, as well as the level of silence.
Hand raised	(Behavioural) Use of the survey options of the handheld and screen sharing respectively.
Screen sharing	
Chat interactions	(Behavioural / Emotional) Use of chat, such as the number of messages, number of questions and use of emoticons.
	(Behavioural)
Sound analysis	Sound quality, noise, volume and discontinuity.
Facial emotion	(Emotional) Identification of participants' emotions.
Lip movement	(Behavioural/Emotional) Detections of yawning or interactions with people outside of the training session. videoconferencing.
Eye-tracking	(Emotional) Characteristics that emerge from the participants' direction of vision.

These categories are fed into a formula called ENQUA(t) that calculates the engagement. The way each factor is obtained can be illustrated in figure 2.

Figure 2

Diagram of the architecture of the software system deployed on the teacher's computer (on the right, in blue). The software connects to a videoconferencing session (Zoom or Teams) and extracts the available information in real time (see table 1)



From this systematised collection of digital data, the analytical model is run repeatedly, making the calculated engagement level values available exclusively to the teacher on a dashboard. Note that, at the architectural level, this approach could be seen as a particular case in which principles of both edge computing (calculation of the engagement level on the border device) and cloud computing (extraction of the parameters associated with the Digital Categories from the cloud of the videoconferencing service provider) are combined. Although this tool was specifically designed to monitor student engagement in synchronous virtual environments, it could also be used to monitor teacher engagement, not only in synchronous virtual environments but also in face-to-face sessions (as intended in this paper). Thus, the teacher would have to (1) create a videoconference session in which he/she would be alone, (2) configure the software to connect to that session, and (3) adjust the parameters of the ENQUA(t) analytical model so that the data displayed on the dashboard would be adjusted to the new reality being monitored (teacher engagement instead of student engagement). In essence, some characteristics from Table 1 where removed to stick with Sound analysis, Facial emotion, Lip movement, Eye-Tracking and Voice interactions.

4. **Experiments to measure engagement and comfort**

Two sessions with two teachers have been carried out with the following characteristics:

— *Experiment 1.* This experiment is focused on observing whether there are relevant influences on the teacher's level of engagement associated with different body and eye behaviours. For this purpose, the teacher deliberately alternates various body postures, inside and outside the camera capture frame, as well as the fixation or withdrawal of the gaze directed at the materials being explained. This experiment aims to evaluate whether the software is able to measure the level of engagement when the teacher moves naturally or, on the contrary, the teacher must be looking at the laptop camera at all times.
— *Experiment 2.* This experiment is focused on observing the software's ability to measure the teacher's level of engagement. To this end, the teacher delivers the same session twice and deliberately changes his or her style, mood and emotional state (happy or joyful) from one session to the next in an attempt to present different levels of engagement. This experiment aims to evaluate the feasibility of using the software to measure the teacher's engagement, with the aim of providing a further tool to support teaching.

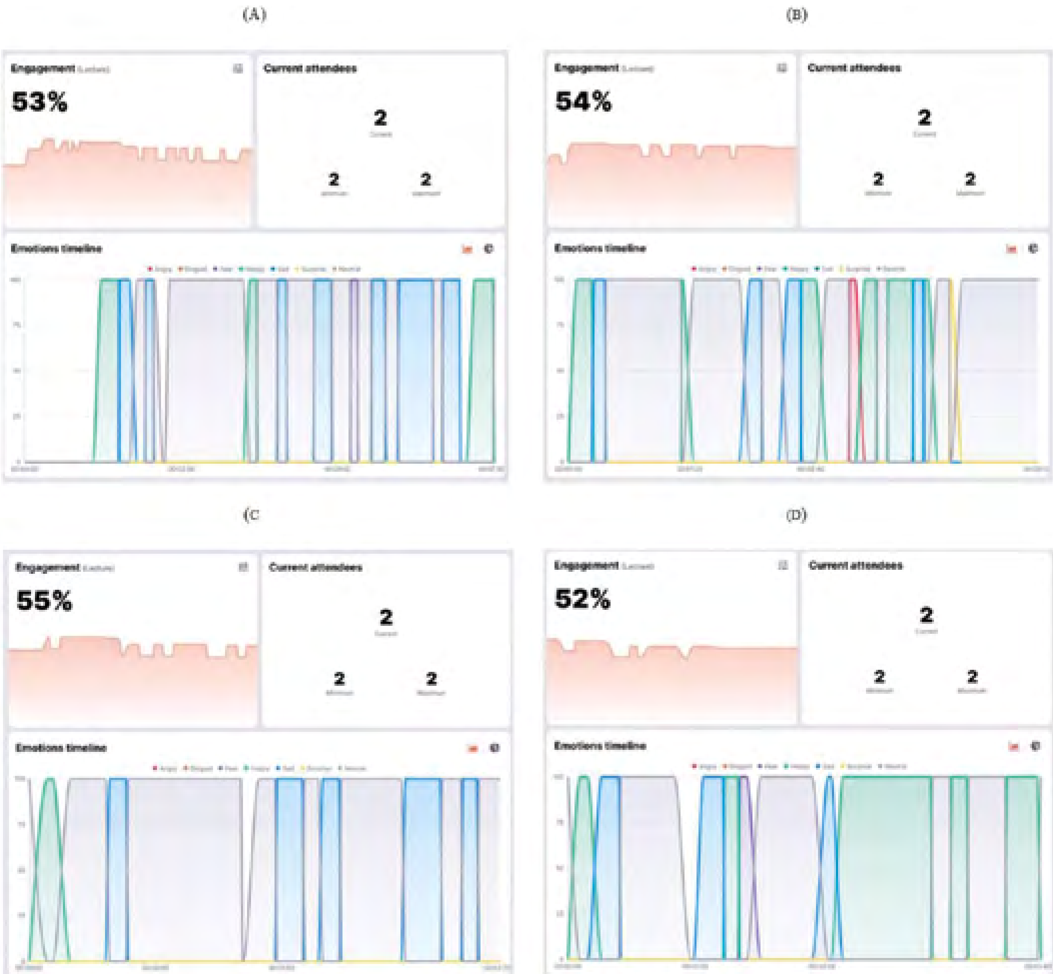
Both experiments were conducted using a laptop computer, connected to a Zoom session, which was monitored by the system [5] in real time. The results of the teacher's engagement level were accessible via the web interface from another computer so as not to influence the teacher's behaviour.

5. **Results**

For the 1st experiment, two professors from the University of Deusto in Bilbao, Spain, were chosen along with a third professor who facilitated the session. Both instructors were tasked with presenting a five-minute lecture on a well-known topic using identical slides to control for content differences. They delivered the lectures under two scenarios: one under ideal conditions where they sat facing the camera with consistent eye contact, and another under less controlled conditions where they stood, occasionally moved out of the camera's main focus, and did not maintain continuous eye contact. This was intended to mimic a more dynamic teaching environment. The objective was to maintain uniformity in the delivery across repetitions to ensure that any differences in engagement levels were attributable solely to their body language and eye dynamics. Figure 3 illustrates the engagement levels of each teacher during these conditions. Teacher 1 exhibited a neutral delivery style, while Teacher 2 displayed a more dynamic approach, generally eliciting positive emotions. However, despite these stylistic differences and scenarios, the observed variations did not significantly influence the measured engagement levels, suggesting the teacher engagement measurement software remained effective under varying conditions. This experiment underscores the system's versatility and reliability in different instructional contexts.

Figure 3

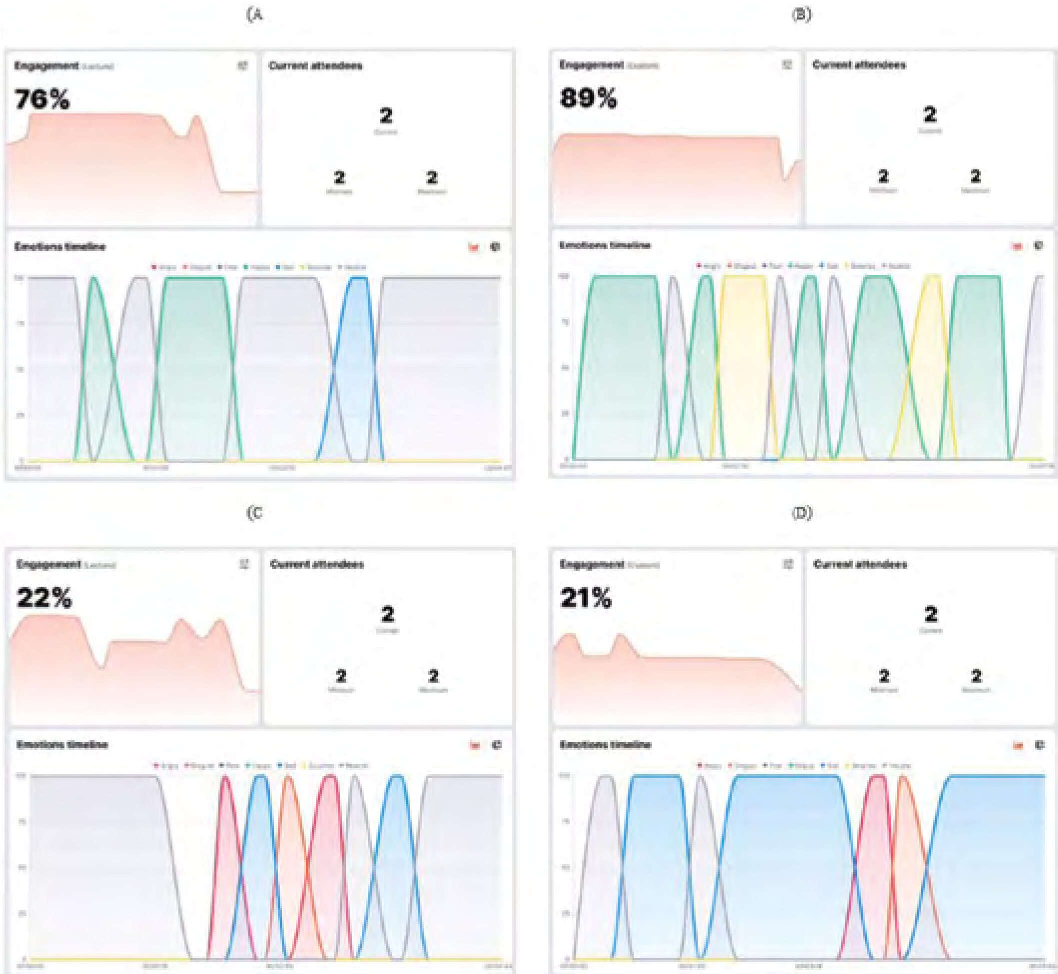
Evolution of the engagement level in experiment 1.
(a) teacher 1 under ideal conditions,
(b) teacher 2 under ideal conditions,
(c) teacher 1 under non-ideal conditions,
(d) teacher 2 under non-ideal conditions



For the 2nd experiment ,the same teachers were selected to deliver a five-minute lecture on a topic they were both well-versed in, under two distinct conditions: (1) Ideal conditions, where the teachers were enthusiastic, engaging through gestures, movement, and rhetorical questions to make the session lively, and (2) Non-ideal conditions, in which the teachers merely stared at the screen and read the content monotonously, simulating the effects of teacher fatigue or burnout. The aim was to keep the content delivery consistent across both scenarios to ensure any observed differences in engagement were solely due to the delivery style. Figure 4 illustrates the engagement levels for each teacher under these conditions. Teacher 3 managed to maintain high engagement despite occasional sadness, which temporarily reduced engagement. Teacher 4, under ideal conditions, displayed high engagement facilitated by positive emotions but experienced a slight dip in engagement when out of camera focus. Under non-ideal conditions, the presence of negative emotions correlated with lower engagement levels. These results confirm the system's ability to detect variations in teaching style and engagement. This experiment supports the system's potential as a tool for teachers to self-assess and adjust their engagement levels during sessions.

Figure 4

Teacher 3 under ideal conditions,
(b) teacher 4 under ideal conditions,
(c) teacher 3 under non-ideal conditions,
(d) teacher 4 under non-ideal conditions



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6. Conclusions

This paper demonstrates the significant potential of integrating Internet of Things (IoT) and digital twin technologies in educational environments to enhance both teacher and student engagement and comfort in classrooms. The innovative IoT device discussed facilitates interactions with virtual replicas of physical objects, offering immersive, real-time learning experiences. By monitoring environmental conditions and student engagement, and providing a web platform for educator feedback, this tool goes beyond traditional educational approaches. The implementation of this technology in a university setting revealed its capability to significantly improve teaching strategies and increase student engagement, although it also highlighted the challenges of integrating such advanced technologies in current educational frameworks. The experiments conducted illustrated that the system could effectively measure and sustain teacher engagement under varying conditions, indicating its robustness and adaptability. Moreover, the study underscores the importance of continued research and development to fully harness the capabilities of IoT and digital twins in education. Such technological advancements can lead to more dynamic, effective, and personalized teaching and learning experiences, ultimately shaping the future of education to better meet diverse needs. Therefore, this research contributes valuable insights into the transformative potential of IoT and digital twin technologies in enhancing educational settings by providing a more interactive, informed, and comfortable learning environment for students and educators alike.

Acknowledgements

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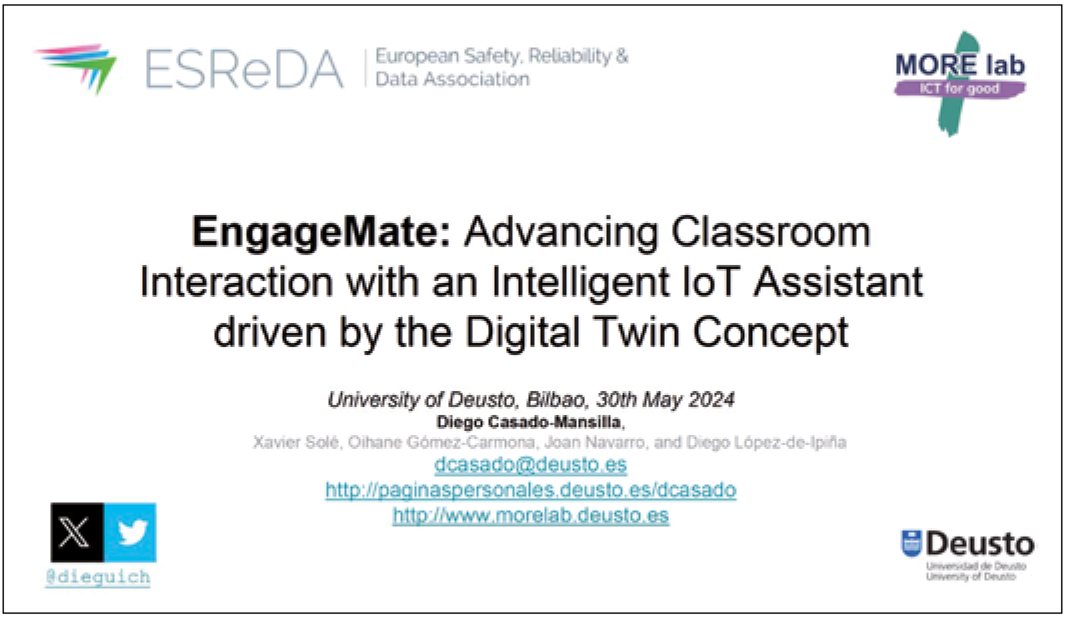
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ICT for good
EngageMate: Advancing Classroom Interaction with an Intelligent IoT Assistant driven by the Digital Twin Concept
University of Deusto, Bilbao, 30th May 2024
Diego Casado-Mansilla,
Xavier Solé, Oihane Gómez-Carmona, Joan Navarro, and Diego López-de-Ipiña
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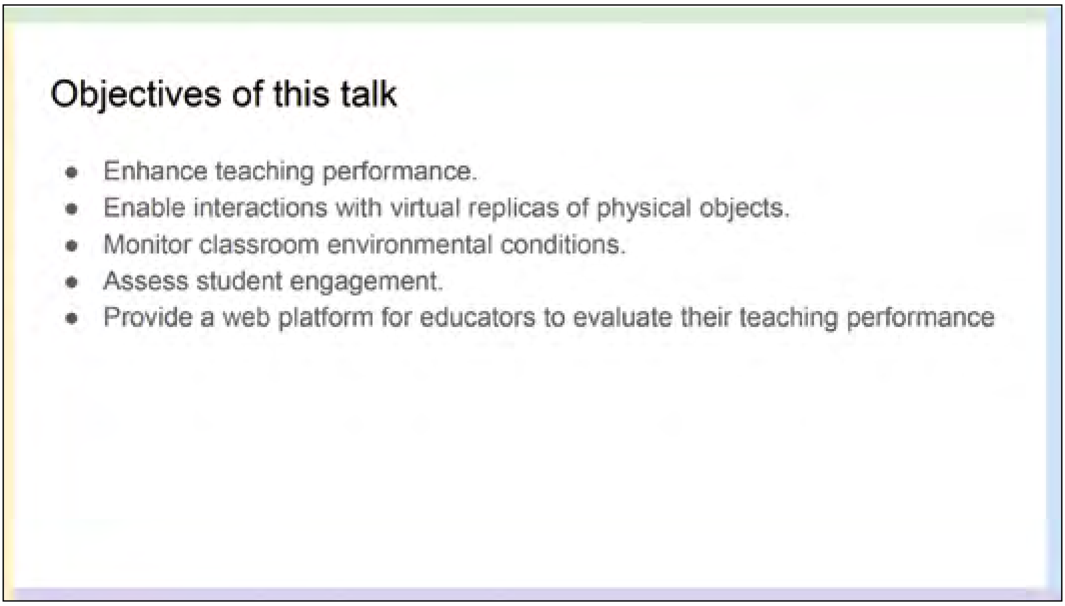
Overview
IoT as a transformative force in education.
Introduction of an innovative IoT device enhanced by digital twin technology.
Aim: Improve teaching efficacy through immersive real-time learning simulations.


Objectives of this talk
Enhance teaching performance.
Enable interactions with virtual replicas of physical objects.
Monitor classroom environmental conditions.
Assess student engagement.
Provide a web platform for educators to evaluate their teaching performance

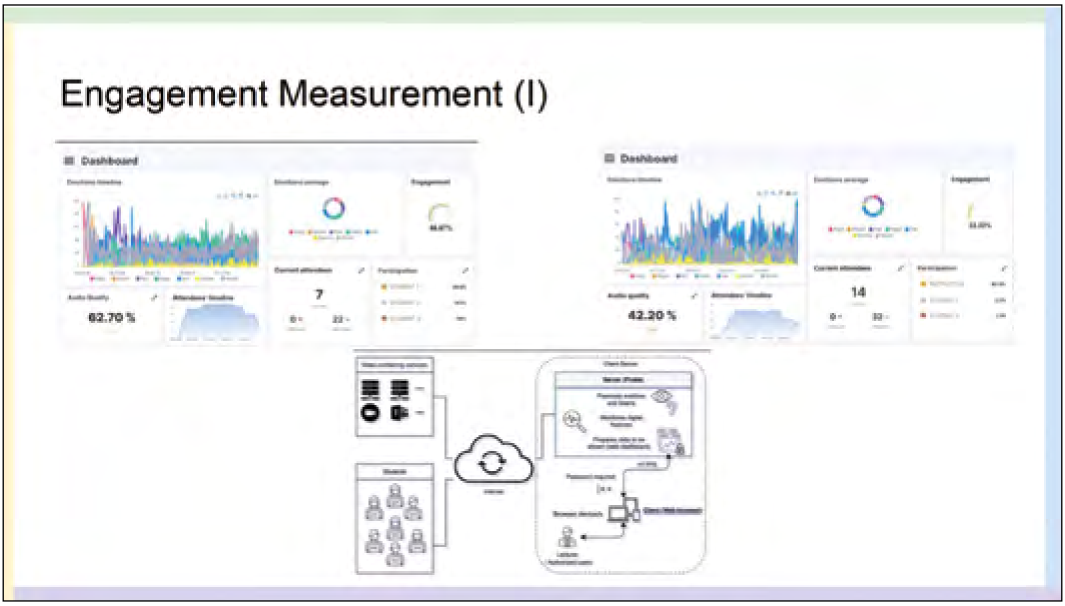

IoT and Digital Twin Technology
IoT: Network of interconnected devices.
Digital Twin: Virtual replicas of physical objects for simulation and interaction.
Benefits: Real-time data, immersive learning, enhanced engagement.
Digital Twins and IoT

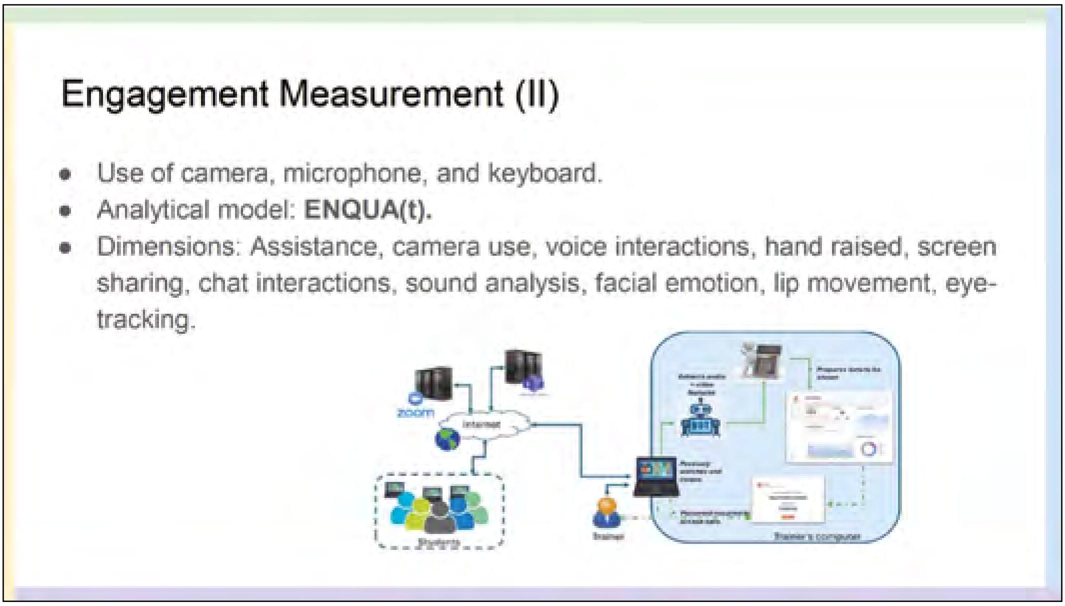
Background

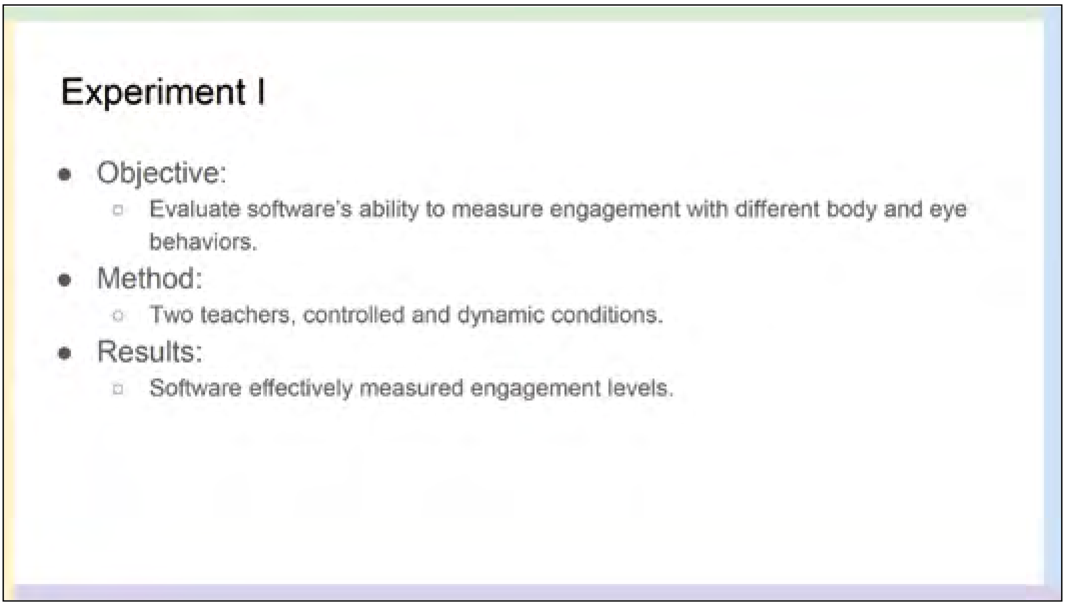
- **Engagement and Comfort - Direct impact on learning quality and student performance.**
  - **Engagement:** Behavioral, cognitive, and emotional dimensions.
  - **Comfort:** Thermal conditions, humidity, lighting, acoustics, air quality.

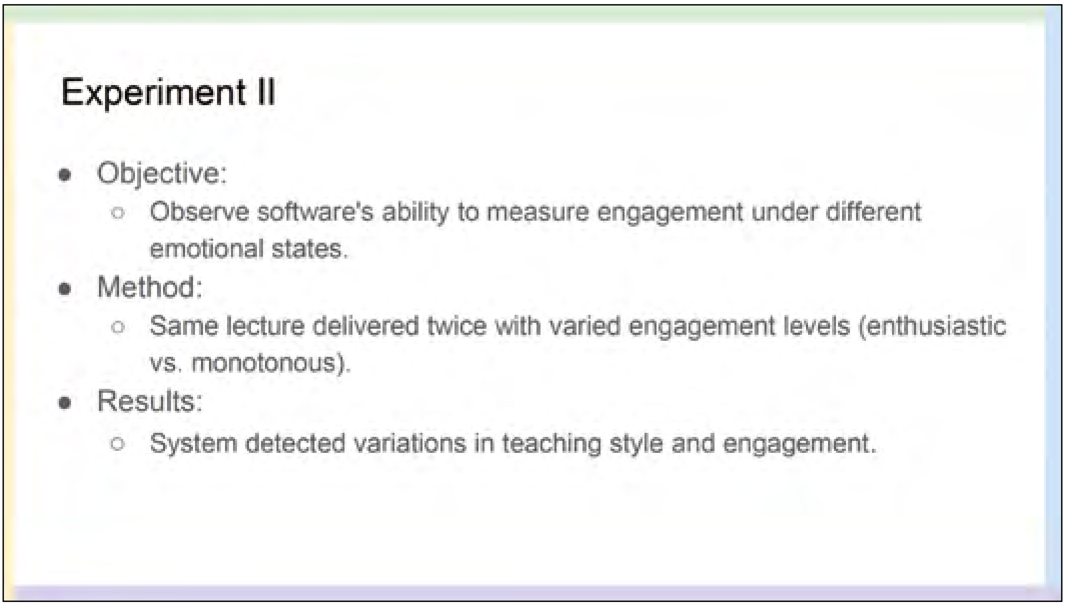
Technological Framework

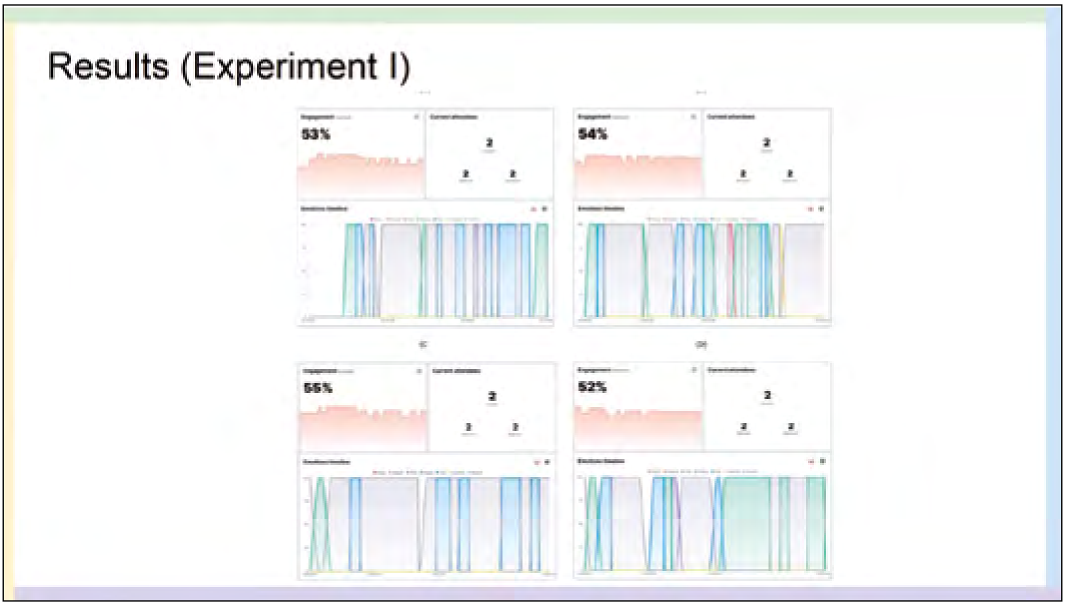
- **IoT Device**

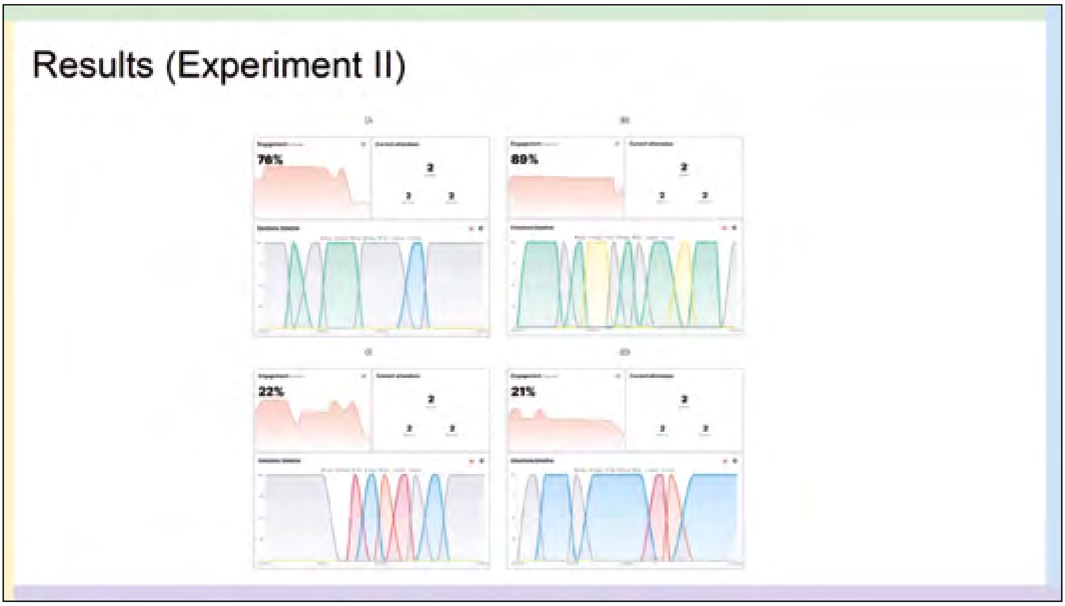

Engagement Measurement (I)
Dashboard
62.70 %
7
Dashboard
42.20 %
14


Engagement Measurement (II)
• Use of camera, microphone, and keyboard.
• Analytical model: **ENQUA(t).**
• Dimensions: Assistance, camera use, voice interactions, hand raised, screen sharing, chat interactions, sound analysis, facial emotion, lip movement, eye-tracking.
zoom
Internet
Students
Trainer
Trainer's computer

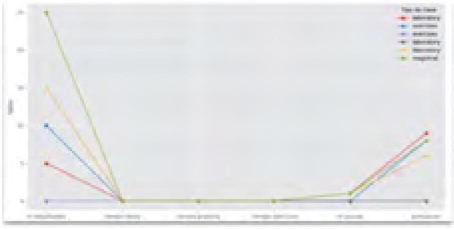

Experiment I
Objective:
Evaluate software's ability to measure engagement with different body and eye behaviors.
Method:
Two teachers, controlled and dynamic conditions.
Results:
Software effectively measured engagement levels.


Experiment II
Objective:
Observe software's ability to measure engagement under different emotional states.
Method:
Same lecture delivered twice with varied engagement levels (enthusiastic vs. monotonous).
Results:
System detected variations in teaching style and engagement.


Results (Experiment I)
53%
54%
55%
52%


Results (Experiment II)
76%
89%
22%
21%

Teachers' reflection over data



Conclusions

- IoT and digital twin technologies hold great potential for enhancing educational environments.
- Need for continued research and development.
- Future of education: More interactive, effective, and personalized learning experiences.

Future Work

- Addressing integration challenges.
- Enhancing system features based on feedback.
- Expanding studies to diverse educational settings

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Questions?

Bases for Ontology of Digital Twin of Maintenance Process. A Railway Application

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Abstract

Determining the exact relationships between each component that comprises a digital twin is necessary for its definition. This study is focused on fully digitizing maintenance activities within a specialized railway maintenance provider. Exploring ontologies reveals relationships that are required to be determined, connecting the entities with essential data sources to build the digital twin of workshop maintenance management process. Objectives include ensuring traceability of records and timely data interpretation. This facilitates defining optimization levels and automation in decision-making, predicting risk levels during each review. Results reveal that the digital twin definition process starts by determining relationships among subsets of elements or entities in the maintenance process in a determinate domain and with the specific semantic. The research's potential extends to all rolling stock elements, emphasizing the current focus on specific mandatory inspections.

1. Introduction and background

To build an accurate and useful digital twin, it is necessary to have a well-defined ontology. An ontology is a conceptual model that describes entities and their relationships within a specific domain (Bao *et al.*, 2021). It provides a shared vocabulary and semantic structure that enables accurate and consistent representation and sharing of knowledge. The main contribution of this study is to lay the foundations of a model to integrate, represent and relate the entities and data of a railway equipment maintenance management process and, from there, the creation of digital twin. For this purpose, a 9-phase process is proposed that considers from the definition of the object, through the identification of domains and ontologies, to the agile testing of the same models in order to obtain a rapid improvement in each twin.

Recent findings reveal a rapid increase in publications on "Digital Twin Railway Ontology" in the last four years, comparisons indicate an early-stage development in railway exploration. The focus remains on engineering stages, linking BIM models to digital twins, rather than representing railway processes directly. Out of 362 SCOPUS

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studied results until 2022 for "Railways Ontologies", only three are related to the Railway, suggesting a wide opportunity for model development and scientific discourse on that topic. Railway field studies emphasize the unique heterogeneity and complexity in rolling stock and infrastructure data due to the industry's historical roots.

Complex studies, like that by (Li *et al.,* 2022), highlight the use of ontology as a knowledge expression method in digital twin composition, integrating entities with key elements. Extracting concepts from (Kim *et al.,* 2020), a standardized structure for defining entities and classification, based on relationships, forms the foundation for building a digital twin. Rescued concepts for constructing data models include Class Subclass, Entity, LOD, Domain, relationship, and connection point, crucial for digital twin development. (Crespo Márquez, 2022a) proposes a model dividing the process into systems, involving data extraction, transformation, and conversion, leading to various systems for effective digital maintenance management. The ontology modelling of the complex system is implemented with the six basic elements of Graph, Object, Point, Property, Role, and Relationship (Lu *et al.,* 2019).

2. **Conceptual model**

The development of a successful digital twin requires a solid methodological foundation that integrates management and computer concepts. The fundamental task is to define entities and relationships (ontologies) in order to form the Digital Twin's data model, which raises the question of where to begin.

2.1. *Bases for Digital Asset Definition*

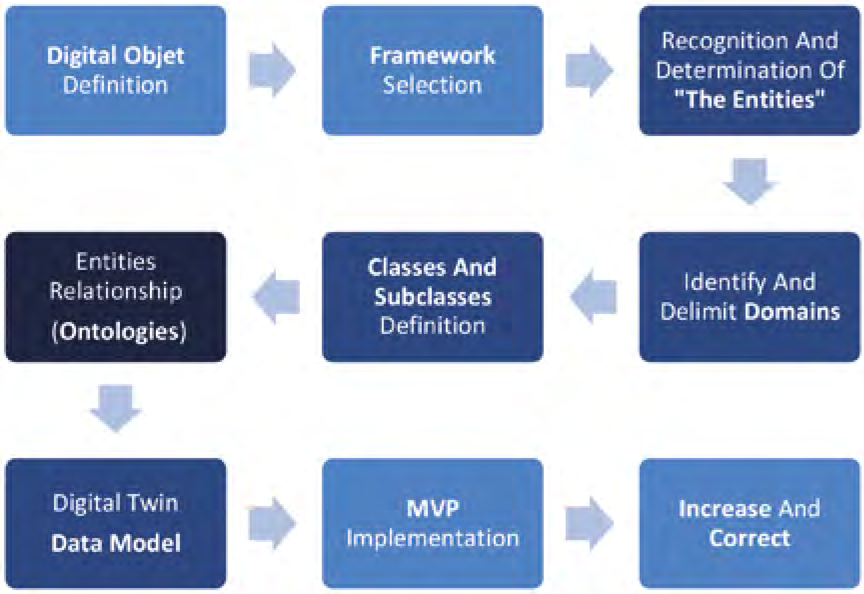
Addressing this, a minimums steps to define a Digital Asset are showing in figure 1, acting as a guide for managing projects involving the generation of digital twins. Even while these processes seem straightforward, there is frequently a lack of practical vision. In digitization projects, diverse perspectives contribute to data confusion (Nagorny *et al.,* 2020) necessitating methodologies to bring order. The proposed steps, crucially applied in our research, align the efforts of various agents involved in twin creation (technologists, clients, academia, business, financial).

Step 1. Digital Object Definition

In order to define a Digital Asset in accordance with the value-adding principle, a physical thing must exist digitally (UNE-ISO 55000, 2015). A clear business objective should be the first step in defining the purpose. Once the purpose has been established, the element to be represented —physical assets, procedures, or services— must be determined.

Figure 1

Minimum steps to define the Bases of a Digital Asset



Step 2. Define the Context of Digitalization (Framework Selection)

The selection of a management framework is essential, with an emphasis on managing physical assets and associated processes to achieve corporate goals. Asset managers anticipate varied scenarios based on asset configuration, necessitating diverse management needs, including asset criticality determination (Crespo Márquez, 2022b).

Step 3. Relevant Entities

Hierarchical attributes are used to identify single entities until an asset is defined (Malakuti *et al*., 2020).

Step 4. Identification of Domains

In defining entities, it is important to specify where they belong or not. Contexts are identified as domains, ensuring the inclusion of properties from diverse sets and domains (Fujitsu *et al*., 2021).

Step 5. Class Identification

Classification is essential in creating a digital twin, describing heterogeneous attributes through ontology modelling (Bao *et al.,* 2021).

Step 6. Definition of Unitary Rules – Entities Relationship

Unitary rules define the Digital Asset, determining relationships, including criticality for asset maintenance management (Crespo Márquez, 2023).

Step 7. Digital Twin Data Model

The Digital Twin integrates data and information about each asset, evolving along the life cycle with two main data models: Engineering models and Data-driven models (Talkhestani *et al.,* 2018).

Step 8. Development of MVP (Minimum Viable Product)

To avoid stagnation, develop small prototypes to measure success or failure, minimizing risk and time (Robinson, 2001).

Step 9. Increase and Correct

Recalibration is essential in the dynamic construction of digital twins, closing the Improve loop in the proposed DMM framework (Candón *et al.,* 2019).

2.2. *Use Case: Procedure for the design of the Digital Twin, Rolling Stock Maintenance & Depot. Mandatory Inspections*

What should be done if paper is the starting point for creating a high-level digital twin? Can this industrial issue be met directly? The current use case's development aims to provide answers to these issues. As a first step, Table 1 shows the business objectives (to be achieved with the Digital Twin), the objects and the relationship with the RAMI 4.0[1] and IIRA[2] models in each of its layers.

---

1 RAMI 4.0: Reference Architecture Model for Industry (Plattform Industrie 4.0 RAMI4.0, 2018).
2 IIRA: Industrial Internet Reference Architecture (Shi-Wan Lin (Thingswise/Intel, 2022).

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Table 1

Object definitions elements

Business objectives	Functions / Objects	Description	RAMI 4.0 Layers	IIRA Layers
Digitization of “Suitability for Service”	Asset control	Real time control of location, situation, status and certification of machines and components. Asset KPIs.	Business	Business view point
	Workshop control	Real-time control of workshop processes and their resources.	Business	Usage view point
	Client interface	Client access to fundamental data of the contracted service.	Business	Usage view point
	Fitness for service control and traceability	Certificate control and traceability of regulated/mandatory maintenance tasks.	Business	Usage view point
Maintenance optimization	Degradation prediction	Flange degradation prediction based on measured data and recorded machine operation data by GPS.	Functional	Usage view point
	Scheduling and planning optimization	Optimization of the scheduling of preventive tasks (dynamic preventive maintenance) Tasks and frequencies that can be modified.	Functional	Usage view point

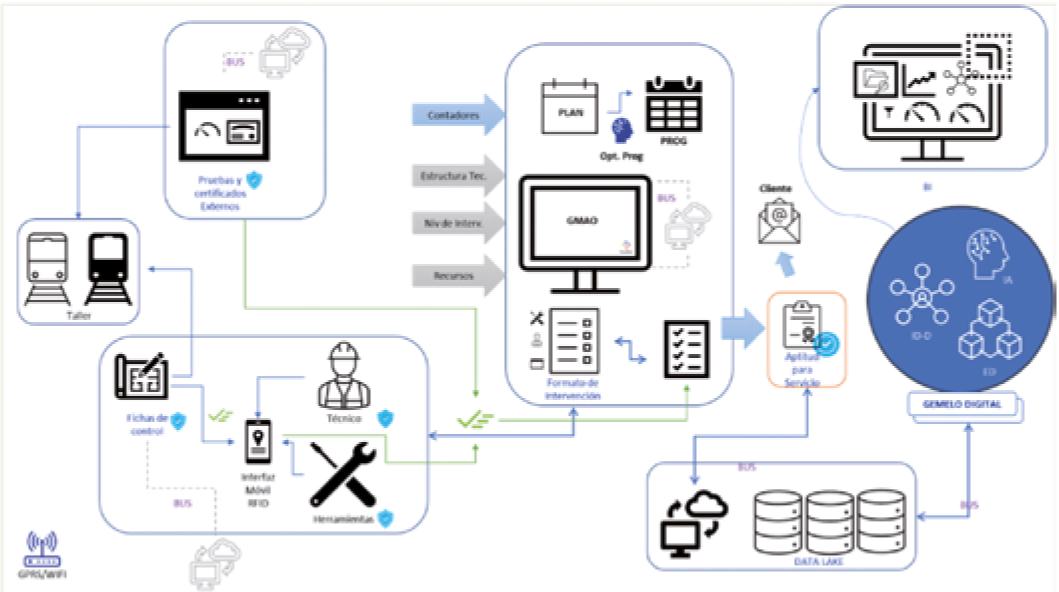
For them they have selected 3 types of digitized elements and specifically the use case focuses on the following systems:

— Physical asset: Rolling system / Axle wheel degradation.
— Process: Completion of the biannual review IS2.
— Service: Control of “Fitness for Service”.

In this regard, once the model’s design has been defined, it is necessary to characterize the data inputs and outputs generated as a result of the suggested reengineering process. This reengineering takes into account the technologies to be integrated and, particularly, the use of a maintenance information system as a basic support for the digitalization of maintenance processes (figure 2).

Figure 2

Schema of relationship of data, systems, technologies, and processes



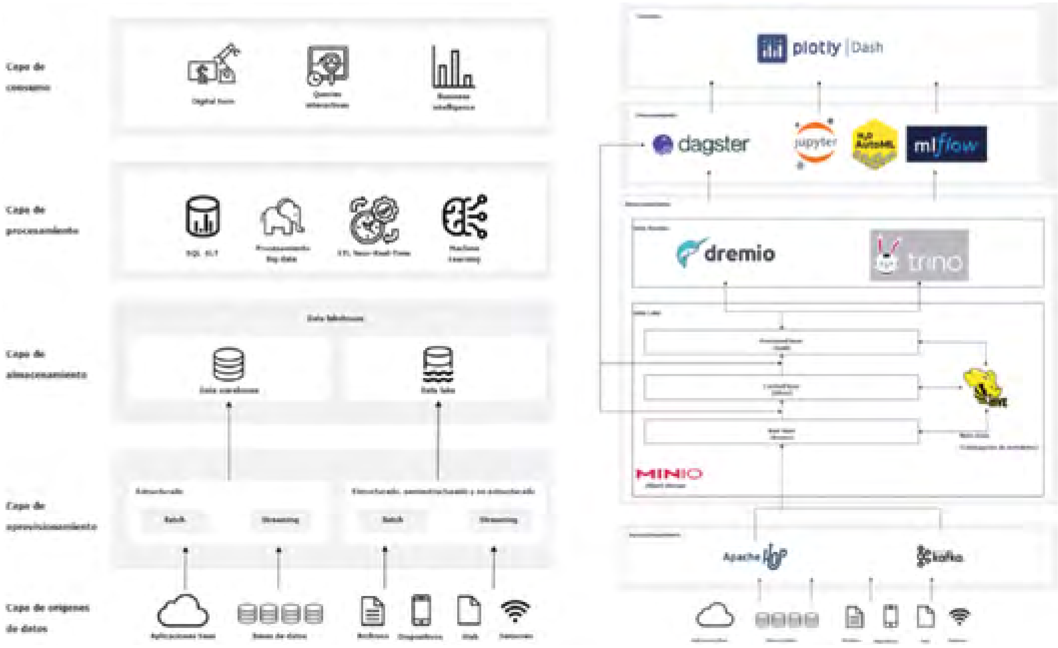
In digitalization, initiating with a Computerized Maintenance Management System (CMMS) is key. Choosing and integrating CMMS wisely, instead of building a platform from scratch, offers significant benefits. This streamlined approach avoids unnecessary elements, ensuring efficient model exploitation. When creating a new digital twin for different processes, entities can be easily redefined with specific attributes for diverse life cycle stages. For example, data needed in Design differs from Maintenance, Operations, or Financial Management. The atomized nature enables a customized digital asset representation through a dedicated ontology.

Data and Systems Requirements

The definition of the system architecture necessary for data extraction, transformation, and processing is another crucial step in the production of digital twins. This ensures timely availability of structured data aligned with the process-specific ontology. The architecture encompasses layers such as Data Source, Provisioning, Storage, Processing, and Consumption (see figure 3).

Figure 3

Data & System Architecture



CLASSIFICATION AND DOMAINS

The stage preceding digital twin construction involves defining its classes and domains. Crucial attributes determining the digital asset and its context are established. Attributes can be single values or functions composed of others derived from a specific model. In our case, we delineate entities for mandatory inspection within the rolling system, encompassing assets, tools, and resources.

ENTITIES ONTOLOGY AND DATA MODEL OF DIGITAL TWINS

The integration of elements defined in figure 1 results in a scheme facilitating the individualization and interrelation of various components: data, systems, processes, people, and technologies. This scheme paves the way for constructing the digital twin. This model (represented in figure 4) is crafted in the latter part of our study as a Minimum Viable Product (MVP). It serves as the foundational structure for computing relationships, giving rise to the digital twin overview.

Figure 4

Ontology and data Model Schematic Overview

2.3. *Future Actions (MPV): Ontology developed on PROTEGÉ*

The next steps aim to develop an ontology scheme in already exists software for ontology creation and management (Standford, 2023.) like a Protégé®. With a user-friendly graphical interface, Protégé allows intuitive ontology creation, editing, and visualization. Leveraging the OWL (Ontology Web Language), it is widely utilized in ontology research. Protégé empowers users to define classes, properties, instances, and relationships within domains. It facilitates ontology import/export, seamlessly integrates with other tools, and incorporates reasoning engines. The ongoing research involves using Protégé or another similar tools to create a real ontology, forming a structured foundation for transforming assets into data for the digital twin model.

3. **Conclusions**

The study's primary contribution is establishing a management process to define a digital twin in a 4.0 industry associated standard, particularly in railway maintenance management context. Although industry opinions on this matter are not currently 100% defined, our process collects your best practices and presents them as a step-by-step encouraging research and possible advancement. The model argues for practical knowledge reflection in ontologies defining digital twins. Aligning with models proposed in RAMI4.0 and IIRA brings a broader context to the management level beyond IT (Information Technology) and OT (Operational Technology) environments. Connecting the digital and management worlds is crucial, avoiding digitization without a clear purpose. Systemic perspectives and hierarchical decision-making, considering criteria like criticality, are vital in digital twin creation. The study aims to kick-start discussions on standard management models in the railway context, fostering practical and applicable digital twins in the industry.

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Bases for Ontology of Digital Twin of Maintenance Process. A Railway Application

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Background

- The Digital Twin as a cornerstone in the evolution of maintenance strategies
- The Digital Twin as a representation of a real object, process, or service
- Ontology as a support for a Digital Twin to effectively represent the relationships among maintenance entities. (Connection point RD/DD/MD)
- Maintenance Management Frameworks as a specific context for defining the digital ecosystem focused on business objectives

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Research Objective and Methodology

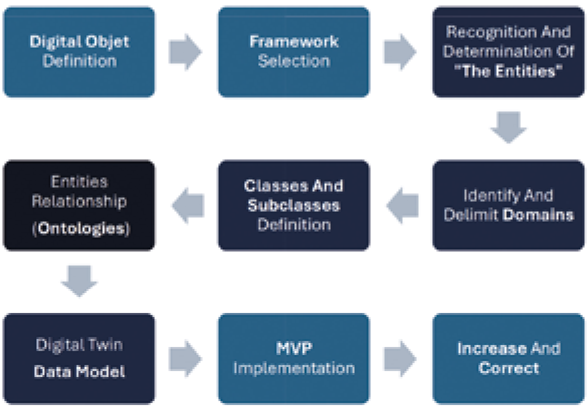
Research Objective:

- Presents the minimum steps to Develop Comprehensive Ontology:
  - Optimize Decision-Making: Predict risks, improve safety and reliability.
  - Facilitate Real-Time Data Use: Utilize digital twin for operational efficiency.

Methodology:

- Structured Development: Systematic approach from ground up.
- Iterative Validation: Continuously refine, ensuring applicability and effectiveness.

9-Phase Process to Build Digital Twin



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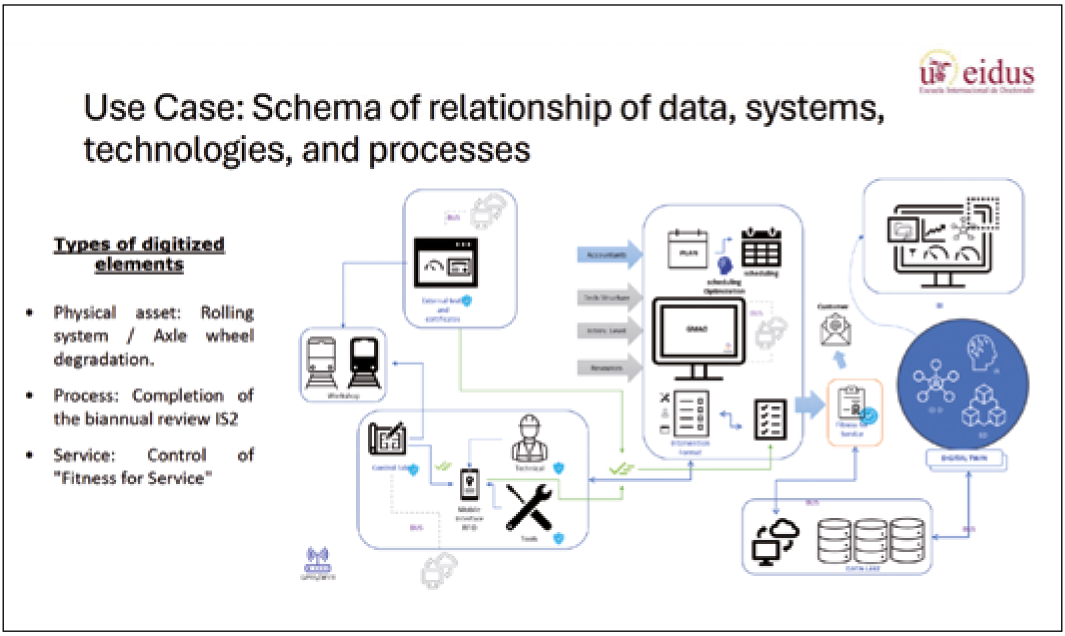
9-Phase Process to Build Digital Twin

Phase	Title	Objective	Approach/Details
1	Digital Object Definition	Define digital assets with a clear business focus.	Define the purpose and scope of digital representations.
2	Context of Digitalization	Choose an appropriate management framework.	Focus on asset management frameworks for corporate goals.
3	Relevant Entities Identification	Clearly identify each entity involved.	Use hierarchical attributes to fully characterize assets.
4	Domain Identification	Establish domains for entity inclusion.	Identify contexts as domains, ensuring comprehensive inclusion.
5	Class Identification	Classify entities to define diverse attributes.	Use ontology modeling to describe heterogeneous attributes.
6	Unitary Rules – Entity Relationships	Define how entities interact and relate.	Establish critical rules for asset maintenance and management.
7	Digital Twin Data Model	Integrate lifecycle data for each asset.	Employ both engineering and data-driven models.
8	MVP Development	Develop and refine prototypes.	Create small-scale models to evaluate success and minimize risks.
9	Continuous Improvement	Enhance and recalibrate the digital twin.	Use the DMM framework to close the improvement loop.

Use Case: Mandatory Inspections Rolling Stock (Depot) Object definitions elements

Business objectives	Functions / Objects	Description	RAMI 4.0 Layers	IIRA Layers
Digitization of "Suitability for Service"	Asset control	Real time control of location, situation, status and certification of machines and components. Asset KPIs	Business	Business view point
	Workshop control	Real-time control of workshop processes and their resources	Business	Usage view point
	Client interface	Client access to fundamental data of the contracted service	Business	Usage view point
	Fitness for service control and traceability	Certificate control and traceability of regulated/mandatory maintenance tasks	Business	Usage view point
Maintenance optimization	Degradation prediction	Flange degradation prediction based on measured data and recorded machine operation data by GPS	Functional	Usage view point
	Scheduling and planning optimization	Optimization of the scheduling of preventive tasks (dynamic preventive maintenance) Tasks and frequencies that can be modified.	Functional	Usage view point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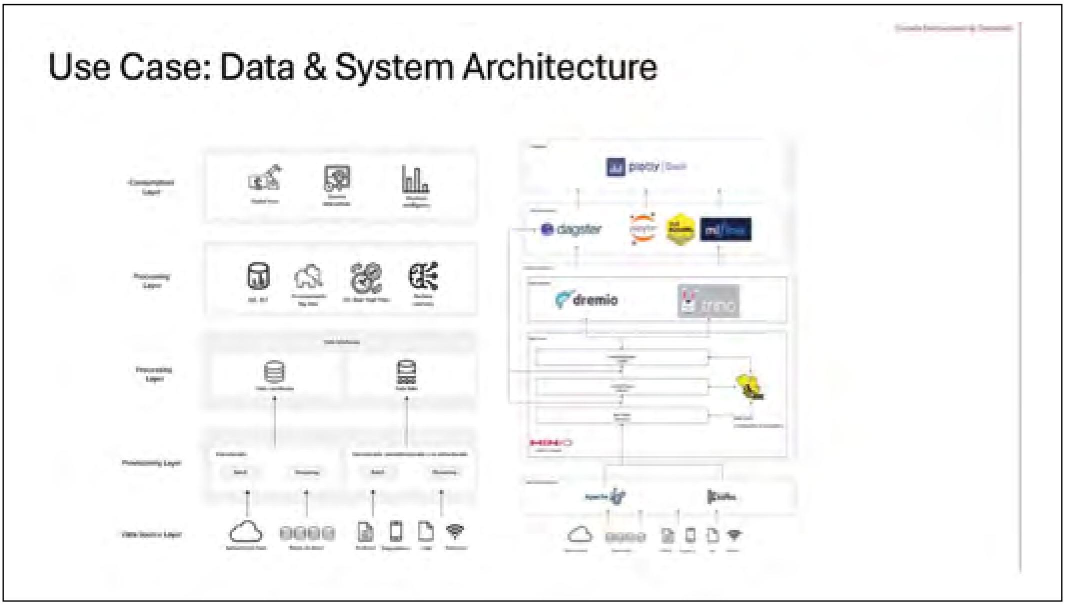
Use Case: Schema of relationship of data, systems, technologies, and processes
Types of digitized elements
• Physical asset: Rolling system / Axle wheel degradation.
• Process: Completion of the biannual review IS2
• Service: Control of "Fitness for Service"


Use Case: Data & System Architecture
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Use Caser: Ontology and data Model Schematic Overview

Conclutions

- Established a nine-phase digital twin framework for railway maintenance within Industry 4.0.
- Advanced railway maintenance ontologies by integrating complex systems with practical knowledge.
- Highlighted interdisciplinary collaboration crucial for aligning technical and business efforts in digital projects.
- Demonstrated practical implementation showing digital twins optimize maintenance and improve inspection processes.
- Outlined future research opportunities to further develop digital twin technologies and encourage industry-wide innovation.


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A Review of Hybrid Prognostics Applications for Power & Energy Systems

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Abstract

Prognostics is the ability to acquire knowledge about events before they occur. In industrial settings, prognostics primarily revolves around predicting the remaining useful life (RUL) of assets. Data-driven (DD) prognostics models capture complex fault-to-failure dynamics but lack of explicability in predictions. Physics-based models make use of physics-of-failure models to predict RUL, albeit at the expense of reduced accuracy compared to DD models. In this context, hybrid prognostics models combine both data-driven and physics-based approaches to enhance accuracy and explicability of results. This paper reviews authors' experience in the development of hybrid prognostics solutions applied to power and energy assets.

1. Introduction

The reliable operation of power assets is crucial to ensure the efficiency of the power grid. However, emerging issues, such as intermittent renewable energy dependencies on weather conditions, fast-switching operation dynamics, and the ever-dominant power-electronics reliability, complicates the efficient and reliable operation power equipment.

Prognostics and health management (PHM) is a health management paradigm, which encompasses different predictive applications for an improved reliability management of engineering systems. PHM is at the hearth of condition monitoring technology, where datasets and engineering knowledge cooperate to develop anomaly detection, diagnostics, and prognostics solutions. Failure prognostics aims to predict the

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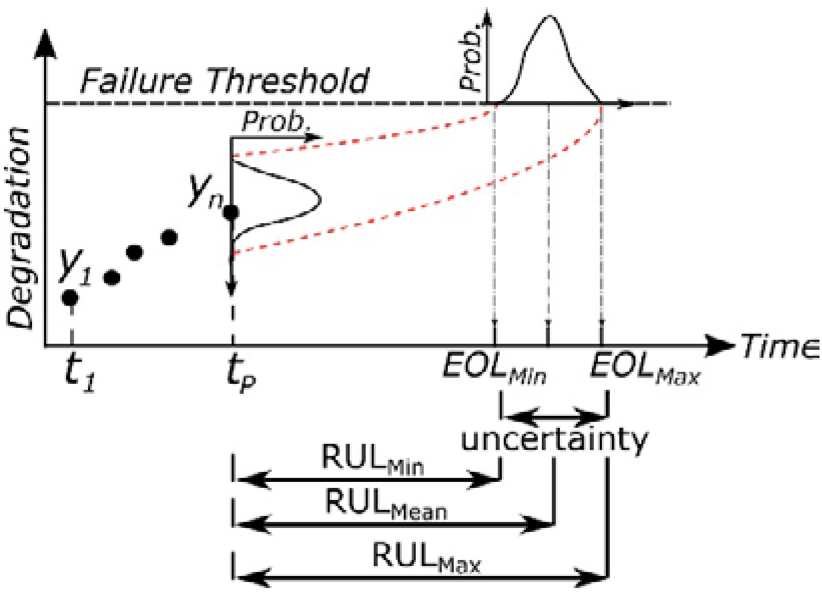
remaining useful life (RUL) of assets to assist asset-management teams in condition-based monitoring and maintenance activities and is the focus of this review. As shown in figure 1 this is achieved through the identification and modelling of system stressors from the initial time instant, t_1, up to the prediction time instant, t_p, $\{y_1, \ldots, y_p\}$, and their influence on the component or system health. Diagnostics tasks focus on current health-state estimation, *i.e*. at the instant t_p and prognostics focuses on future RUL estimation based on hypothetical likely stress trajectories and end-of-life (EOL) criteria.

Figure 1

RUL concept [1]



The RUL estimation focuses on the quantification of future operation and degradation trajectories, and therefore, it should be determined including uncertainty estimates. The RUL specification including uncertainties can be performed with the probability density function (PDF). From the PDF of the RUL, it is possible to infer different statistics, such as mean, maximum and minimum RUL values.

Hybrid prognostics methodologies are gaining momentum owing to their ability to model physics-based ageing phenomena along with data-driven operation and degradation trajectories [2]. Compared with classical data-driven prognostics methods, their main advantage is the ability to provide reliable prognostics estimates regulated by physics laws. Accordingly, in this paper a brief review of the authors' experience is provided in the application of hybrid prognostics methodologies for power asset prognostics.

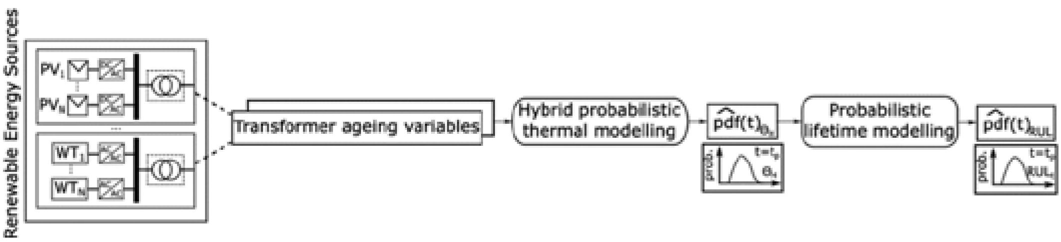
2. **Hybrid Error-Correction for Power Transformer Prognostics**

Transformers are key components for the safe and reliable operation of power grids. The degradation mechanisms of transformer subsystems are complex, surrounded by uncertainty, and in some cases, not directly measurable. This is the case of the insulation degradation, which is one of the major transformer failure causes. The main factor that affects insulation degradation is the hottest-spot temperature (HST), θ_H. The transformer insulation heat is distributed over different surface areas, and this complicates the HST estimation process. Accordingly, it is generally indirectly estimated from top-oil measurements, θ_{TO}.

In this context, as shown in Figure 2, a hybrid transformer prognostics model has been proposed [2]. The approach starts from the *hybrid probabilistic thermal modelling* stage. The hybrid model integrates physics-based and probabilistic forecasting models adapted for transformers operated in renewable energy applications. This is achieved through the integration of a thermal model with probabilistic forecasting models in an error-correction configuration. For the probabilistic lifetime estimation, the approach is subsequently embedded in a *probabilistic lifetime estimation* framework to integrate the hybrid forecasting estimates within the lifetime model and propagate associated uncertainties. The integration of uncertainty enables to design a prognostics approach which provides uncertainty bounds according to the model confidence.

Figure 2

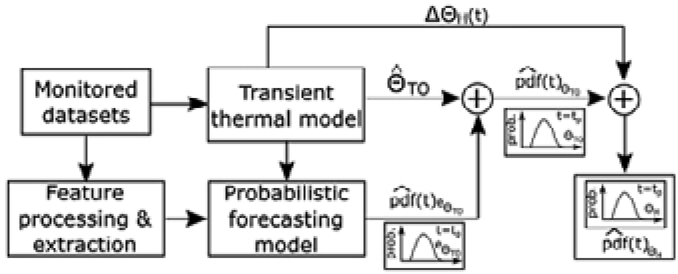
Hybrid transformer prognostics framework [2]



As shown in figure 3, the hybrid probabilistic thermal model focuses on the integration of probabilistic error forecasting model, $\widehat{pdf_{e\theta\tau o}}$, with the IEC 60076-7 standard-based transient thermal model. The standard defines a simplified physics-based model for transformer thermal modelling.

Figure 3

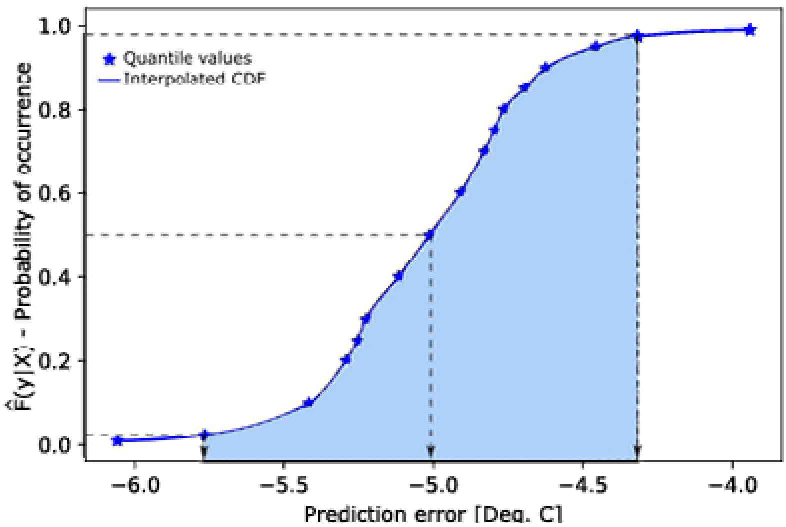
Error-correction configuration [2]



The design of the error correction model is based on probabilistic forecasting strategies. Namely, a set of models are designed including lagged TOT influential variables, such as oil time constant and cross-correlation delayed variables, and the best model is selected based on the Continuously Ranked Probability Score, which is an error metric for PDFs [2]. A probabilistic error forecasting example is shown in Figure 4, with probability of occurrence values associated with different prediction values.

Figure 4

Probabilistic error forecasting result example [2]



After selecting the most accurate error forecasting model, accurate HST predictions are obtained, specified as full PDFs. The HST predictions are then connected to the transformer lifetime equation model, which models the loss-of-life during an operation period T, $LoL_{T_T}(T)$ defined as follows [2]:

$$LoL_{T_T}(T) = \sum_{i=1}^{T} \upsilon(t_i)\Delta t \tag{1}$$

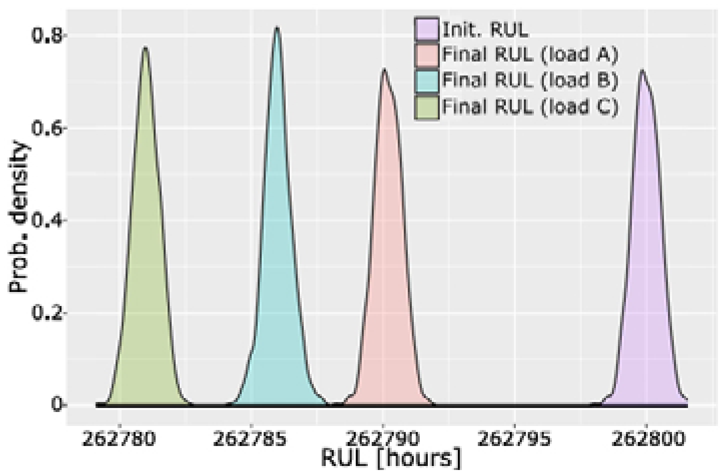
$$\upsilon(t) = 2^{(98-\Phi_H(t))/6} \tag{2}$$

where Δt is the sampling rate, $\upsilon(t)$ is the ageing rate, and θ_H is the transformer HST given in Kelvin [K].

To integrate different sources of uncertainty the transformer lifetime model is framed within a Particle Filtering approach, which integrates measurement and process noise and enables the RUL estimation under uncertainty. The proposed approach is tested and validated with monitored data of a distribution transformer operating on a floating solar power plant. Figure 5 shows obtained RUL prediction examples for different loading profiles.

Figure 5

RUL prediction for different generation loads [2]



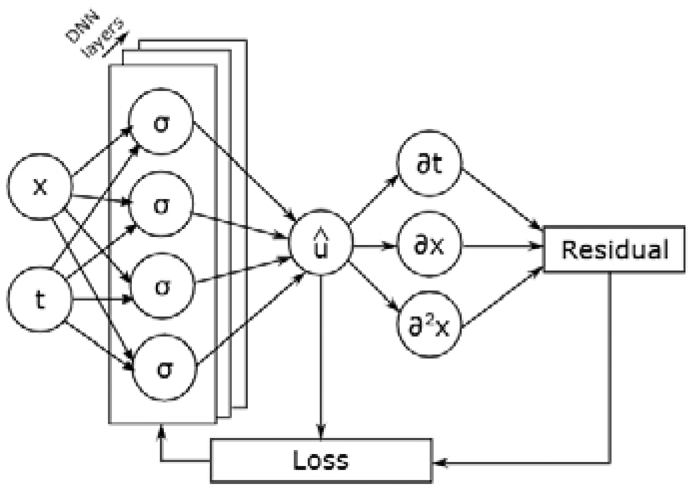
The paper informs asset-management teams on how they can improve transformer lifetime prediction practice by accurately considering uncertainty and fast-switching events coming from renewable energy sources [2].

3. Physics Informed Neural Networks for Transformer Prognostics

Physics informed neural networks (PINNs) were introduced by the seminal work by Raissi *et. al*. [3]. PINNs regulate the learning of the architecture of the Neural Network (NN) through a physics-based equation, instead of a data-driven loss function as in classical NN architectures. The PINN concept is shown in figure 6, where x and t are spatiotemporal inputs, which are processed through neurons in different layers. The outcome of the net, $\hat{u}$, is differentiated with respect to time and space, and finally, the residual function is defined which integrates previous derivatives and the prediction of the net, according to a partial differential equation (PDE).

Figure 6

PINN general architecture example [4]



The loss function integrates the residual along with initial and boundary conditions and this is used to regulate the weight and bias of the NNs. Training PINNs is a challenging process. Training points include residual points (N_r), initial conditions (N_0), boundary condition values (N_c). If available, measurements may be used to guide the training process and validate the obtained results.

For power transformers, the heating process can be modelled through basic heat-diffusion model [4]:

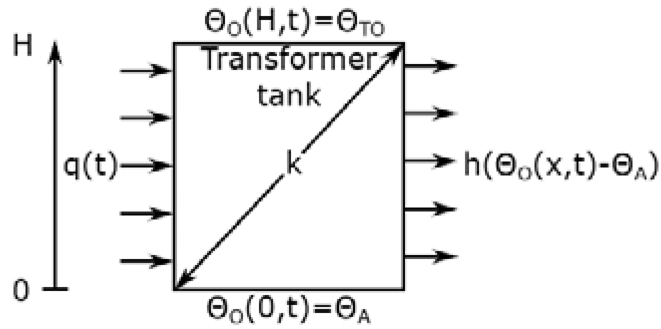
$$k\frac{\partial^2 \Theta_0}{\partial x^2} + q = \rho c_p \frac{\partial \Theta_0}{\partial t} \Rightarrow \frac{\partial^2 \Theta_0}{\partial x^2} + \frac{q}{k} = \frac{1}{\alpha}\frac{\partial \Theta_0}{\partial t} \tag{3}$$

where θ_{TO} is given in Kelvin [K], k is the thermal conductivity [W/m.K], c_p is the specific heat capacity [J/kg.K], ρ is the density [kg/m^3], q is the rate of heat generation [W/m^3], and α is the thermal diffusivity [m^2/s].

Figure 7 shows the thermal parameters of the heat-diffusion equation model, considering a uniform heat source, $q(t)$ and convective heat transfer, and boundary conditions, *i.e*. ambient temperature at the bottom of the tank and top oil at the top of the top of the tank.

Figure 7

Transformer heat diffusion model [4]



The loss function can be accordingly modelled as:

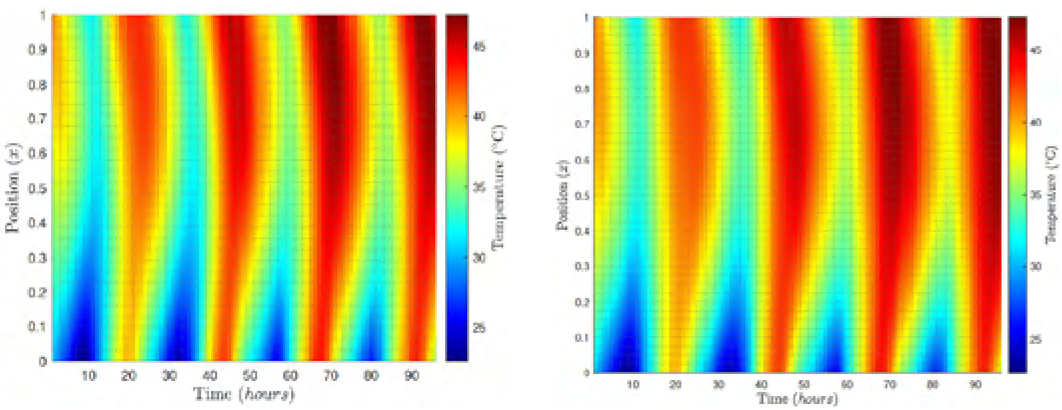
$$Loss = MSE_{\Theta_0} + MSE_{P_k} + MSE_{\Theta_A} + \lambda_r MSE_r \tag{4}$$

where the residual point is evaluated through minimization of the residual, and the rest of variables are minimised with respect to measured values.

The PINN transformer model is accordingly applied to the case study introduced in [4]. In order to validate the solution, firstly PDE is solved using numerical solvers, and PINN results are compared with PDE solver results as shown in figure 8.

Figure 8

Spatio-temporal transformer oil estimation via PDE (left) and PINN (right) [4]



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Subsequently, after validating the obtained PINN model, it is possible to couple the PINN model with the lifetime estimation model in Eq. (1) to estimate the lifetime.

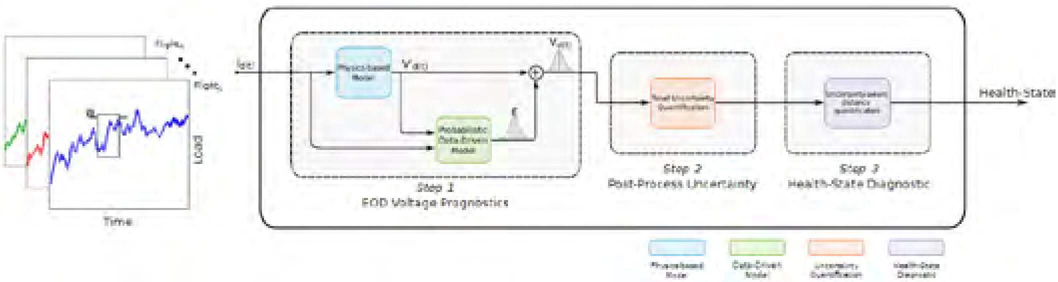
4. Hybrid Probabilistic Error-Correction for Drone Battery Prognostics

Health monitoring of remote critical infrastructure is a complex and expensive activity due to the limited infrastructure accessibility. Inspection drones are ubiquitous assets that enhance the reliability of critical infrastructures through improved accessibility. However, due to the harsh operation environment, it is crucial to monitor their health to ensure successful inspection operations.

The battery is a key component that determines the overall reliability of the inspection drones and, with an appropriate health management approach, contributes to reliable and robust inspections. In this context, as shown in figure 9, a hybrid probabilistic approach for battery end-of-discharge (EOD) voltage prediction of Li-Po batteries has been proposed [5]. The hybridization is achieved in an error-correction configuration, which combines physics-based discharge and probabilistic error-correction models to quantify the aleatoric and epistemic uncertainty.

Figure 9

Uncertainty-aware battery health management approach [5]

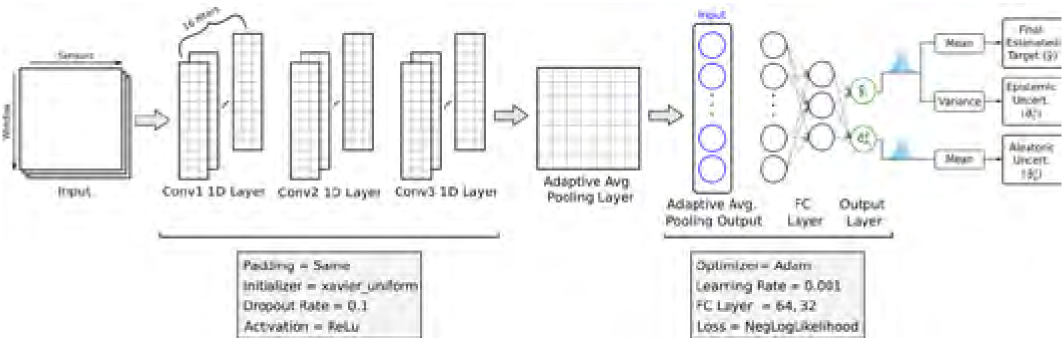


For the error-correction stage, a probabilistic Convolutional Neural Network (CNN) has been developed due to its feature extraction and uncertainty estimation capability. Identifying and quantifying uncertainty in drone operations is crucial. Aleatoric uncertainty increases due to the inherent randomness within the system, such as wind variability, sensor errors, and diverse operational conditions. Conversely, epistemic uncertainty arises from a lack of knowledge, including modelling errors. Therefore, distinguishing between these types of uncertainties is essential for effective decision-making, as it enables operators to mitigate risks associated with uncertain information.

The use of CNN with Monte Carlo dropout demonstrates that integrating dropout during both training and testing phases, significantly improves the robustness of CNNs providing a more comprehensive probabilistic interpretation of model predictions [6]. The structure of the proposed CNN based error-correction model is shown in figure 10.

Figure 10

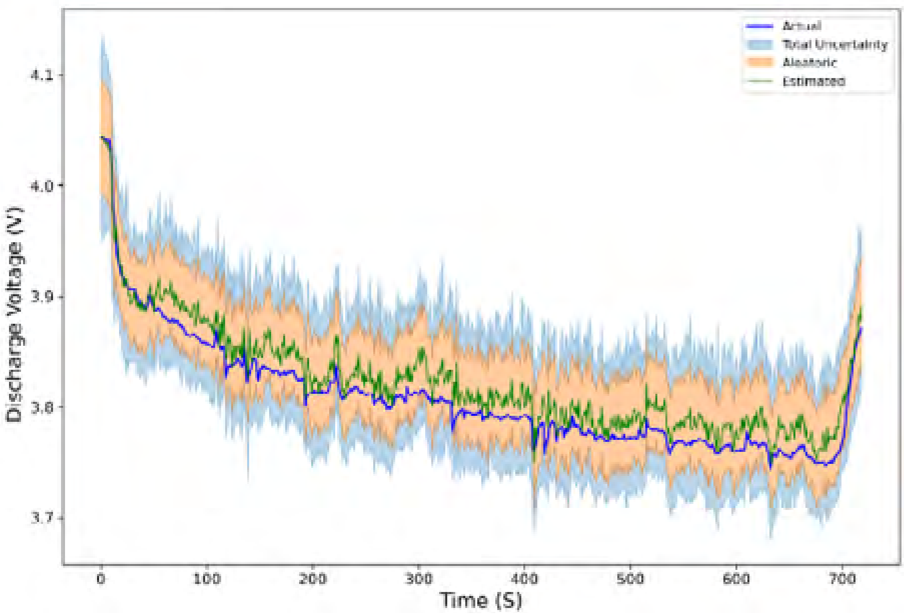
Structure of the proposed uncertainty-aware CNN architecture [5]



Based on the prediction error, figure 11 shows the complete voltage drop of a single-cell battery with the associated uncertainty for a real inspection drone flight. It clearly differentiates between two sources of uncertainty, enhancing the accuracy of the predictive probability.

Figure 11

Estimation of EOD Voltage of a battery cell in a drone flight using CNN MC dropout [5]



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The proposed approach has been tested with different probabilistic methods (QLR, QRF and QGB) and demonstrates 14.8% improved performance in probabilistic accuracy compared to the best probabilistic method (QGB). In addition, aleatoric and epistemic uncertainties provide robust estimations to enhance the diagnosis of battery health-states.

5. Conclusions

Hybrid configurations are gaining momentum in the prognostics and health management arena owing to the improved prediction accuracy and interpretation of the model and obtained results. Focusing on prognostics models, this paper reviews authors' experience in the development of hybrid prognostics solutions for different power assets.

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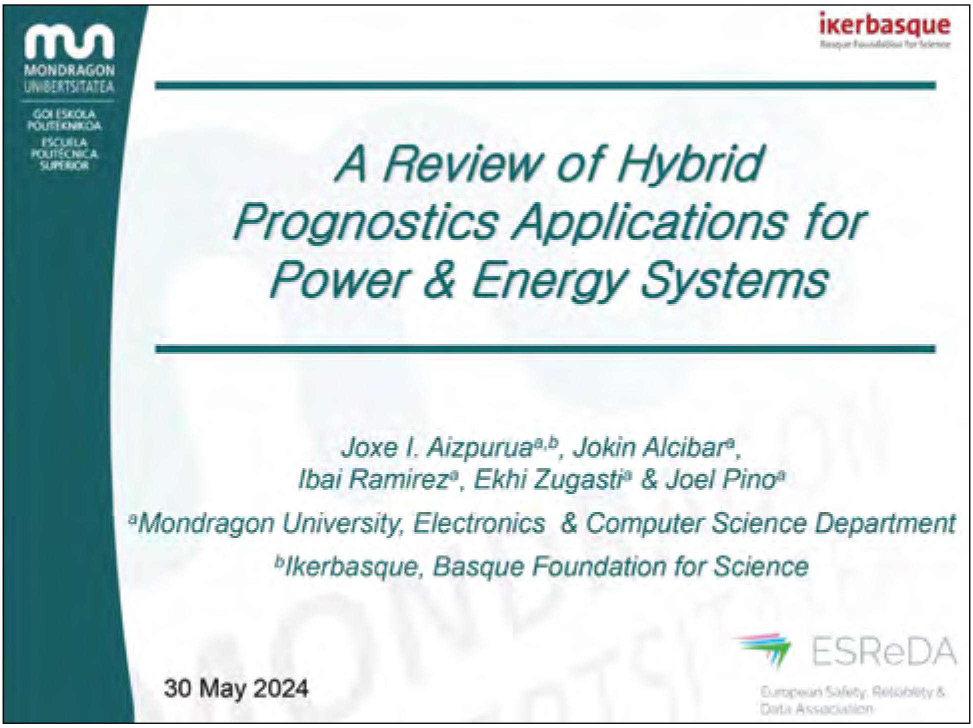
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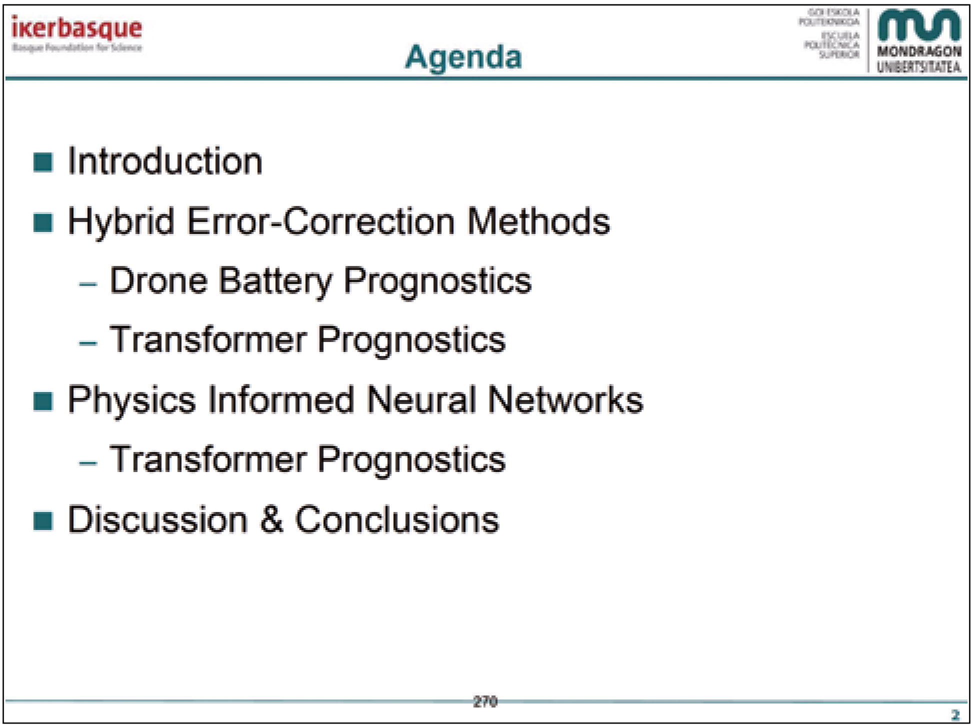
A Review of Hybrid Prognostics Applications for Power & Energy Systems
Joxe I. Aizpurua[a,b], Jokin Alcibar[a],
Ibai Ramirez[a], Ekhi Zugasti[a] & Joel Pino[a]
[a]Mondragon University, Electronics & Computer Science Department
[b]Ikerbasque, Basque Foundation for Science
ESReDA
30 May 2024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Introduction
Hybrid Error-Correction Methods
– Drone Battery Prognostics
– Transformer Prognostics
Physics Informed Neural Networks
– Transformer Prognostics
Discussion & Conclusions
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- **Introduction**
- Hybrid Error-Correction Methods
  - Drone Battery Prognostics
  - Transformer Prognostics
- Physics Informed Neural Networks
  - Transformer Prognostics
- Discussion & Conclusions

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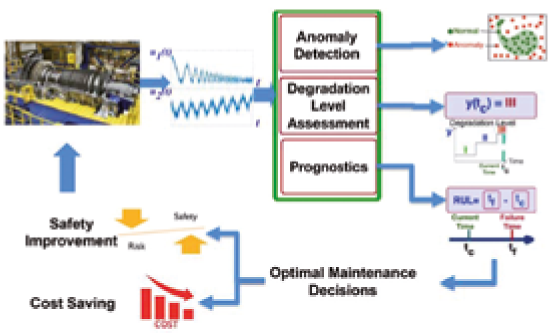
Introduction

- Prognostics & Health Management
  - Anomaly Detection
  - Diagnostics
  - **Prognostics**
  - Maintenance Planning



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Introduction

- Prognostics ("prog" + "gnosis")
- Ability to acquire knowledge of events before they occur

- Failure prognostics → Prediction of asset (system) remaining useful life (RUL)
- Modelling of the fault-to-failure progression of the asset (system) under study

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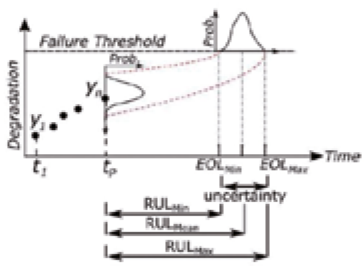
Introduction

- Main prognostics modelling strategies
  - Data-driven approaches: run-to failure data
  - Physics-based approaches: degradation equations, physics-of-failure
  - <u>**Hybrid approaches**</u>



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Introduction

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- Advantages
  - Improved accuracy
  - Out of distribution predictions
  - More robust predictions with less data
  - Uncertainty management
  - …

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Introduction

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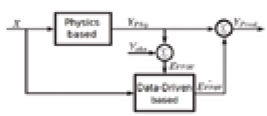
- Possible hybrid configurations
  - Sequential Hybrid

  - Parallel Hybrid
    - ***Error correction***



  - ***Physics Informed Neural Networks (PINNs)***
  - …

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Agenda

- Introduction
- **Hybrid Error-Correction Methods**
  - Drone Battery Prognostics
  - Transformer Prognostics
- Physics Informed Neural Networks
  - Transformer Prognostics
- Discussion & Conclusions

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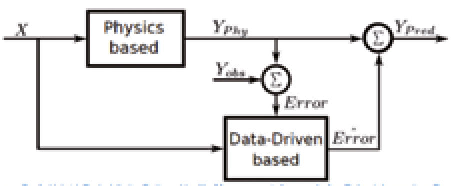
Hybrid Error-Correction Methods

- Correct physics-based model's error through data-driven techniques
- Requires designing an error prediction model for the physics-based model
  - Uncertainty consideration



Aizpurua, J. Aizpurua, JI, Zugasti, E. Penagarikano, O. A Hybrid Probabilistic Battery Health Management Approach for Robust Inspection Drone Operations. arXiv preprint arXiv:2405.00055 2024 Apr/24.

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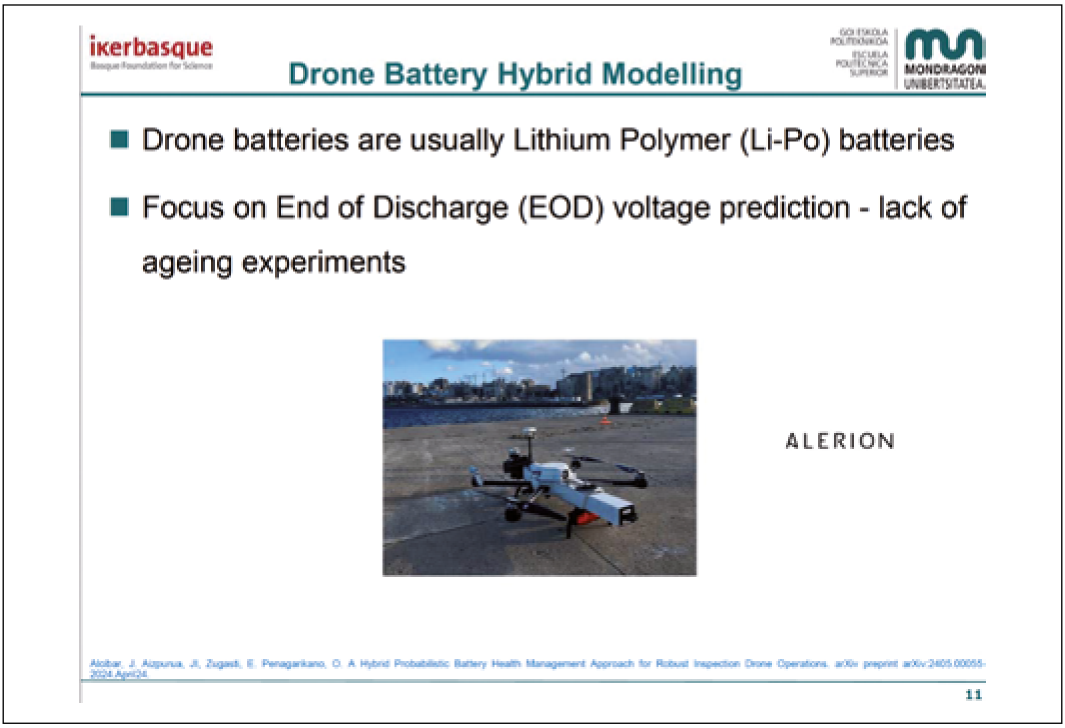
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Drone Battery Hybrid Modelling
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Drone batteries are usually Lithium Polymer (Li-Po) batteries
Focus on End of Discharge (EOD) voltage prediction - lack of ageing experiments
ALERION
Alcibar, J. Aizpurua, JI, Zugasti, E. Penagarikano, O. A Hybrid Probabilistic Battery Health Management Approach for Robust Inspection Drone Operations. arXiv preprint arXiv:2405.00055. 2024 Apr 24.
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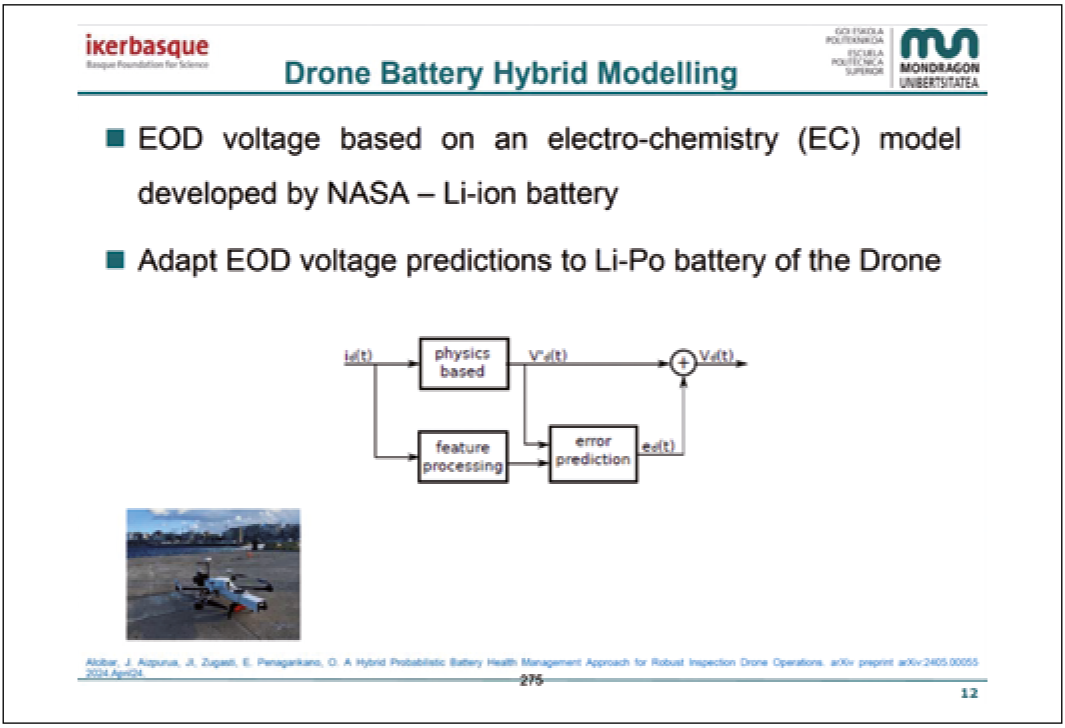
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Drone Battery Hybrid Modelling
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EOD voltage based on an electro-chemistry (EC) model developed by NASA – Li-ion battery
Adapt EOD voltage predictions to Li-Po battery of the Drone
physics based
feature processing
error prediction
Alcibar, J. Aizpurua, JI, Zugasti, E. Penagarikano, O. A Hybrid Probabilistic Battery Health Management Approach for Robust Inspection Drone Operations. arXiv preprint arXiv:2405.00055. 2024 Apr 24.
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Drone Battery Hybrid Modelling

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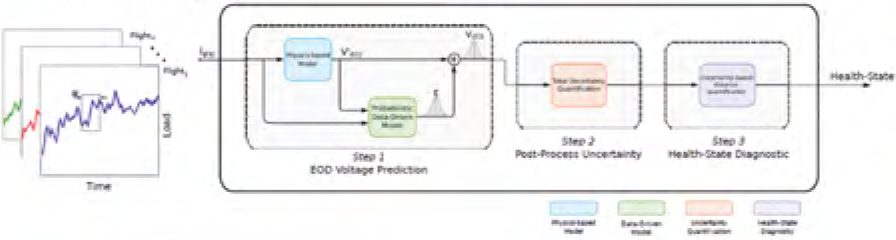
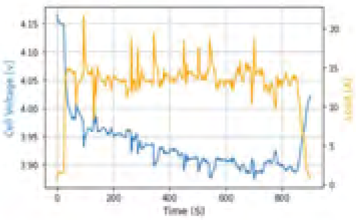
- *Methodology*





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Drone Battery Hybrid Modelling

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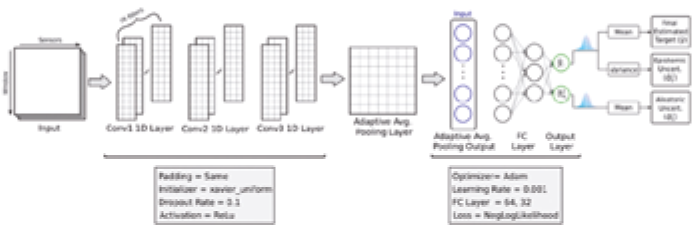
- Probabilistic data-driven error-correction
  - Convolutional Neural Network Monte Carlo dropout
  - Quantile based methods: Quantile Linear Regression (QLR), Quantile Gradient Boosting (QGB), Quantile Random Forest (QRF)



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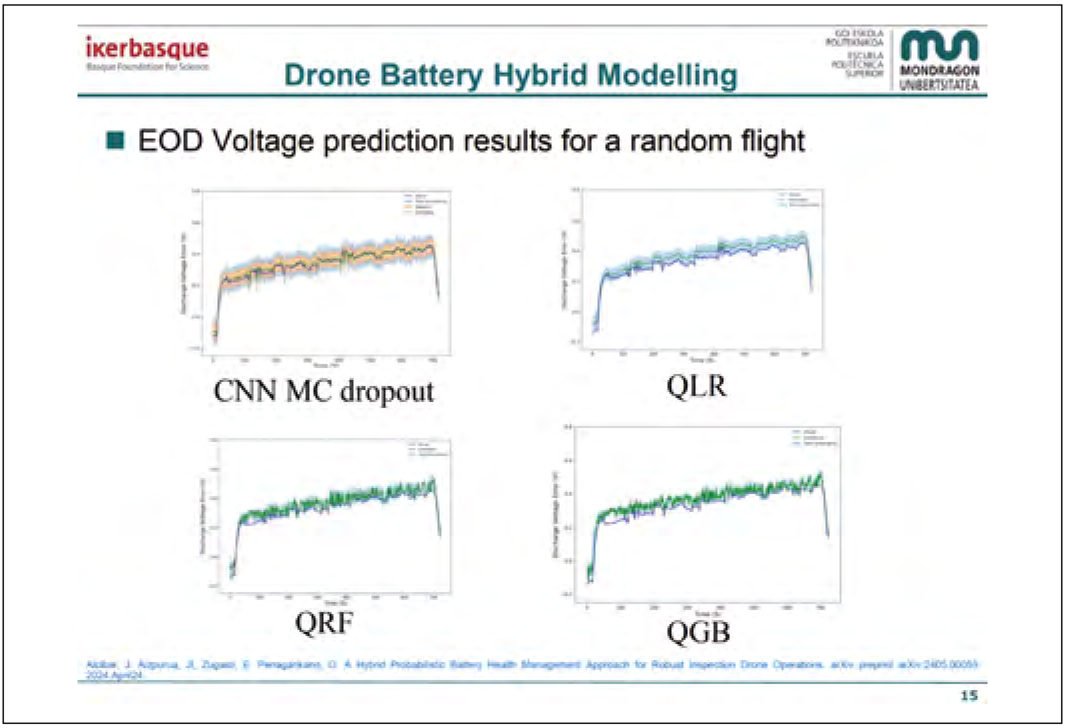
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EOD Voltage prediction results for a random flight
CNN MC dropout
QLR
QRF
QGB
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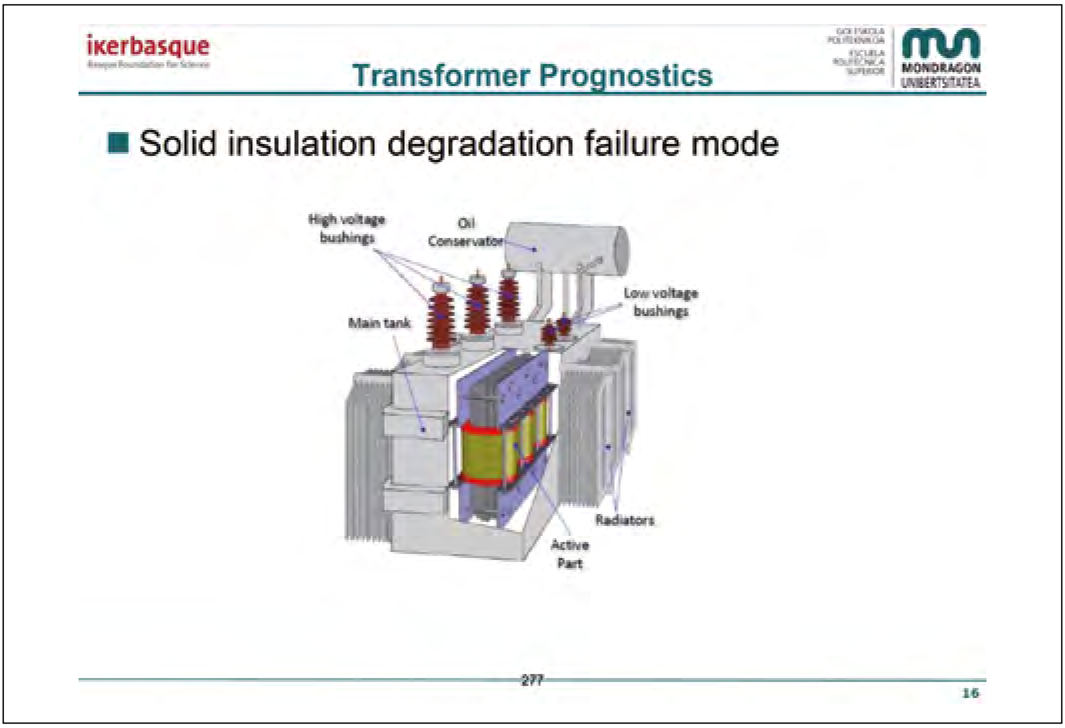
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Solid insulation degradation failure mode
High voltage bushings
Oil Conservator
Low voltage bushings
Main tank
Radiators
Active Part
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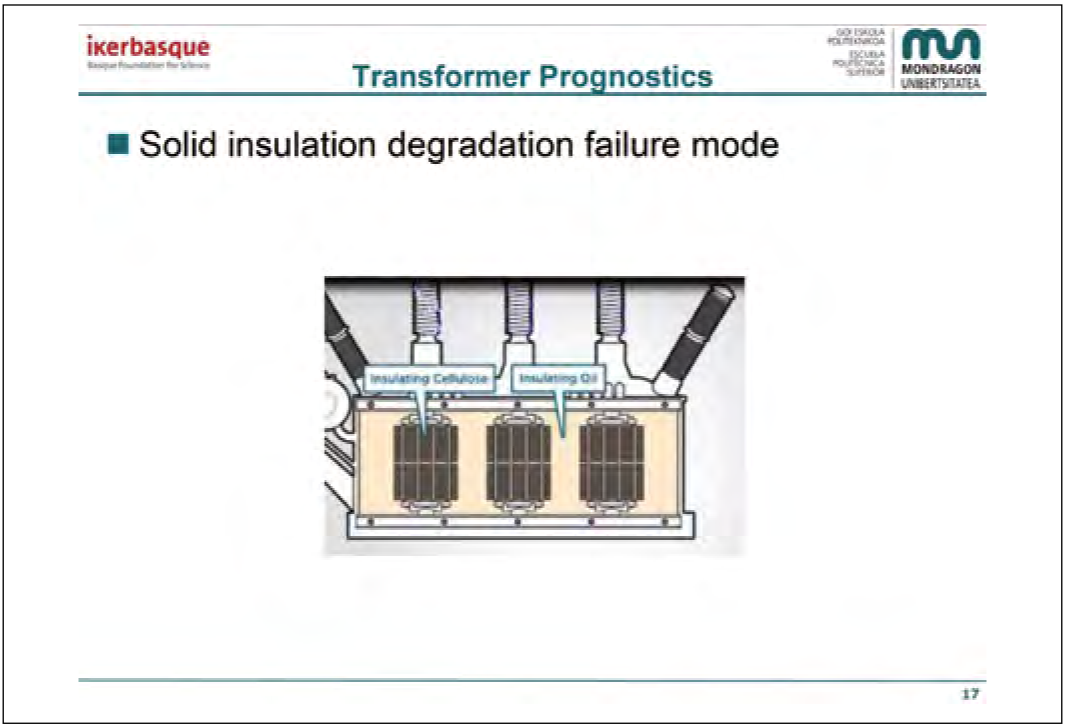
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Solid insulation degradation failure mode
Insulating Cellulose
Insulating Oil
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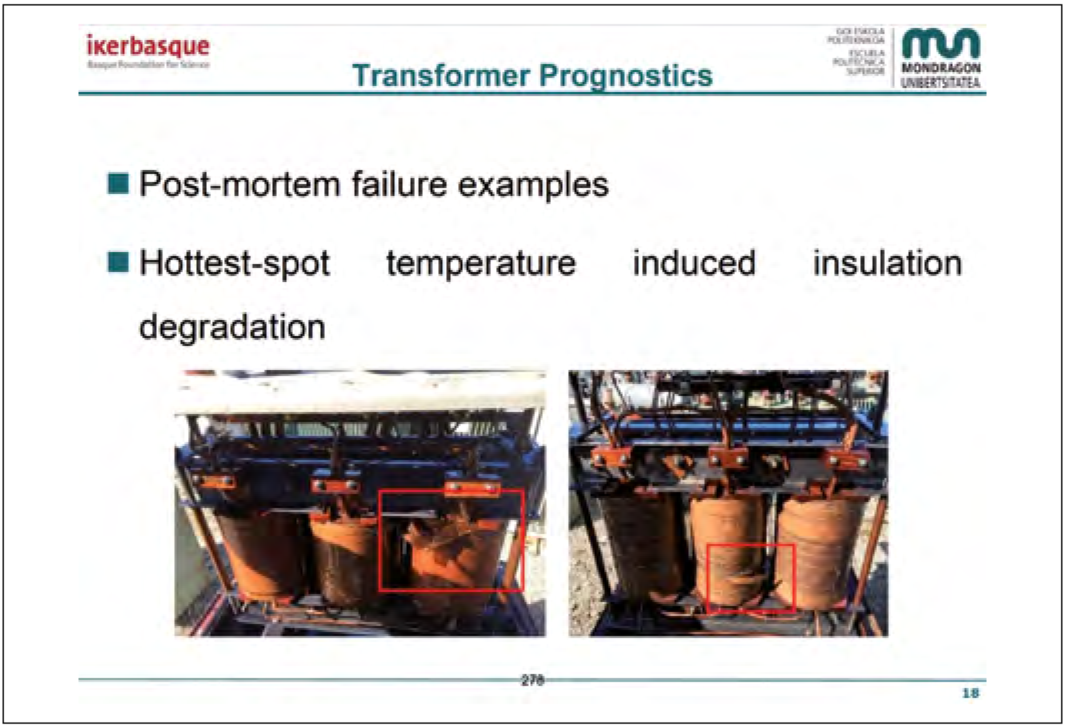
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Post-mortem failure examples
Hottest-spot temperature induced insulation degradation
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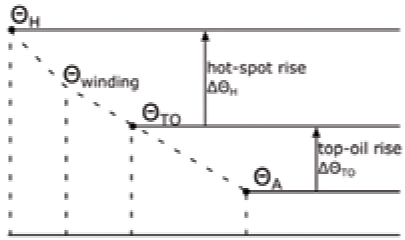
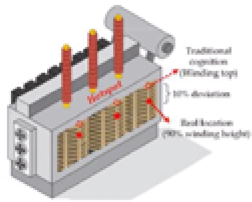
Transformer insulation degradation

- IEEE C57.91 y IEC 60076-7 define the calculation of the hotspot temperature (HST) through thermal time constants





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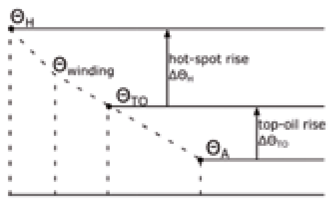
Transformer insulation degradation

- Solid insulation degradation is a function of the hotspot temperature, $\Theta_H(t)$

$$\Theta_H = \Theta_A + \Delta\Theta_{TO} + \Delta\Theta_H$$

where *$\Theta_{TO}(t)$ is the top oil temperature, $\Theta_A(t)$ is the ambient temperature*



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Transformer insulation degradation

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- In the simplest form (steady-state)
- $\Delta\Theta_H(t)$ is a function of transformer design parameters, m, and input load (per unit), K

$$\Delta\Theta_H = \Delta\Theta_{H,R} K_u^{2m}$$

where $\Delta\Theta_{H,R}(t)$ is obtained from heat-run tests done at the design of the transformer

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Transformer insulation degradation

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- Steady-state conditions
- $\Delta\Theta_{TO}(t)$ is a function of transformer design parameters, n, ratio of load losses (R) and input load (per unit), K

$$\Delta\Theta_{TO} = \Delta\Theta_{TO,R}\left(\frac{K^2 R + 1}{R + 1}\right)^n$$

where $\Delta\Theta_{TO,R}(t)$ is obtained from heat-run tests done at the design of the transformer

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Transformer insulation degradation

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- The law of degradation (ageing factor), in a simplified form is defined as follows

$$F_{AA} = e^{\frac{15000}{383} - \frac{15000}{\Theta_H + 273}}$$

- It is a function of the hotspot temperature!
- It can be rearranged as follows

$$L_t = L_{t-1} - e^{\frac{15000}{383} - \frac{15000}{\Theta_H(t) + 273}}$$

where L_t is the lifetime at time instant t

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Transformer insulation degradation

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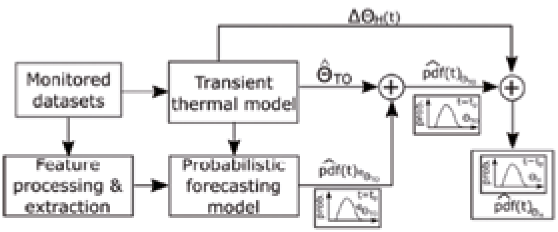
- Hybrid HST estimation model



Aizpurua, J.I, Ramired, I, Lasa, I., del Rio, L, Ortiz, A. and Stewart, B. Hybrid Transformer Prognostics Framework for Enhanced Probabilistic Predictions in Renewable Energy Applications. IEEE Transactions on Power Delivery, 2022, doi: 10.1109/TPWRD.2022.3203873

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Transformer insulation degradation

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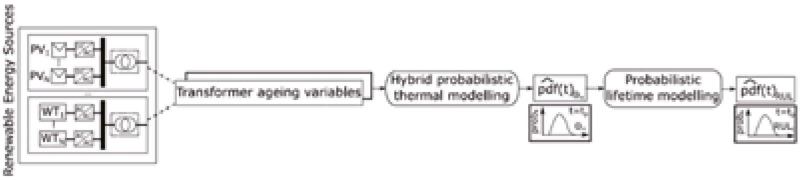
- RUL approach



- Hybrid probabilistic thermal model connected with Particle Filtering for RUL estimation
  - Degradation equation
  - Sources of uncertainty

Aizpurua, J.I, Ramirez, I, Lasa, I., del Rio, L. Ortiz, A. and Stewart, B. Hybrid Transformer Prognosics Framework for Enhanced Probabilistic Predictions in Renewable Energy Applications. IEEE Transactions on Power Delivery, 2022, doi: 10.1109/TPWRD.2022.3203873

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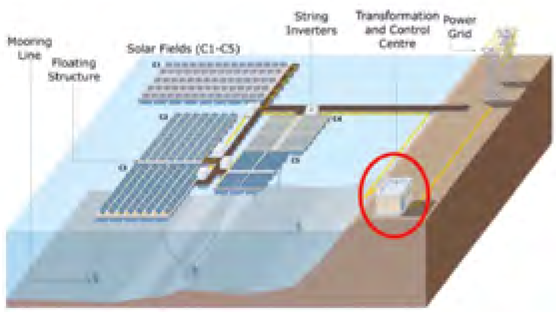
- Floating PV Case Study – Sierra Brava (Caceres, Spain)



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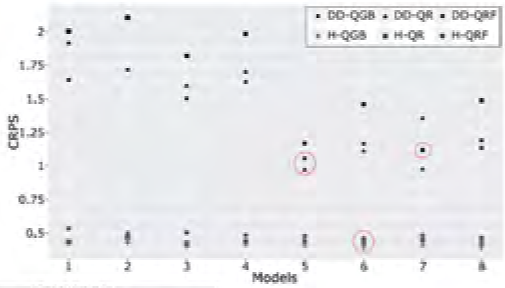
Hybrid Thermal Model



Feature	Model Number							
	1	2	3	4	5	6	7	8
$i(t-1)$	✓	✓	✓	✓	✓	✓	✓	✓
$\theta_A(t-1)$	✓	✓	✓	✓	✓	✓	✓	✓
$R(t)$	✓	✓	✓	✓	✓	✓	✓	✓
$i(t-\tau_{TO})$	✓	✓	✓	✓	✓	✓	✓	✓
$\theta_A(t-\tau_{TO})$	×	×	×	×	✓	✓	✓	✓
$i(t-\tau_X)$	×	✓	×	✓	×	✓	×	✓
$\theta_A(t-\tau_X)$	×	×	✓	✓	×	×	✓	✓

Aizpurua, J.I., Ramirez, I., Lasa, I., del Rio, L., Ortiz, A. and Stewart, B. Hybrid Transformer Prognostics Framework for Enhanced Probabilistic Predictions in Renewable Energy Applications. IEEE Transactions on Power Delivery, 2022. doi: 10.1109/TPWRD.2022.3203873

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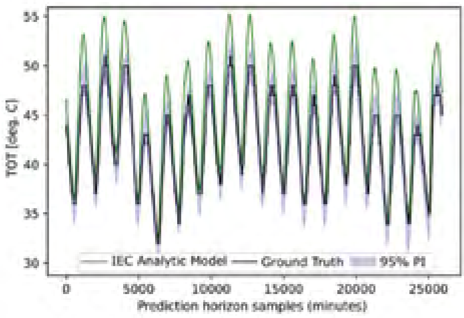
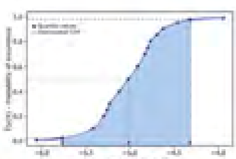
Hybrid Thermal Model





Aizpurua, J.I., Ramirez, I., Lasa, I., del Rio, L., Ortiz, A. and Stewart, B. Hybrid Transformer Prognostics Framework for Enhanced Probabilistic Predictions in Renewable Energy Applications. IEEE Transactions on Power Delivery, 2022. doi: 10.1109/TPWRD.2022.3203873

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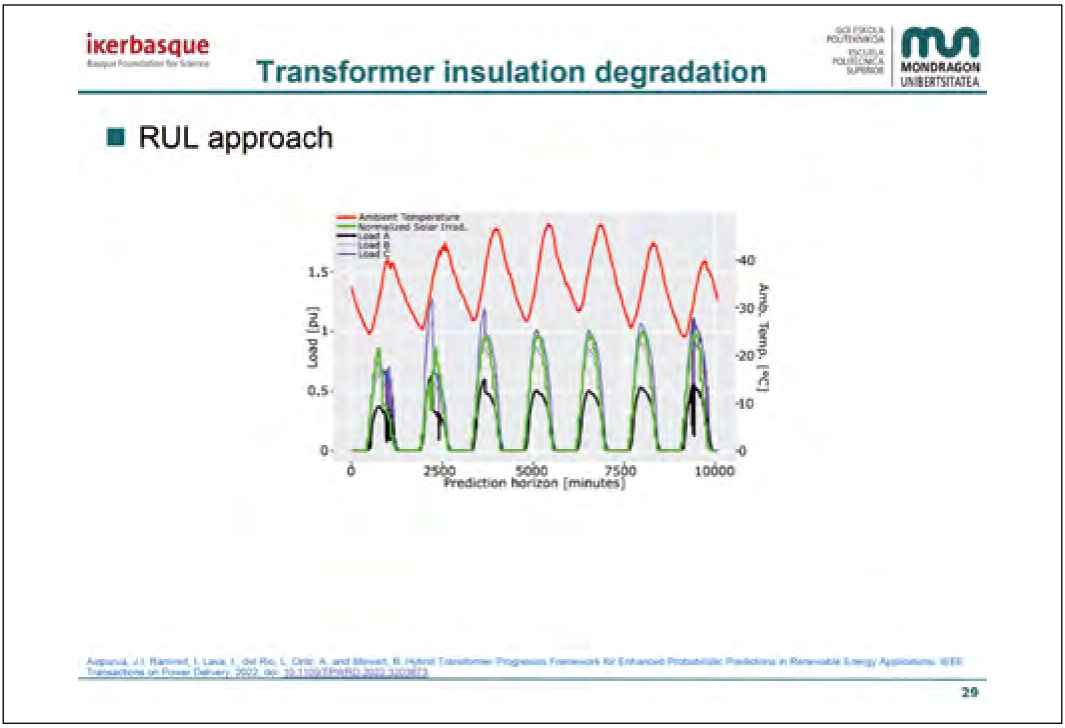
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Transformer insulation degradation
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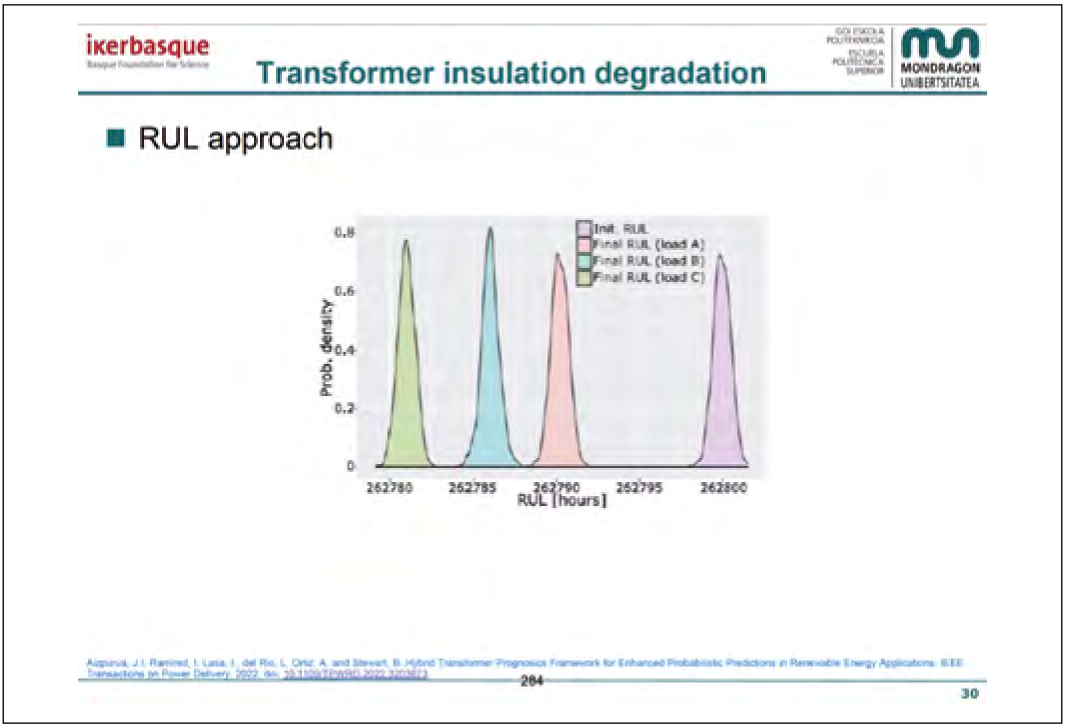
RUL approach
Ambient Temperature
Normalized Solar Irrad.
Load A
Load B
Load C
Load [pu]
Amb. Temp. [ºC]
Prediction horizon [minutes]
29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Transformer insulation degradation
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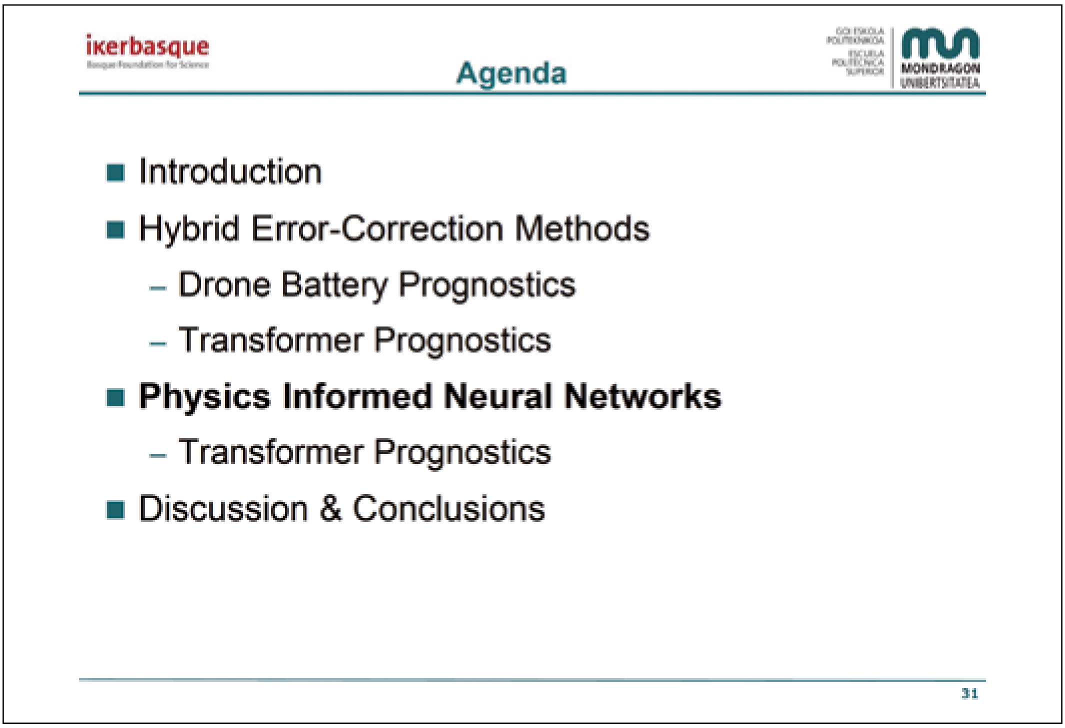
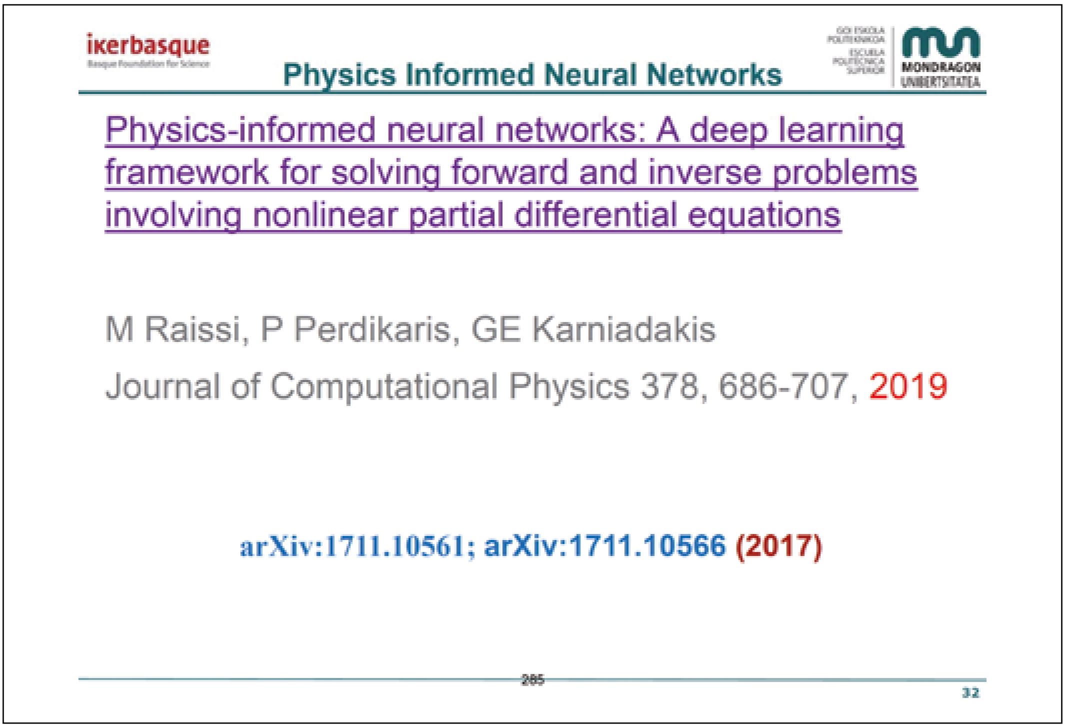
RUL approach
Init. RUL
Final RUL (load A)
Final RUL (load B)
Final RUL (load C)
Prob. density
RUL [hours]
284
30





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Physics Informed Neural Networks

- Embed physics laws and data into the loss function of the Neural Network (NN)
- Update NN architecture in agreement with data and physics laws
- Physics laws defined via Partial Differential Equations (PDEs)

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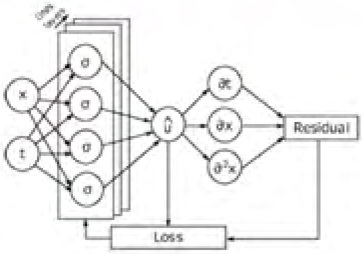
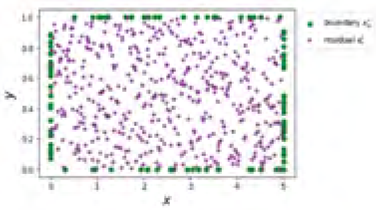
Physics Informed Neural Networks





➢ Minimize:

$$MSE = MSE_u + MSE_f,$$

$$MSE_u = \frac{1}{N_u}\sum_{i=1}^{N_u} |u(t_u^i, x_u^i) - u^i|^2,$$

$$MSE_f = \frac{1}{N_f}\sum_{i=1}^{N_f} |f(t_f^i, x_f^i)|^2.$$

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PINNs for transformers

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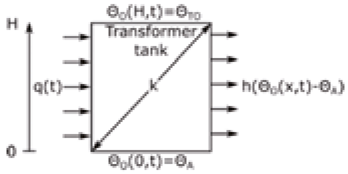
- 1D thermal model – heat diffusion, uniform heat



Where q is the uniform heat source and h is the convection coefficient

$$q(x,t) = P_0 + P_K(t) - h(\Theta_O(x,t) - \Theta_A(t))$$

- The heat diffusion is defined as follows:

Parameter	Description
T	Temperature (K)
k	Thermal conductivity $(W/m \cdot K)$
c_p	Specific heat capacity $(J/kg \cdot K)$
ρ	Density (kg/m^3)
q	Rate of heat generation (W/m^3)
$\alpha = \frac{k}{\rho c_p}$	Thermal diffusivity (m^2/s)

$$k\frac{\partial^2\Theta_O}{\partial x^2} + q = \rho c_p \frac{\partial \Theta_O}{\partial t} \Rightarrow \frac{\partial^2\Theta_O}{\partial x^2} + \frac{q}{k} = \frac{1}{\alpha}\frac{\partial \Theta_O}{\partial t}$$

Ramirez, I. Pino, J. Pardo, D., Sanz, M. del Rio, L., Ortiz, A. Morozovska, K. Aizpurua, J. Residual-based Attention Physics-informed Neural Networks for Spatio-Temporal Ageing Assessment of Transformers Operated in Renewable Power Plants. arXiv preprint arXiv:2405.06443. 2024 May10.

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$$k\frac{\partial^2\Theta_O}{\partial x^2} + q = \rho c_p \frac{\partial \Theta_O}{\partial t} \Rightarrow \frac{\partial^2\Theta_O}{\partial x^2} + \frac{q}{k} = \frac{1}{\alpha}\frac{\partial \Theta_O}{\partial t}$$

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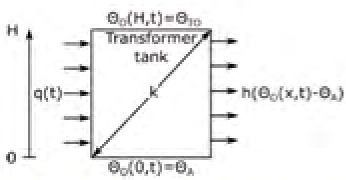
q	Rate of heat generation (W/m^3)
$\alpha = \frac{k}{\rho c_p}$	Thermal diffusivity (m^2/s)

$$\Downarrow$$

$$r = \frac{\rho c_p}{k}\hat{\Theta}_{O_t} - \hat{\Theta}_{O_{xx}} - \frac{1}{k}(P_0 + P_K - h(\hat{\Theta}_O - \Theta_A))$$

$$\Theta_O(0,t) = \Theta_A$$
$$\Theta_O(H,t) = \Theta_{TO}$$



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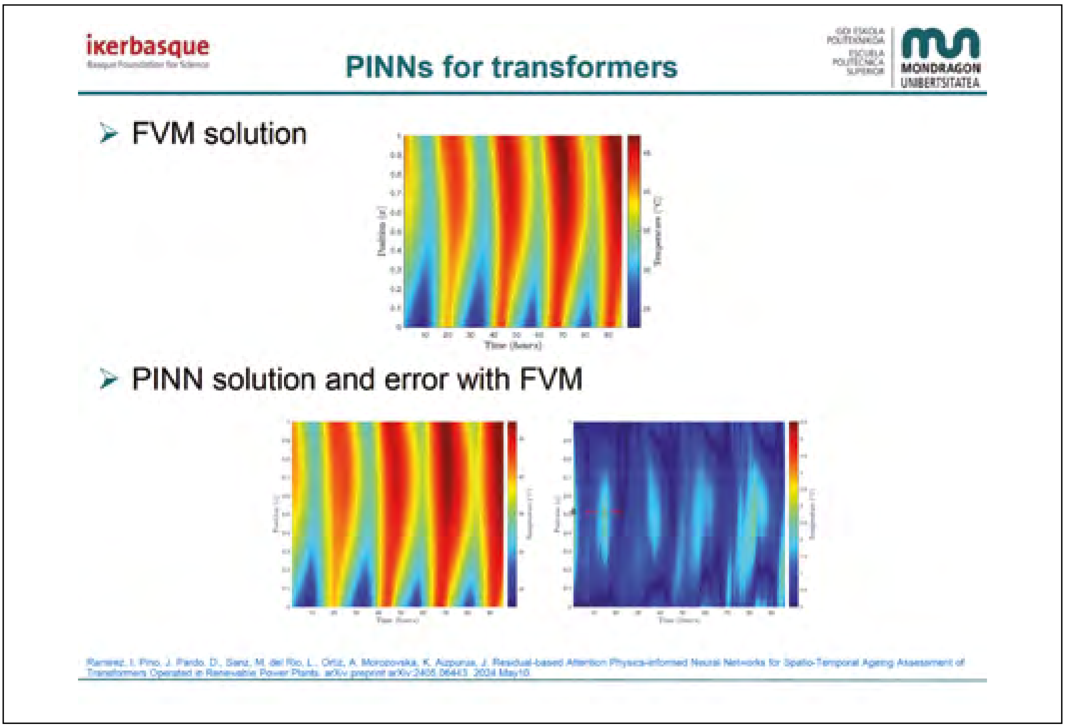
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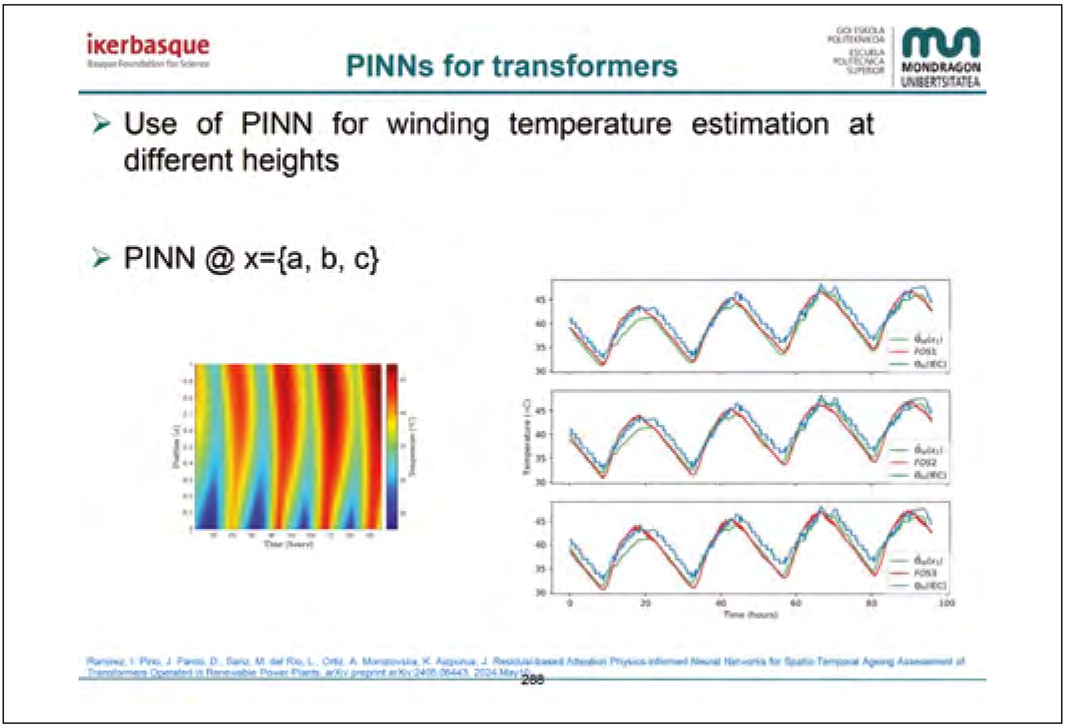
FVM solution
Time (hours)
PINN solution and error with FVM
Ramirez, I. Pino, J. Pardo, D., Sanz, M. del Rio, L., Ortiz, A. Morozovska, K. Aizpurua, J. Residual-based Attention Physics-informed Neural Networks for Spatio-Temporal Ageing Assessment of Transformers Operated in Renewable Power Plants. arXiv preprint arXiv:2405.06443. 2024 May10.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Use of PINN for winding temperature estimation at different heights
PINN @ x={a, b, c}
Time (hours)
FOS1
FOS2
FOS3
Ramirez, I. Pino, J. Pardo, D., Sanz, M. del Rio, L., Ortiz, A. Morozovska, K. Aizpurua, J. Residual-based Attention Physics-informed Neural Networks for Spatio-Temporal Ageing Assessment of Transformers Operated in Renewable Power Plants. arXiv preprint arXiv:2405.06443. 2024 May10.
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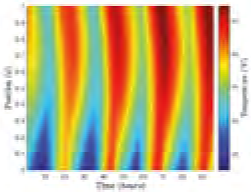
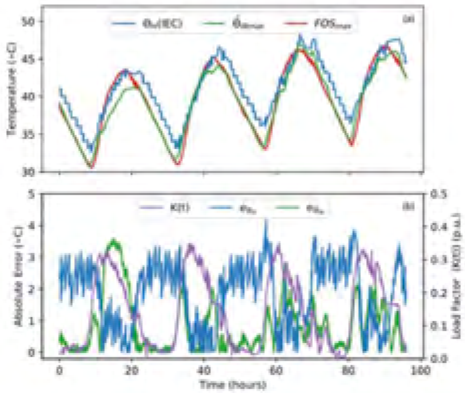
- Use of PINN for maximum temperature estimation at different instants
- Max. PINN temperature





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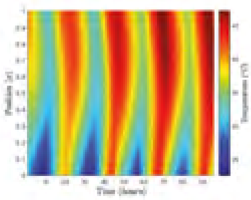
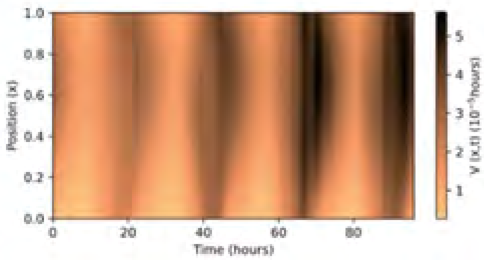
- Spatiotemporal transformer ageing estimation
- PINN + ageing equations





Ramirez, I. Pino, J. Pardo, D., Sanz, M. del Rio, L., Ortiz, A. Morozovska, K. Aizpurua, J. Residual-based Attention Physics-informed Neural Networks for Spatio-Temporal Ageing Assessment of Transformers Operated in Renewable Power Plants. arXiv preprint arXiv:2405.06443. 2024 May10.

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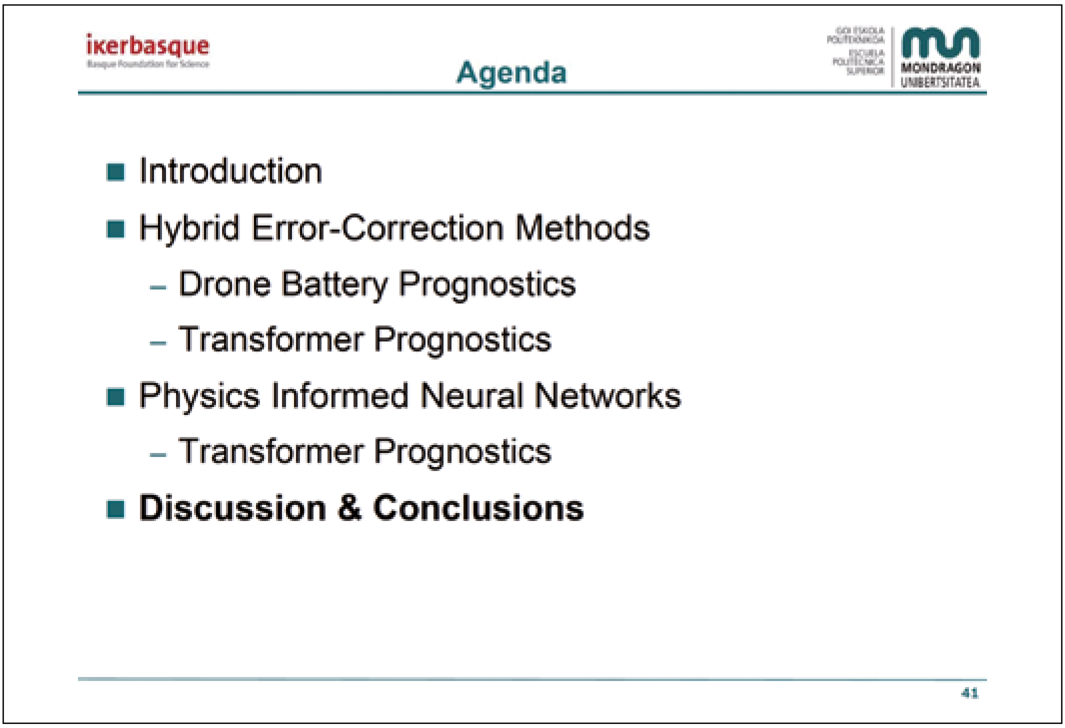

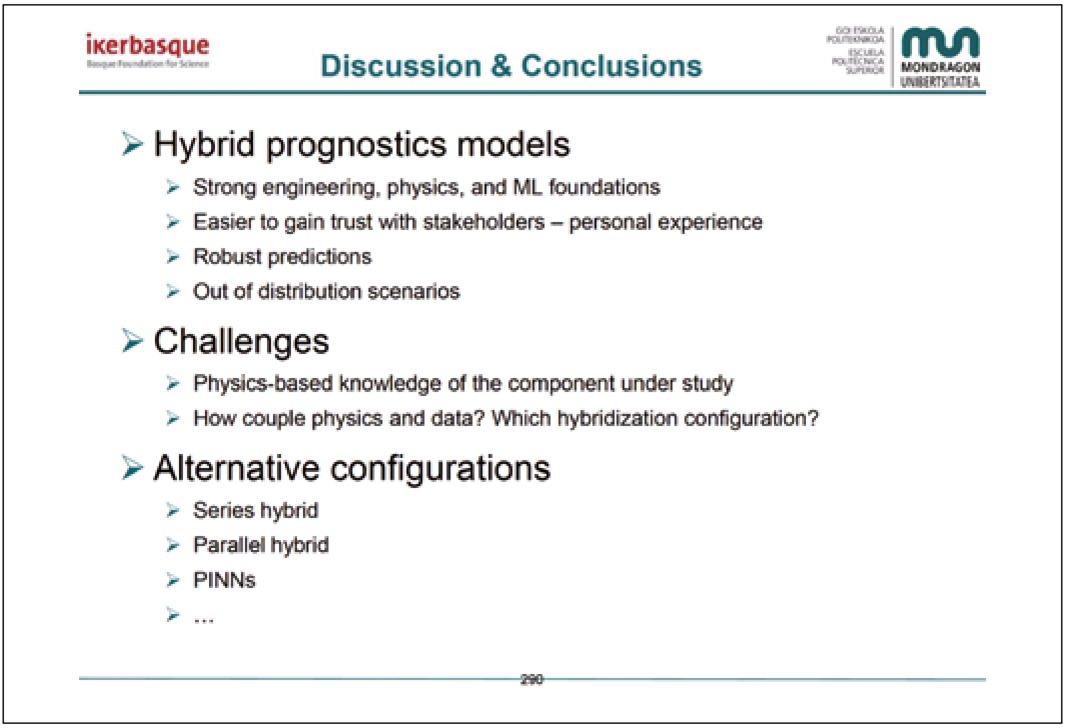

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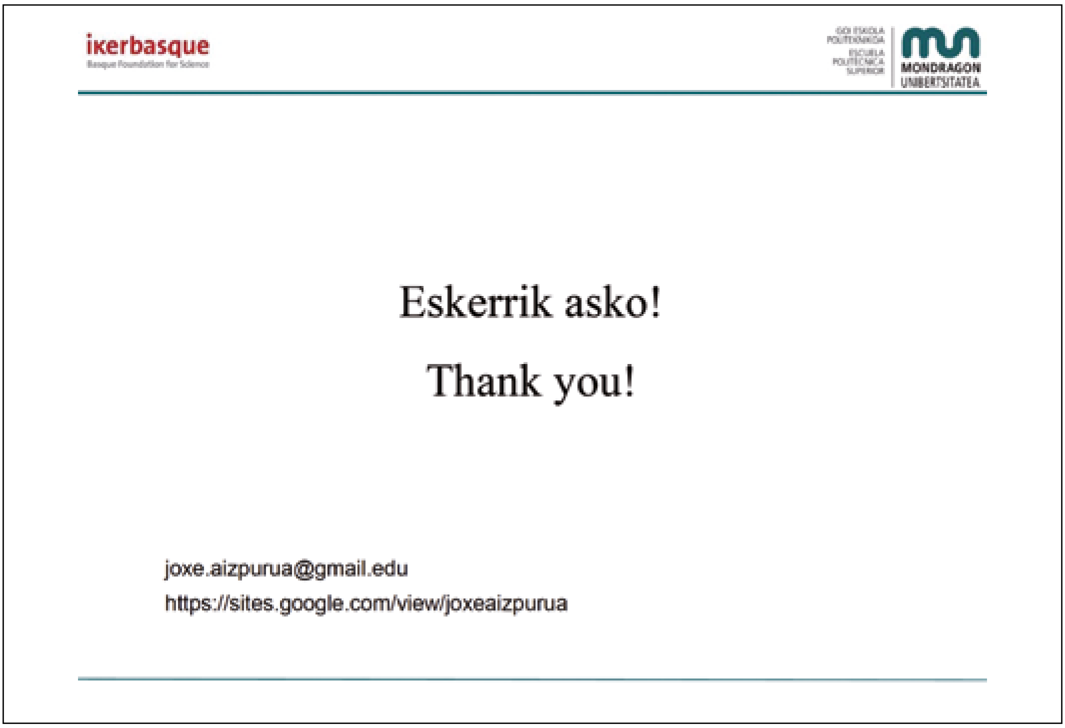
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Eskerrik asko!
Thank you!
joxe.aizpurua@gmail.edu
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Digital Twin-Assisted Predictive Maintenance (DT-PdM) Framework for Complex Systems: Preliminary Research through a Pilot Study

Huxiao Shi, Gabriele Baldissone, Micaela Demichela

Safety, Reliability and Risk centre (SAfeR), Department of Applied Science and Technology, Politecnico di Torino, Turin, Italy

Abstract

Currently, predictive maintenance is already gaining popularity across a wide range of industries due to its ability to forecast system performance and apply dynamic maintenance solutions that provide better outcomes and financial advantages. However, according to the fact that conventional maintenance paradigms continue to be the common solutions, there are some challenges needed to be addressed to broaden the real application of condition-based maintenance. This paper discusses Digital Twin (DT) as a potent tool for advancing and assisting with predictive maintenance (PdM) in engineering domains. The framework of digital twin-assisted predictive maintenance (DT-PdM) is proposed with regard to industrial complex systems. A pilot study is conducted as preliminary and fundamental research to test the feasibility of the proposed framework.

Keywords. Digital Twin, Predictive Maintenance, Complex System, Real-Time Monitoring, Intelligent Maintenance.

1. **Introduction**

As a crucial part of production systems, maintenance strategies support engineers and managers to conduct manufacturing processes with high quality, productivity, and reliability while also reducing costs and saving energy (Gutschi *et al.,* 2019). Traditional maintenance strategies for Corrective Maintenance and Preventive Maintenance are exposed to many limitations, like longer and unnecessary checking time, higher costs, and loss of production capacity, which stress the significance of alternative maintenance approaches (Demichela *et al.,* 2018). At present, though the concept of Predictive Maintenance (PdM) brings more potential in the maintenance field as an intelligent maintenance strategy, with the consideration of decreasing the unnecessary checking time and releasing the maximum production capacity of the system (Gutschi *et al.,* 2019), conventional maintenance paradigms continue to be the common solutions. Three crucial challenges are present:

1. *Expand the application of PdM from single component to complex systems.* Till now, single component is commonly focused by researchers when conducting PdM. However, such methods are limited when coming to system levels,

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especially complex systems in process industries with the characteristic of the diversity of specialized equipment and machinery (Duffuaa *et al.,* 2024).

2. *The reliability of analysis approaches and the dependability of analysis results.* To broaden the application range of PdM strategies and convince actual industry practitioners, methodology credibility is one crucial part, with consideration of reliability of analysis approaches, dependability of analysis results, and the most important part: explainability of each research step and all results.
3. *The availability of timely feedback from the analysis through modeling and simulation.* To differ from traditional passive maintenance approaches, PdM benefits by providing proactive solutions, involving dynamic monitoring and real-time responsiveness. Thus, the design of PdM approaches should maximize these advantages in real cases, with clarified needed resources as input, expectable results as output, and a well-defined operating process in actual industry domains that guarantee feasibility.

This study aims to explore the potential of the Digital Twin (DT) as a prominent solution for the above challenges. As a burgeoning concept that has gained tons of attention since it was first introduced in 2002, DT shows its advancements in combining streaming Industry 4.0 technologies, such as the Internet of Things (IoT), cloud and edge computing, machine learning and artificial intelligence, modeling and simulation approaches, and others (Flammini, 2021; Sen *et al.,* 2023; Koo and Yoon, 2024). Zio and Miqueles (2024) comprehensively summarize the potential and effectiveness of DT applications in the domains of safety analysis, risk assessment, component health monitoring and predictive maintenance in the engineering domains. Current researchers and engineers do not hold uniform recognitions for DT, but with one common perception, which is to create a "virtual replica", or "virtual space", "digital systems", "digital replica" to replicate the behavior of physical entities (Lin *et al.,* 2023; Sama *et al.,* 2023). With this characteristic, DT is naturally appropriate to be applied in the PdM field, since the virtual replica supports modeling and simulating the behavior of physical entities and further conducting prediction activities based on their behavior models without influencing their planned operating activities. Therefore, a digital twin-assisted predictive maintenance framework (DT-PdM) is designed in the following part with preliminary research through a pilot study. The results of this study are expected to draw a relatively transparent and feasible pattern of digital twin-assisted predictive maintenance for complex systems.

2. Digital twin-assisted predictive maintenance framework (DT-PdM)

This section explores the potential of DT to assist with the above-mentioned challenges from the perspective of theories. The DT-PdM is provided as shown in figure 1, how does this framework benefit addressing concerned challenges are discussed accordingly.

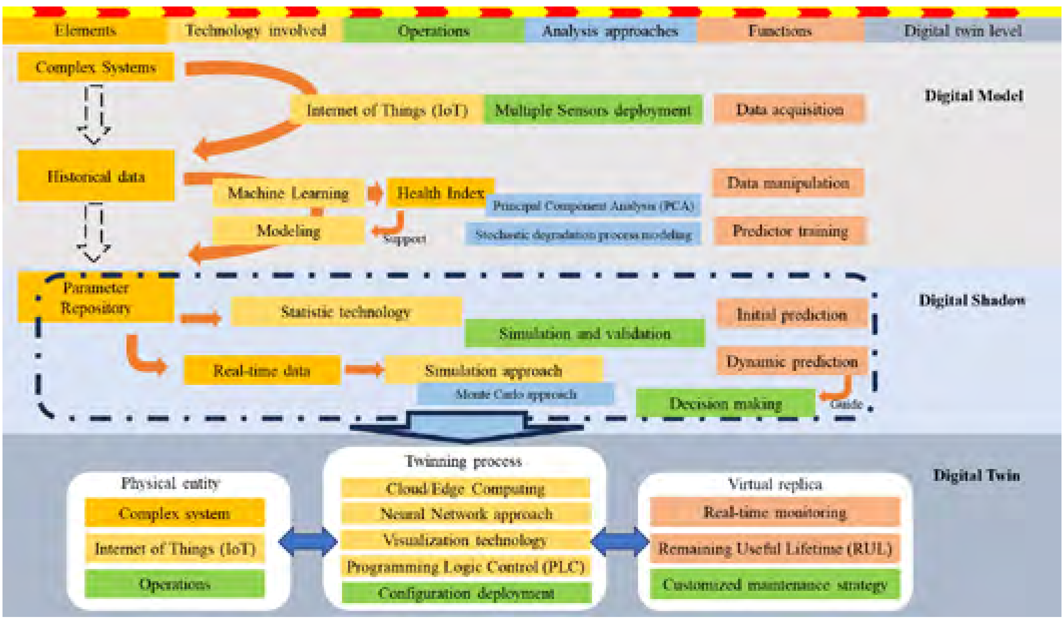
Three layers are defined in the designed framework, which align with three types of DT according to the way it has been deployed: digital model, digital shadow, and digital twin (Epiphaniou *et al.*, 2023). Specifically, Digital Model stresses function achievement without considering automatic data exchange. Digital Shadow achieves one-way automatic data transmission from a physical entity to its virtual counterpart, while Digital Twin also involves the data exchange from digital to virtual objects. Based on it, the DT-PdM defines three main layers, as well as involved elements, technologies, actual operations, analysis approaches, and expected functions.

— PdM Digital Model: As the first layer, the PdM Digital Model aims to achieve functions of data acquisition, data manipulation, and predictor training, which is regarded as the foundation for later layers. The model is limited in historical data.
— PdM Digital Shadow: The second layer achieves the function of prediction towards real-time data, with the support of simulation technologies.
— PdM Digital Twin: The final layer clarifies the physical object and its virtual counterpart as replica.

The interaction between them is defined.

Figure 1

Digital twin-assisted predictive maintenance framework



2.1. *PdM Digital Model*

In the layer of PdM Digital Model, data acquisition is supported by the deployment of multiple sensors in complex systems through the application of IoT technology. In actual scenarios, the deployment of sensors in this part, e.g., mainly relies on the experiences of experts in order to collect run-to-failure data on target systems. This part could be conducted in experimental scenarios. Collected run-to-failure data forms the historical data repository, which is furtherly used in data manipulation and predictor training processes. Within the analysis process, machine learning techniques and modeling approaches are significant, where machine learning techniques such as Principal Component Analysis (PCA) are applied to extract the Health Index, which represents the health situation of target systems with a degradation trend. Modeling techniques such as stochastic process modeling benefit modeling the degradation process of complex systems, contributing to the parameter repository.

The first challenge is expected to be addressed in this layer, by collecting data for complex systems instead of single component or facility. Moreover, the defining of the health index from machine learning techniques tackles the difficulty of processing high dimension data, which is also a common problem faced in challenge 1. Especially, the reliability of the Health Index extracted from high dimension sensor data is significant, and whether it can be used to represent systems' health situation is discussed theoretically. According to Mackiewicz and Ratajczak (1993), PCA technique aims to find the PCA space to represent the direction of the maximum variance of the given data. When comes to actual system operating processes in industrial fields, the maximum variance direction is connected to the degradation trends of target systems, and it is with high confidence level that sensors deployed could catch systems' degradation trends after a long-time running. In this case, it is achievable to model the system behavior with considering its degradation.

2.2. *PdM Digital Shadow*

The PdM Digital Shadow layer stresses to conduct initial and dynamic prediction based on the built parameter repository from the first layer. The parameter repository collects modeled stochastic degradation process parameters, it supports the simulation for new systems. The prediction functions are achievable through three aspects: when comes to a new system without any monitored data available, the initial prediction could be conducted based on the statistic of historical data of similar systems. Once the initial health situation of this system is available, for example, the initial health index is gained after its deployment, simulation techniques such as Monte Carlo approach helps to simulate all possible degradation routes. Each possible route contributes to one possible lifetime according to predefined failure thresholds, thus, the Remaining Useful Life (RUL) could be calculated in the different conditions. Moreover, during the system running process, with conditional (real-time) data available through timely monitoring, simulation approaches provide more precise prediction results for target systems. All prediction results support the decision-making processes, helping to design customized maintenance strategies, involving intelligent warning system, barrier management, risk management, and other operations like cleaning, inspection, replacement, etc. With designed modeling, simulation as well as decision-making process, the second challenge is expected to be addressed after the second layer.

2.3. *PdM Digital Twin*

PdM Digital Twin aims to benefit the last challenge: the availability of timely feedback from the analysis through modeling and simulation. In this layer, DT related resources, technologies are broadly applied. With prediction functions achieved in the PdM Digital Shadow, the time consuming is massive, which hinders availability of timely feedbacks in real scenarios and influences the afterward decision-making processes. In order to solve this problem, Neural Network approaches are applied in this layer to train time-saved simulators forming the twinning process based on procedures defined in PdM Digital Shadow. Here provides the mechanism of the prediction process: complex systems are defined as the physical entity in DT with the help of IoT, its operating data is transmitted into the twinning process. Trained time-saved simulators take such data as input and predict the output in a timely manner, and the output is defined as systems' current health situations and dynamic updated RUL values. On the other hand, following the customized maintenance strategies defined in the virtual replica, the twinning process transmits them back to the physical entity, and reflects them as practical operations.

The configuration deployment in the twinning process needs to be supported by multiple technologies, for example, Could/Edge Computing benefits data management, response time, energy efficiency, and even cybersecurity. Visualization technologies facilitate interactions between operators and complex systems with better Human-Machine Interface (HMI) defined and applied. The adoption of Programmable Logic Control (PLC) guarantees the information transmission from the virtual replica to the physical entity. The actions or activities decided in the virtual replica are transferred as actual operations in actuators. Such technologies are necessary to achieve key functions and deploy the PdM Digital Twin, with the increase of maturity levels of different industries, it is possible to involve more technologies to guarantee the reliability of DT, like cybersecurity technologies, blockchain, and even virtual reality and augmented reality, etc.

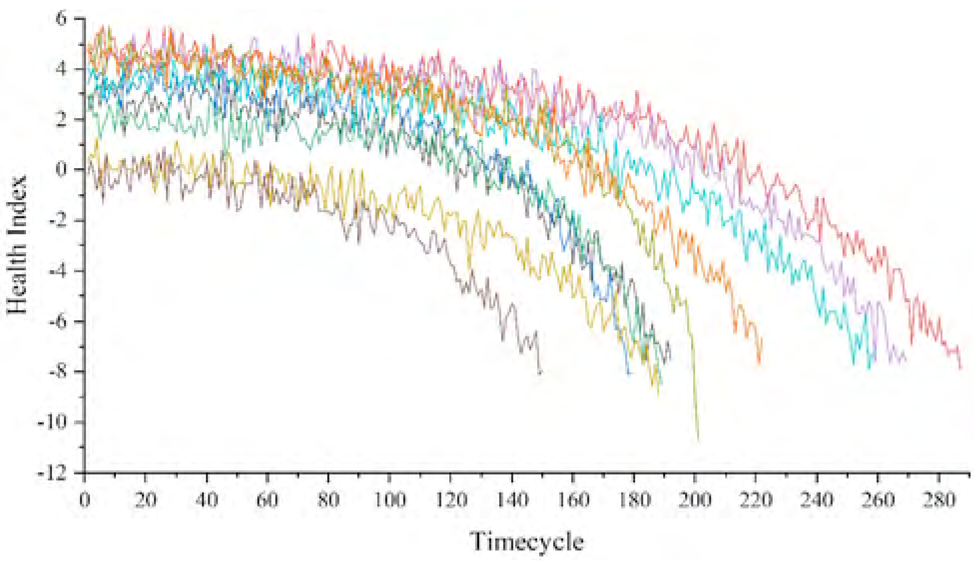
3. **Pilot study**

In this part, a pilot study is conducted as the preliminary research, by building the first two layers: PdM Digital Model and PdM Digital Shadow. The feasibility of the proposed framework for first two layers are validated, which are regarded as research foundation for PdM Digital Twin.

The pilot study is conducting based on the analysis on CMAPSS Dataset, one popular turbofan engines datasets (Frederick *et al.,* 2007). This dataset offers run-to-failure data of one hundred engines monitored by 21 sensors with three operational setting. The dataset FD001 is chosen in this study, with High-Pressure Turbine (HPT) degradation as the fault mode. Even though this dataset is focusing on the turbofan instead of complex systems, it still supports the validation on the feasibility of proposed framework towards complex systems, with considering not only the multiple sensor data, but also different setting operations. For complex systems, data types could be different based on the actual configurations. With the help of PCA, the long-term trend of system performance, which is also the maximum variance direction from a mathematical point of view, could be mapped to system degradation. Figure 2 shows the degradation process of the first 10 samples in the database based on their run-to-failure data collected. Each declining line with a different color shows the degradation route of different samples. Thus, extracted Principal Component (PC) value which reflects such degradation performance could be considered as the health index of each sample. According the figure, the sample fails when its health index reaching a certain level, which supports the define of the failure threshold.

Figure 2

The run-to-failure degradation process of first 10 samples in the database



The degradation processes of each sample are modelled by stochastic process modeling techniques, which contribute to defining two types of parameters. The drift part reveals how systems degrade with continuous operation processes, and the diffusion part reflects the variabilities that occurred in the health index: the individual-to-individual variability inherent with the system in a population and the temporal variability (volatility) that happens over time due to the random errors in measurements and the uncertainty in the system's working environments and operations. The advantages and advancements of applying stochastic process modeling techniques are discussed and validated by some researchers, with prominent potential for capturing stochastic dynamics in degradation processes (Zhang *et al.,* 2018). In the pilot study, stochastic degradation process modeling is conducted for all samples by choosing appropriate regression methods. Figure 3 shows the modeling result for sample 1, and the polynomial regression is adopted to tarin drift parameters. The standard deviation between estimated values and the reference health index is taken as the drift parameter. Based on trained parameters, the prediction of RUL in the test set is achieved with the application of Monte Carlo simulation approaches, by continuously conducting simulations with provided couple of conditional data in the test set. Each simulation represents one potential degradation route with a RUL value, and the mean value of RULs calculated from all degradation routes is taken as the final predicted RUL. The result (figure 4) shows the histogram of estimated RUL after simulate 1,000 times, with the mean of 21.73 cycles, and the actual RUL of this sample is 20. The Mean Absolute Error (MAE) of prediction in the whole dataset is 23.21, which sacrifices some prediction accuracy compared with other neural network-related approaches (e.g., 22.991, 17.768, 12.508, 10.957, etc.), but with higher explainable level, less data processing requirements, and the capability of considering digital twin solutions in complex systems. According to the prediction results, customized maintenance strategies are expected to be made. For example, by knowing when systems have higher possibility to fail, maintenance activities could be scheduled at the necessary time without being based on constant time intervals, which avoids premature maintenance. Besides, systems with longer RUL can devote to less resources compared with those with shorter RUL, which optimizes the allocation of maintenance resources. Moreover, by analyzing multiple simulated RULs for the same system, certain maintenance measures may be found to be ineffective and require adjustment or replacement.

The limitations of this pilot study come from two aspects: 1. The researched dataset has only one fault mode. 2. The proposed methods in this study should be applied to real complex systems as validation.

Figure 3

Stochastic degradation process modeling for the sample 1

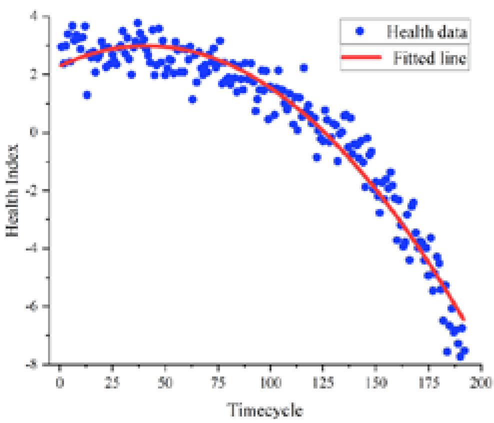
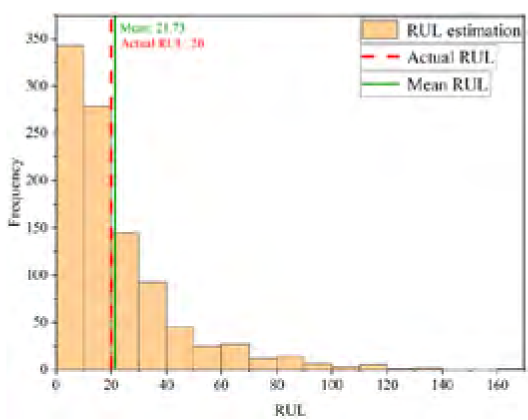


Figure 4

Prediction result of a sample based on Monte Carlo simulation



4. Discussion and conclusion

This paper aims to explore the potential of DT to assist the predictive maintenance in industrial fields. A digital twin-assisted predictive maintenance framework is proposed with three layers: PdM Digital Model, PdM Digital Shadow, and PdM Digital Twin. A pilot study is conducted as preliminary research to validate the feasibility and reliability of building the PdM Digital Model layer and the PdM Digital Shadow layer, discovering that the proposed framework benefits the predictive maintenance of complex systems, also with the capability of combining the strength of digital twin. In the future, more validation is needed to not only test the feasibility and reliability of building the PdM Digital Twin layer, but also to validate the applicability of the proposed framework in more industrial scenarios.

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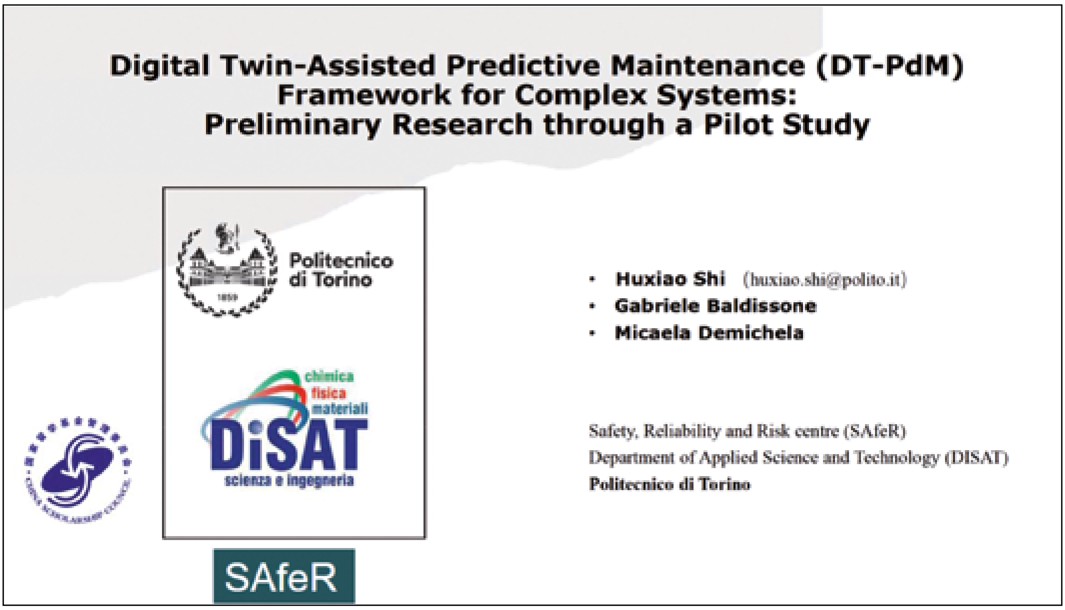
Digital Twin-Assisted Predictive Maintenance (DT-PdM)
Framework for Complex Systems:
Preliminary Research through a Pilot Study
Politecnico di Torino
chimica
fisica
materiali
DiSAT
scienza e ingegneria
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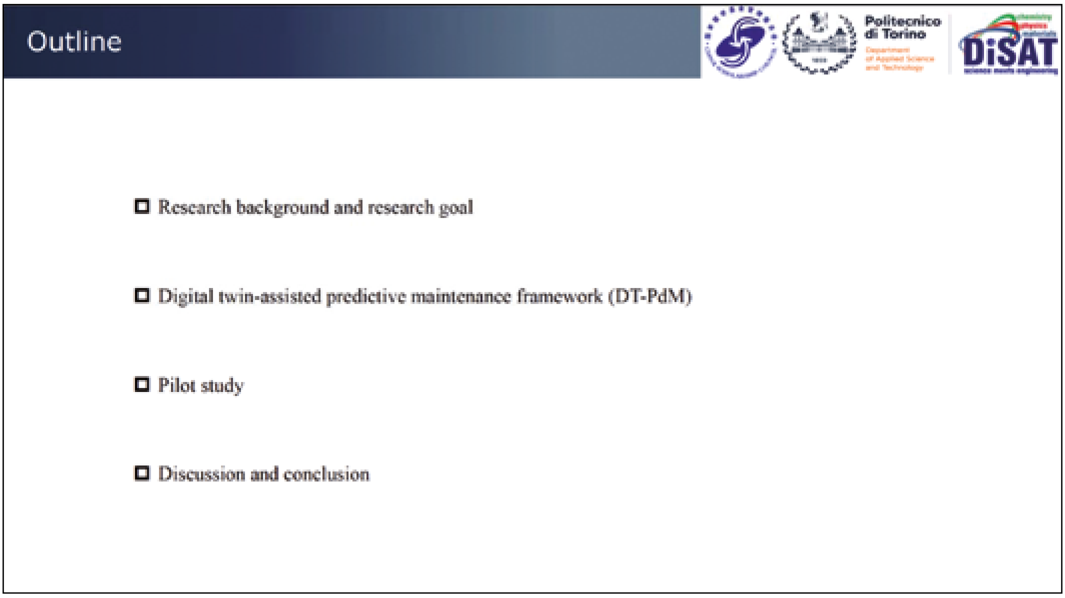
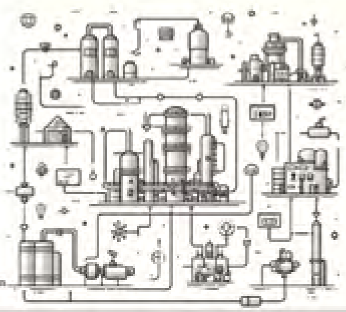

Outline
Politecnico di Torino
DiSAT
Research background and research goal
Digital twin-assisted predictive maintenance framework (DT-PdM)
Pilot study
Discussion and conclusion

Research background

- The significant role played by maintenance strategies in industrial activities
  - Benefit Asset Management (AM) and Reliability Engineering
  - High quality, productivity, reliability
  - Reducing costs and saving energy
- Traditional maintenance strategies for Corrective Maintenance and Preventive Maintenance could be exposed to some limitations
  - Longer and unnecessary checking time
  - Higher operational costs
  - loss of production capacity
  - …
- The potential of Predictive Maintenance (PdM)
  - Make decisions based on prediction results
  - Maximize production capacity of industrial systems



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Current challenge

❶ Expand the application of PdM from single component to complex systems
- Single component is commonly focused
- Lack of uniformity at system level, especially in process industries
- Variability of specialized equipment and machinery

❷ The reliability of methodology and results
- Credibility and reliability of analysis approaches
- Dependability of analysis results
- Explainability of each research step and all results

❸ The availability of timely feedback from the analysis through modeling and simulation
- PdM shall benefit dynamic monitoring
- Real-time responsiveness is expected
- Guaranteed feasibility, with clarified input, output, and processes

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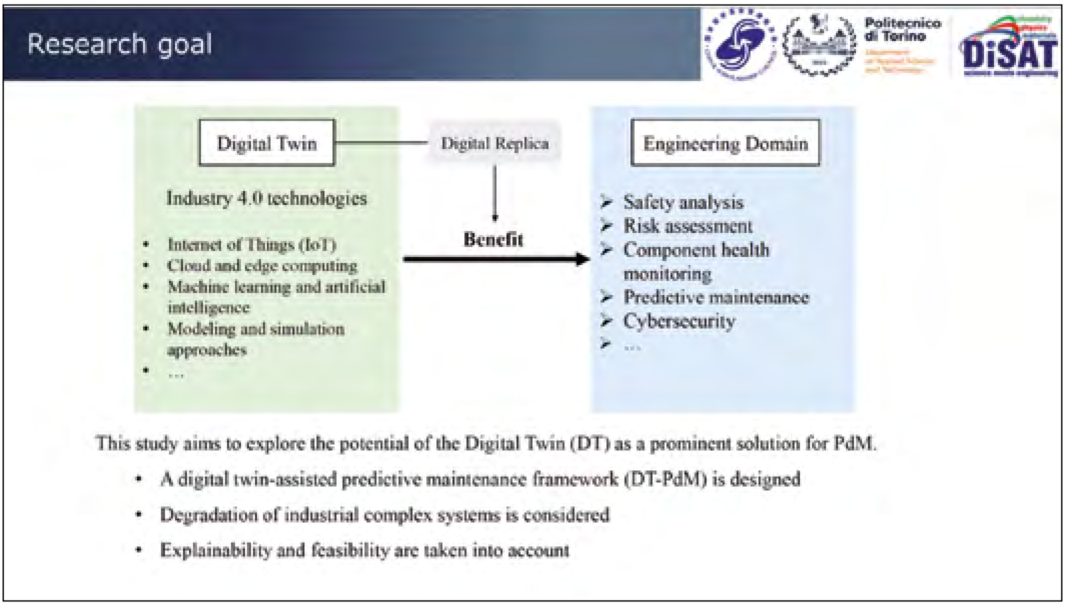
Research goal
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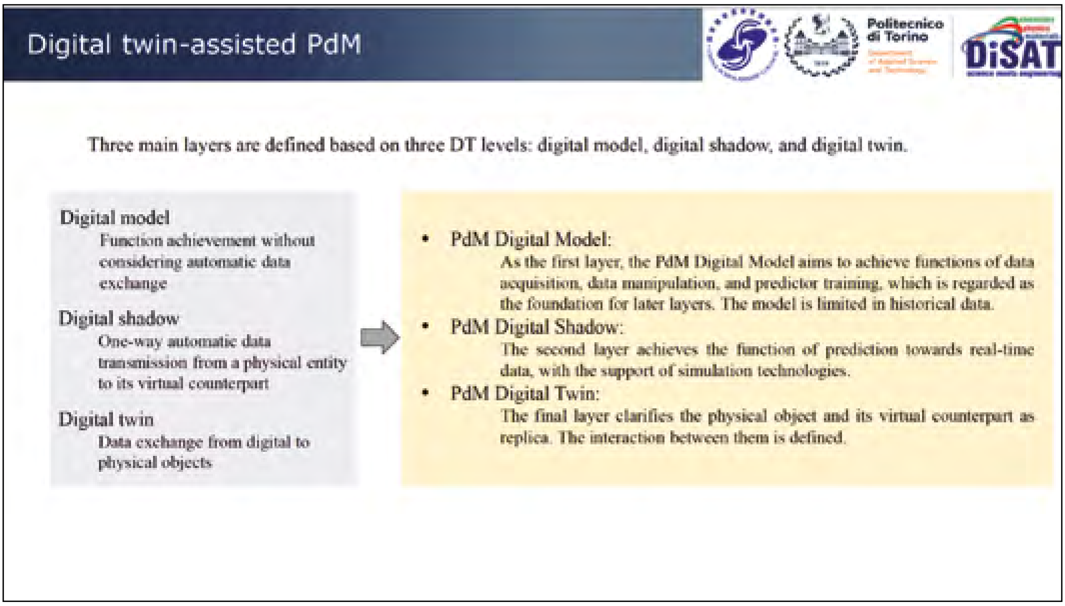
Digital Twin
Digital Replica
Engineering Domain
Industry 4.0 technologies
• Internet of Things (IoT)
• Cloud and edge computing
• Machine learning and artificial intelligence
• Modeling and simulation approaches
• …
Benefit
➢ Safety analysis
➢ Risk assessment
➢ Component health monitoring
➢ Predictive maintenance
➢ Cybersecurity
➢ …
This study aims to explore the potential of the Digital Twin (DT) as a prominent solution for PdM.
• A digital twin-assisted predictive maintenance framework (DT-PdM) is designed
• Degradation of industrial complex systems is considered
• Explainability and feasibility are taken into account


Digital twin-assisted PdM
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Three main layers are defined based on three DT levels: digital model, digital shadow, and digital twin.
Digital model
Function achievement without considering automatic data exchange
Digital shadow
One-way automatic data transmission from a physical entity to its virtual counterpart
Digital twin
Data exchange from digital to physical objects
• PdM Digital Model:
As the first layer, the PdM Digital Model aims to achieve functions of data acquisition, data manipulation, and predictor training, which is regarded as the foundation for later layers. The model is limited in historical data.
• PdM Digital Shadow:
The second layer achieves the function of prediction towards real-time data, with the support of simulation technologies.
• PdM Digital Twin:
The final layer clarifies the physical object and its virtual counterpart as replica. The interaction between them is defined.

Digital twin-assisted PdM

- Digital twin-assisted predictive maintenance framework

Layer	Digital twin level	Element	Function
1	PdM Digital Model	Complex system Historical data Health Index	Data acquisition Data manipulation Predictor training
2	PdM Digital Shadow	Parameter repository Real-time data	Initial prediction Dynamic prediction
3	PdM Digital Twin	Physical entity Twinning process Virtual replica	Real-time monitoring Remaining Useful Life (RUL)

Digital twin-assisted PdM

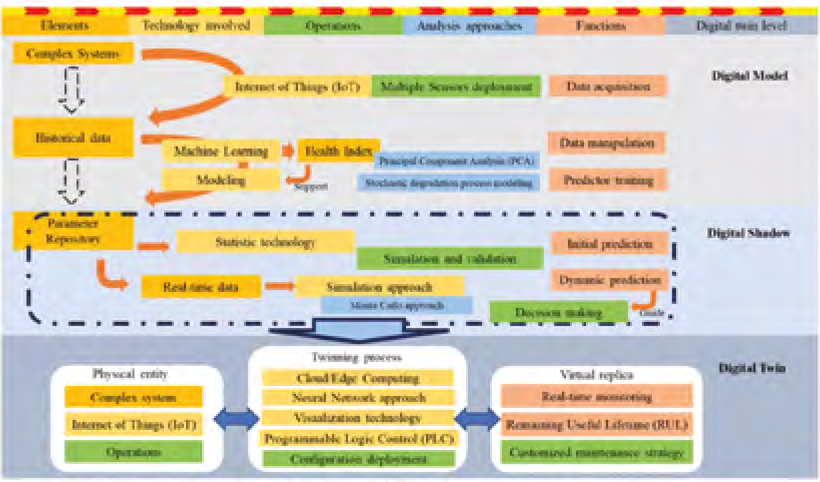
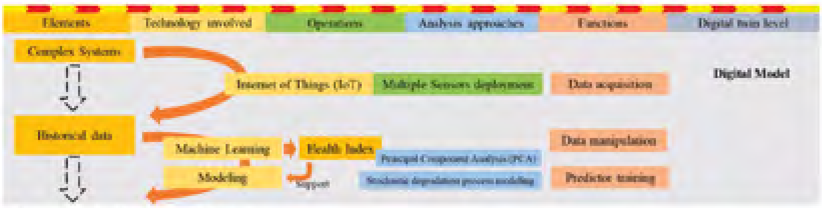


Figure. Digital twin-assisted predictive maintenance framework

PdM Digital Model



Function 1: Data acquisition

Multiple sensors deployment in complex systems relying on the experiences of experts.

Directly conduct monitoring in the system level → Expansion from components to systems

Function 2: Data manipulation

Principal Component Analysis (PCA), to extract the Health Index

Find the PCA space with the maximum variance direction → Degradation trend

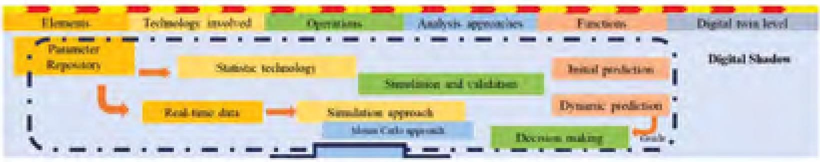
Function 3: Predictor training

Stochastic degradation process modeling, contributing to the parameter repository.

Capturing stochastic dynamics in degradation processes:

- Random errors in measurements
- Uncertainties in the working environments of the systems
- Individual variability of the systems within a population

PdM Digital Shadow



Function 1: Initial prediction

New system without any monitored data available

Prediction based on statistic of historical data of similar systems.

Function 2: Dynamic prediction

- Initial health situation defined for target system

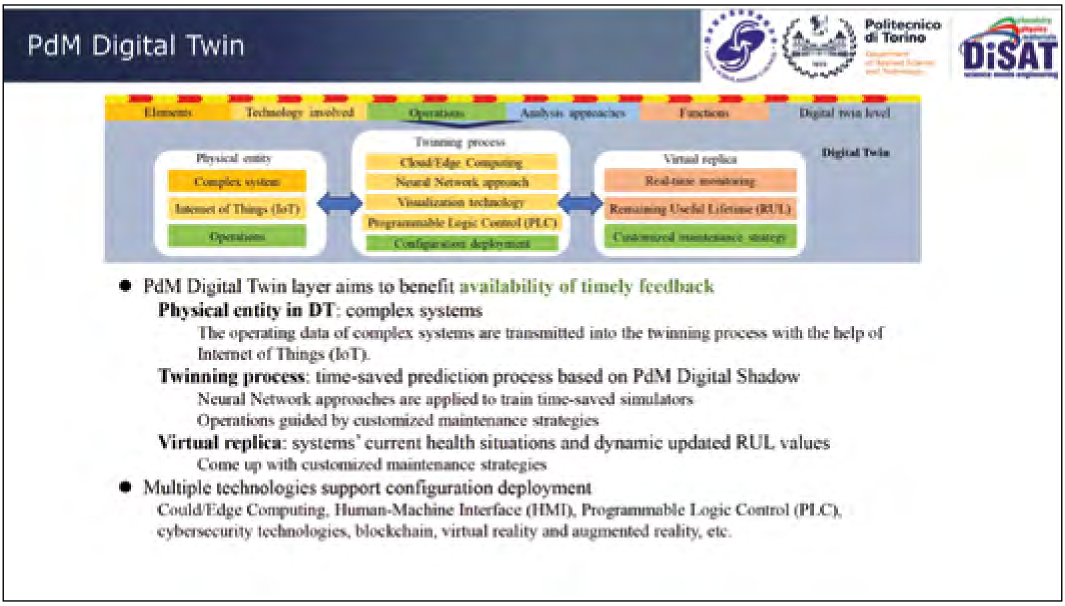
  Prediction based on simulation techniques → All possible degradation routes
- Conditional (real-time) data available through timely monitoring

  Simulation approaches provide more precise prediction results.

Prediction results support decision-making process

Design customized maintenance strategies, involving intelligent warning system, barrier management, risk management, and other operations like cleaning, inspection, replacement, etc.

→ Reliability of decision-making process


PdM Digital Twin
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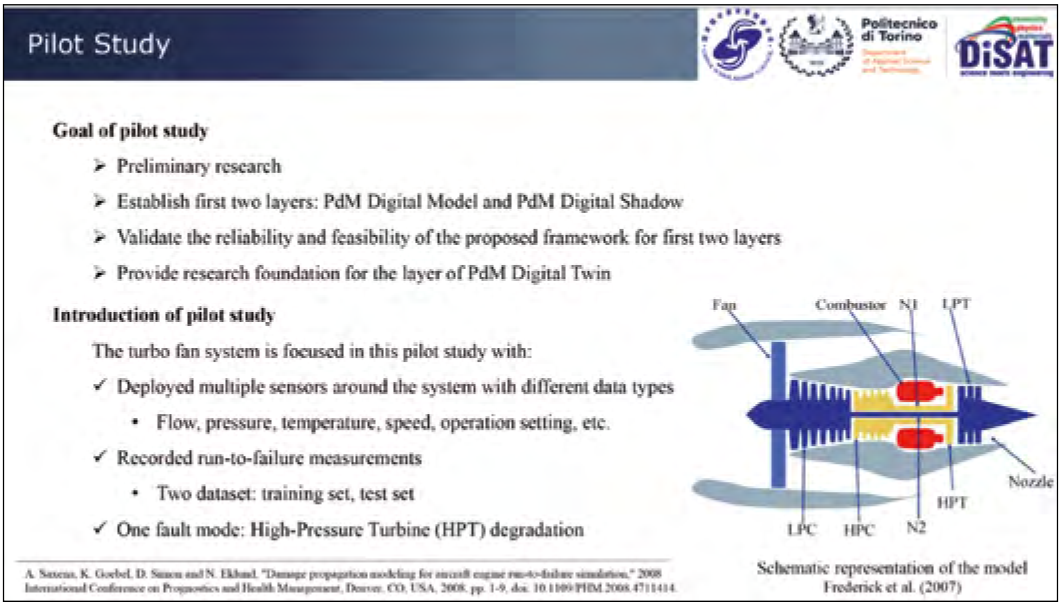
Elements
Technology involved
Operations
Analysis approaches
Functions
Digital twin level
Twinning process
Digital Twin
Physical entity
Complex system
Internet of Things (IoT)
Operations
Cloud/Edge Computing
Neural Network approach
Visualization technology
Programmable Logic Control (PLC)
Configuration deployment
Virtual replica
Real-time monitoring
Remaining Useful Lifetime (RUL)
Customized maintenance strategy
● PdM Digital Twin layer aims to benefit availability of timely feedback
Physical entity in DT: complex systems
The operating data of complex systems are transmitted into the twinning process with the help of Internet of Things (IoT).
Twinning process: time-saved prediction process based on PdM Digital Shadow
Neural Network approaches are applied to train time-saved simulators
Operations guided by customized maintenance strategies
Virtual replica: systems' current health situations and dynamic updated RUL values
Come up with customized maintenance strategies
● Multiple technologies support configuration deployment
Could/Edge Computing, Human-Machine Interface (HMI), Programmable Logic Control (PLC), cybersecurity technologies, blockchain, virtual reality and augmented reality, etc.


Pilot Study
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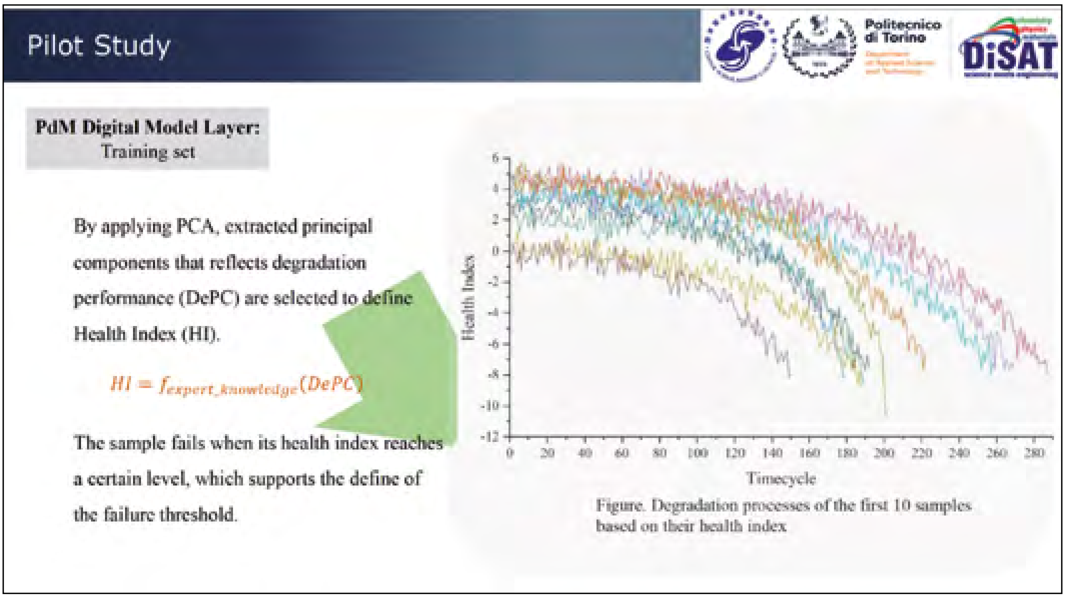
Goal of pilot study
➢ Preliminary research
➢ Establish first two layers: PdM Digital Model and PdM Digital Shadow
➢ Validate the reliability and feasibility of the proposed framework for first two layers
➢ Provide research foundation for the layer of PdM Digital Twin
Introduction of pilot study
The turbo fan system is focused in this pilot study with:
✓ Deployed multiple sensors around the system with different data types
• Flow, pressure, temperature, speed, operation setting, etc.
✓ Recorded run-to-failure measurements
• Two dataset: training set, test set
✓ One fault mode: High-Pressure Turbine (HPT) degradation
Fan
Combustor
N1
LPT
Nozzle
HPT
LPC
HPC
N2
Schematic representation of the model
Frederick et al. (2007)
A. Saxena, K. Goebel, D. Simon and N. Eklund, "Damage propagation modeling for aircraft engine run-to-failure simulation," 2008 International Conference on Prognostics and Health Management, Denver, CO, USA, 2008, pp. 1-9, doi: 10.1109/PHM.2008.4711414.


Pilot Study
Politecnico di Torino
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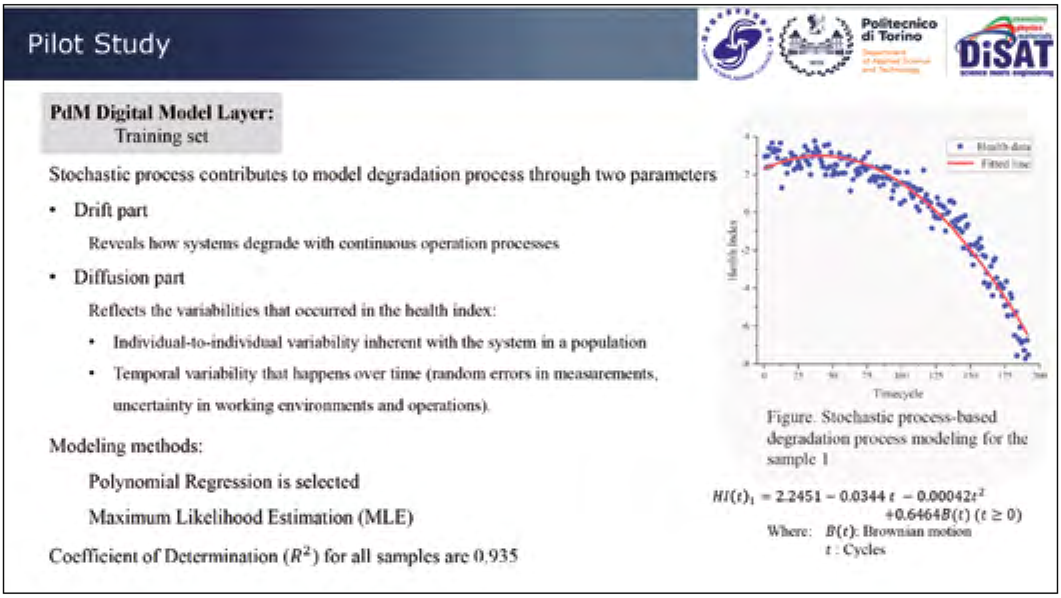
PdM Digital Model Layer:
Training set
By applying PCA, extracted principal components that reflects degradation performance (DePC) are selected to define Health Index (HI).
$HI = f_{expert\_knowledge}(DePC)$
The sample fails when its health index reaches a certain level, which supports the define of the failure threshold.
Health Index
6
4
2
0
-2
-4
-6
-8
-10
-12
0
20
40
60
80
100
120
140
160
180
200
220
240
260
280
Timecycle
Figure. Degradation processes of the first 10 samples based on their health index


Pilot Study
Politecnico di Torino
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PdM Digital Model Layer:
Training set
Stochastic process contributes to model degradation process through two parameters
• Drift part
Reveals how systems degrade with continuous operation processes
• Diffusion part
Reflects the variabilities that occurred in the health index:
• Individual-to-individual variability inherent with the system in a population
• Temporal variability that happens over time (random errors in measurements, uncertainty in working environments and operations).
Modeling methods:
Polynomial Regression is selected
Maximum Likelihood Estimation (MLE)
Coefficient of Determination (R^2) for all samples are 0.935
Health data
Fitted line
Health index
Timecycle
Figure. Stochastic process-based degradation process modeling for the sample 1
$HI(t)_1 = 2.2451 - 0.0344\,t - 0.00042t^2 + 0.6464B(t)\ (t \geq 0)$
Where: $B(t)$: Brownian motion
t : Cycles

Pilot Study

PdM Digital Shadow Layer:
Test set

- Prediction of RUL based on Monte Carlo simulation approaches

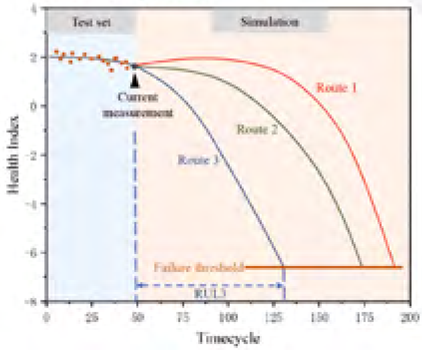
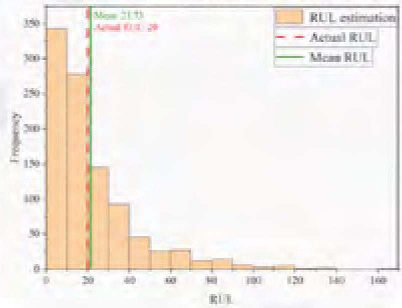


Figure. Prediction result of a sample based on Monte Carlo simulation after simulate 1000 times



Pilot Study

- Evaluation of results

The simulation is conducted on MATLAB R2023a with the computer parameters provided as: Intel(R) Core(TM) i7-6700 CPU @ 3.40GHZ 3.41GHZ; RAM: 32.0 GB

Simulation times	MAE	RMSE	Time consumed
100	23.6	30.473	0.679 h / 2442.9443s
500	23.17	30.523	3.012h / 10840.6558s
1000	23.21	30.434	6.139h / 22099.713s

The Mean Absolute Error (MAE) of prediction after 1000 simulation times is 23.21, which sacrifices some prediction accuracy compared with other neural network-related approaches (e.g., 22.991, 17.768, 12.508, 10.957, etc.), but with **higher explainable level**, **less data processing requirements**, and **the capability of considering digital twin solutions in complex systems**.

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Pilot Study

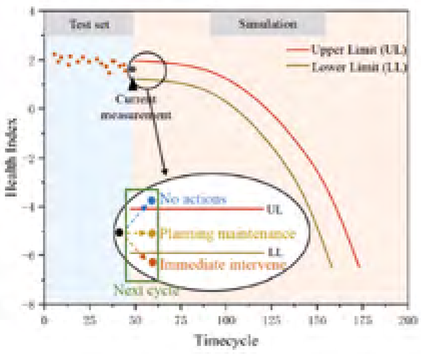
- Decision-making process

-Customized maintenance strategies based on prediction results.

E.g.,

- ✓ By knowing when systems have higher possibility to fail, maintenance activities could be scheduled at the necessary time without being based on constant time intervals, which avoids premature maintenance.
- ✓ Systems with longer RUL can devote to less resources compared with those with shorter RUL, which optimizes the allocation of maintenance resources.
- ✓ By analyzing multiple simulated RULs for the same system, certain maintenance measures may be found to be ineffective and require adjustment or replacement.
- ✓ ...

-To guide: when to conduct maintenance actions



Discussion and conclusion

- Conclusions
  - Digital twin-assisted predictive maintenance framework is proposed
    - ➢ Three layers are designed by defining required elements, techniques, and expected functions.
    - ➢ Digital twin solutions in predictive maintenance
  - A pilot study is conducted to validate the feasibility and reliability of first two layers.
  - The discussion of how this framework benefits predictive maintenance is provided
- Limitations
  - The feasibility and reliability of PdM Digital Twin layers is theoretically established and discussed.
  - Lack validation in real industrial complex systems
- Future work

PdM Digital Twin layer is need to be established according to the availability of data, the applicability of the proposed framework is expected to be evaluated in more industrial scenarios.

Digital Twin Technologies (DTT) for Digitalization of Railway Maintenance Services

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Abstract

The adoption of Digital Twin Technologies (DTT) is transforming maintenance services, particularly in sectors with stringent safety requirements, such as railways. This paper explores the integration of DTT into maintenance processes, leveraging IoT, BIM, and advanced data models to enhance decision-making and compliance with EU safety regulations. A model-based approach is introduced as a core component, ensuring a structured framework for the development of asset management (AM) solutions, aligned with maintenance strategies and lifecycle optimization. The model-based approach proposed in this work enables the design of a scalable architecture and platform, supporting the deployment of various functionalities and services within the Digital Twin (DT) ecosystem. A case study on railway rolling stock maintenance illustrates how DTT enables predictive analytics, improves asset lifecycle management, and supports the digitalization of key services, demonstrating the potential of a model-driven, structured digitalization strategy.

1. Introduction

Digitalization and servitization are reshaping asset management and operational optimization across critical sectors such as railways. Within this context, maintenance has emerged as a strategic pillar for ensuring operational efficiency, sustainability, and compliance with stringent safety regulations, including Regulation (EU) 2019/779. The maintenance of railway fleets, comprising rolling stock, associated machinery, and workshops, requires an integrated approach to managing data, models, and decision-making processes throughout the asset lifecycle. Digitalization through Digital Twins (DT) offers an advanced framework, incorporating IoT monitoring for real-time data capture, predictive analytics for failure diagnostics and preventive actions, and simulation and optimization tools for dynamic maintenance planning and investment strategies. Additionally, technical and functional models, such as those enabled by BIM (Building Information Modeling), play a critical role in representing and analyzing assets and systems.

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Figure 1

Proposed Digital Twin (DT) concept applied to the digitalization of railway maintenance services, including fleets, workshops, and the decision-making structure based on ECM

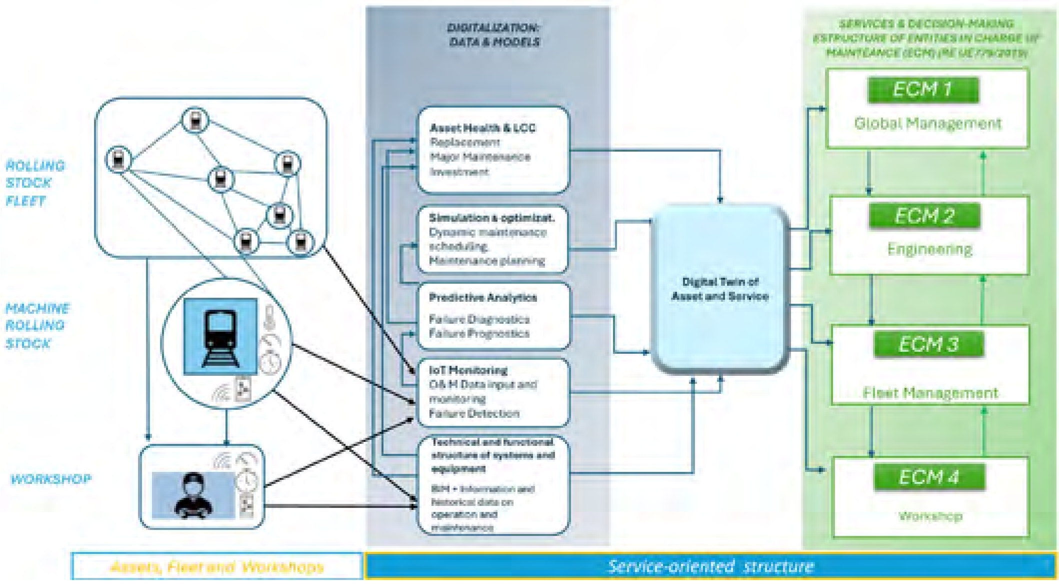


Figure 1 illustrates the proposed Digital Twin concept, which applies to the digitalization of railway maintenance services. This framework integrates fleets, workshops, and a structured decision-making model based on the Entities in Charge of Maintenance (ECM). The ECM model, as established by EU regulations, identifies four primary functions: Global Management (ECM1), Engineering (ECM2), Fleet Management (ECM3), and Workshop (ECM4). Each ECM function focuses on distinct decision-making processes, supported by data and models delivered through the Digital Twin. These decisions are optimized via advanced tools, including machine learning, simulations, and risk analysis, enhancing the precision and reliability of maintenance strategies. Digital Twin representation emerges, as is shown in the figure, as a digital entity that integrates all models defining the asset or the processes to be managed. This entity serves as the foundation for the structured digitalization of valuable services, such as maintenance and safety management, which is the focus of this work.

This document outlines a research and development proposal on the digitalization of highly specialized technical services. The project investigates the design, development, and application of Digital Twin Technology (DTT) in maintenance services, specifically within the railway sector. The proposal is anchored in the DF-MAS project, which addresses the challenge of digitally transforming systems with low or nonexistent levels of initial digitalization, a characteristic of many railway applications.

2. Evolution of Digital Maintenance and Digital Twins

Asset and maintenance management face significant structural challenges driven by emerging technologies such as AI/ML, Big Data, IoT, and advanced representations (BIM, VR, AR), which are revolutionizing the paradigm of industrial maintenance [1]. Over the next years, an even more significant transformation is expected, guided by customer demand, market changes, and the adoption of new technologies [2]-[4]. According to the Industrial Internet Consortium (IIC), maintenance is one of the areas expected to experience the greatest impact from this transformation [5]. The shift toward prescriptive maintenance stands out as a key change, optimizing task planning and resource use. This approach surpasses traditional preventive and predictive methods by integrating advanced technologies, improving asset performance and operational efficiency [6]. However, one of the biggest challenges is the effective integration of technology and people, aligning with the principles of Industry 5.0 (I5.0), which prioritizes human interaction and sustainability in industrial systems [7]. A recent report by the GFMAM (Global Forum on Maintenance and Asset Management), based on a global survey, identifies key barriers to adopting artificial intelligence in maintenance. These include a lack of integration between existing systems and emerging technologies, resistance to change, and a shortage of technical skills [8]. These barriers limit the adoption of advanced digital solutions and complicate the standardization of workflows for data analysis. Digital Twin, or in a more extended concept Digital Twin Technology (DTT), emerges as a solution to address these challenges. DTT offers transformative potential in the railway industry by enhancing safety, efficiency, and sustainability across various operational and maintenance processes.

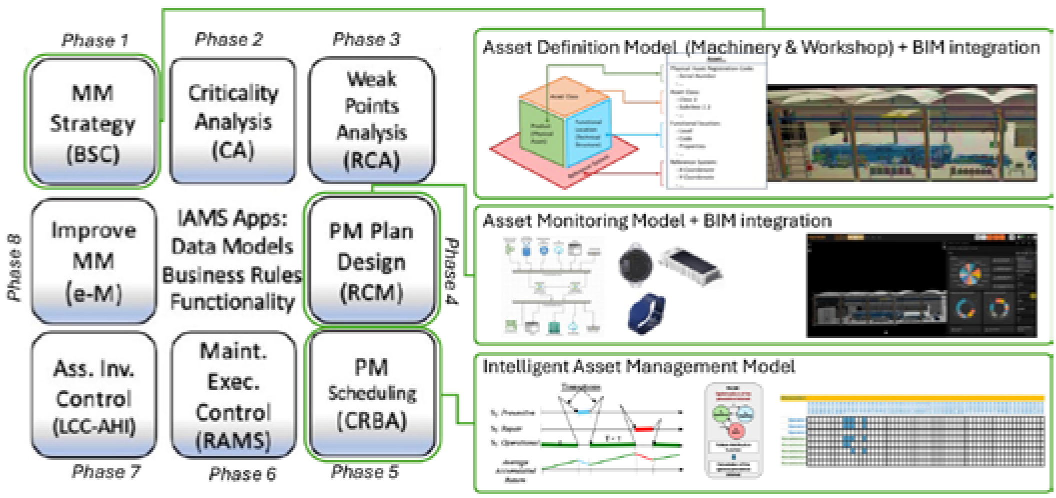
Digital Twins (DTs) play a crucial role in asset management and maintenance within critical infrastructures such as railways, where operational reliability, safety, and efficiency are paramount. A foundational study by Zhou *et al.* (2022) introduced a conceptual model-based DT platform for large-scale railway infrastructure systems, highlighting the integration of subsystems such as tracks, trains, and signaling systems into a unified digital framework. This integration facilitates real-time operational monitoring, diagnostics, and prognostics, improving decision-making and optimizing system reliability and performance [9]. In the context of safety, Aksenov *et al.* (2022) explored how DT reduces work-related injuries in railway operations. By enabling remote control of mechanized railway track machinery, DT minimizes the need for human presence in hazardous zones, significantly reducing injury rates and enhancing safety protocols [10]. Similarly, Adeagbo *et al.* (2024) emphasized the role of DT in structural health monitoring, predicting potential failures to extend infrastructure lifespan and reduce unexpected downtime [11]. The integration of DT with wireless networks further enhances railway safety and operational efficiency. Guan *et al.* (2024) discussed key technologies for wireless network DT towards intelligent railway systems, illustrating how advanced communication technologies synergize with DT to improve real-time decision-making and strategic planning [12]. DT also serves as a powerful asset management tool, as demonstrated by Stalder *et al.* (2023) in SNCF Réseau's railway infrastructure management. This study showcased how DT transforms raw data into actionable insights, facilitating lifecycle management and improving operational efficiencies. Advanced technologies like LIDAR, photogrammetry, and IoT devices were employed to ensure up-to-date digital representations of assets [13]. Shen *et al*. (2023) advanced the field of railway track maintenance by employing axle box accelerations (ABA) within a DT framework to evaluate track stiffness. This innovative method captures real-time vehicle-track interactions, enabling precise maintenance interventions and improving track safety under operational conditions [14].

3. Asset management framework for Model-Based DT approach

One of the key aspects of Digital Twin (DT) evolution is model management, which goes beyond mere data management. This general approach has great potential and is reflected in technologies such as the Asset Administration Shell (AAS) and Model-Based System Engineering (MBSE). AAS, a key concept in Industry 4.0, standardizes information and ensures interoperability, enabling modular representations of assets [15]. MBSE, through the digital thread, facilitates the design, simulation, and lifecycle management of complex systems, improving accuracy and traceability [16]. While these technologies highlight the importance of model management, they are not its only applications. The IEC 81346 standard provides a structured framework for efficient data and model management, supporting scalable strategies and digital transformation in asset management.

Figure 2

Use of a Maintenance Framework for the Development of Digital Models to Be Integrated into the Digital Twin



Digital Twins (DTs) address the challenge of systematically integrating data and models for asset management and maintenance in the short, medium, and long term,

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ensuring a lifecycle approach. They serve as the foundation for standardizing the digitalization of assets, processes, and services, enabling scalability without requiring significant changes to the underlying infrastructure. By leveraging DTs, organizations can design and develop digital solutions capable of managing higher data volumes, complexity, and workload, optimizing decision-making and achieving enhanced performance levels through advanced technology. The maintenance management framework proposed by [5] serves as a fundamental methodological support to guide the development of these digital models. By establishing clear requirements and development pathways, it ensures that digital representations are not only accurate but also functional, delivering actionable insights for decision-making and asset lifecycle management. This approach allows digital solutions to align with the operational and strategic objectives of maintenance systems.

Scalability is a cornerstone of the digitalization lifecycle in DT, allowing digital representations to evolve in line with the growing needs and complexities of services. By avoiding unnecessary complexity, the framework facilitates the efficient integration of models, ensuring that maintenance solutions remain agile and adaptable to changing conditions. This scalable approach also enables the progressive incorporation of advanced functionalities, such as predictive analytics and IoT integration, optimizing maintenance ecosystems. Moreover, the proposed framework highlights the importance of integrating evolving models based on service requirements. The ability to dynamically adapt to new challenges and technological advancements allows DTT- based solutions to provide scalable results that enhance decision-making, optimize resource allocation, and improve overall system reliability. This comprehensive approach strengthens the role of digital technologies as key tools for the modernization and continuous improvement of maintenance processes. Based on these considerations, in the use case presented in this study, the following models have been developed, each corresponding to different phases of the framework:

— ADM (Asset Definition Model) – Phase 1: This model defines the data structure for all considered entities (machinery, workshop, operators). It includes different definition aspects such as technical structure, classification, and unique physical elements. All these elements are integrated into a BIM data model and connected to a specific ontology of digital entities, hosted within the platform/architecture that supports the Digital Twin (DT).
— AMM (Asset Monitoring Model) – Phase 4: This model establishes the set of variables and properties to be integrated as part of the digital entity, including the selection of IoT technologies for integration into the platform and the design of the data management process, enabling the representation and interpretation of variables. It also incorporates monitoring data into the BIM data model and interface.
— IAMM (Intelligent Asset Management Models) – Phases 4 & 5: This model includes the development of predictive models (CBM-Condition-Based Maintenance) based on data provided by the AMM. Additionally, it incorporates a preventive maintenance optimization model, which interprets the results from

CBM and reliability analysis. Furthermore, a job-shop task rescheduling model has been developed.

4. Use case: Digital Twin Technology in Railway Rolling Stock Maintenance. Principal outcomes and conclusions

The use case focuses on the digitalization of maintenance services for a fleet of machinery dedicated to railway infrastructure preservation. This fleet includes various types of machines: tampers, profilers, ballast cleaners, stabilizers, trolleys, locomotives, and wagons. Proper maintenance of this fleet directly impacts railway safety levels. The Digital Twin DFMAS (GD DFMAS) concept is highly advanced, comprehensive, and ambitious. It transforms assets, personnel, and resources into interactive digital entities, enables process digitalization, employs a model-based approach for the scalable development of digitalized entities, and integrates multiple decision-making centers and services within a common unified architecture. This necessitates an integration approach from the outset, based on a shared software architecture and a specific design for model ontologies that digitally define assets, processes, and services. The architecture, built on open-source software, supports data management, incorporating AI capabilities (predictive analytics, simulation) as well as advanced visualization and interface tools. The IoT/IoE (Internet of Everything) environment enables physical connectivity through the Digital Twin, linking equipment, personnel, and all resources involved in maintenance. Finally, BIM technology capabilities have been fully integrated into the architecture, including point cloud-based asset virtualization, 3D representation, and collaborative data management.

Figure 3

Images of digitalized entities: machinery and workshop

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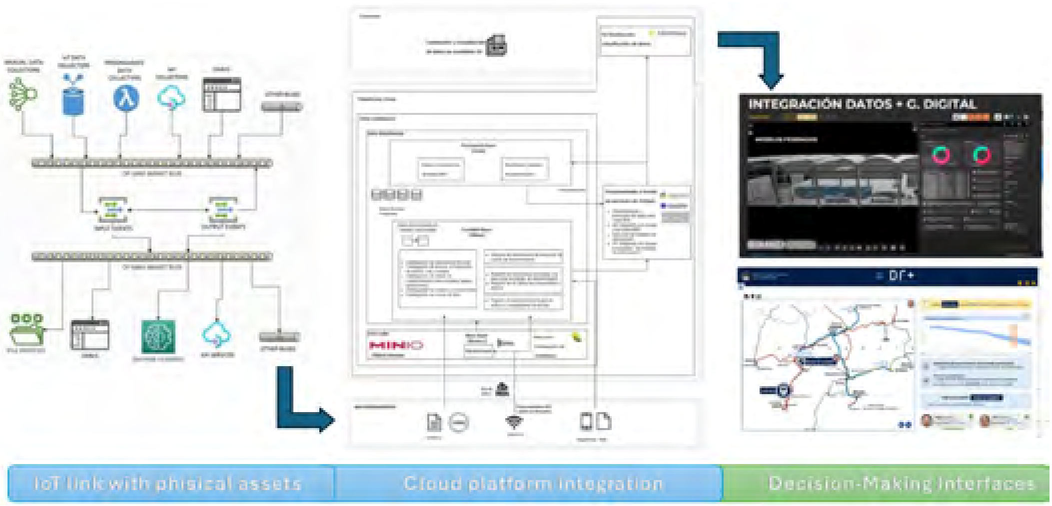
A proof of concept for the proposed digitalization solution has been successfully carried out, allowing for the validation of innovation in both the development and architecture of the Digital Twin as well as its application to advanced maintenance digitalization. An initial innovative path has been explored and tested, confirming the feasibility and effectiveness of the proposed solution. It is considered complete not because it is «finished» but because the proof of concept has incorporated all key elements, tested and integrated into a functional and viable concept. Figure 4 represents the technological composition scheme of the DFMAS digitalization solution, structured into three main blocks: physical connectivity and mobility through the IoT ecosystem; a flexible open-source platform for data and model management (AI and ontologies) and service integration; and interfaces for information access, decision support, and maintenance execution.

Figure 4

Technological composition scheme of the DFMAS digitalization solution



In this scheme, it is essential to highlight that user interfaces are decoupled from entity modeling, allowing for multiple interfaces tailored to specific needs. The requirements of these interfaces are linked to the development of ECM functions, providing dynamic and interactive access to the necessary information for the individualized management of each ECM. The ontology that ultimately integrates the Digital Twin (DT) content, based on the various digitalized entities and employed models, is centralized in the cloud platform, facilitating entity and model management as well as the execution of services necessary to bring the DT to life. In DFMAS 2, the proof of concept has focused on ECM 4, achieving significant advancements in digitalization and Digital Twin (DT) application for railway rolling stock maintenance:

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— All entities involved in ECM 4 maintenance processes have been digitalized, creating digital counterparts for machines, equipment, personnel, tools, and spare parts within a scalable data management platform.
— An IoT ecosystem has been developed for the physical connectivity of the DT and the digital interconnection of all entities involved in maintenance (assets, personnel, workshop resources). This facilitates workshop digitalization and process automation, as well as asset monitoring. It includes devices and platforms for real-time monitoring, an RFID/NFC system for precise tracking and identification of assets and personnel, and mobility tools to enhance workshop staff interaction, improving efficiency and accuracy in maintenance processes.
— A flexible, scalable open-data management platform has been created, deployable on-premise or in the cloud. Using the Lakehouse concept and a Medallion Architecture data processing design, it ensures data quality, performance, security, and governance, supporting entity ontology integration, AI models, and software services necessary for DT operation.
— A BIM digital model of the workshop and its components has been developed, along with a Work Breakdown Structure (WBS) based on maintenance data models. Additionally, interfaces have been created for DT representation and interaction with different operational and management roles, utilizing tools for interactive data visualization and maintenance control within the BIM model.

The designed Digital Twin enables various capabilities, including real-time tracking of machines and equipment, monitoring their condition, predicting its evolution based on data, planning preventive maintenance based on optimal intervention intervals, scheduling and optimizing workshop interventions with resource allocation, digitalizing and controlling inspection processes, and tracking changes or replacements of machine components. All of this is supported by interactive interfaces, facilitating maintenance execution and control for the different human roles involved in these processes.

Acknowledgment

The authors A. G.-L. and A.S.-M. want to thank the support from Grant PID2022-137748OB-C32 funded by MCIN/AEI/ 10.13039/501100011033.

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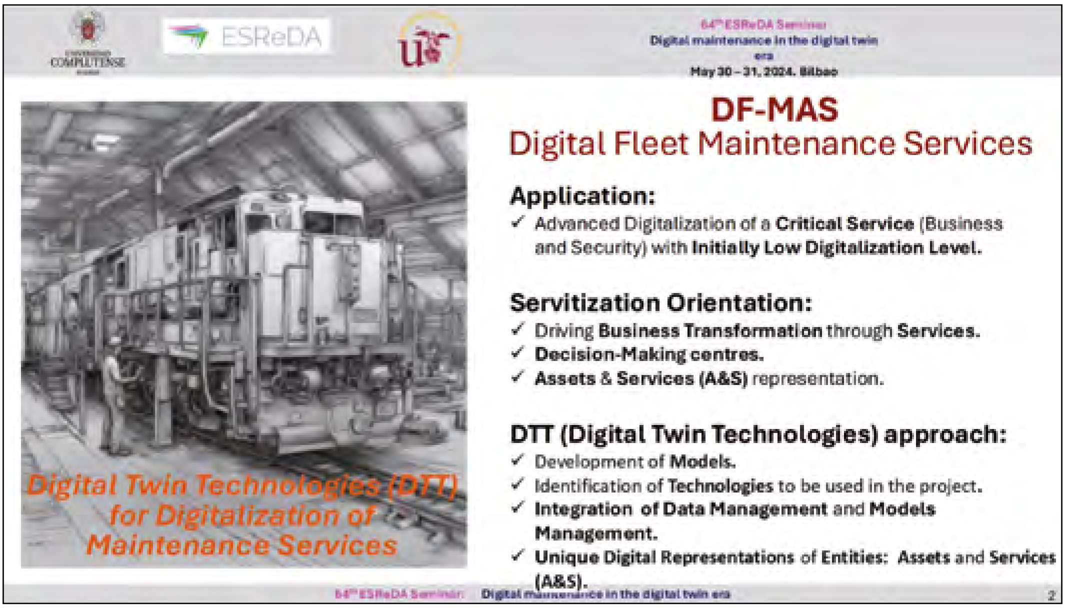

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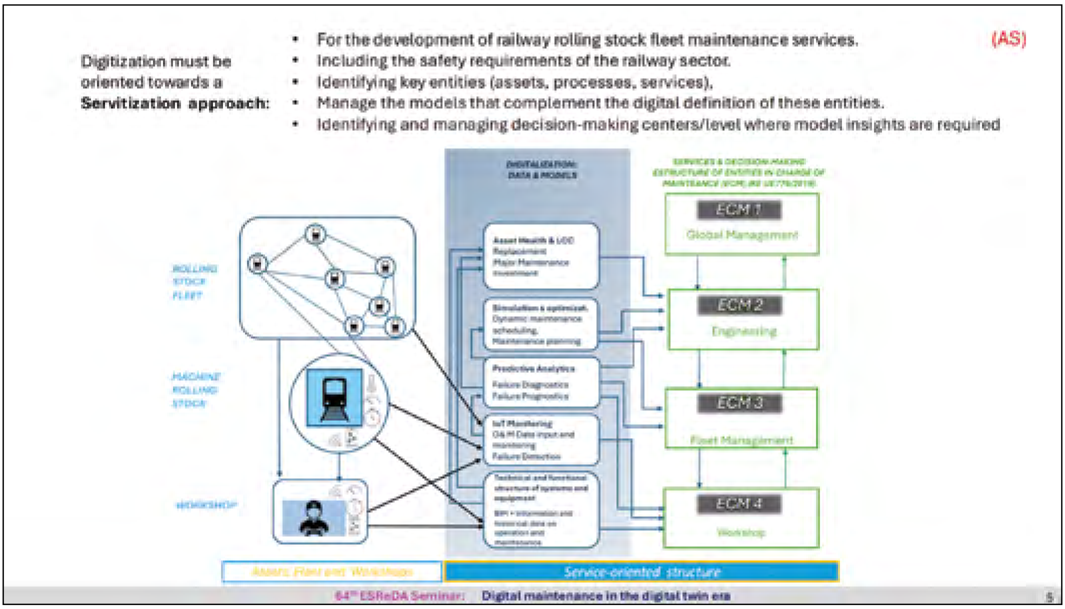
(AS)
Digitization must be oriented towards a **Servitization approach:**
• For the development of railway rolling stock fleet maintenance services.
• Including the safety requirements of the railway sector.
• Identifying key entities (assets, processes, services),
• Manage the models that complement the digital definition of these entities.
• Identifying and managing decision-making centers/level where model insights are required
ROLLING STOCK FLEET
MACHINE ROLLING STOCK
WORKSHOP
DIGITALIZATION: DATA & MODELS
Asset Health & LCC
Replacement
Major Maintenance
Investment
Simulation & optimizat.
Dynamic maintenance scheduling.
Maintenance planning
Predictive Analytics
Failure Diagnostics
Failure Prognostics
IoT Monitoring
O&M Data input and monitoring
Failure Detection
Technical and functional structure of systems and equipment
BIM + information and historical data on operation and maintenance
SERVICES & DECISION-MAKING (STRUCTURE OF ENTITIES IN CHARGE OF MAINTENANCE (ECM) IRE UE779/2019)
ECM 1
Global Management
ECM 2
Engineering
ECM 3
Fleet Management
ECM 4
Workshop
Assets, Fleet and Workshops
Service-oriented structure
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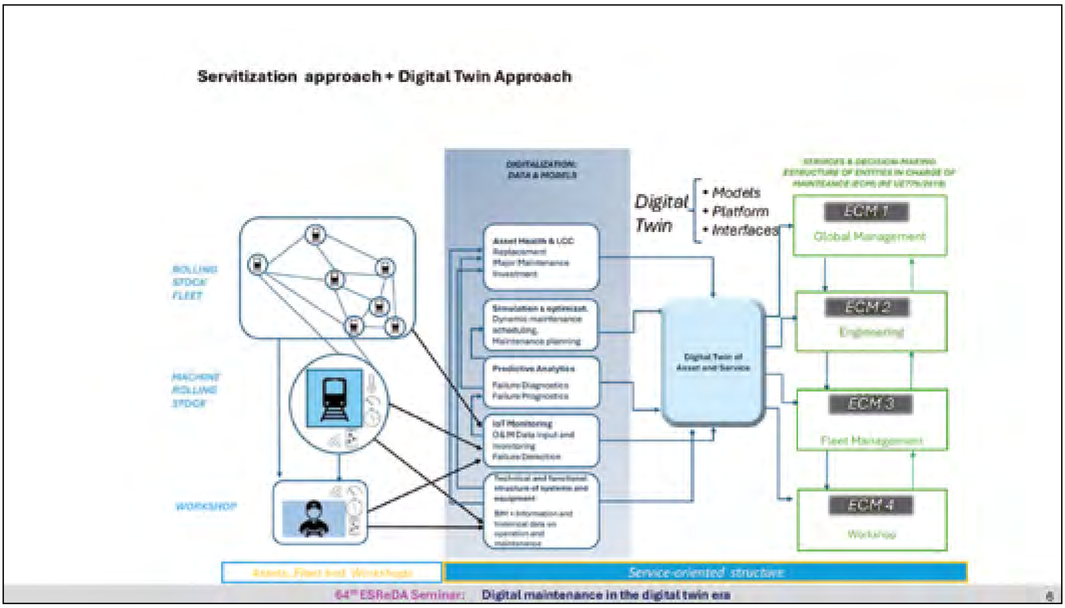
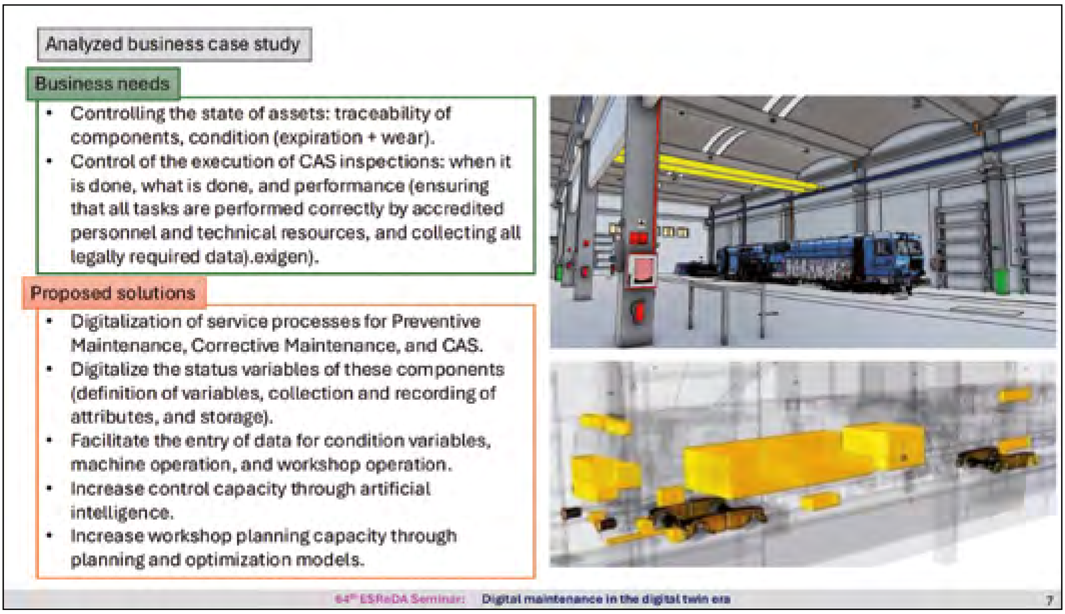
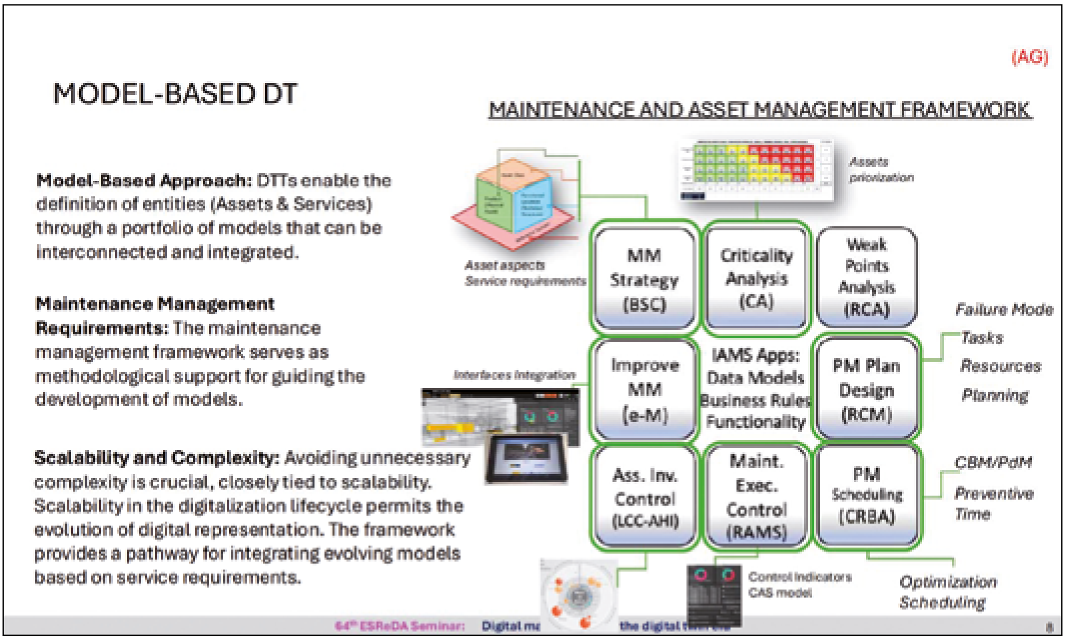
5


Servitization approach + Digital Twin Approach
ROLLING STOCK FLEET
MACHINE ROLLING STOCK
WORKSHOP
DIGITALIZATION: DATA & MODELS
Asset Health & LCC
Replacement
Major Maintenance
Investment
Simulation & optimizat.
Dynamic maintenance scheduling.
Maintenance planning
Predictive Analytics
Failure Diagnostics
Failure Prognostics
IoT Monitoring
O&M Data input and monitoring
Failure Detection
Technical and functional structure of systems and equipment
BIM + information and historical data on operation and maintenance
Digital Twin
• Models
• Platform
• Interfaces
Digital Twin of Asset and Service
SERVICES & DECISION-MAKING (STRUCTURE OF ENTITIES IN CHARGE OF MAINTENANCE (ECM) IRE UE779/2019)
ECM 1
Global Management
ECM 2
Engineering
ECM 3
Fleet Management
ECM 4
Workshop
Assets, Fleet and Workshops
Service-oriented structure
64th ESReDA Seminar: Digital maintenance in the digital twin era
6





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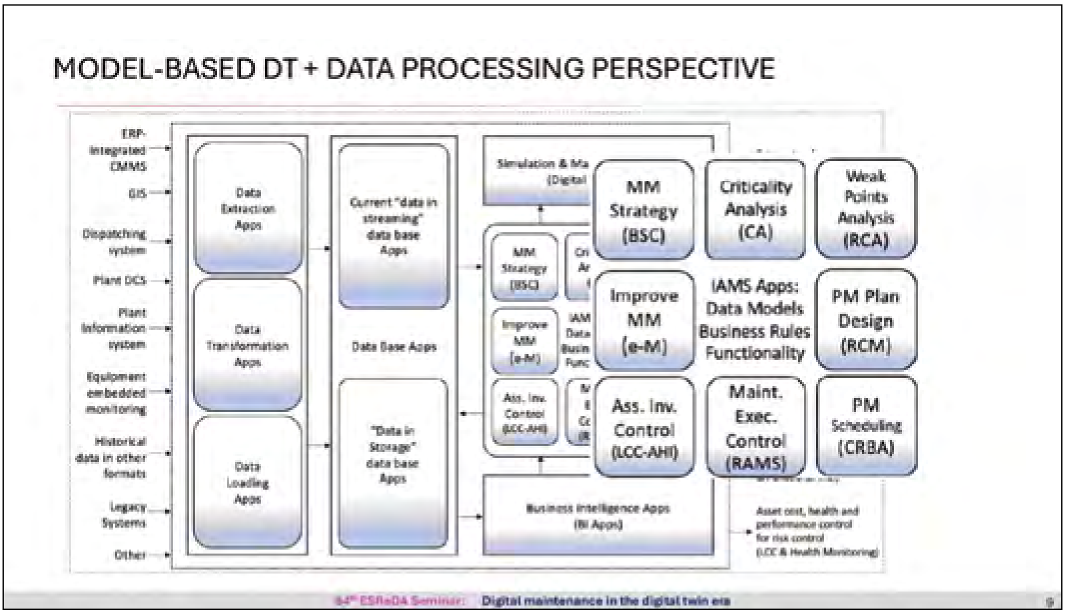
MODEL-BASED DT + DATA PROCESSING PERSPECTIVE
ERP-integrated CMMS
GIS
Dispatching system
Plant DCS
Plant Information system
Equipment embedded monitoring
Historical data in other formats
Legacy Systems
Other
Data Extraction Apps
Data Transformation Apps
Data Loading Apps
Current "data in streaming" data base Apps
Data Base Apps
"Data in Storage" data base Apps
MM Strategy (BSC)
Improve MM (e-M)
Ass. Inv. Control (LCC-AHI)
Business Intelligence Apps (BI Apps)
MM Strategy (BSC)
Criticality Analysis (CA)
Weak Points Analysis (RCA)
Improve MM (e-M)
IAMS Apps: Data Models Business Rules Functionality
PM Plan Design (RCM)
Ass. Inv. Control (LCC-AHI)
Maint. Exec. Control (RAMS)
PM Scheduling (CRBA)
Asset cost, health and performance control for risk control (LCC & Health Monitoring)
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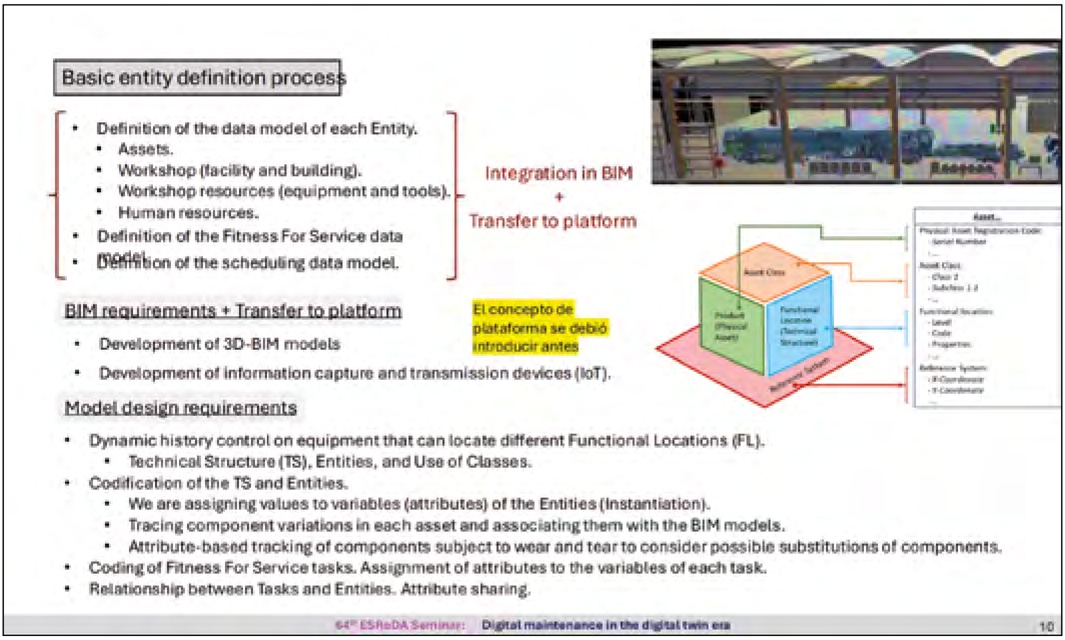
9


Basic entity definition process
Definition of the data model of each Entity.
Assets.
Workshop (facility and building).
Workshop resources (equipment and tools).
Human resources.
Definition of the Fitness For Service data model.
Definition of the scheduling data model.
Integration in BIM
+
Transfer to platform
BIM requirements + Transfer to platform
Development of 3D-BIM models
El concepto de plataforma se debió introducir antes
Development of information capture and transmission devices (IoT).
Model design requirements
Dynamic history control on equipment that can locate different Functional Locations (FL).
Technical Structure (TS), Entities, and Use of Classes.
Codification of the TS and Entities.
We are assigning values to variables (attributes) of the Entities (Instantiation).
Tracing component variations in each asset and associating them with the BIM models.
Attribute-based tracking of components subject to wear and tear to consider possible substitutions of components.
Coding of Fitness For Service tasks. Assignment of attributes to the variables of each task.
Relationship between Tasks and Entities. Attribute sharing.
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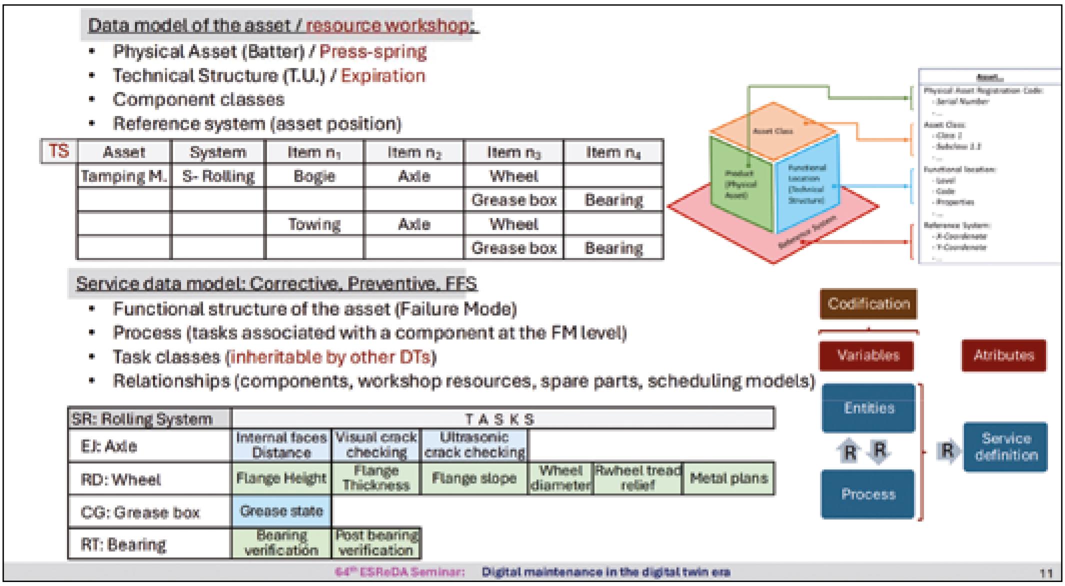
10


Data model of the asset / resource workshop:
Physical Asset (Batter) / Press-spring
Technical Structure (T.U.) / Expiration
Component classes
Reference system (asset position)
TS
Asset
System
Item n1
Item n2
Item n3
Item n4
Tamping M.
S- Rolling
Bogie
Axle
Wheel
Grease box
Bearing
Towing
Axle
Wheel
Grease box
Bearing
Service data model: Corrective, Preventive, FFS
Functional structure of the asset (Failure Mode)
Process (tasks associated with a component at the FM level)
Task classes (inheritable by other DTs)
Relationships (components, workshop resources, spare parts, scheduling models)
Codification
Variables
Atributes
Entities
Process
Service definition
R
SR: Rolling System
T A S K S
EJ: Axle
Internal faces Distance
Visual crack checking
Ultrasonic crack checking
RD: Wheel
Flange Height
Flange Thickness
Flange slope
Wheel diameter
Rwheel tread relief
Metal plans
CG: Grease box
Grease state
RT: Bearing
Bearing verification
Post bearing verification
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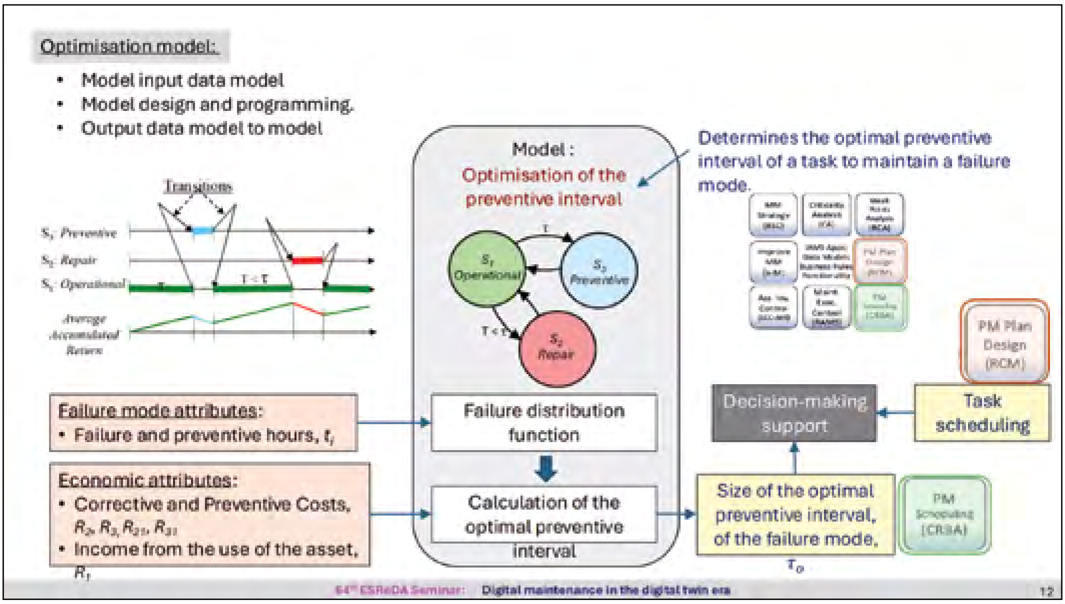
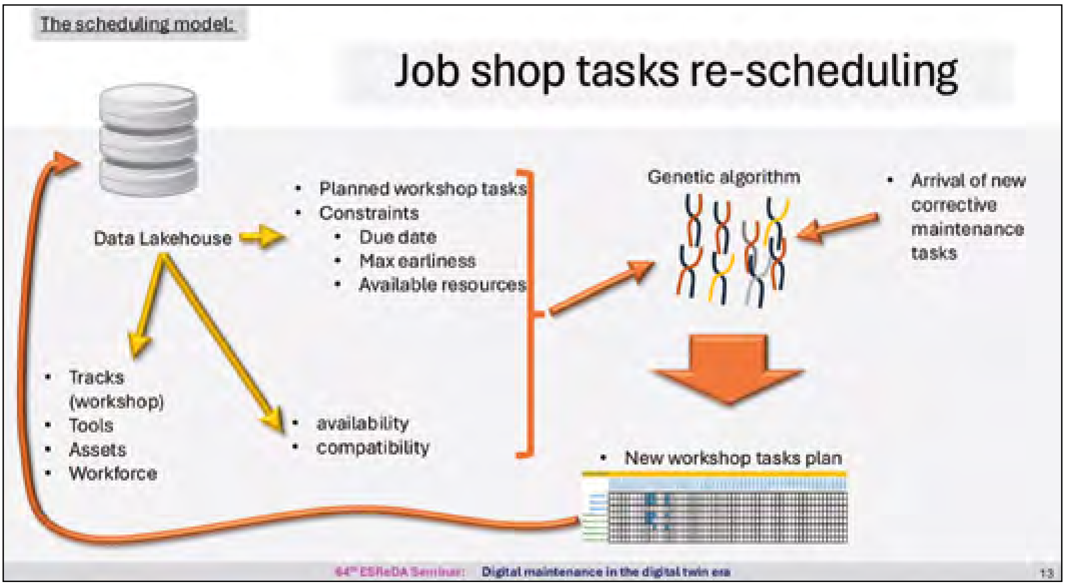
11


Optimisation model:
Model input data model
Model design and programming
Output data model to model
Transitions
S1 Preventive
S2 Repair
S1 Operational
Average Accumulated Return
Model :
Optimisation of the preventive interval
S1 Operational
S2 Preventive
S3 Repair
Determines the optimal preventive interval of a task to maintain a failure mode.
PM Plan Design (RCM)
Failure mode attributes:
Failure and preventive hours, t_i
Economic attributes:
Corrective and Preventive Costs, R_2, R_3, R_{21}, R_{31}
Income from the use of the asset, R_1
Failure distribution function
Calculation of the optimal preventive interval
Decision-making support
Task scheduling
Size of the optimal preventive interval, of the failure mode, τ_0
PM Scheduling (CRBA)
64th ESReDA Seminar: Digital maintenance in the digital twin era
12


The scheduling model:
Job shop tasks re-scheduling
Data Lakehouse
Planned workshop tasks
Constraints
Due date
Max earliness
Available resources
Genetic algorithm
Arrival of new corrective maintenance tasks
Tracks (workshop)
Tools
Assets
Workforce
availability
compatibility
New workshop tasks plan
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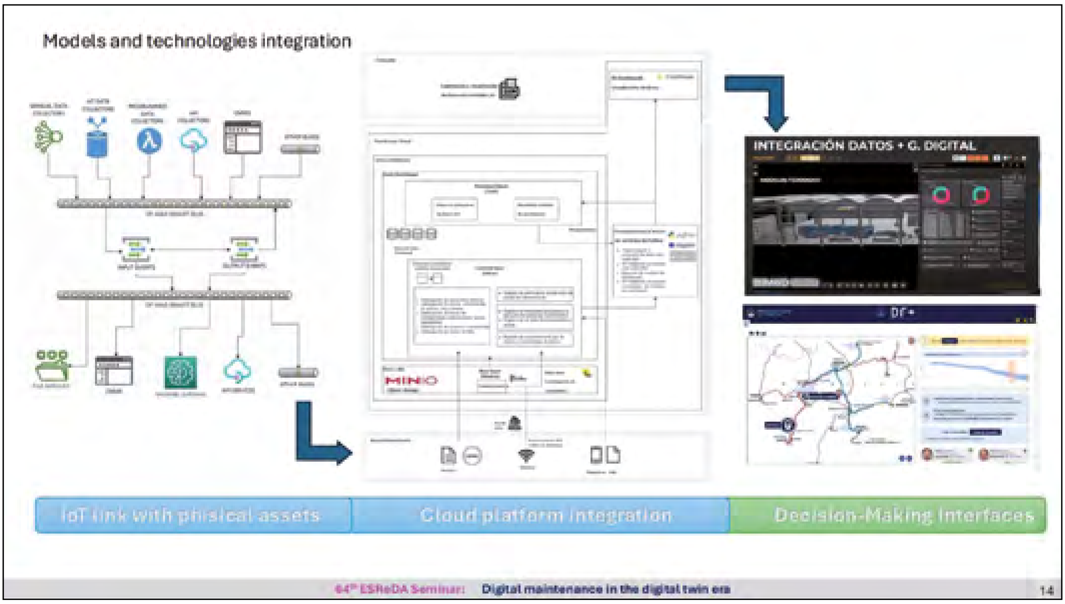
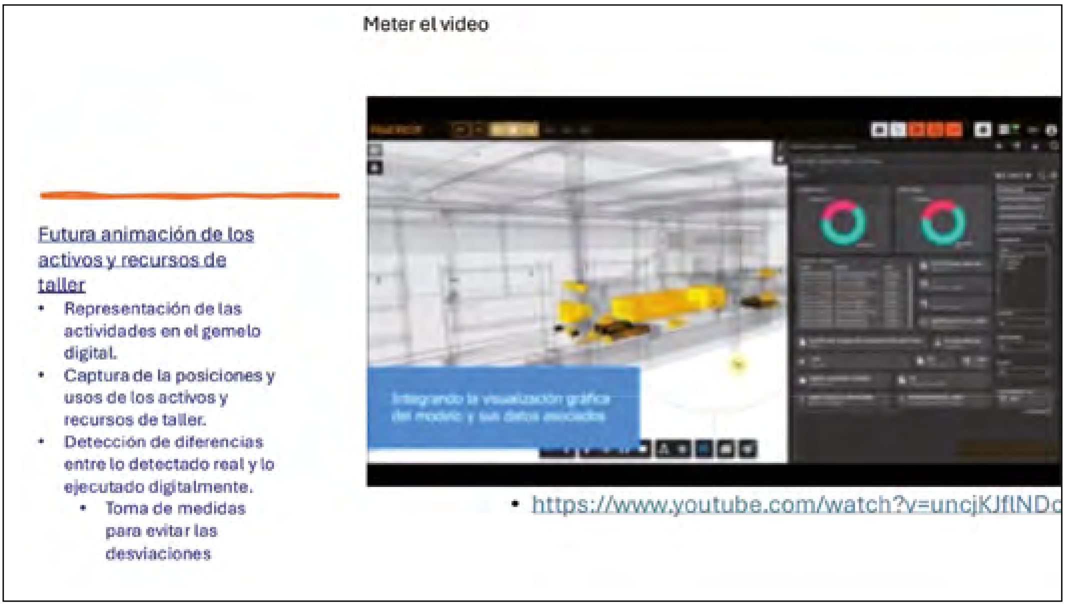
13


Models and technologies integration
INTEGRACIÓN DATOS + G. DIGITAL
MINIO
IoT link with phisical assets
Cloud platform integration
Decision-Making Interfaces
64th ESReDA Seminar: Digital maintenance in the digital twin era
14


Meter el video
Futura animación de los activos y recursos de taller
• Representación de las actividades en el gemelo digital.
• Captura de la posiciones y usos de los activos y recursos de taller.
• Detección de diferencias entre lo detectado real y lo ejecutado digitalmente.
• Toma de medidas para evitar las desviaciones
• https://www.youtube.com/watch?v=uncjKJfINDc


ESReDA
64th ESReDA Seminar
Digital maintenance in the digital twin era
May 30 – 31, 2024. Bilbao
The authors A. G.-L. and A.S.-M. want to thank the support from Grant PID2022-137748OB-C32 funded by MCIN/AEI/ 10.13039/501100011033
Project: digest
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Digital Twins For Power Converter Application: Implementation From A Basic Architecture

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José López Domínguez
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CEN SOLUTIONS

Abstract

The implementation of Digital Twins (DT) in industrial settings presents both opportunities and challenges. While DTs are revolutionizing asset management and maintenance, their adoption is hindered by key obstacles, particularly the lack of standardization and interoperability. This document explores a reference architecture and a development model that emphasizes standardization, ensuring seamless integration within commercial Cloud/IoT platforms. A case study focusing on power converters for renewable energy and electrical storage demonstrates the benefits of DTs in predictive maintenance, efficiency optimization, and cost reduction. The findings highlight the importance of structured modeling, advanced analytics, and machine learning integration, reinforcing the role of Digital Twins as a transformative tool for industry.

1. Introduction

Digital Twins (DT) are transforming asset management and industrial maintenance, yet their implementation faces multiple challenges. Among these, the lack of standardization emerges as a key obstacle, hindering interoperability between systems and integration into commercial Cloud/IoT solutions. This presentation explores a reference architecture to address this challenge and a development model based on Digital Twin standardization, enabling effective implementation across different industrial sectors.

Adopting Digital Twins involves technical and organizational challenges, with standardization of data and models being one of the main concerns. The absence of a common framework complicates integration across platforms, while interoperability with legacy systems requires careful planning. As ecosystems grow, scalability becomes increasingly complex, and high initial costs for hardware, software, and training present financial barriers. The development of advanced models, incorporating simulation, machine learning, and artificial intelligence, is essential for the continued evolution of Digital Twins. To tackle these challenges, a reference architecture is proposed,

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structuring the development and implementation of Digital Twins in distinct phases to ensure smooth integration into modern business environments.

2. Use Case: Asset Management and Maintenance of Power Converters

A practical application of this approach is demonstrated in asset management and the maintenance of power converters for renewable energy and electrical storage. The proposed model is based on standardization of key Digital Twin components, ensuring compatibility with commercial Cloud/IoT platforms. This architecture includes structured modeling based on open standards, seamless integration with cloud environments for real-time connectivity and data analysis, and the use of commercial IoT platforms such as Azure Digital Twins. Predictive and prescriptive capabilities are incorporated through machine learning and simulations, alongside advanced data management solutions. The developed Digital Twin enables real-time monitoring of power converters, predictive fault analysis based on behavioral patterns and wear, and optimized maintenance through preventive and prescriptive strategies. Integration with Cloud/IoT platforms facilitates automated data management and alert generation. This case demonstrates how combining a standardized architecture with advanced models enhances reliability, reduces operational costs, and improves energy efficiency in critical infrastructures.

Effective asset management relies on an integrated system that enhances performance and availability. A unified digital framework enables remote access to disparate elements while leveraging artificial intelligence for rapid decision-making. Cloud-based solutions provide an efficient means to manage the vast volume of data, enabling predictive intelligence to correlate product quality variations with asset degradation across its lifecycle.

Cloud solutions must be developed following fundamental software principles such as flexibility, modularity, scalability, interoperability, confidentiality, and integrity. These solutions should facilitate end-to-end asset management, incorporating real-time monitoring, simulation, and predictive analytics. By integrating diverse enterprise systems, cloud platforms streamline data correlation, enhance interoperability, minimize redundant data inputs, and simplify administrative processes.

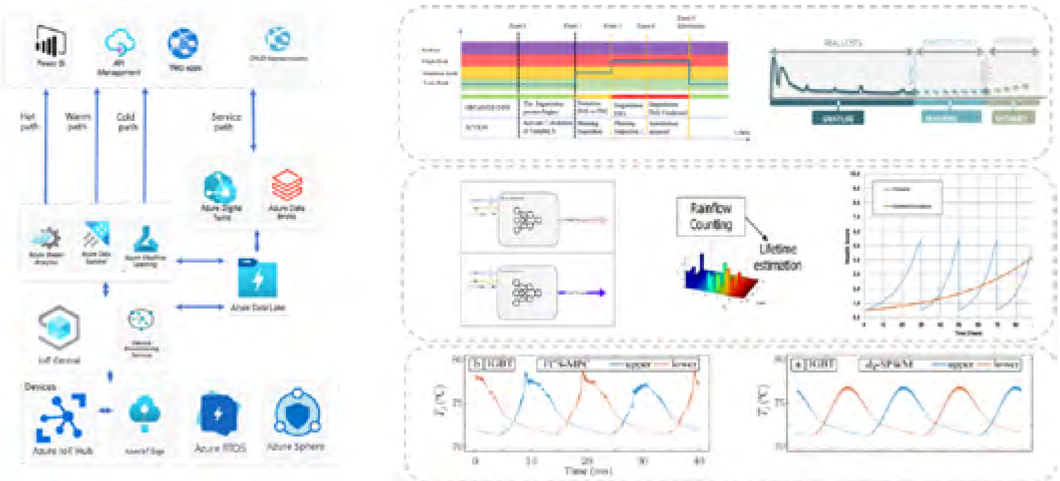
A well-structured cloud system enhances the maintenance lifecycle by automating detection, analysis, execution, and predictive modeling. Ensuring sustainability and scalability, such systems must adhere to interoperability standards and asset management frameworks. They support strategic, tactical, and operational decision-making while extending existing enterprise solutions through scientific management models and AI-driven decision-making.

Operationally, real-time monitoring and predictive simulations generate automated risk alerts, optimizing asset performance and triggering corrective actions. Strategically, such systems estimate asset lifespans, informing long-term planning and investment decisions. Effective interconnection and standardization of data facilitate seamless knowledge transfer and improved communication across systems.

To develop a robust digital twin model aligned with industry standards, organizations should adhere to best practices: leveraging industry-recognized data models, implementing comprehensive data frameworks, ensuring contextualized integration of multiple data sources, and constructing behavioral models to enable simulation and prediction. Additionally, scalability and flexibility must be prioritized to accommodate evolving business needs and technological advancements. A cloud-based asset management solution supports decision-making at all business levels —strategic, tactical, and operational— by integrating AI-driven reasoning. This approach optimizes process efficiency, enhances predictive capabilities, and maximizes asset value, ultimately contributing to improved operational resilience and long-term sustainability.

Figure 1

Interpretation of the architecture or references and model representation within the use case



3. Conclusions

Standardization and integration with commercial solutions are key to the success of Digital Twins. A reference architecture and a development model based on standardization facilitate adoption, ensuring compatibility and scalability. Through the power converter use case, it is evident how Digital Twins can revolutionize asset management and maintenance, enabling a smarter, predictive, and more efficient approach. With the continuous advancements in artificial intelligence and cloud platforms, Digital Twins will not only refine predictive maintenance strategies but also enable fully autonomous decision-making frameworks, reshaping the future of asset management and industrial efficiency.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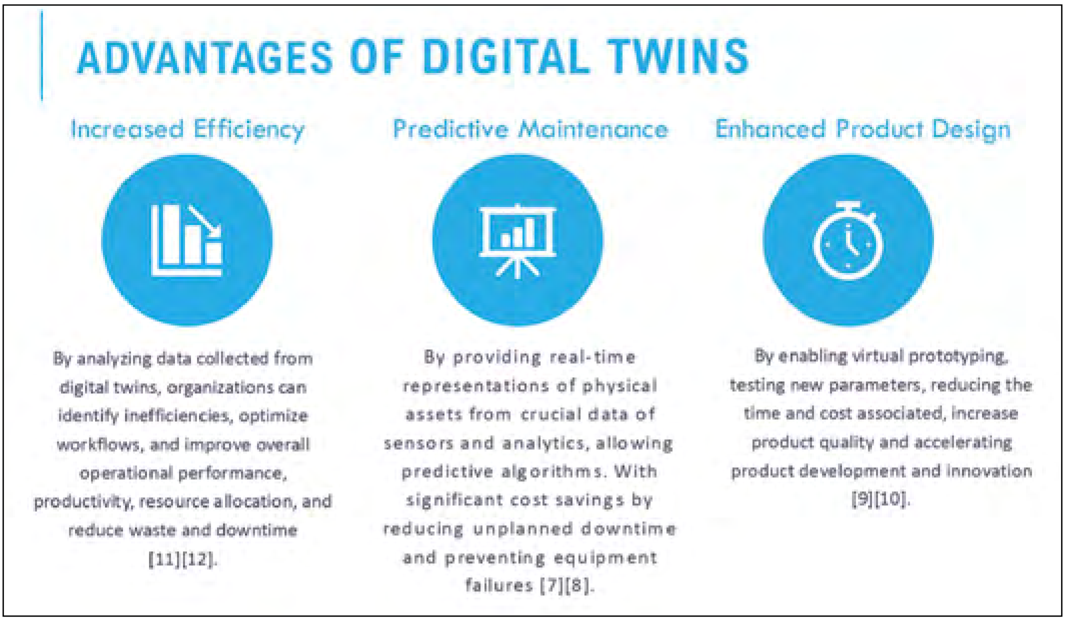
CTA
DIGITAL TWINS FOR POWER CONVERTER APPLICATION:
IMPLEMENTATION FROM A BASIC ARCHITECTURE
Juan Francisco Gómez Fernandez
Seville University
José López Domínguez
CEN SOLUTIONS

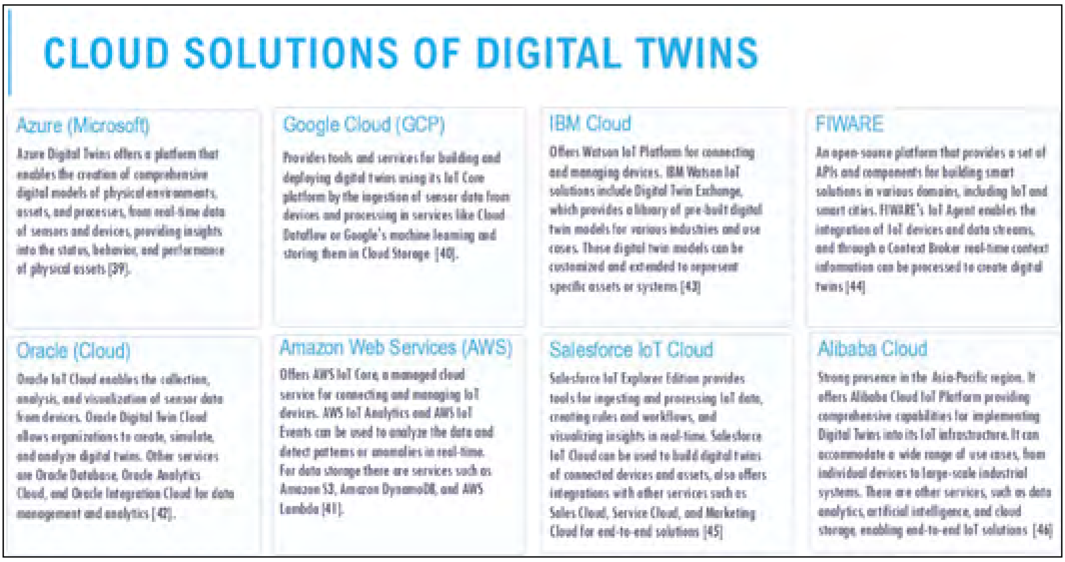

Our Company
We provide products and services for the energy transition in the core segments: energy, Oil&Gas, industry, water and datacenters
Our Customers
aes
Iberdrola
EADS
enel
acciona
eks
REPSOL
Technology and Innovation
✓ Energy storage
✓ Hydrogen
✓ Energy management
Company Video: https://youtu.be/KaXRTYuwgWY
Our Activities
• Complete electrical equipment production from design to delivery
• Services
censolutions
Technological solutions for sustainable development
Our Products
Strategic Highlights
• Consolidated activity with extensive track record in supply of equipment for critical power.
• Best-in-class in electrical equipment supply for low voltage and medium voltage with >25 years experience
• Total BESS systems delivered >3GWh and additional 1,3GWh under production
• More than 500 full eHouses supplied worldwide
• Own engineering and know-how
• Vertical integration in key activities
• Recurrent customer base
• Extensive installed fleet
• Customer focused business model, providing tailor-made solutions

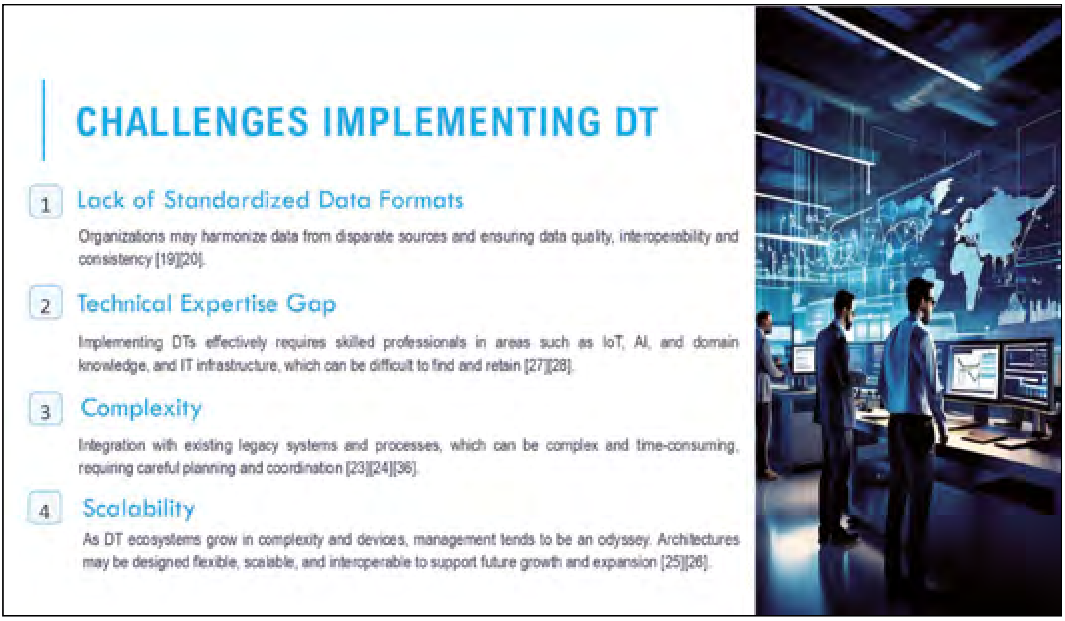

PRODUCTION CAPACITY
censolutions
censolutions
Dos Hermanas
Sevilla
2000 m² Offices
10.000 m²
External integration area
~ 250
Employees
~ 38.000 m²
Facilities (*)
~ 300,000
Horas-hombre / año


PRODUCT PORTFOLIO
censolutions
Fossil Generation
Nuclear PP
Renewables
Oil&Gas
Industry & Datacenters
MV Switchgears
LV Switchboards
Modular Equipment (eRooms, power modules, BESS)
Power Electronics & Special Manufacturings
4


DEFINING DIGITAL TWIN
1
Origins
The digital twin concept was first proposed by Michael Grieves in the early 2000s, with further contributions from researchers like David Gelernter and the National Institute of Standards and Technology (NIST).
2
Core Concept
A digital twin is a virtual replicas of a physical assets, process o service, that uses real-time data, simulation, and machine learning to mirror its real-world counterpart across the entire lifecycle in a digital environment [1][2].
3
Key Capabilities
Increasingly recognized for driving digital transformation in industries, providing valuable insights, improve efficiency, and reduce costs [3][4].
Thanks to proactive management of assets and making data-driven decisions [5][6].


ADVANTAGES OF DIGITAL TWINS
Increased Efficiency
Predictive Maintenance
Enhanced Product Design
By analyzing data collected from digital twins, organizations can identify inefficiencies, optimize workflows, and improve overall operational performance, productivity, resource allocation, and reduce waste and downtime [11][12].
By providing real-time representations of physical assets from crucial data of sensors and analytics, allowing predictive algorithms. With significant cost savings by reducing unplanned downtime and preventing equipment failures [7][8].
By enabling virtual prototyping, testing new parameters, reducing the time and cost associated, increase product quality and accelerating product development and innovation [9][10].





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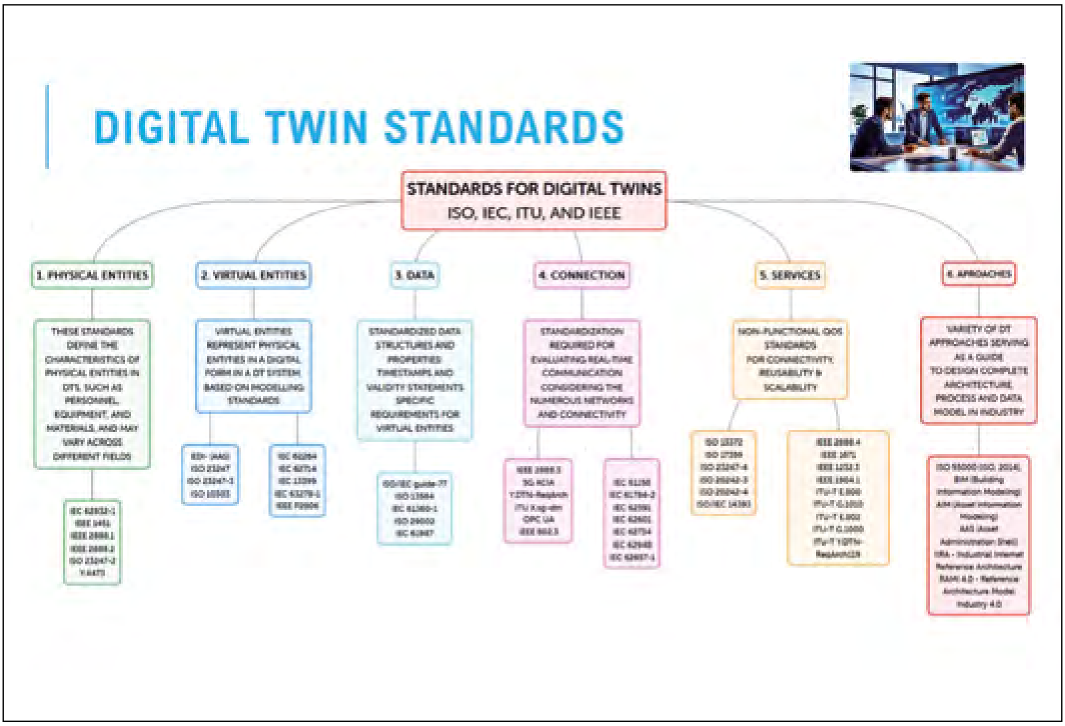
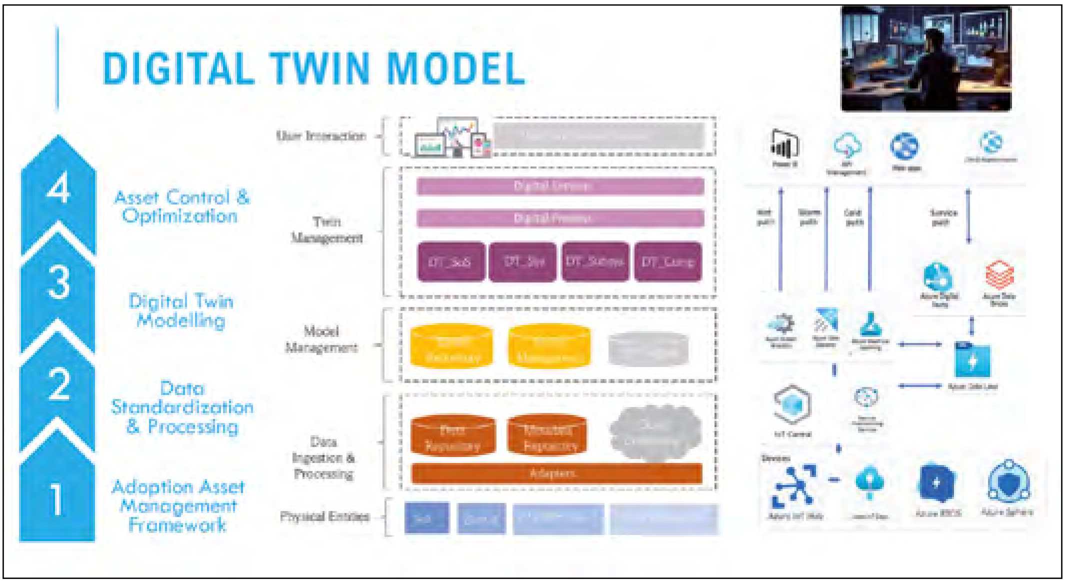
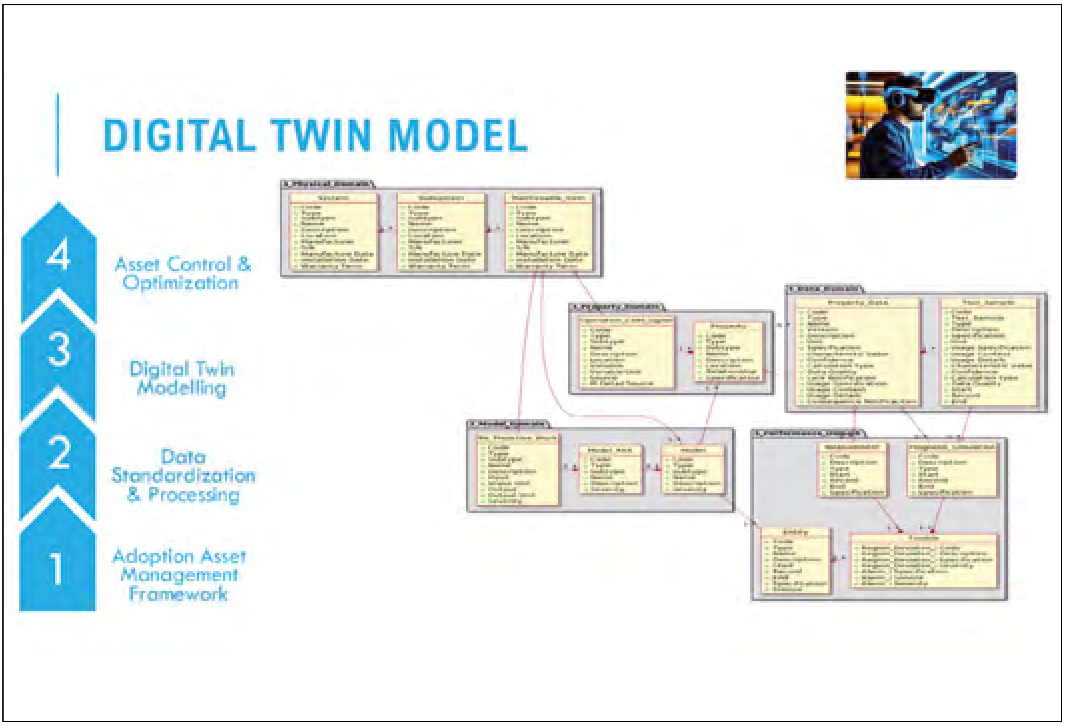
CHALLENGES IMPLEMENTING DT
5
Change and Maintenance Management
DT technology requires adaptation to new ways of working, it may meet resistance from employees. Keeping DT current and up-to-date requires ongoing effort and resources [38].
6
Regulatory Compliance
DT may involve the use of sensitive data that must comply with various regulations, implementing robust security measures and data governance frameworks to protect and mitigate privacy risks [21][22]
7
High Initial Costs
Usually requires significant investment in hardware, software, and expertise, which can be a barrier for some organizations [35].
8
Value Demonstration
ROI and KPIs have to demonstrate the impact of DT on key business objectives: operational efficiency, cost savings, and revenue generation, for securing buy-in and funding for implementation [29][30].


DIGITAL TWIN STANDARDS
STANDARDS FOR DIGITAL TWINS
ISO, IEC, ITU, AND IEEE
1. PHYSICAL ENTITIES
THESE STANDARDS DEFINE THE CHARACTERISTICS OF PHYSICAL ENTITIES IN DTS, SUCH AS PERSONNEL, EQUIPMENT, AND MATERIALS, AND MAY VARY ACROSS DIFFERENT FIELDS
2. VIRTUAL ENTITIES
VIRTUAL ENTITIES REPRESENT PHYSICAL ENTITIES IN A DIGITAL FORM IN A DT SYSTEM BASED ON MODELLING STANDARDS
3. DATA
STANDARDIZED DATA STRUCTURES AND PROPERTIES TIMESTAMPS AND VALIDITY STATEMENTS SPECIFIC REQUIREMENTS FOR VIRTUAL ENTITIES
ISO/IEC guide-77
4. CONNECTION
STANDARDIZATION REQUIRED FOR EVALUATING REAL-TIME COMMUNICATION CONSIDERING THE NUMEROUS NETWORKS AND CONNECTIVITY
OPC UA
5. SERVICES
NON-FUNCTIONAL QOS STANDARDS FOR CONNECTIVITY, REUSABILITY & SCALABILITY
6. APROACHES
VARIETY OF DT APPROACHES SERVING AS A GUIDE TO DESIGN COMPLETE ARCHITECTURE, PROCESS AND DATA MODEL IN INDUSTRY


DIGITAL TWIN MODEL
4
Asset Control & Optimization
3
Digital Twin Modelling
2
Data Standardization & Processing
1
Adoption Asset Management Framework
User Interaction
Twin Management
Digital Process
DT_SoS
DT_Sys
DT_Subsys
DT_Comp
Model Management
Data Ingestion & Processing
Adapters
Physical Entities


DIGITAL TWIN MODEL
4
Asset Control & Optimization
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Digital Twin Modelling
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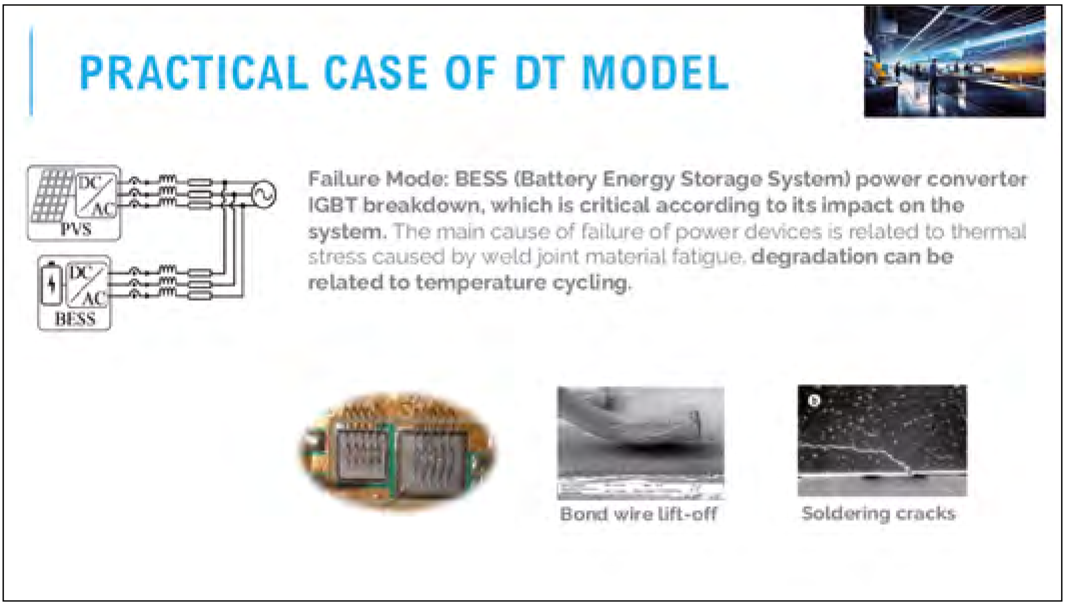
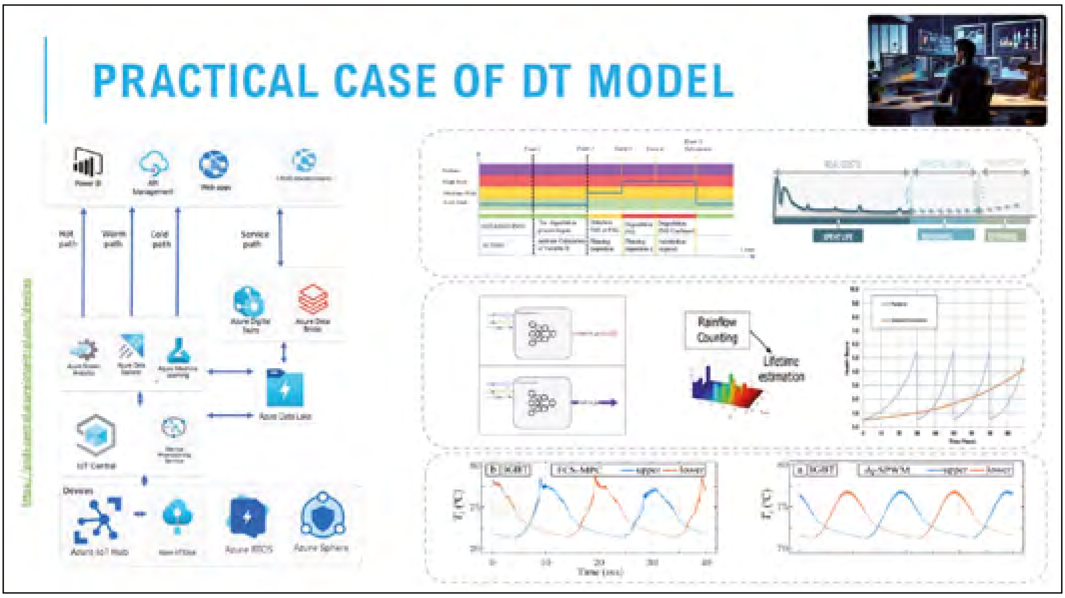
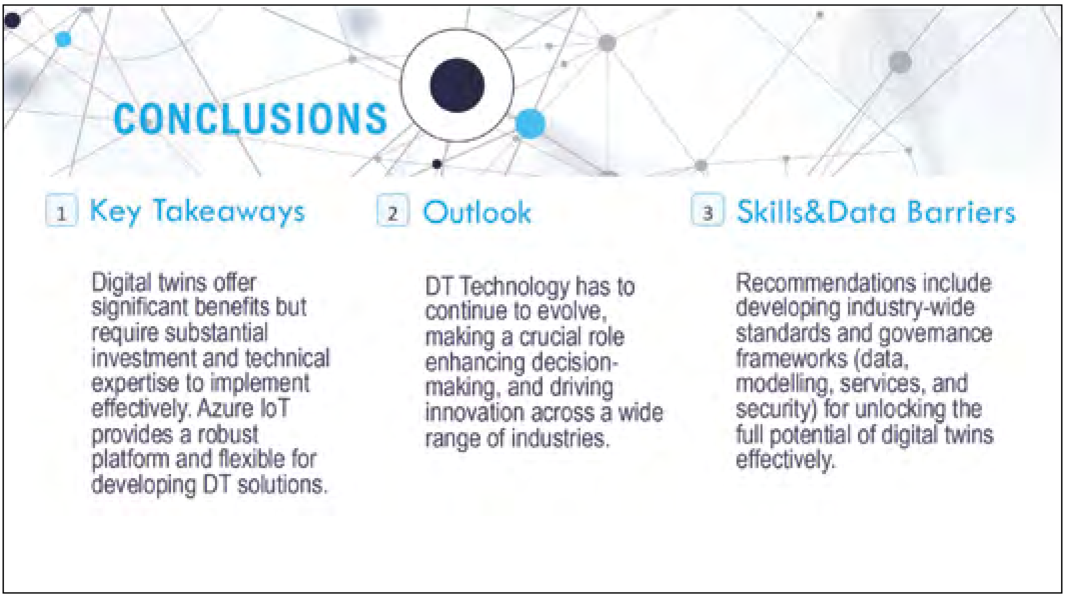
Adoption Asset Management Framework


PRACTICAL CASE OF DT MODEL
DC/AC
PVS
DC/AC
BESS
Failure Mode: BESS (Battery Energy Storage System) power converter IGBT breakdown, which is critical according to its impact on the system. The main cause of failure of power devices is related to thermal stress caused by weld joint material fatigue. degradation can be related to temperature cycling.
Bond wire lift-off
Soldering cracks


PRACTICAL CASE OF DT MODEL
Power BI
API Management
Web apps
Hot path
Warm path
Cold path
Service path
Azure Digital Twins
Azure Data Lake
IoT Central
Devices
Azure IoT Hub
Azure RTOS
Azure Sphere
Rainflow Counting
Lifetime estimation
Time (ms)



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Digital Twin technology in Civil Engineering: research vision from the ENHAnCE and BUILDCHAIN european projects

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Associate Professor, University of Granada

Extended abstract

Civil engineering structures, including bridges, dams, and large buildings, constructed primarily during the first half of the 20th century, are now reaching the end of their useful life. With an optimistic estimate of 100 years of service for reinforced concrete and steel structures, many of these constructions are nearing the limits of their operational lifespan. In addition to the age of these structures, modern societal factors such as population growth, increased traffic, heavier vehicles, and changes in usage patterns have imposed additional stresses, often leading to the overloading of structural elements. Moreover, environmental factors, including climate change, introduce new challenges that these aging structures must be able to withstand. As a result, ongoing and effective maintenance is essential to adapt these structures to evolving usage and environmental conditions [1].

Significant resources are being allocated to the inspection and maintenance of these structures, though current practices rely primarily on traditional methods. These methods, which often involve visual inspections, tend to be reactive and may not always detect underlying issues in time to prevent failures. This can result in partial assessments, delayed responses, and suboptimal decision-making regarding whether to repair or demolish structures. Such delays or misjudgments can compromise safety, sustainability, and economic efficiency. Given that the construction sector is one of the largest consumers of economic resources globally, these decisions have far-reaching implications. According to the United Nations Environment Programme (UNEP), the architecture, engineering, construction, operations, and maintenance (AECO) sector accounts for nearly 40% of global CO_2 emissions related to energy use, primarily due to the energy consumption and materials employed in construction [2].

Simultaneously, digital technologies are rapidly transforming society. The proliferation of the Internet of Things (IoT) and advancements in sensor technology have enabled the real-time collection of vast amounts of environmental and structural data. This data can be quickly processed and analyzed, leading to more informed and timely decision-making. Within this context, the concept of the Digital Twin (DT) has emerged as a critical innovation driving the digital transformation of civil engineering.

The Digital Twin is a sophisticated cyber-physical system that establishes bidirectional communication between the physical and digital worlds. This allows for continuous monitoring and analysis of a physical asset through its digital counterpart. The origins of the DT concept can be traced back to NASA's Apollo missions in the 1960s when a digital replica of the spacecraft was used to simulate the conditions faced by the actual spacecraft in space. The idea was to create a «living model» that could help solve technical issues in real time by providing insights into both the physical system and its operating environment. Although the term «Digital Twin» was coined in 2002 by Michael Grieves, it has only recently found applications in civil engineering. In aerospace, for example, DT technology was applied as early as 2012 [3].

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Today, the Digital Twin operates using autonomous analytics and artificial intelligence (AI), offering capabilities such as structural health monitoring (SHM) and prognosis and health management (PHM). These tools help diagnose current conditions and predict future performance, thereby enhancing decision-making processes [4]. The DT is not a single technology but rather an integration of multiple technologies that collectively improve asset management and operational efficiency.

In civil engineering, the Digital Twin can be applied across the entire lifecycle of infrastructure—from design and construction to ongoing operation and maintenance. The DT provides a virtual representation of the asset, continuously synchronized with its physical counterpart via sensor data. This enables real-time monitoring of structural conditions and facilitates automated or assisted actions aimed at optimizing performance. By leveraging the data gathered, the DT can help address challenges such as overloading, aging infrastructure, and climate-induced stresses, while also improving sustainability.

Despite its potential, the adoption of Digital Twin technology in civil engineering has lagged behind other sectors, such as aerospace and manufacturing, where it has been well established for years. One reason for this delay is the unique nature of civil engineering assets, which are typically designed for specific environments and intended to last for decades or even centuries. In contrast, industries like mechanical engineering deal with assets that have much shorter lifespans and can be mass-produced. Additionally, the complexity and scale of civil engineering projects have made it more difficult to implement modern sensing and monitoring technologies, though interest in these tools has grown significantly in recent years. The increased attention to Digital Twin technology is likely driven by the rise of the industrial IoT, coupled with growing demands for more resilient infrastructure in the face of climate change and increased usage.

While still in its early stages, the potential for Digital Twin technology to revolutionize civil engineering is becoming more widely recognized. Technology consultants such as Gartner have identified it as a key driver of industrial development, particularly as it aligns with trends toward hyperautomation and AI-driven decision-making in the context of Industry 4.0. As the AECO sector continues to embrace digitalization, the application of DTs in civil engineering is expected to accelerate, leading to smarter, more sustainable infrastructure management. However, significant challenges remain in terms of integrating this technology into existing practices and ensuring that it is applied effectively across the wide range of assets that characterize the civil engineering landscape [5].

This presentation gives an overview of the approach by the researchers of iPMLab at the University of Granada (https://ipmlab.ugr.es/) under the perspective offered by the participation of a number of European research projects about Digital Twin. The presentation introduces the formulation of the DT within the context of the AECO sector, explains three case studies about DT implementations in buildings using both, the digital and the physical twins, and provides concluding remarks about the research findings and also gives perspective for future research direction about this trending research topic.

References

[1] Van Breugel, K. (2017). Societal burden and engineering challenges of ageing infrastructure. *Procedia Engineering,* 171, 53-63.

[2] Zarco-Periñán, P. J., Zar5co-Soto, F. J., Zarco-Soto, I. M., Martínez-Ramos, J. L., & Sánchez-Durán, R. (2022). CO_2 emissions in buildings: a synopsis of current studies. *Energies,* 15(18), 6635.

[3] Grieves, Michael W. «Digital twins: past, present, and future.» The digital twin. *Cham: Springer International Publishing,* 2023. 97-121.

[4] Chiachío, Manuel *et al*. «Structural digital twin framework: Formulation and technology integration.» *Automation in Construction* 140 (2022): 104333.

[5] Megía, M. Digital Twins in Civil Engineering: Conceptual Framework and Real-World Implementations. PhD thesis, 2024, ISBN: 9788411953306. https:// hdl.handle.n et/10481/9 2528


"Digital Twin technology in Civil Engineering: research vision from the ENHANCE and BUILDCHAIN European project
Dr. Manuel Chiachío
Associate Professor
Univ. of Granada (Spain)
64TH ESREDA SEMINAR
31 th MAY, 2024
UNIVERSIDAD DE GRANADA
Departamento de Mecánica de Estructuras e Ingeniería Hidráulica
iPM Lab UGR


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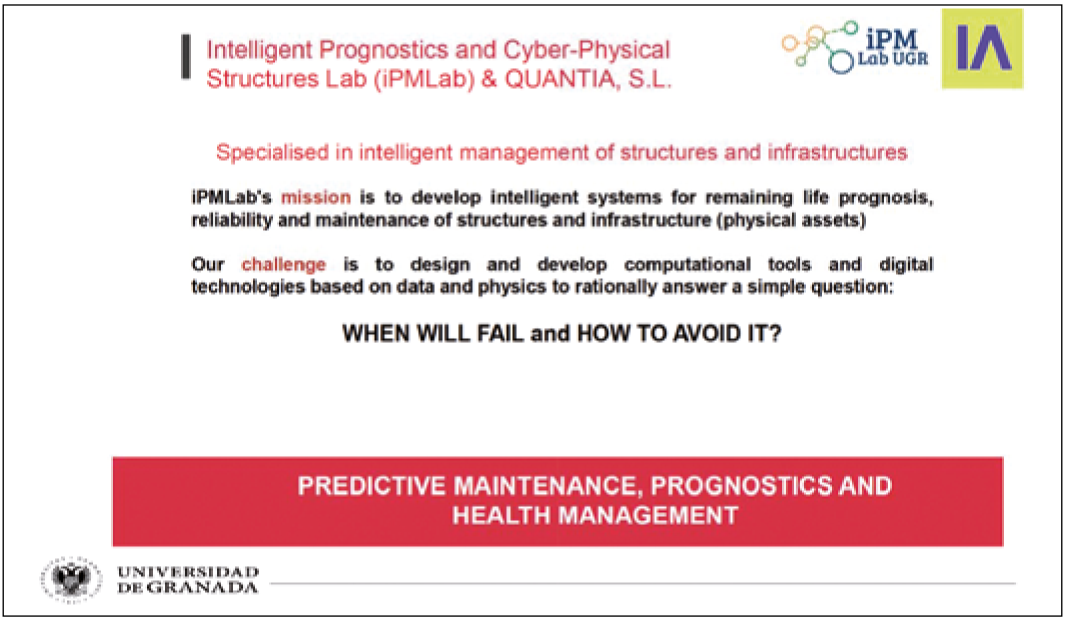
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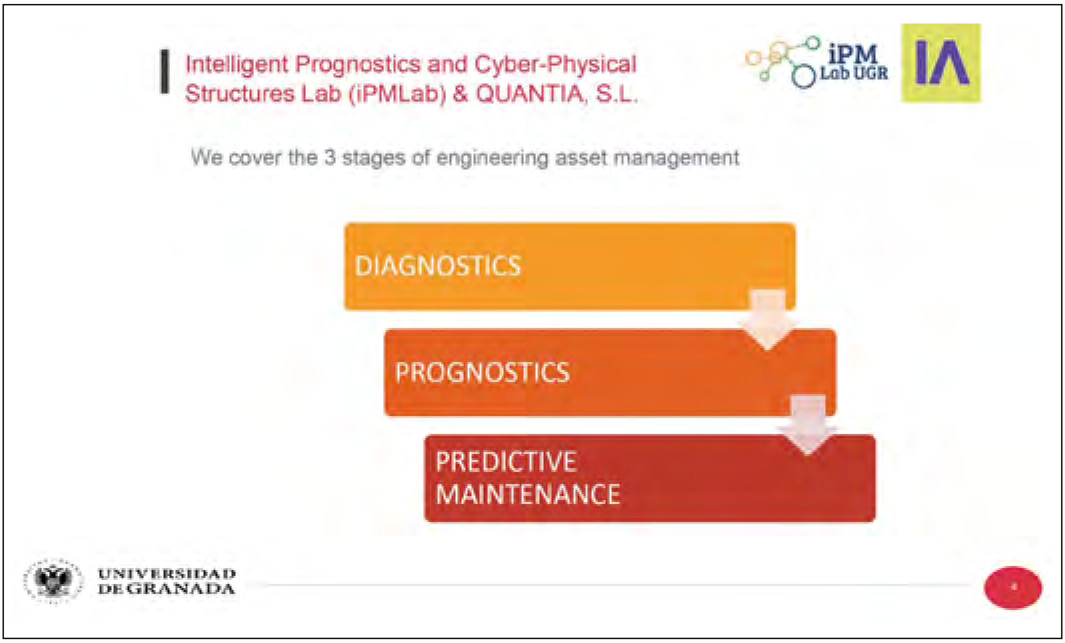
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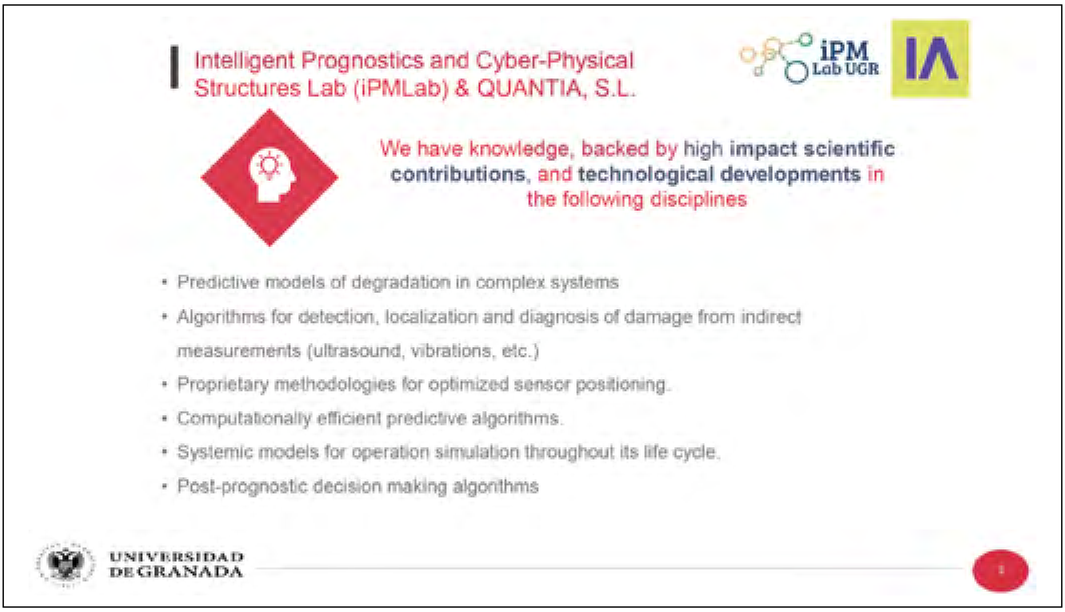
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• Systemic models for operation simulation throughout its life cycle.
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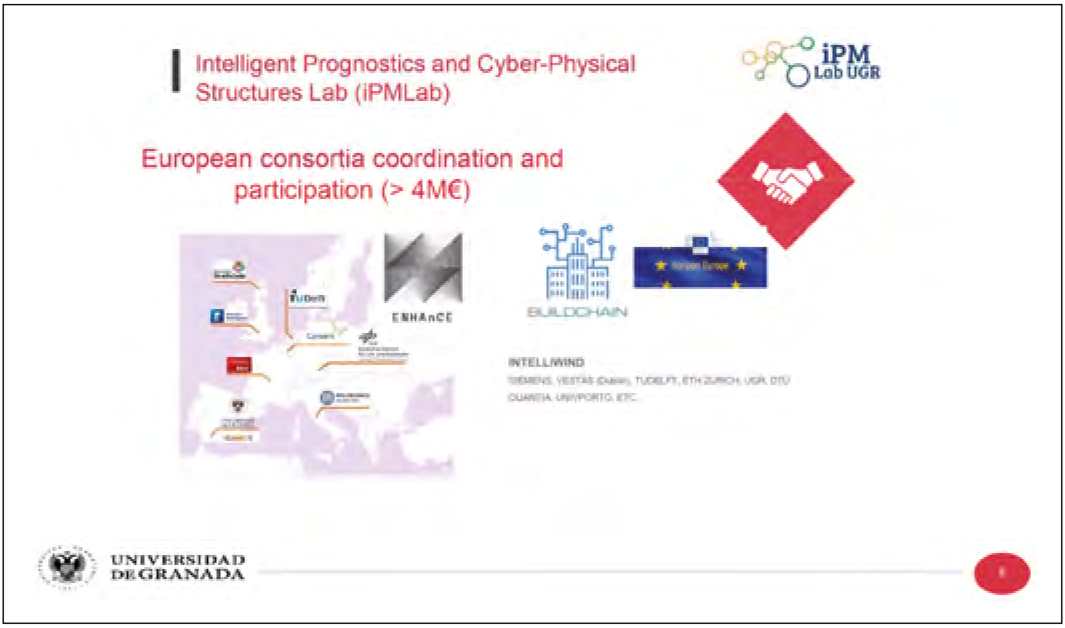
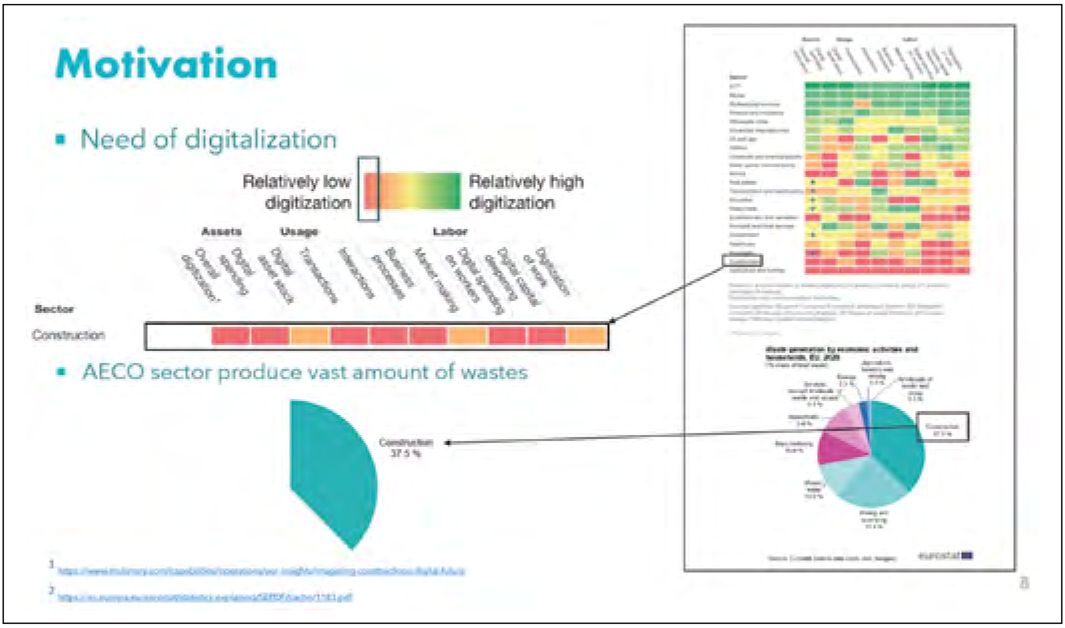

Intelligent Prognostics and Cyber-Physical Structures Lab (iPMLab)
iPM Lab UGR
European consortia coordination and participation (> 4M€)
ENHAnCE
BUILDCHAIN
INTELLIWIND
UNIVERSIDAD DE GRANADA



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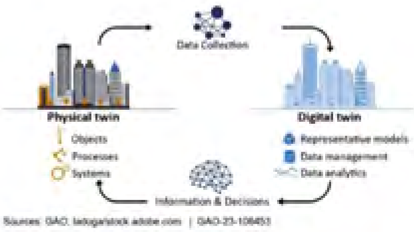
DIGITAL TWIN

THE CONCEPT

- The Digital Twin (DT) is a **virtual replica** of a real-world object, process, or system to bi-directionally and in real-time connect the physical and virtual worlds, making possible:
- OPTIMIZATION
- INTELLIGENT DECISION-MAKING
- DISCOVERY/LEARNING



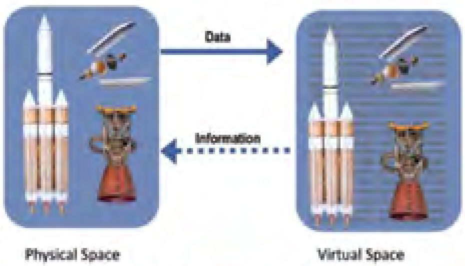
9

DIGITAL TWIN

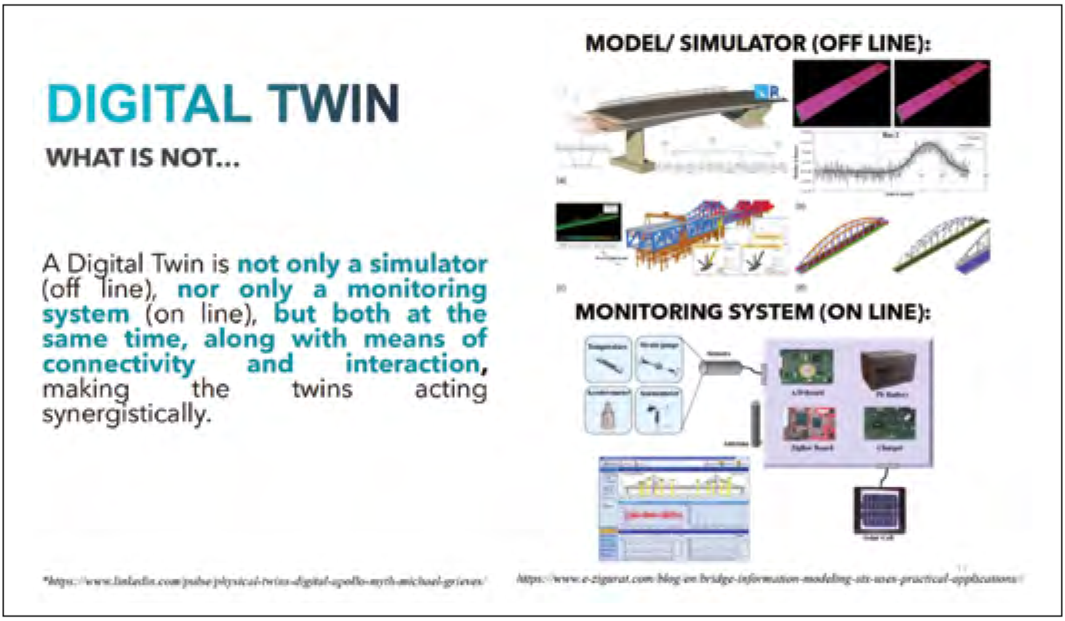
ORIGIN

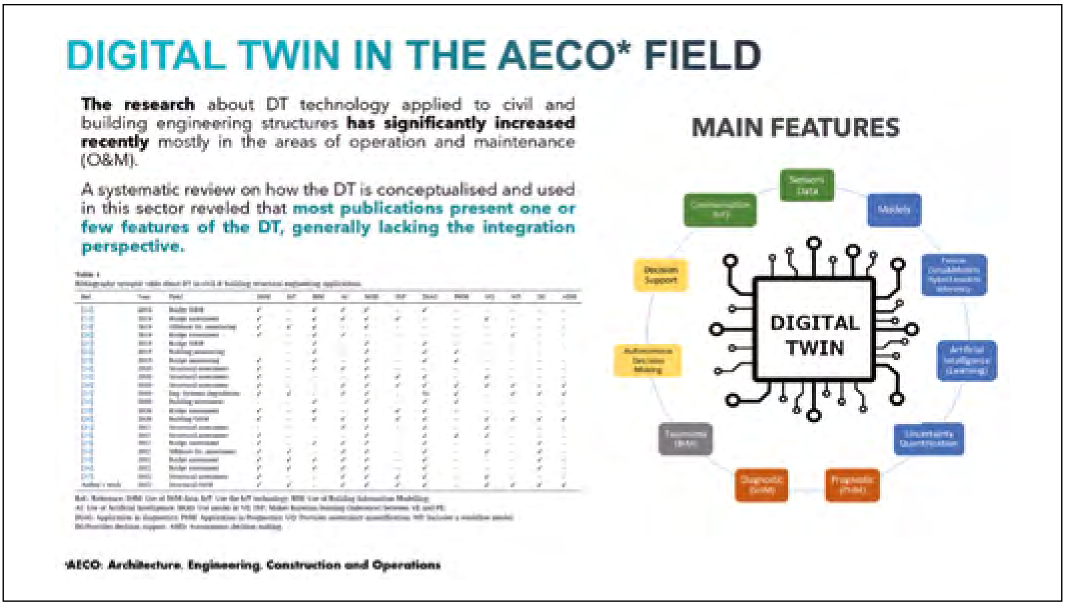
- The DT as it was initially conceived by NASA in the Apollo XIII mission (1970), as an **as-built system** that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding real-life twin.

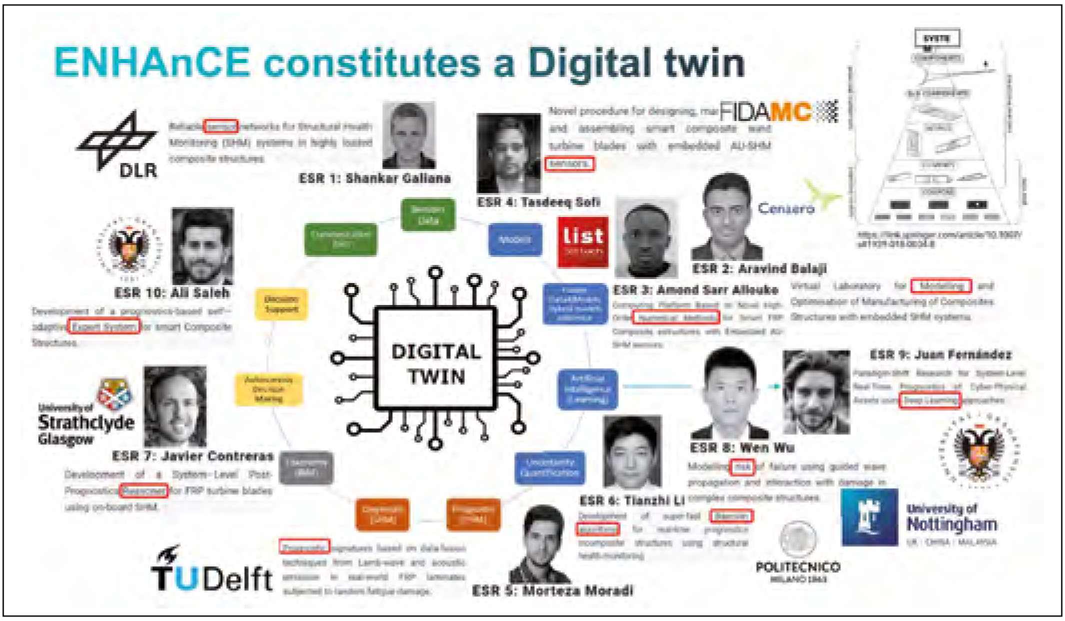
Digital Twin Model

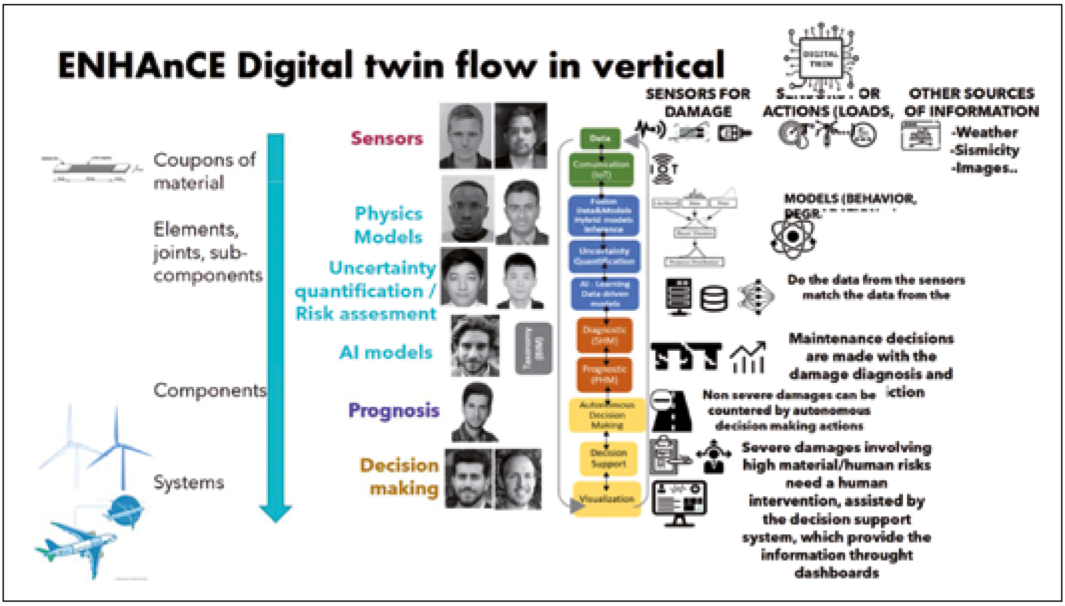


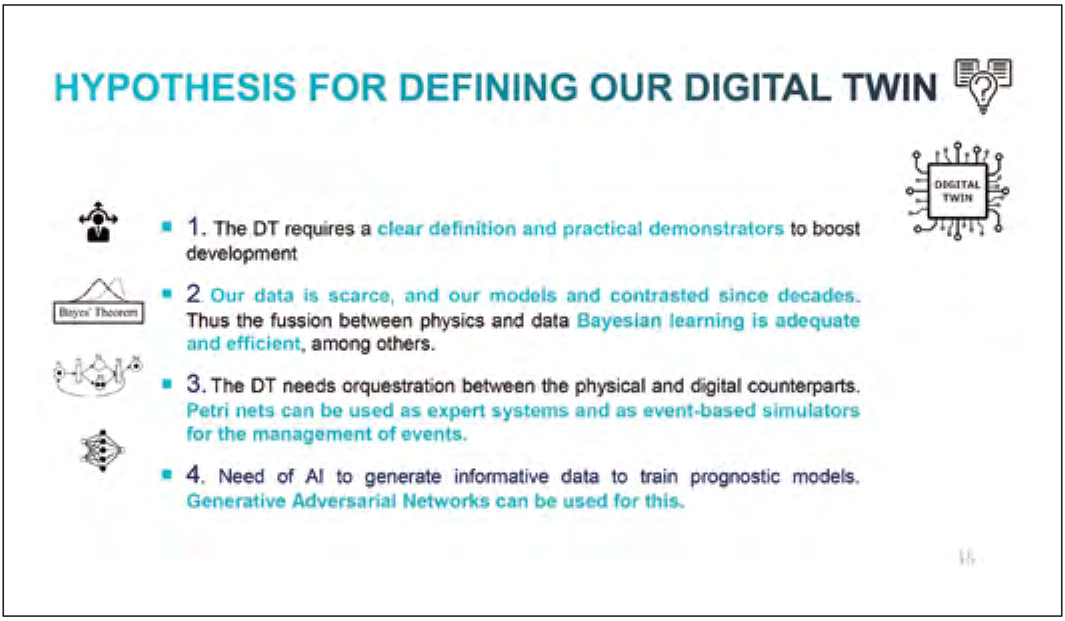
The continuous two-way flow of information from/to the real twin and the virtual one is one of the main features of the DT, along with its (almost) real-time model updating capability, ensuring the best possible decision at any time.

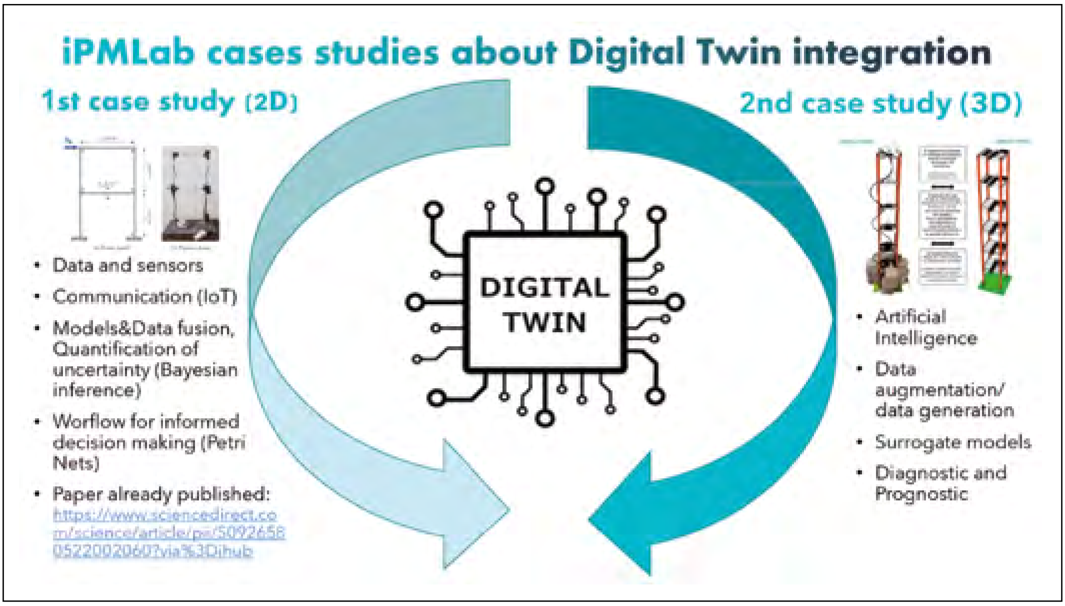

DIGITAL TWIN
WHAT IS NOT...
A Digital Twin is not only a simulator (off line), nor only a monitoring system (on line), but both at the same time, along with means of connectivity and interaction, making the twins acting synergistically.
MODEL/ SIMULATOR (OFF LINE):
MONITORING SYSTEM (ON LINE):
*https://www.linkedin.com/pulse/physical-twins-digital-apollo-myth-michael-grieves/
https://www.e-zigurat.com/blog/en/bridge-information-modeling-six-uses-practical-applications/


DIGITAL TWIN IN THE AECO* FIELD
The research about DT technology applied to civil and building engineering structures has significantly increased recently mostly in the areas of operation and maintenance (O&M).
A systematic review on how the DT is conceptualised and used in this sector reveled that most publications present one or few features of the DT, generally lacking the integration perspective.
MAIN FEATURES
Sensors Data
Models
Communication IoT
Decision Support
DIGITAL TWIN
Autonomous Decision Making
Taxonomy (BIM)
Diagnostic
Prognostic
Uncertainty Quantification
Artificial Intelligence
*AECO: Architecture, Engineering, Construction and Operations


ENHAnCE constitutes a Digital twin
DLR
FIDAMC
ESR 1: Shankar Gallana
ESR 4: Tasdeeq Sofi
Censero
ESR 2: Aravind Balaji
ESR 10: Ali Saleh
DIGITAL TWIN
ESR 3: Amond Sarr Allouko
ESR 9: Juan Fernández
University of Strathclyde Glasgow
ESR 7: Javier Contreras
ESR 8: Wen Wu
ESR 6: Tianzhi Li
University of Nottingham
POLITECNICO
TUDelft
ESR 5: Morteza Moradi


ENHAnCE Digital twin flow in vertical
Coupons of material
Elements, joints, sub-components
Components
Systems
Sensors
Physics Models
Uncertainty quantification / Risk assesment
AI models
Prognosis
Decision making
SENSORS FOR DAMAGE
OTHER SOURCES OF INFORMATION
-Weather
-Sismicity
-Images..
Maintenance decisions are made with the damage diagnosis and
Severe damages involving high material/human risks need a human intervention, assisted by the decision support system, which provide the information throught dashboards





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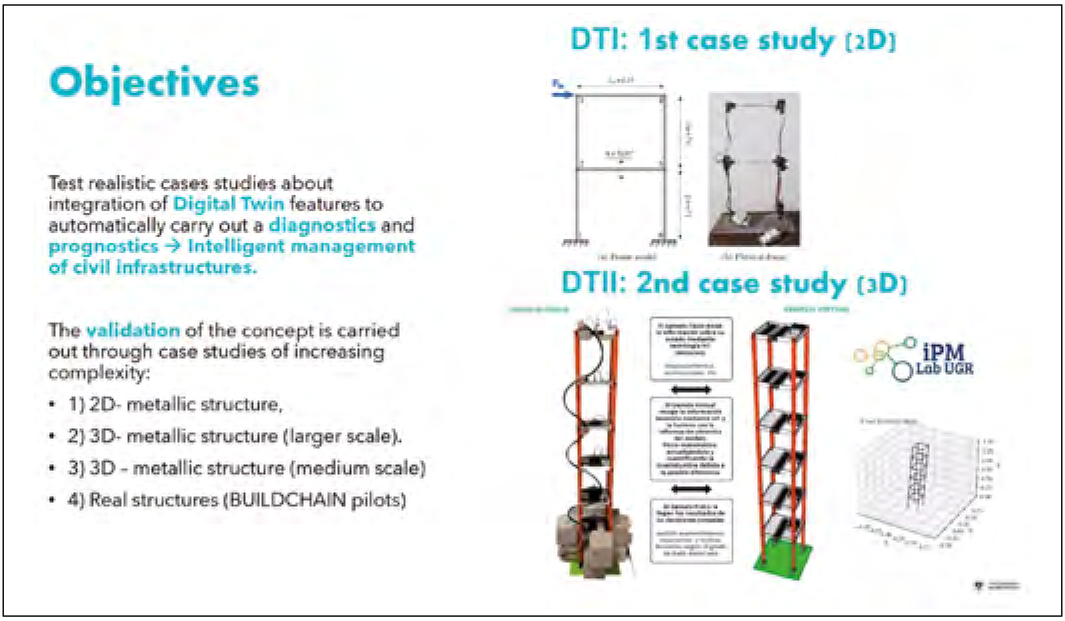
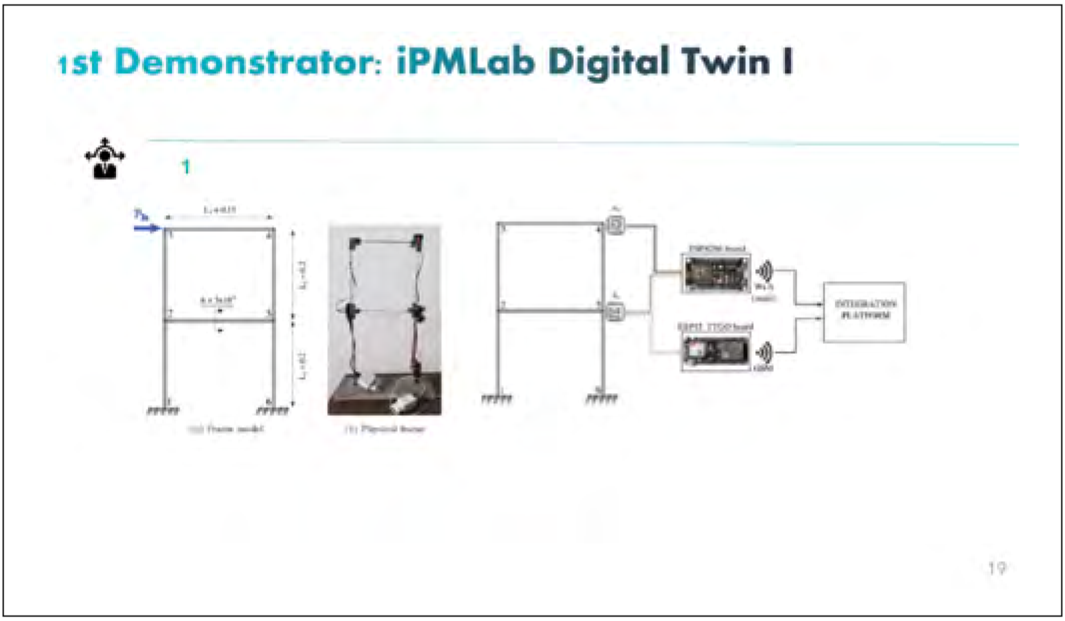
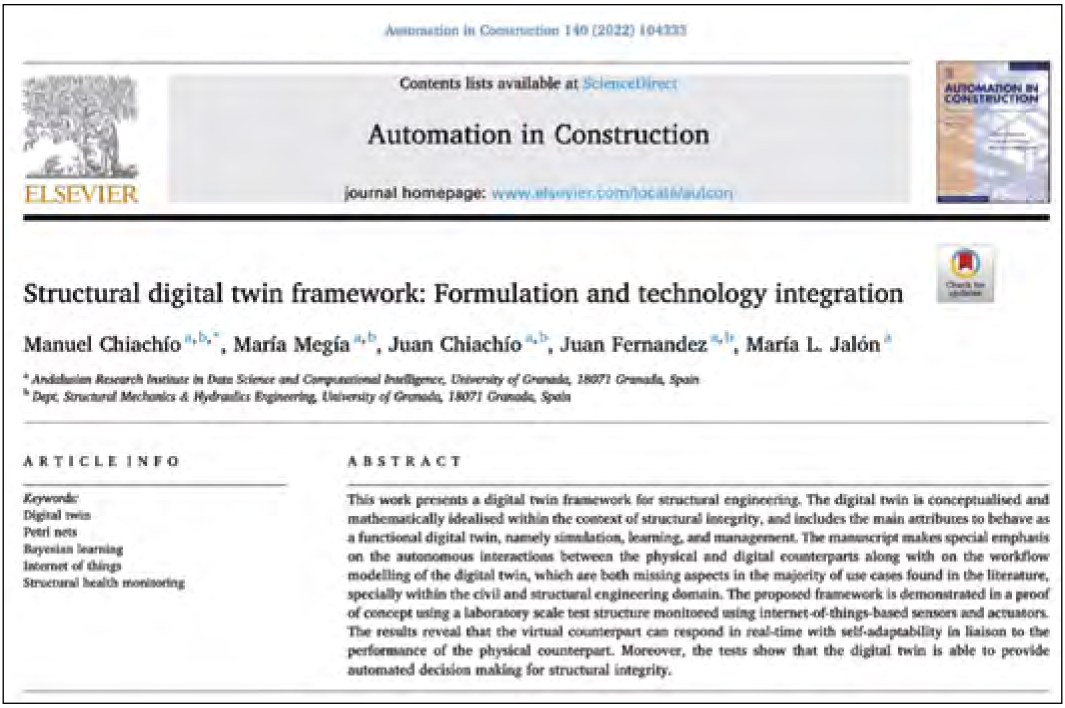

Objectives
Test realistic cases studies about integration of Digital Twin features to automatically carry out a diagnostics and prognostics → Intelligent management of civil infrastructures.
The validation of the concept is carried out through case studies of increasing complexity:
• 1) 2D- metallic structure,
• 2) 3D- metallic structure (larger scale).
• 3) 3D - metallic structure (medium scale)
• 4) Real structures (BUILDCHAIN pilots)
DTI: 1st case study (2D)
DTII: 2nd case study (3D)
iPM Lab UGR


Case studies continued
The validation of the concept is carried out through 2 case studies of increasing complexity, through the BUILDCHAIN EU project
4) DReal structures (BUILDCHAIN pilots)
BUILDing knowledge book in the blockCHAIN distributed ledger
further details are given below
DTIII: 3rd case study (3D)
BUILDCHAIN Pilot 1
BUILDCHAIN Pilot 5




Automation in Construction 140 (2022) 104333

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Structural digital twin framework: Formulation and technology integration

Manuel Chiachío [a,b,*], María Megía [a,b], Juan Chiachío [a,b], Juan Fernandez [a,b], María L. Jalón [a]

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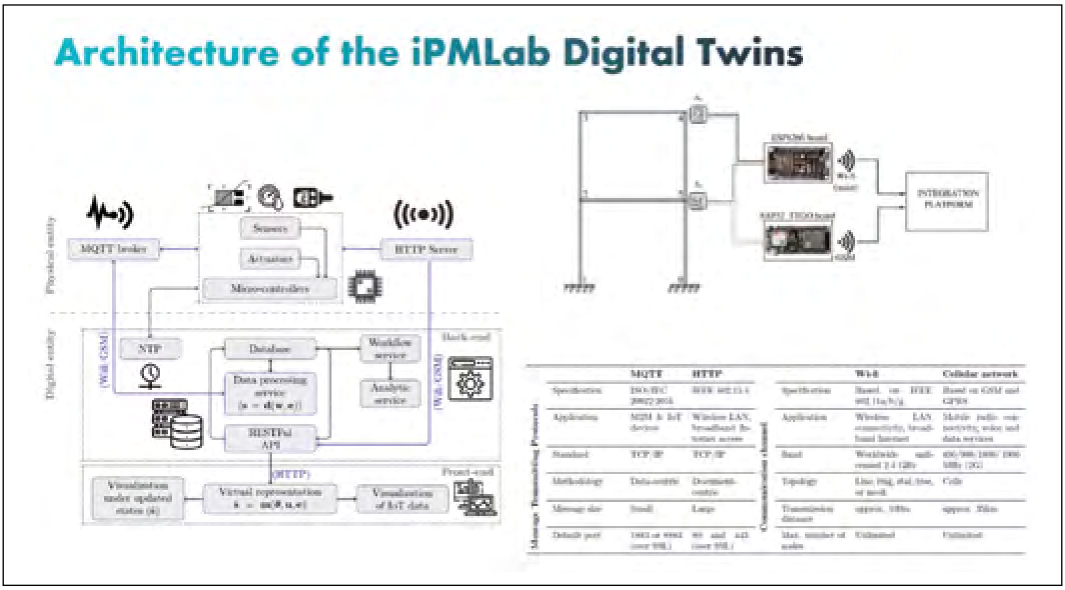
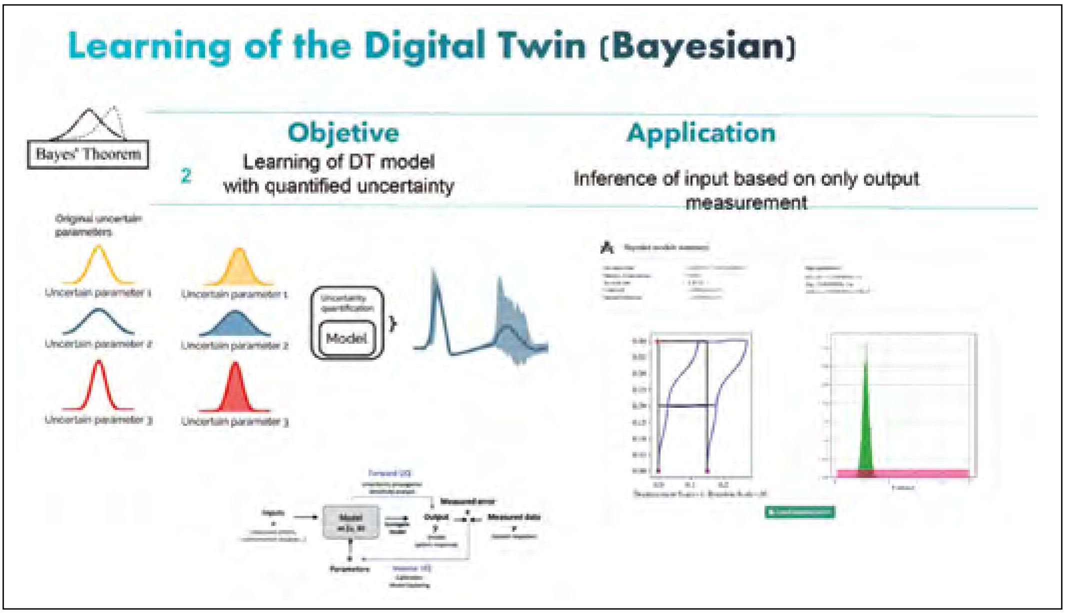
ARTICLE INFO

Keywords:
Digital twin
Petri nets
Bayesian learning
Internet of things
Structural health monitoring

ABSTRACT

This work presents a digital twin framework for structural engineering. The digital twin is conceptualised and mathematically idealised within the context of structural integrity, and includes the main attributes to behave as a functional digital twin, namely simulation, learning, and management. The manuscript makes special emphasis on the autonomous interactions between the physical and digital counterparts along with on the workflow modelling of the digital twin, which are both missing aspects in the majority of use cases found in the literature, specially within the civil and structural engineering domain. The proposed framework is demonstrated in a proof of concept using a laboratory scale test structure monitored using internet-of-things-based sensors and actuators. The results reveal that the virtual counterpart can respond in real-time with self-adaptability in liaison to the performance of the physical counterpart. Moreover, the tests show that the digital twin is able to provide automated decision making for structural integrity.





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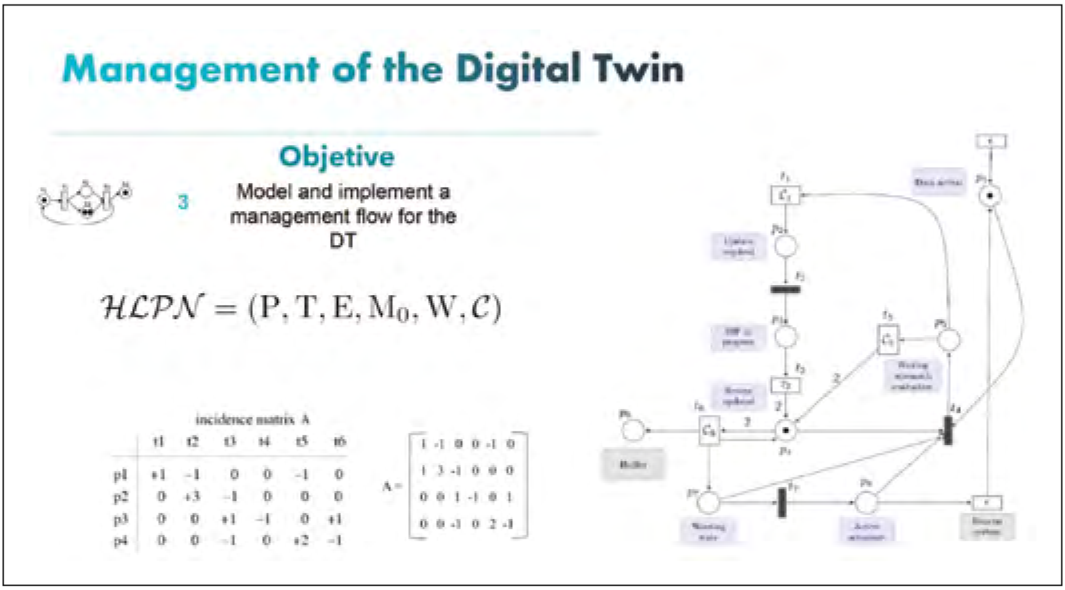

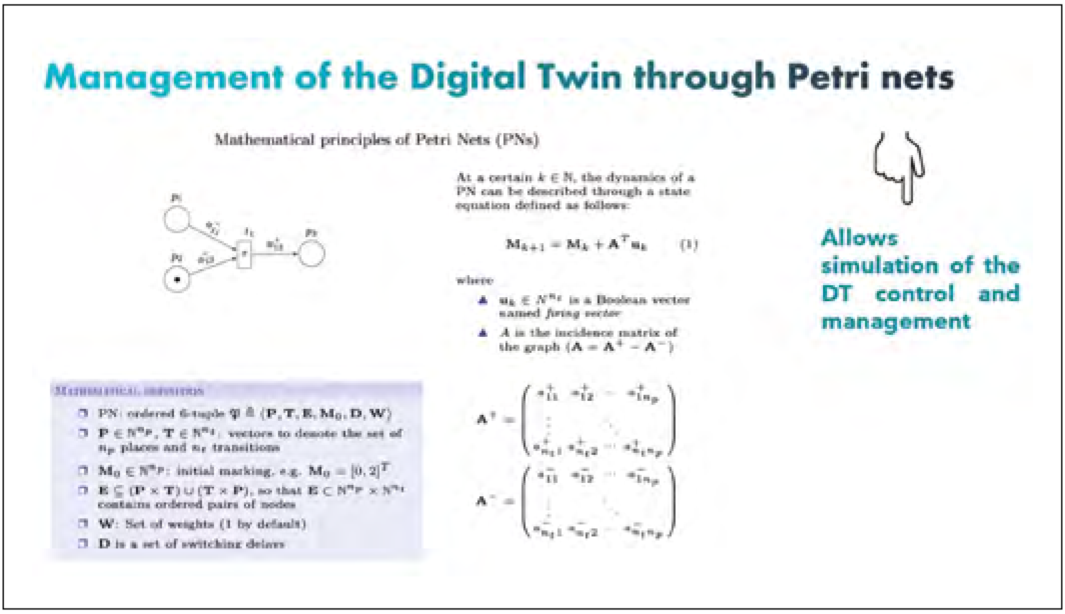

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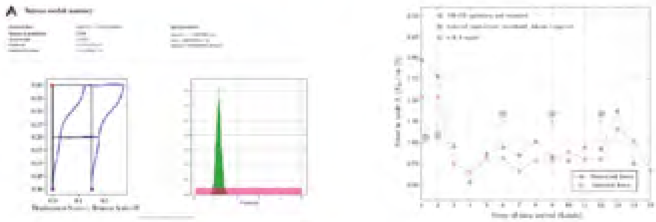
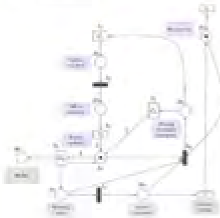
Results of the 1st Demonstrator (DT I)

ANALYTIC SERVICE



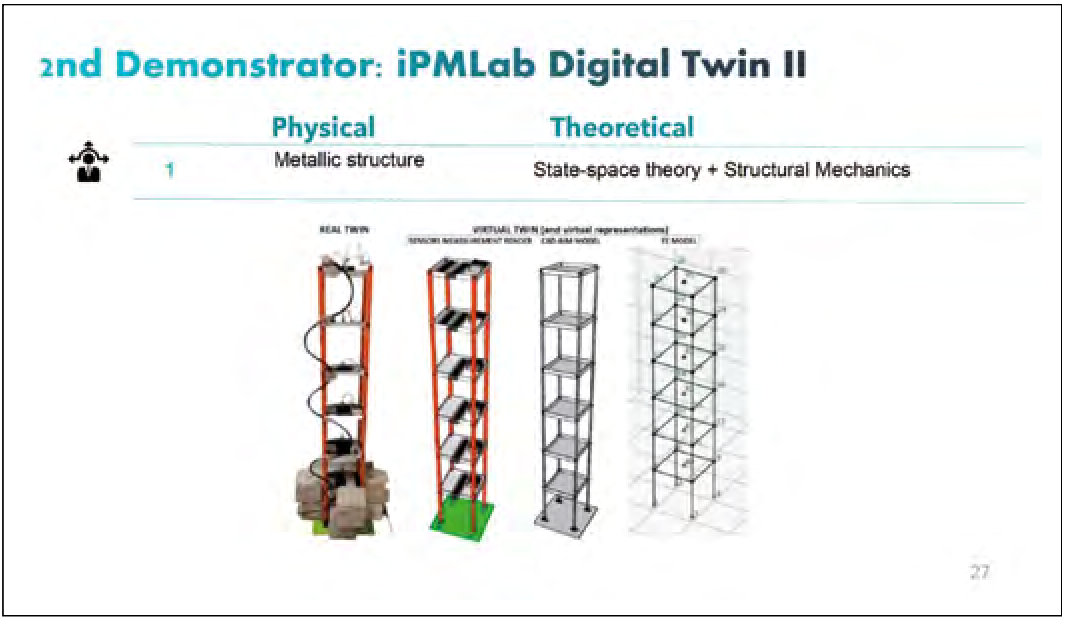
WORKFLOW SERVICE

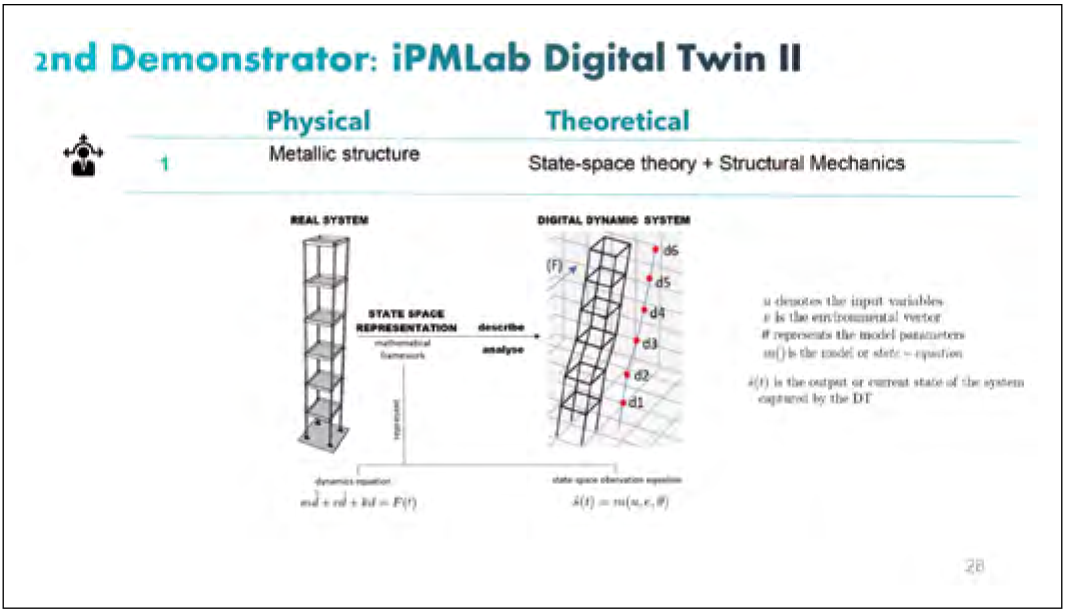


Transition	Type	Rule	Description
t_1	Conditional	$\mathcal{C}_1: \{j \geq 0.1\}$	Evaluates mismatch
t_2	Symbolic	-	Call the BIP module
t_3	Timed	Enabled after τ_1	Execute the BIP
t_4	Symbolic	-	Initiates VE-PE mismatch
t_5	Conditional	$\mathcal{C}_5: \{j < 0.1\}$	Evaluates mismatch
t_6	Conditional	$\mathcal{C}_6: \{\text{mean}(P_{0s}) \geq P_f\}$	Checks value of inferred force
t_7	Symbolic	-	Activates actuator

25

NEXT STEPS





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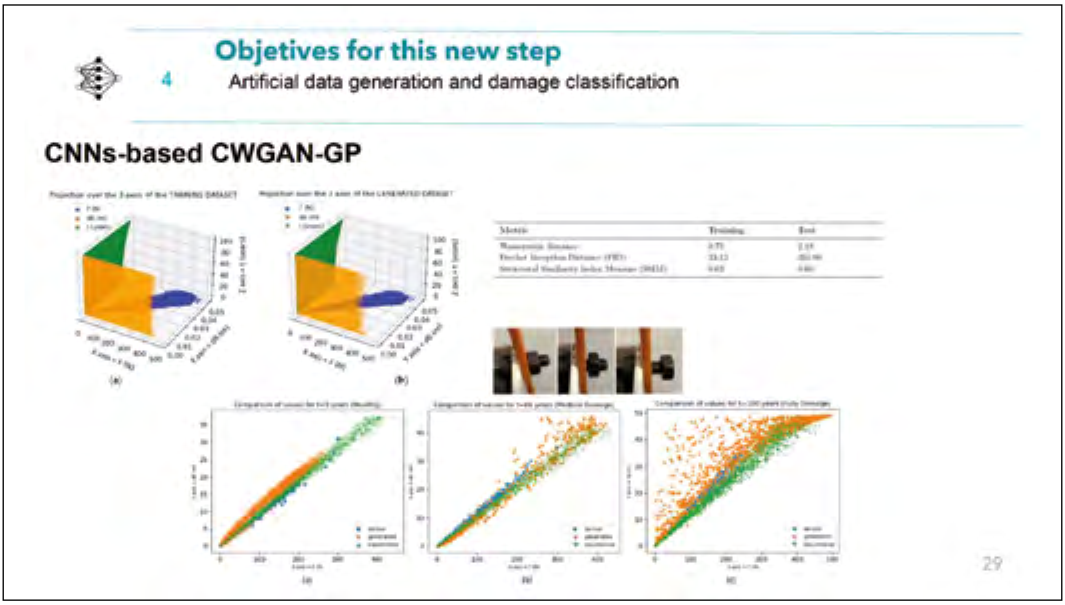
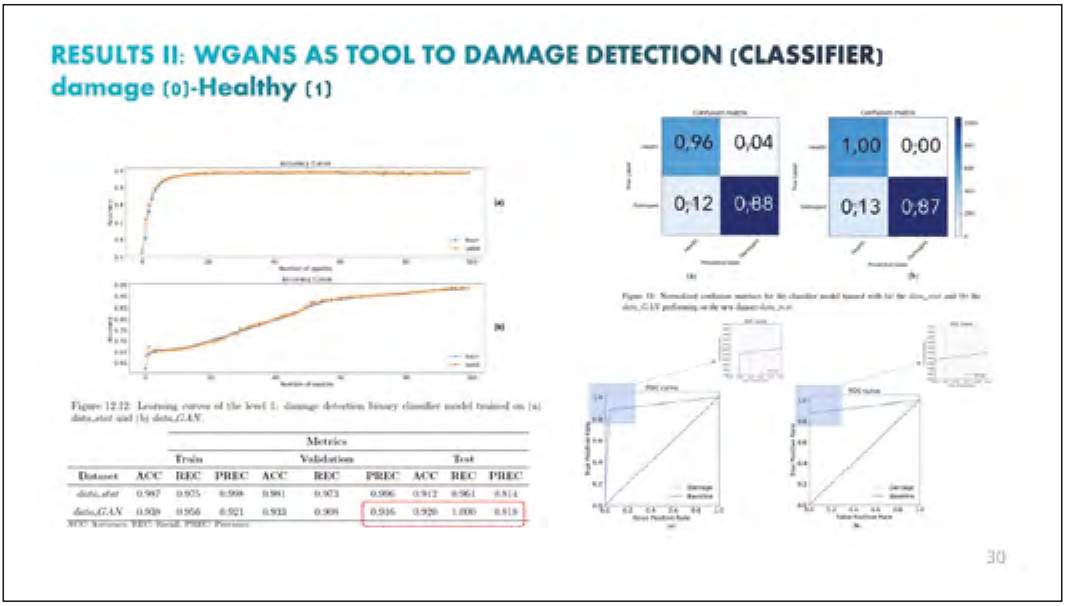
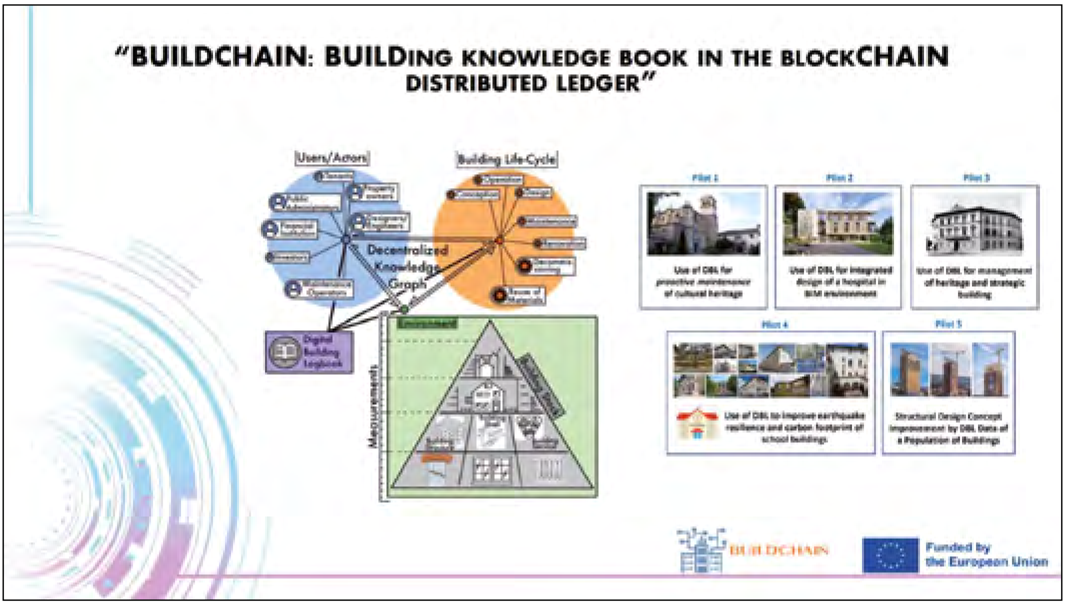
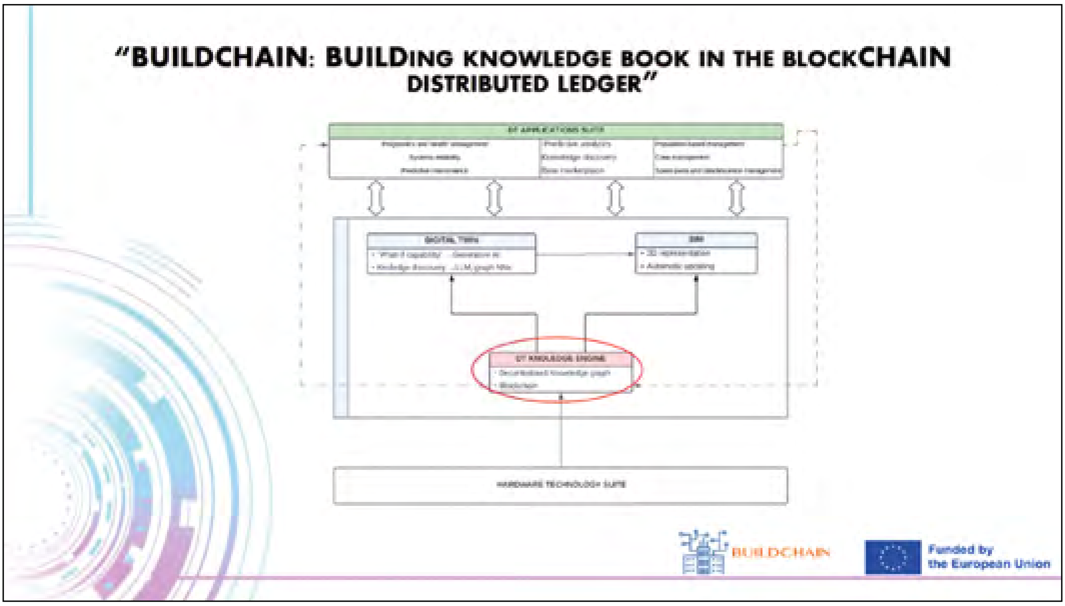
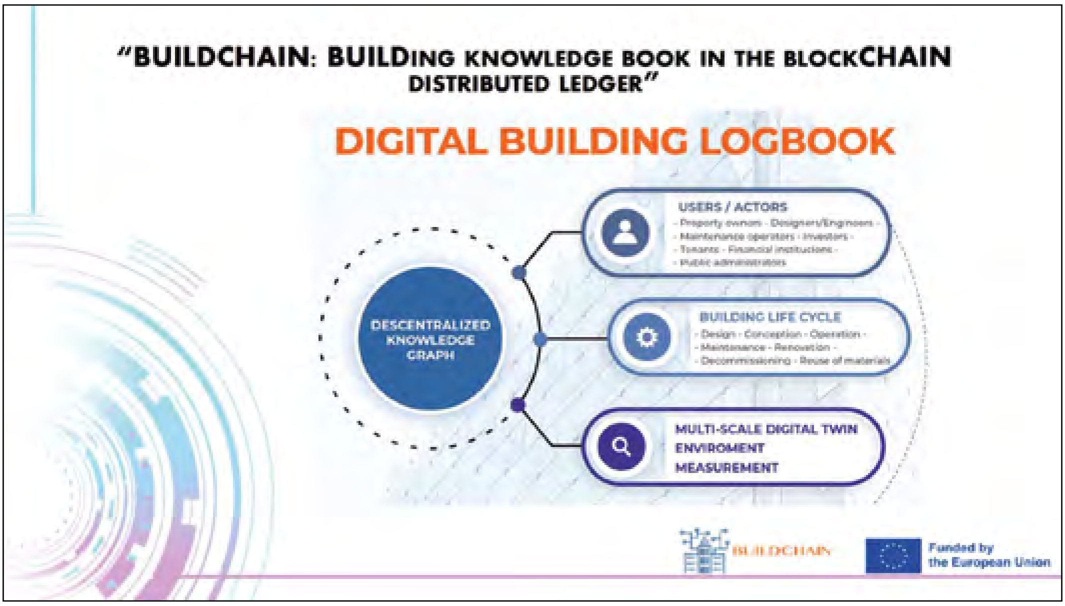
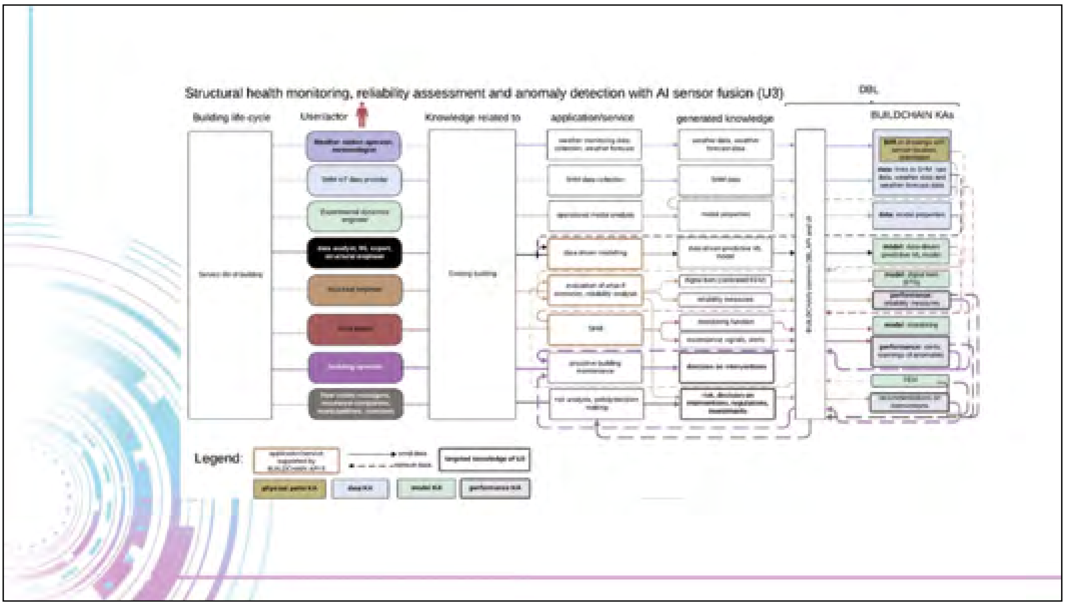

4
Objetives for this new step
Artificial data generation and damage classification
CNNs-based CWGAN-GP
29


RESULTS II: WGANS AS TOOL TO DAMAGE DETECTION (CLASSIFIER)
damage (0)-Healthy (1)
0,96
0,04
0,12
0,88
1,00
0,00
0,13
0,87
Metrics
Train
Validation
Test
Dataset
ACC
REC
PREC
30


"BUILDCHAIN: BUILDING KNOWLEDGE BOOK IN THE BLOCKCHAIN DISTRIBUTED LEDGER"
Users/Actors
Building Life-Cycle
Decentralized Knowledge Graph
Digital Building Logbook
Environment
Measurements
Pilot 1
Pilot 2
Pilot 3
Pilot 4
Pilot 5
Use of DBL to improve earthquake resilience and carbon footprint of school buildings
Structural Design Concept improvement by DBL Data of a Population of Buildings
BUILDCHAIN
Funded by the European Union


"BUILDCHAIN: BUILDING KNOWLEDGE BOOK IN THE BLOCKCHAIN DISTRIBUTED LEDGER"
BUILDCHAIN
Funded by the European Union





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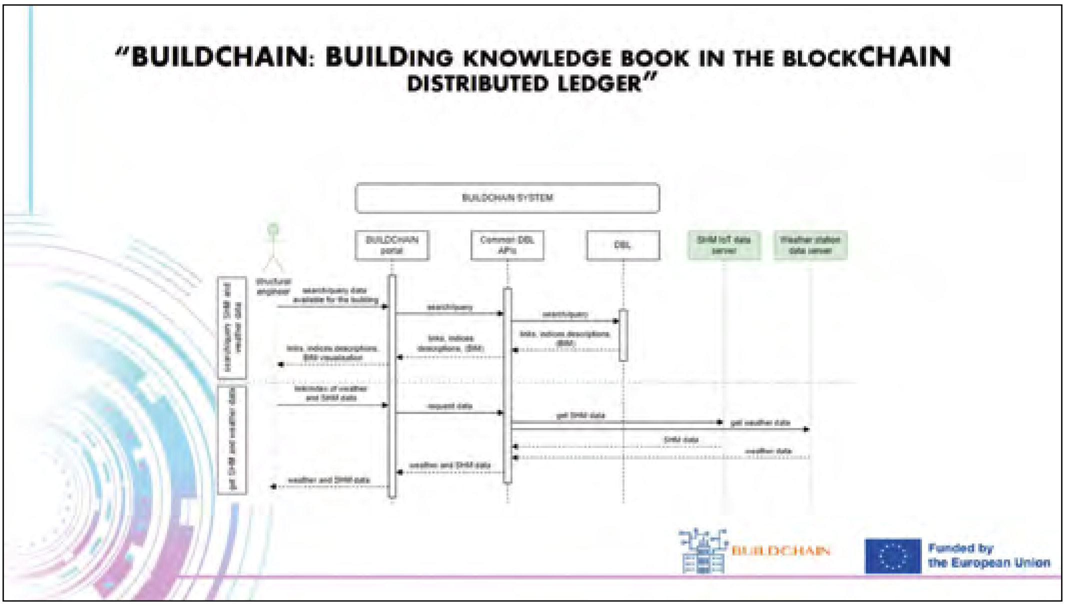
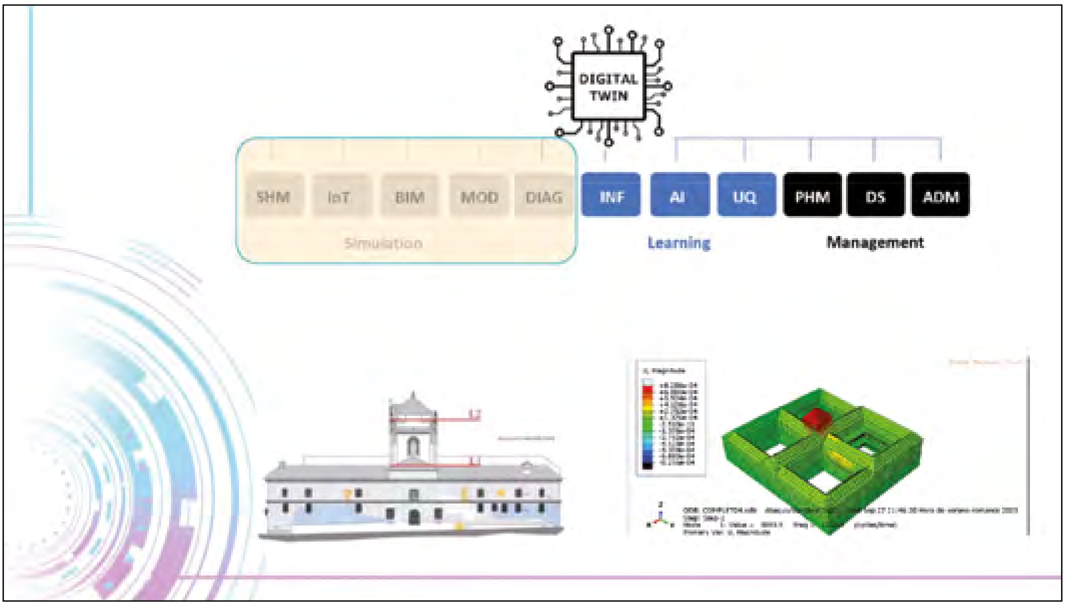
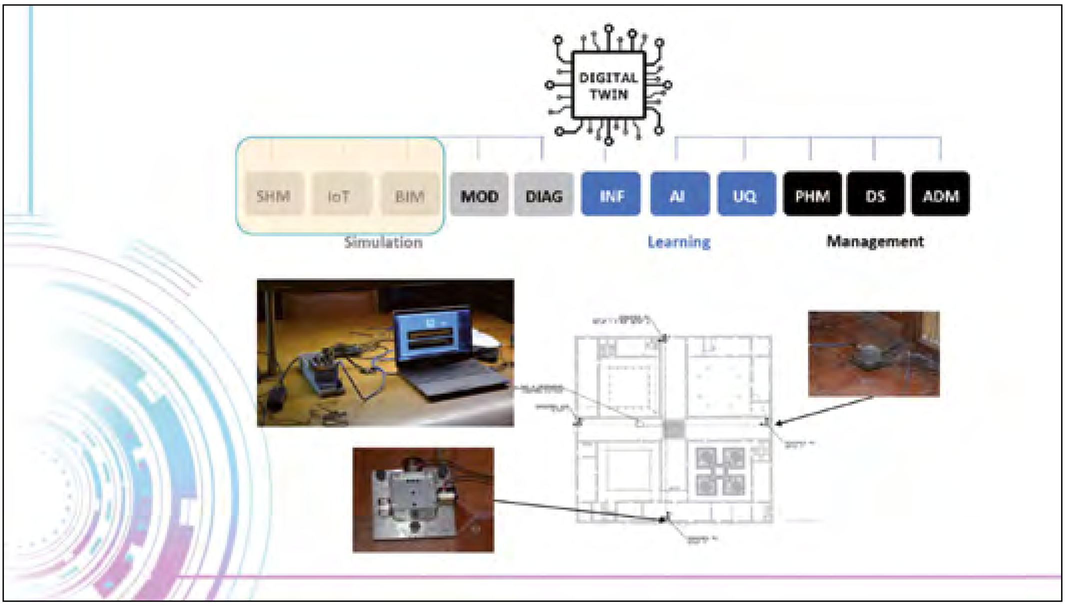
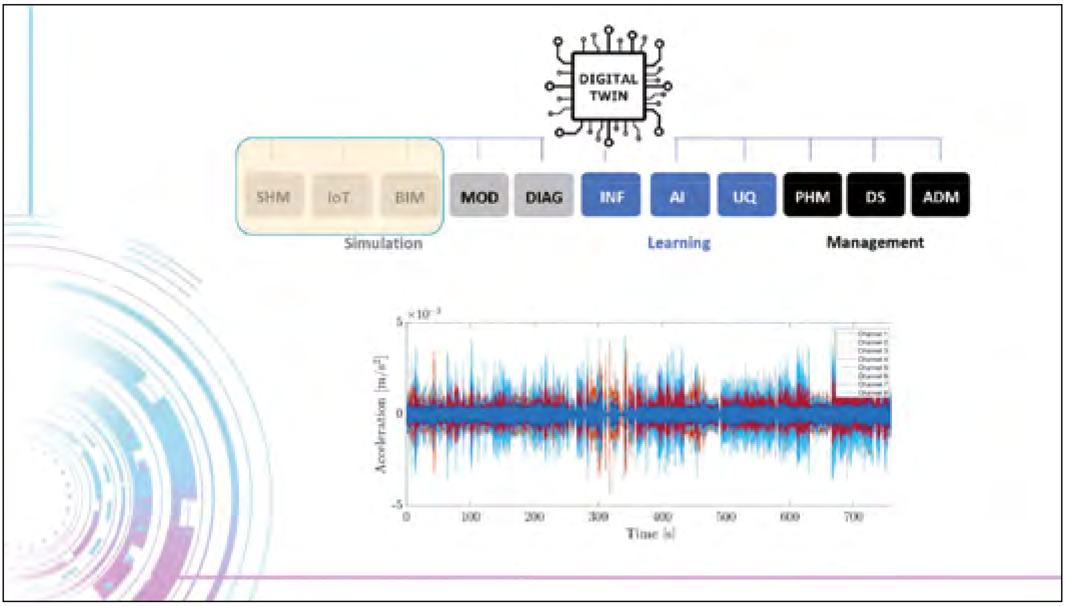
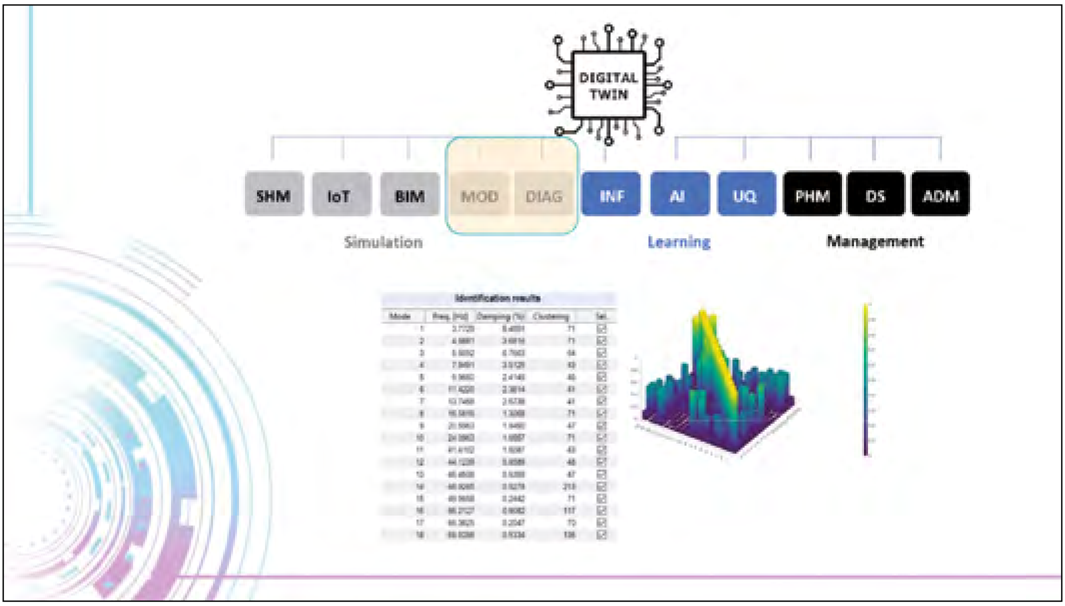
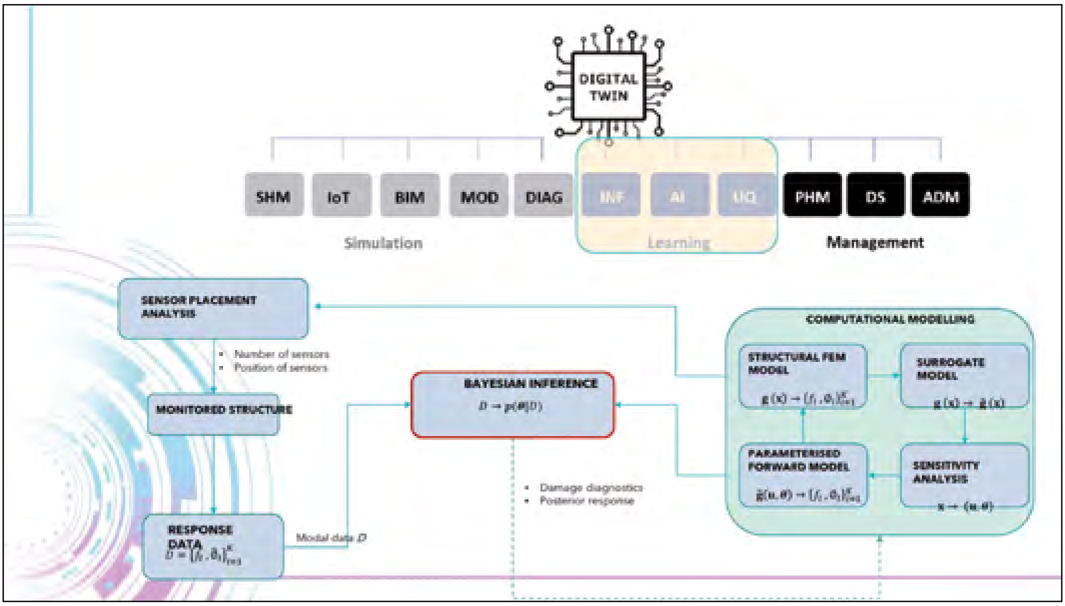

"BUILDCHAIN: BUILDING KNOWLEDGE BOOK IN THE BLOCKCHAIN DISTRIBUTED LEDGER"
BUILDCHAIN SYSTEM
BUILDCHAIN portal
Common DBL APIs
DBL
SHM IoT data server
Weather station data server
Structural engineer
search/query data available for the building
search/query
links, indices descriptions, BIM visualisation
links, indices descriptions, (BIM)
request data
get SHM data
get weather data
SHM data
weather data
weather and SHM data
BUILDCHAIN
Funded by the European Union


DIGITAL TWIN
SHM
IoT
BIM
MOD
DIAG
Simulation
INF
AI
UQ
PHM
DS
ADM
Learning
Management


DIGITAL TWIN
SHM
IoT
BIM
MOD
DIAG
INF
AI
UQ
PHM
DS
ADM
Simulation
Learning
Management


DIGITAL TWIN
SHM
IoT
BIM
MOD
DIAG
INF
AI
UQ
PHM
DS
ADM
Simulation
Learning
Management
Acceleration [m/s²]
Time [s]





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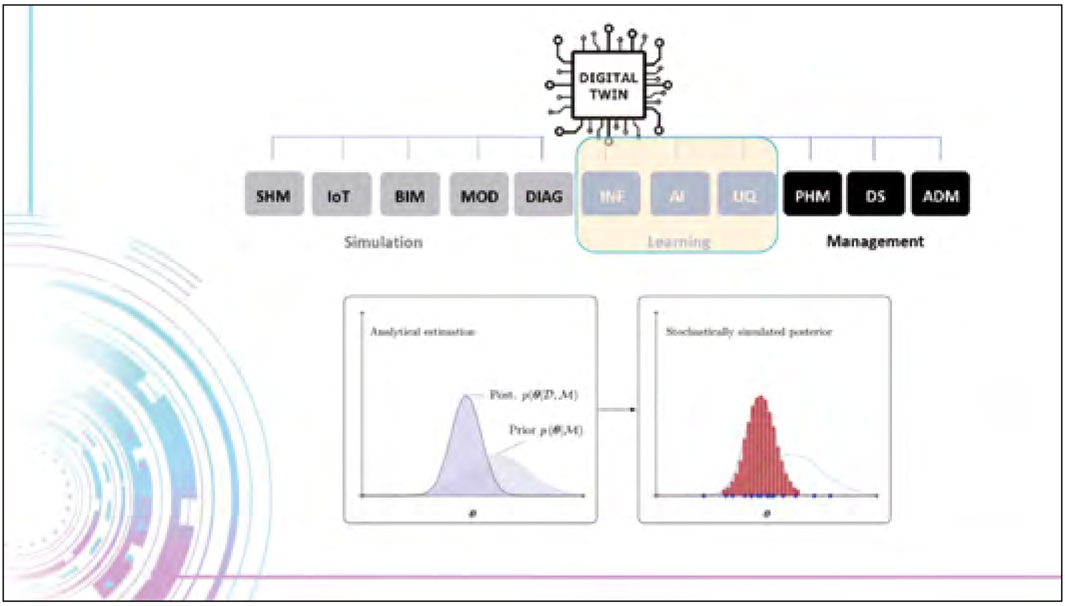
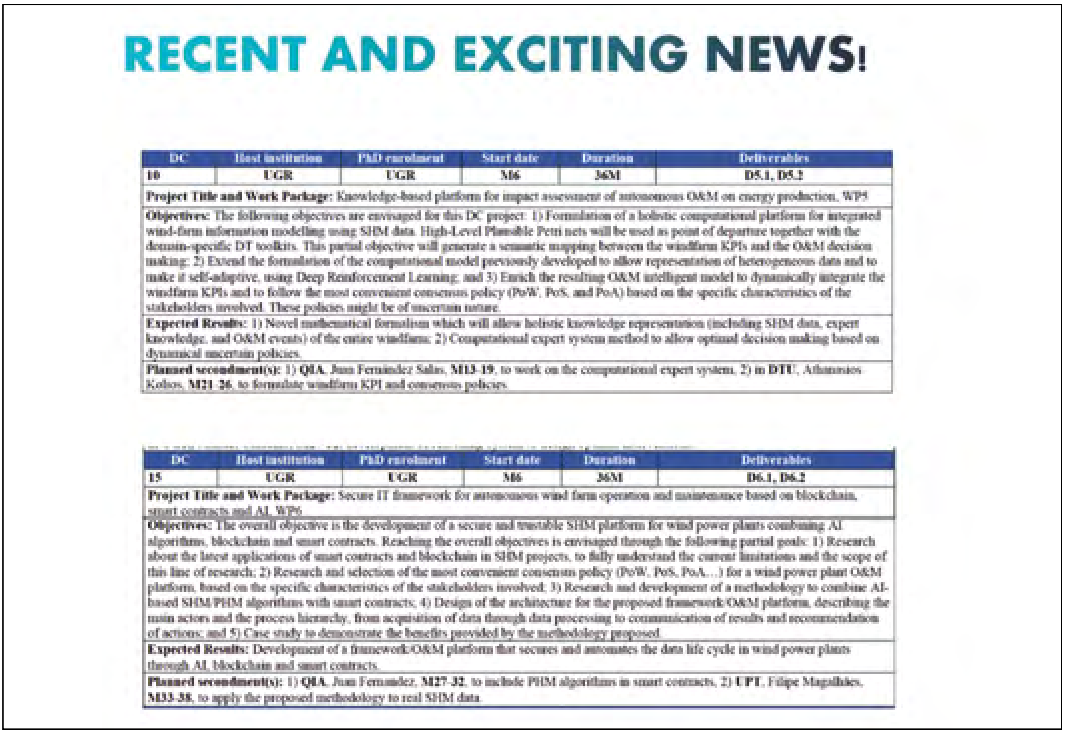


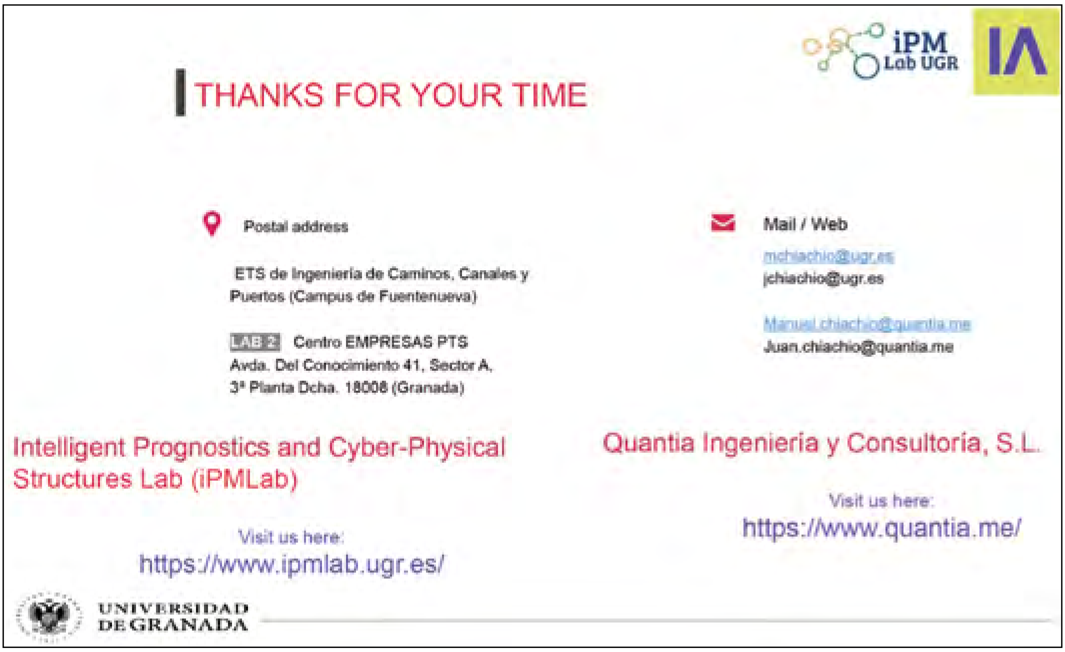
FUTURE TRENDS

New trends of AI and IoT (hardware):

- Explainable AI (XAI), Thrustable AI, Responsible AI
- Cyber-physical security (considering the interaction between the cyber and physical security)
- Human centric Digital Twins (LLM)
- Distributed DT through Edge/FoG computing
- Self-concious and self-awarness DTs (optimal data activation)
- Automatic Discovery of DTs through Generative AI, Generic AI (GAI)
- Collaborative twins (public/service DTs as benchmarks)


RECENT AND EXCITING NEWS!
Call: HORIZON-MSCA-2023-DN-01
(MSCA Doctoral Networks 2023)
Topic: HORIZON-MSCA-2023-DN-01-01
"IntelliWind – Intelligent systems for autonomous Wind power plant operations"
IntelliWind
There will be opportunities for 15 Marie Curie researchers to work in these institutions
List of participating organisations
Country
1 DANMARKS TEKNISKE UNIVERSITET DK Coordinator
2 TECHNISCHE UNIVERSITAET MUENCHEN DE Partner
3 UNIVERSIDAD DE CASTILLA - LA MANCHA ES Partner
4 TECHNISCHE UNIVERSITEIT DELFT NL Partner
5 UNIVERSIDAD DE GRANADA ES Partner
6 UNIVERSIDADE DO PORTO PT Partner
7 SIEMENS INDUSTRY SOFTWARE NV BE Partner
8 FRAUNHOFER GESELLSCHAFT ZUR FORDERUNG DER ANG DE Partner
9 Ventient Energy Serviços PT Partner
10 EIDGENOESSISCHE TECHNISCHE HOCHSCHULE ZURICH CH Associated
11 VESTAS WIND SYSTEMS A/S DK Associated
12 GW Offshore S.L. ES Associated
13 ENGIE information et technologies FR Associated
14 SOLUCIONES Y DESARROLLOS DE INGENIERÍA Y SERVICIOS ES Associated
15 QUANTIA INGENIERÍA Y CONSULTORÍA, S.L. ES Associated
16 RTDT Laboratories AG CH Associated
17 RAMBOLL DEUTSCHLAND GMBH DE Associated
18 VATTENFALL VINDKRAFT A/S DK Associated


RECENT AND EXCITING NEWS!
DC | Host institution | PhD enrolment | Start date | Duration | Deliverables
10 | UGR | UGR | M6 | 36M | D5.1, D5.2
Project Title and Work Package: Knowledge-based platform for impact assessment of autonomous O&M on energy production, WP5
Objectives: The following objectives are envisaged for this DC project: 1) Formulation of a holistic computational platform for integrated wind-farm information modelling using SHM data. High-Level Plausible Petri nets will be used as point of departure together with the domain-specific DT toolkits. This partial objective will generate a semantic mapping between the windfarm KPIs and the O&M decision making; 2) Extend the formulation of the computational model previously developed to allow representation of heterogeneous data and to make it self-adaptive, using Deep Reinforcement Learning; and 3) Enrich the resulting O&M intelligent model to dynamically integrate the windfarm KPIs and to follow the most convenient consensus policy (PoW, PoS, and PoA) based on the specific characteristics of the stakeholders involved. These policies might be of uncertain nature.
Expected Results: 1) Novel mathematical formalism which will allow holistic knowledge representation (including SHM data, expert knowledge, and O&M events) of the entire windfarm; 2) Computational expert system method to allow optimal decision making based on dynamical uncertain policies.
Planned secondment(s): 1) QIA, Juan Fernández Salas, M13-19, to work on the computational expert system, 2) in DTU, Athanasios Kolios, M21-26, to formulate windfarm KPI and consensus policies.
DC | Host institution | PhD enrolment | Start date | Duration | Deliverables
15 | UGR | UGR | M6 | 36M | D6.1, D6.2
Project Title and Work Package: Secure IT framework for autonomous wind farm operation and maintenance based on blockchain, smart contracts and AI, WP6
Objectives: The overall objective is the development of a secure and trustable SHM platform for wind power plants combining AI algorithms, blockchain and smart contracts. Reaching the overall objectives is envisaged through the following partial goals: 1) Research about the latest applications of smart contracts and blockchain in SHM projects, to fully understand the current limitations and the scope of this line of research; 2) Research and selection of the most convenient consensus policy (PoW, PoS, PoA…) for a wind power plant O&M platform, based on the specific characteristics of the stakeholders involved; 3) Research and development of a methodology to combine AI-based SHM/PHM algorithms with smart contracts; 4) Design of the architecture for the proposed framework/O&M platform, describing the main actors and the process hierarchy, from acquisition of data through data processing to communication of results and recommendation of actions; and 5) Case study to demonstrate the benefits provided by the methodology proposed.
Expected Results: Development of a framework/O&M platform that secures and automates the data life cycle in wind power plants through AI, blockchain and smart contracts.
Planned secondment(s): 1) QIA, Juan Fernandez, M27-32, to include PHM algorithms in smart contracts, 2) UPT, Filipe Magalhães, M33-38, to apply the proposed methodology to real SHM data.



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BIM and Digital Twins: Revolutionising Asset Management and Infrastructure Lifecycle

Francisco Carmona
francisco.carmona@quantia.es

QUANTIA, Founding Partner and Director - Infrastructure Sector

Abstract

The integration of Building Information Modelling (BIM) and Digital Twin technologies represents a paradigm shift in the way assets are managed and infrastructure is operated throughout their lifecycle. This presentation, delivered during the ESReDA seminar on Digital Twins, delves into the transformative potential of these technologies, highlighting their ability to enhance collaboration, optimise decision-making, and improve operational efficiency.

1. BIM: A Collaborative Framework for Information Management

BIM is presented as a methodology that enables the structured and collaborative management of information across the lifecycle of an asset, from design and construction to operation and maintenance. The presentation emphasises the importance of collaboration in BIM, where the exchange of information between stakeholders is facilitated through a Common Data Environment (CDE). This environment ensures that all agents involved in the construction process work with a «single source of truth,» reducing inefficiencies and fostering innovation.

The discussion includes an overview of BIM maturity levels, as defined by ISO 19650 standards, and their implications for project management. The transition from Project Information Models (PIM) to Asset Information Models (AIM) is explored, showcasing how structured and unstructured data, federated models, and collaborative environments contribute to the effective management of assets. The presentation also highlights the role of information requirements (e.g., PIR, EIR, OIR) in ensuring that data is managed and exchanged effectively throughout the lifecycle of a project.

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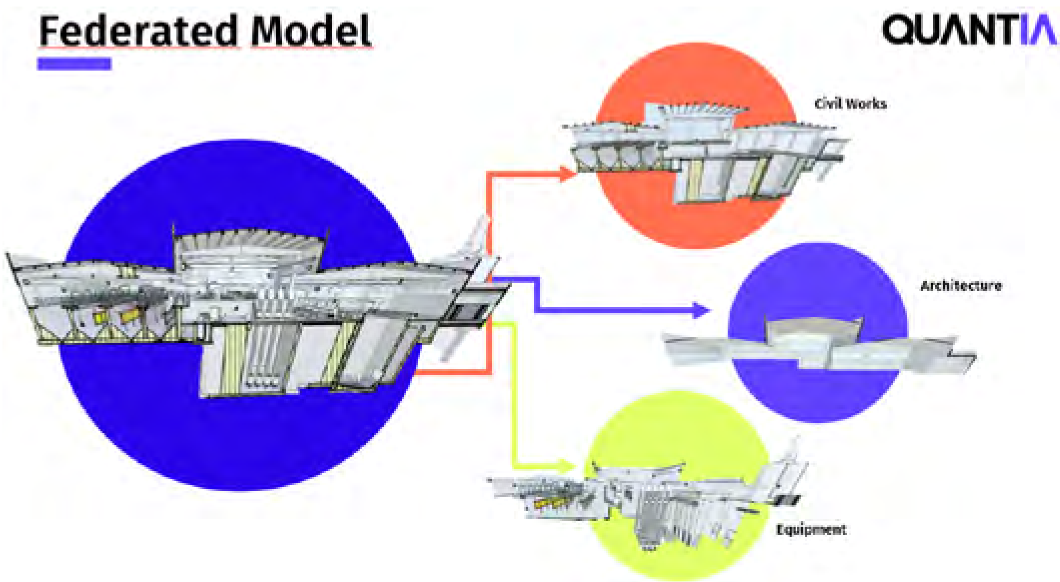
Figure 1

BIM Federation: An example on how BIM models can be internaly organised



2. Digital Twins: A Dynamic Representation of Physical Assets

The concept of Digital Twins is introduced as a dynamic, real-time digital representation of physical infrastructure. A Digital Twin integrates geometric models, IoT data, and advanced analytics to simulate, analyse, and predict the behaviour and performance of an asset. This capability enables informed decision-making, optimised maintenance, and improved operational efficiency.

The presentation outlines the maturity levels of Digital Twins, ranging from basic asset records with non-geometric attributes to fully autonomous systems capable of self-learning and decision-making. These levels reflect the increasing sophistication of Digital Twins, from simple data visualisation to real-time data exchange and predictive analytics. The integration of external data sources, such as weather conditions or other Digital Twins, further enhances their utility.

Applications and Real-World Case Studies. Several practical applications of Digital Twins are discussed, demonstrating their potential to revolutionise asset management and infrastructure operations. Key use cases include:

— *Predictive and Preventive Maintenance*. By analysing trends and patterns, Digital Twins enable the anticipation of potential issues, reducing downtime and maintenance costs.

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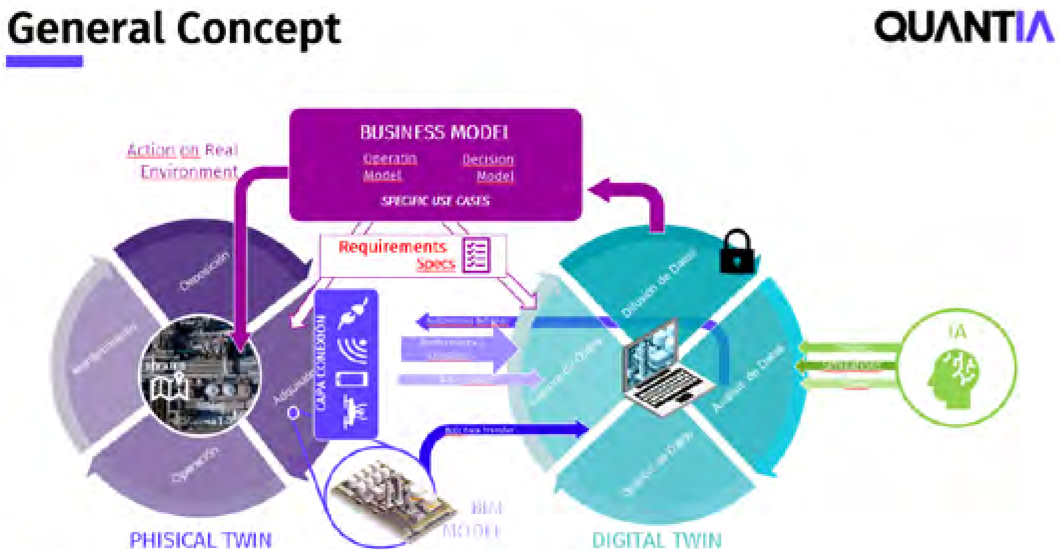
Figure 2

Conceptual representation of an advanced Digital Twin



— *Real-Time Monitoring*. Sensors and IoT devices provide continuous data on the state of infrastructure, facilitating proactive management and rapid emergency responses.
— *Scenario Simulations*. Digital Twins allow for the virtual testing of different scenarios, such as environmental impact studies or operational improvements, enabling informed decision-making and risk reduction.

The presentation also features real-world case studies that illustrate the implementation of these technologies. One notable example is the deployment of a Digital Twin for a desalination plant, where 3D modelling, artificial intelligence, and IoT were used to optimise energy efficiency and improve operational processes. Another case study highlights the use of augmented reality (AR) in airport construction, where AR abilities were integrated with BIM models to enhance issue management and on-site decision-making.

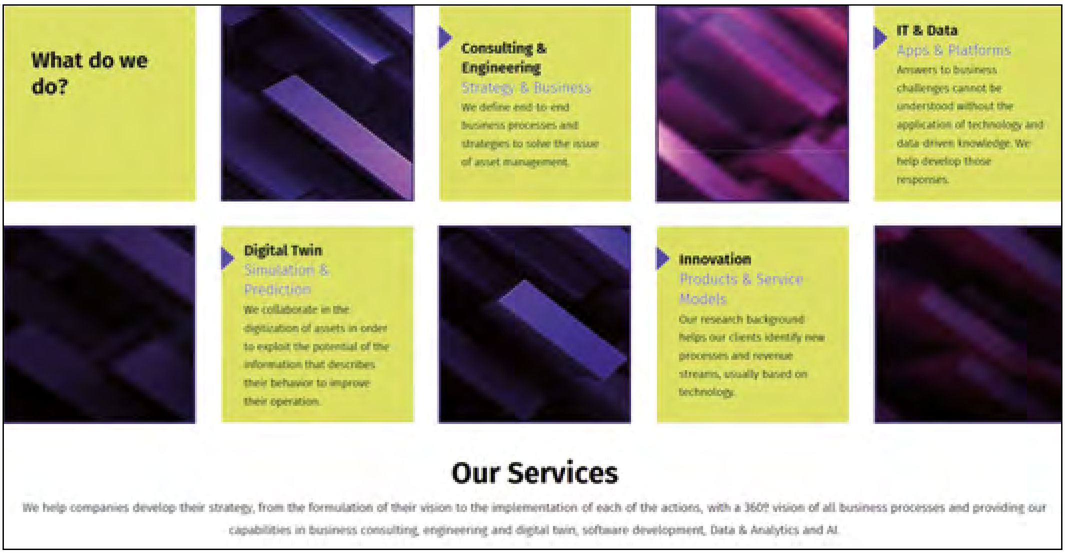
The Future of BIM and Digital Twins. The presentation concludes by emphasising the importance of integrating advanced technologies, such as artificial intelligence, machine learning, and IoT, with BIM and Digital Twins. This integration not only addresses the challenges of modern infrastructure management but also unlocks new opportunities for efficiency, sustainability, and innovation. By leveraging these technologies, organisations can transition from reactive to proactive management, ensuring that assets are optimised throughout their lifecycle.

3. Conclusion

BIM and Digital Twins are not merely abilities but transformative methodologies that redefine how we design, build, and manage infrastructure. Their ability to integrate data, foster collaboration, and provide actionable insights makes them indispensable for addressing the complexities of modern asset management. As demonstrated through the case studies, these technologies have the potential to drive significant improvements in efficiency, sustainability, and decision-making, paving the way for a smarter and more connected future.


BIM Technologies &
Digital Twinning
ESReDA
Digital Twin Week: the 64th ESReDA
Seminar & Doctoral Workshop


About us
Quantia is a spin-off company of the University of Granada. Its team includes scientific staff trained in some of the world's leading research centers in the computation of cyber-physical systems, as well as professors and researchers. Our researchers also have an important international career. This team of high scientific and technical level also works side by side with professionals who come from the world of engineering and consulting. The people in our organization and their high technological level guarantee excellence in the execution of your projects and the feasibility of obtaining solutions to complicated technical challenges.



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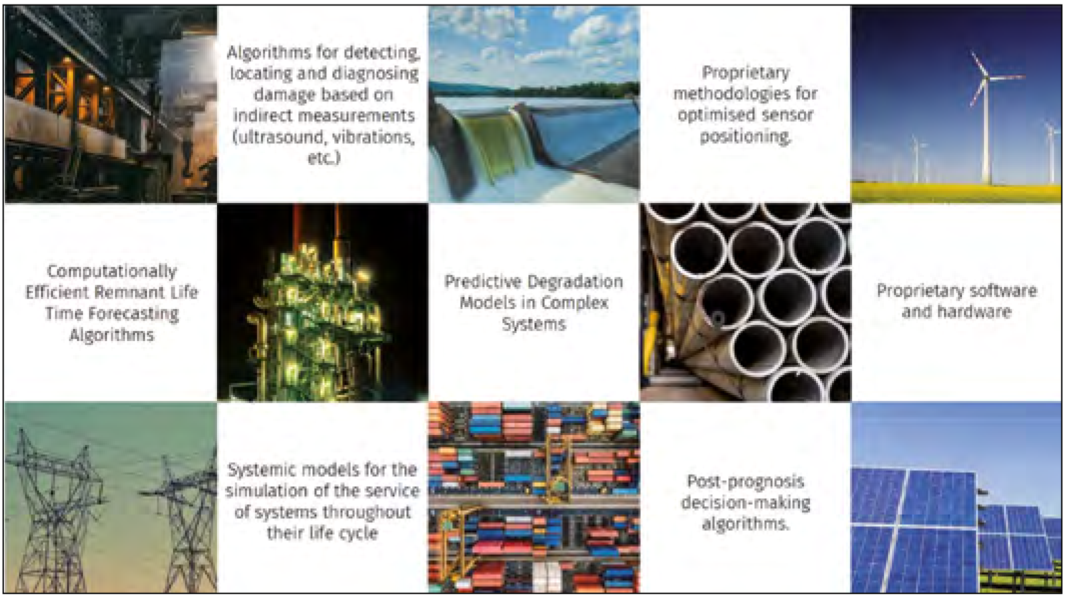
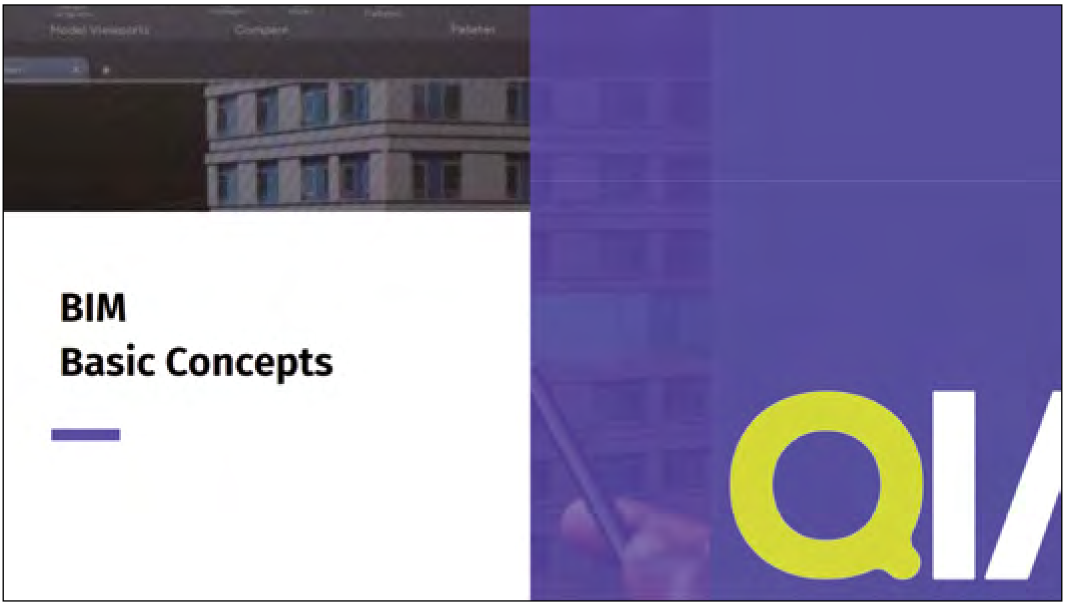
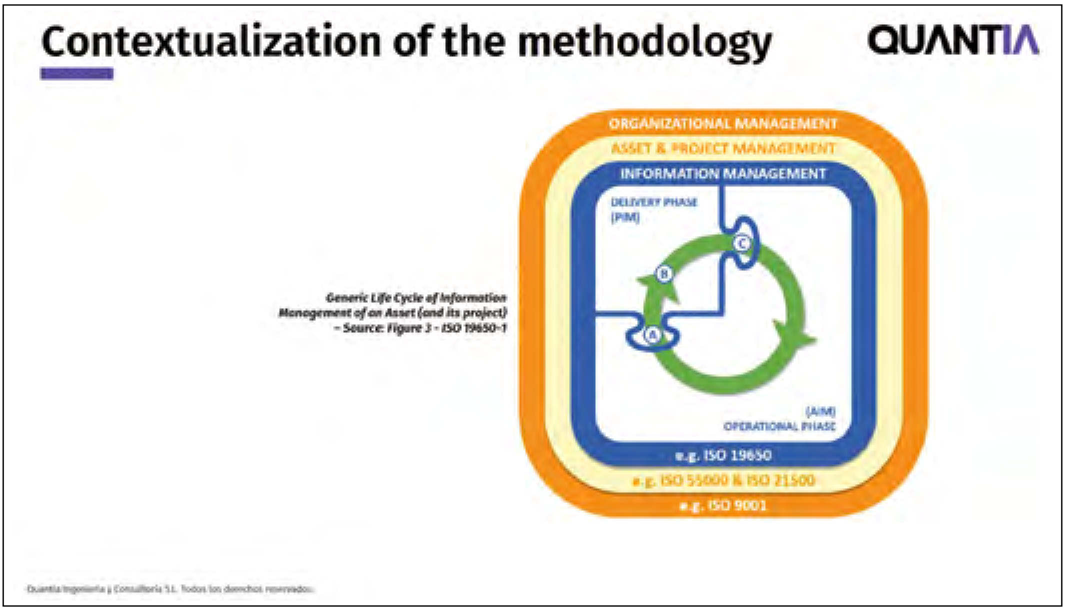

Algorithms for detecting, locating and diagnosing damage based on indirect measurements (ultrasound, vibrations, etc.)
Proprietary methodologies for optimised sensor positioning.
Computationally Efficient Remnant Life Time Forecasting Algorithms
Predictive Degradation Models in Complex Systems
Proprietary software and hardware
Systemic models for the simulation of the service of systems throughout their life cycle
Post-prognosis decision-making algorithms.


BIM
Basic Concepts


Contextualization of the methodology
QUANTIA
Generic Life Cycle of Information Management of an Asset (and its project) – Source: Figure 3 - ISO 19650-1
ORGANIZATIONAL MANAGEMENT
ASSET & PROJECT MANAGEMENT
INFORMATION MANAGEMENT
DELIVERY PHASE (PIM)
A
B
C
(AIM) OPERATIONAL PHASE
e.g. ISO 19650
e.g. ISO 55000 & ISO 21500
e.g. ISO 9001
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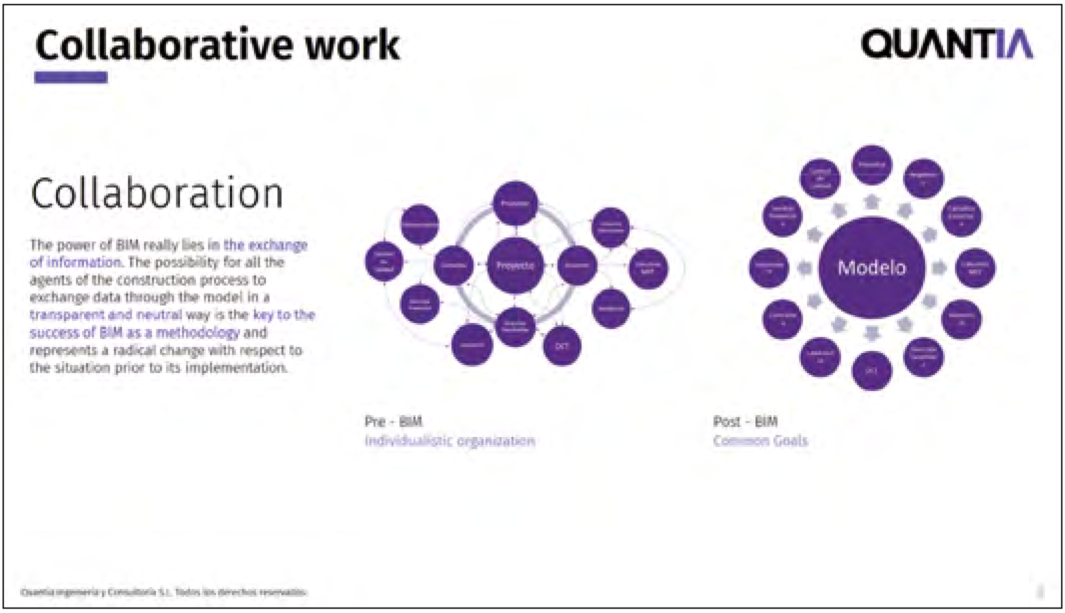
Collaborative work
QUANTIA
Collaboration
The power of BIM really lies in the exchange of information. The possibility for all the agents of the construction process to exchange data through the model in a transparent and neutral way is the key to the success of BIM as a methodology and represents a radical change with respect to the situation prior to its implementation.
Proyecto
Modelo
Pre - BIM
Individualistic organization
Post - BIM
Common Goals
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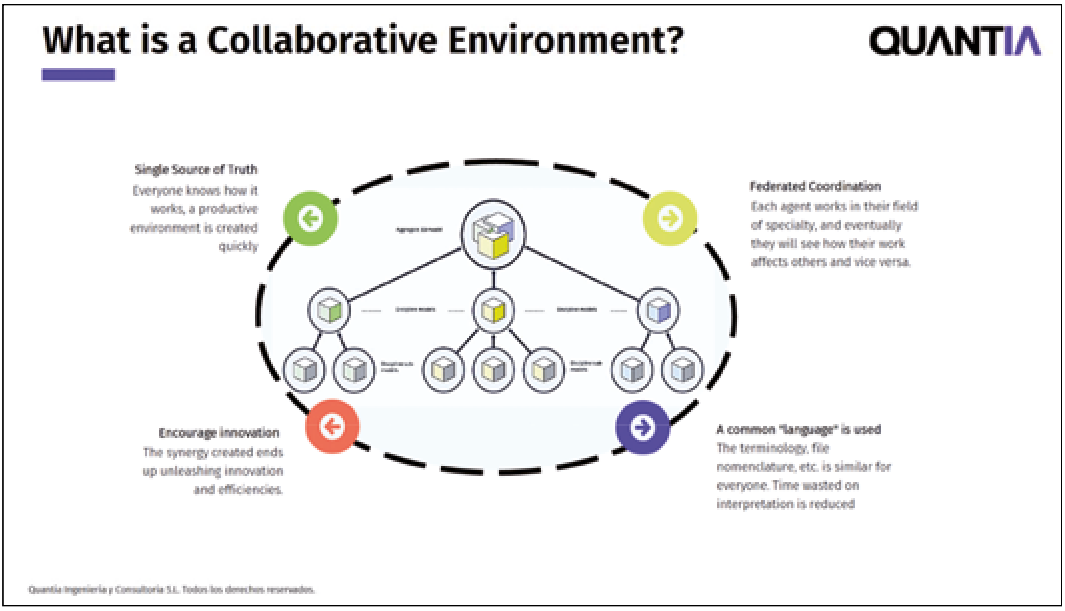
What is a Collaborative Environment?
QUANTIA
Single Source of Truth
Everyone knows how it works, a productive environment is created quickly
Federated Coordination
Each agent works in their field of specialty, and eventually they will see how their work affects others and vice versa.
Encourage innovation
The synergy created ends up unleashing innovation and efficiencies.
A common "language" is used
The terminology, file nomenclature, etc. is similar for everyone. Time wasted on interpretation is reduced
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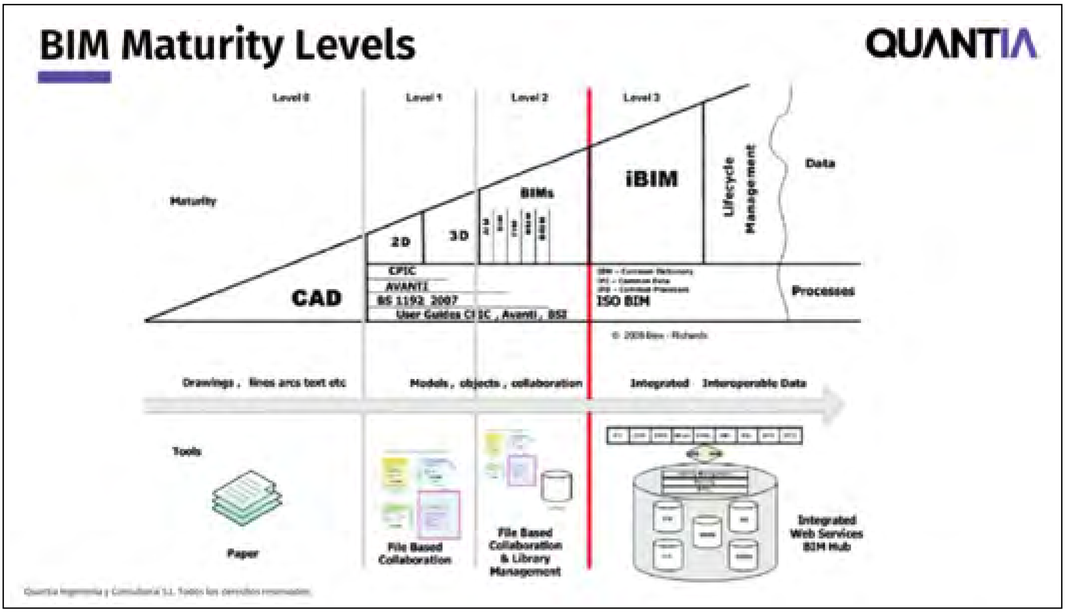
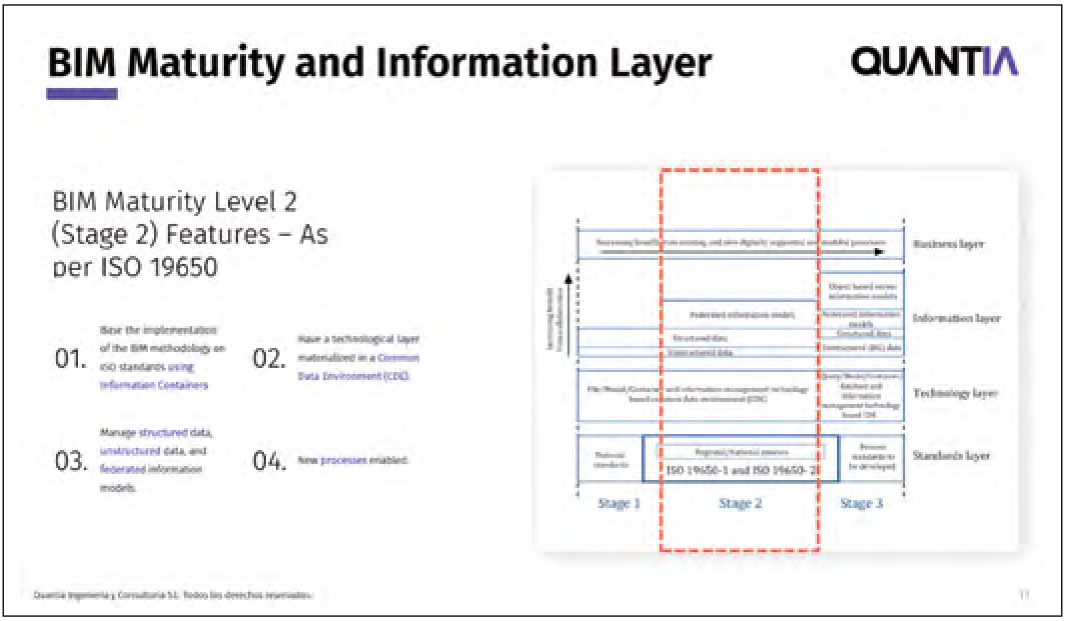
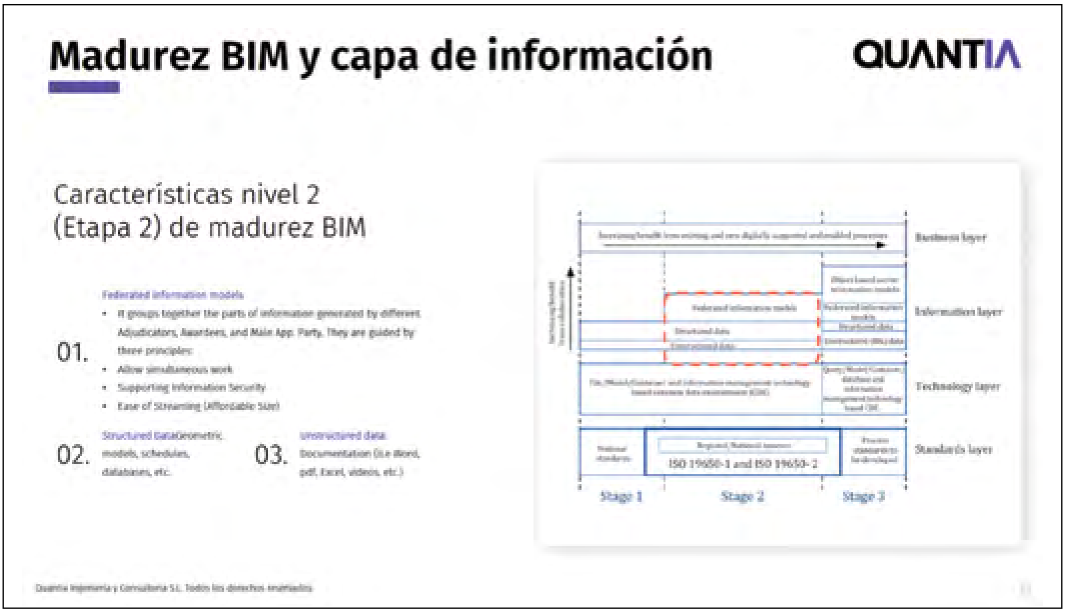

BIM Maturity Levels
QUANTIA
Level 0
Level 1
Level 2
Level 3
Maturity
CAD
2D
3D
BIMs
iBIM
Lifecycle Management
Data
Processes
CPIC
AVANTI
BS 1192 2007
User Guides CPIC, Avanti, BSI
ISO BIM
Drawings, lines arcs text etc
Models, objects, collaboration
Integrated Interoperable Data
Tools
Paper
File Based Collaboration
File Based Collaboration & Library Management
Integrated Web Services BIM Hub





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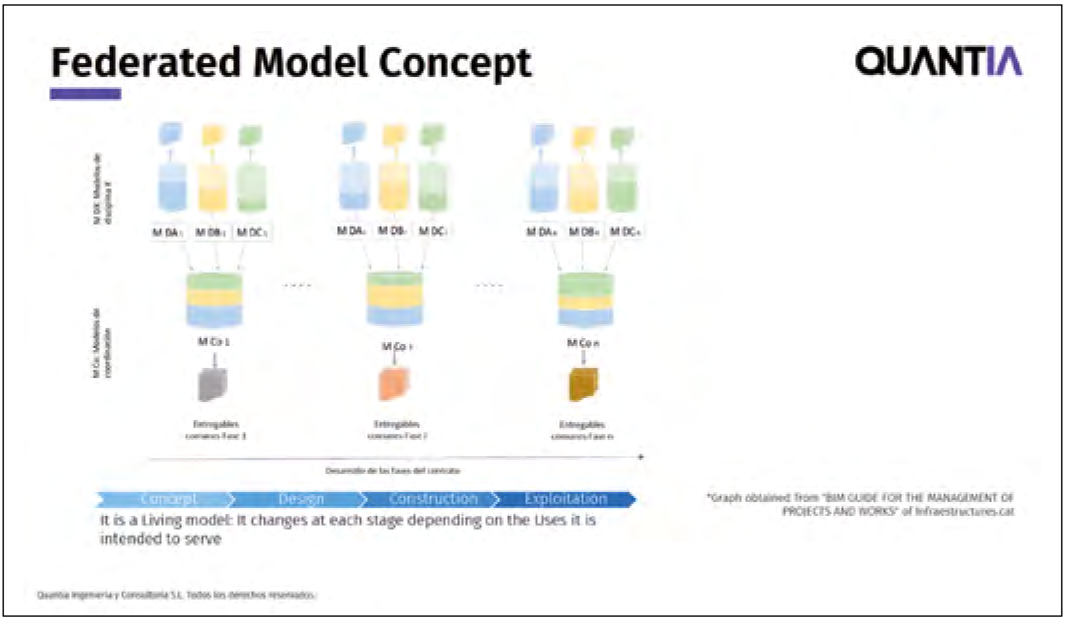
Federated Model Concept
QUANTIA
Concept
Design
Construction
Exploitation
It is a Living model: It changes at each stage depending on the Uses it is intended to serve
*Graph obtained from "BIM GUIDE FOR THE MANAGEMENT OF PROJECTS AND WORKS" of Infraestructures.cat
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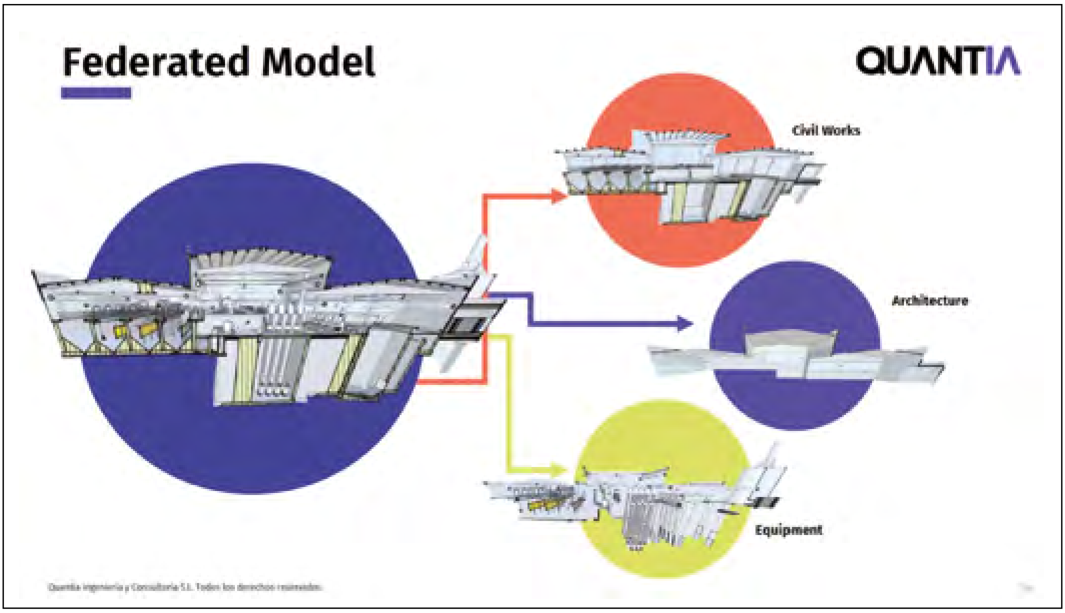
Federated Model
QUANTIA
Civil Works
Architecture
Equipment
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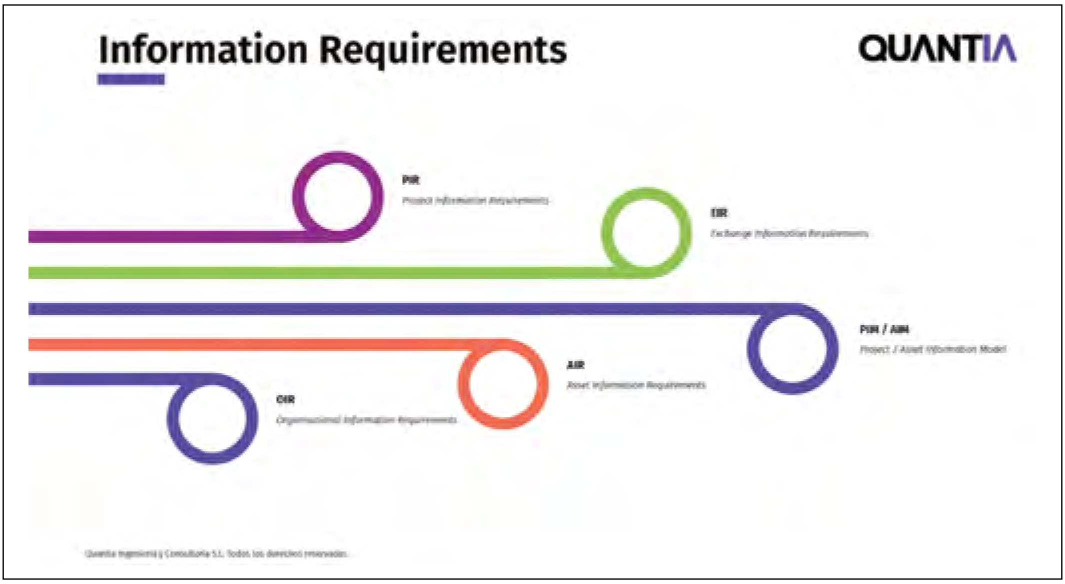
Information Requirements
QUANTIA
PIR
Project Information Requirements
EIR
Exchange Information Requirements
PIM / AIM
Project / Asset Information Model
AIR
Asset Information Requirements
OIR
Organizational Information Requirements
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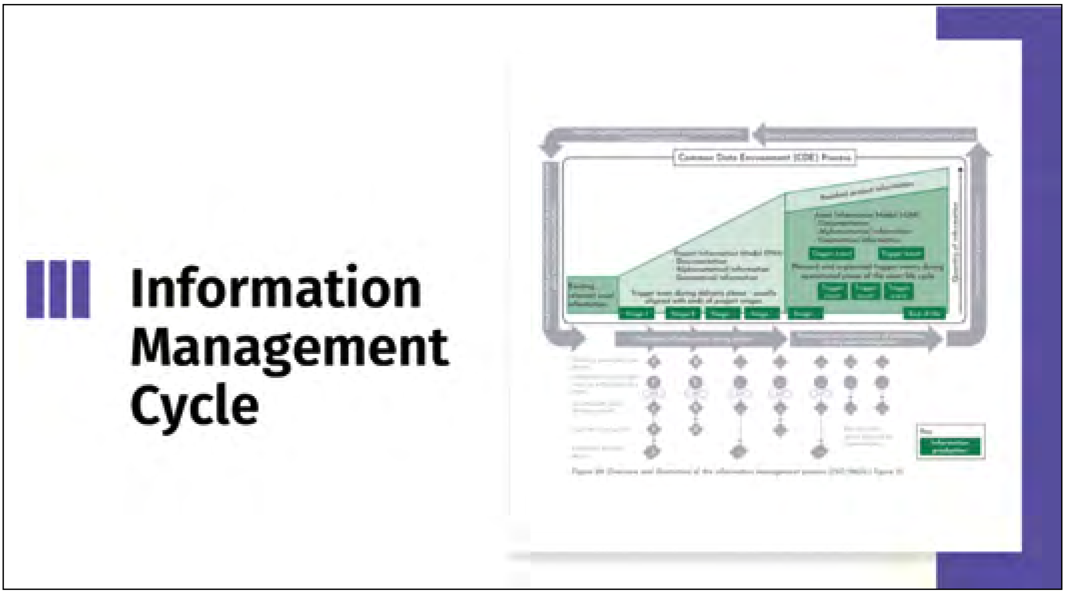
III
Information Management Cycle
Common Data Environment (CDE) Process


From PIM to AIM
QUANTIA
01 Project Information Model (PIM)
Life of the Project
Project Information
Project Decisions
Collaborative Environment
Design Team Production Environment
Collaborative Environment in Construction
Original Models
Native Formats
High Qualification in BIM
Norma ISO 19650
Regulated by Part 2 of the standard
02 Contract-Regulated Information Exchange
Life Based
PUBLISHED INFORMATION
Information defined in the EIR
Documents & Data (Operation & Maintenance)
Other BIM Uses
Geometric Model Visualizations
References between models to create a Federated Model
Review & Validation Process
Project governance through VALIDATION of information
03 Asset Information Model
Asset Life
Organizational Information
Organizational Decisions
Organizational Collaboration Environment
Client's O&M environment managed by several agents.
Modelos Open BIM
Open Formats
Integration into Internal Work System
Low BIM Qualification
Norma ISO 19650
Regulated by Part 3 of the standard.
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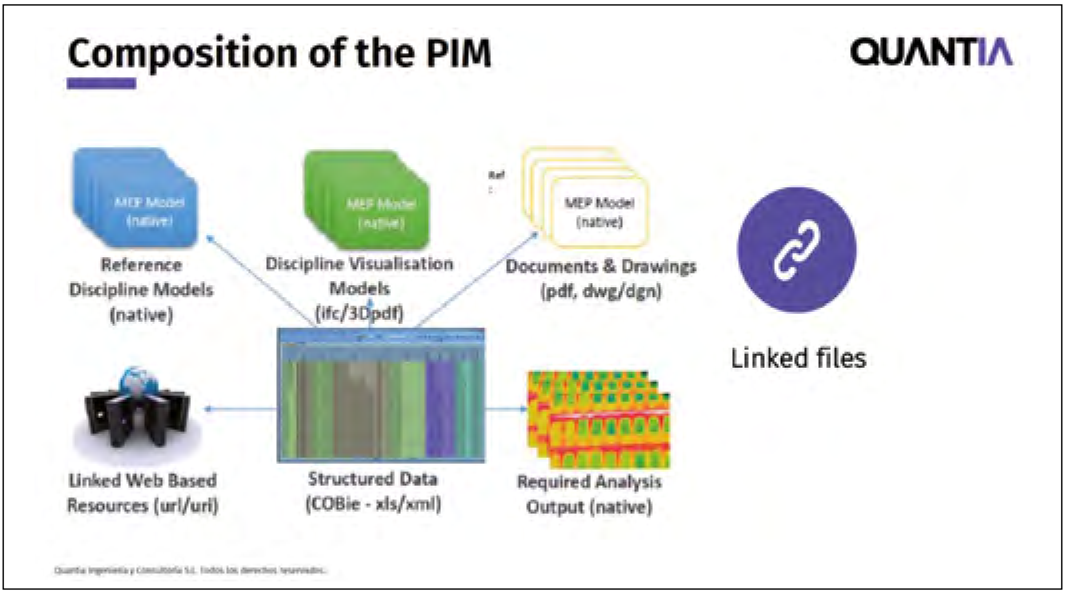
Composition of the PIM
QUANTIA
MEP Model (native)
Reference Discipline Models (native)
MEP Model (native)
Discipline Visualisation Models (ifc/3Dpdf)
MEP Model (native)
Documents & Drawings (pdf, dwg/dgn)
Linked files
Linked Web Based Resources (url/uri)
Structured Data (COBie - xls/xml)
Required Analysis Output (native)
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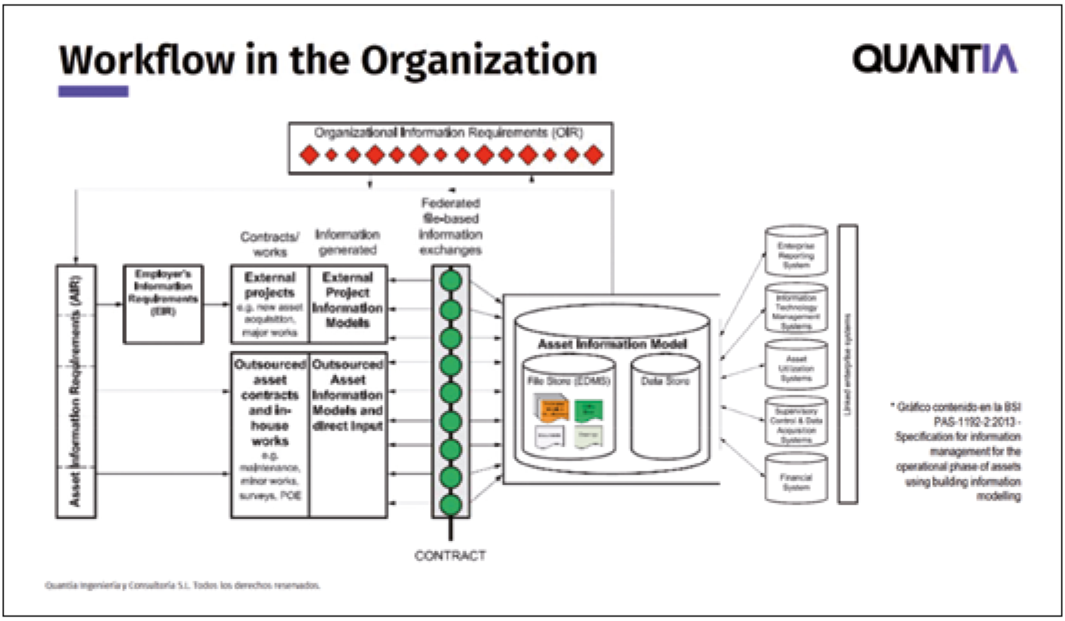
Workflow in the Organization
QUANTIA
Organizational Information Requirements (OIR)
Federated file-based information exchanges
Contracts/ works
Information generated
Asset Information Requirements (AIR)
Employer's Information Requirements (EIR)
External projects
External Project Information Models
Outsourced asset contracts and in-house works
Outsourced Asset Information Models and direct Input
Asset Information Model
File Store (EDMS)
Data Store
CONTRACT
* Gráfico contenido en la BSI PAS-1192-2:2013 - Specification for information management for the operational phase of assets using building information modelling
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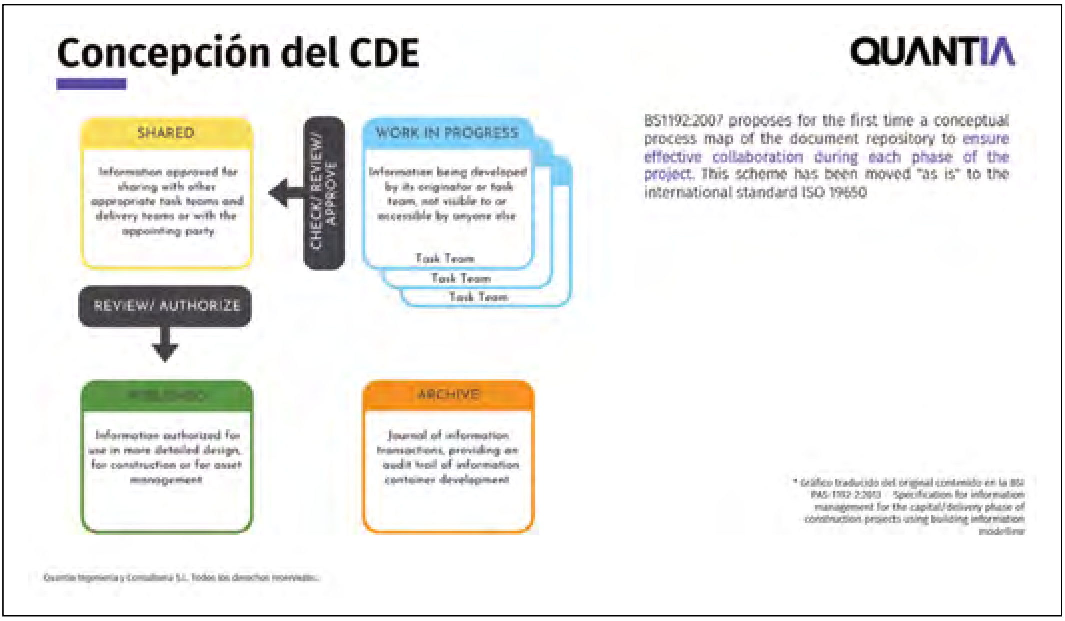
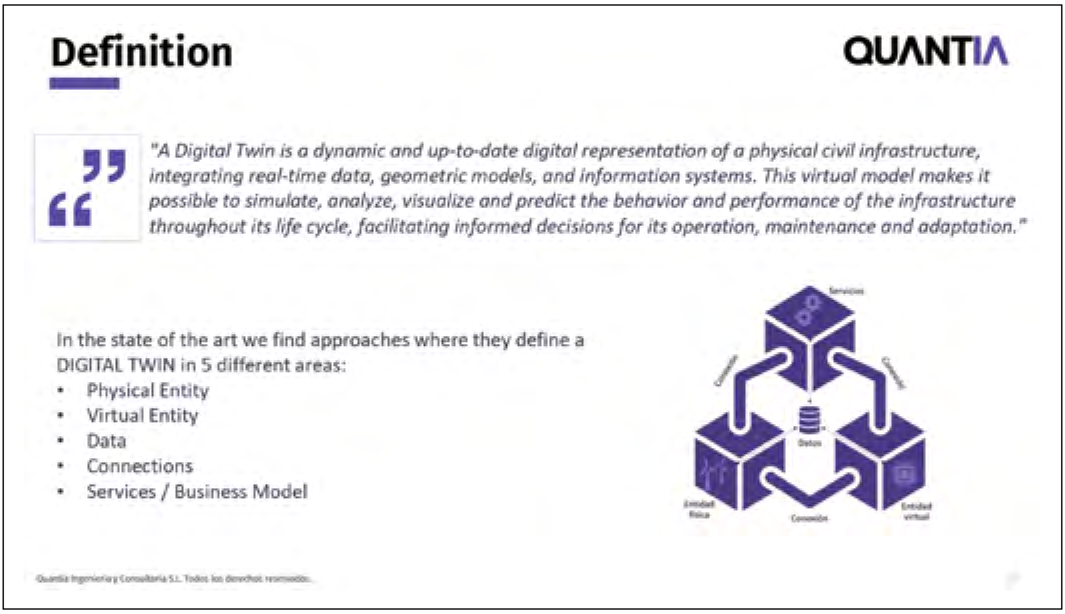
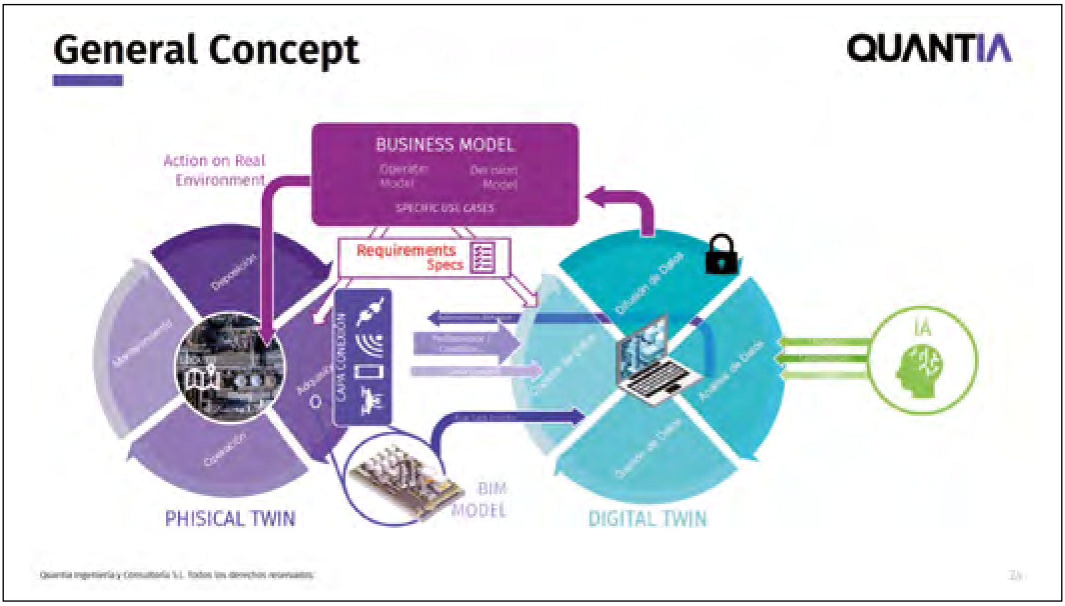
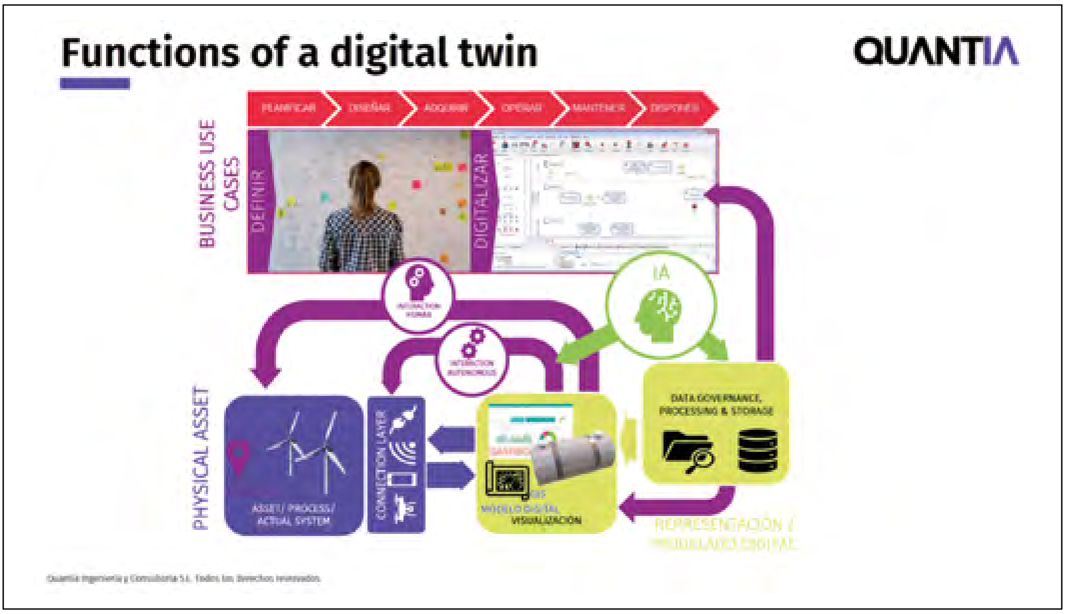
Common Data Environment

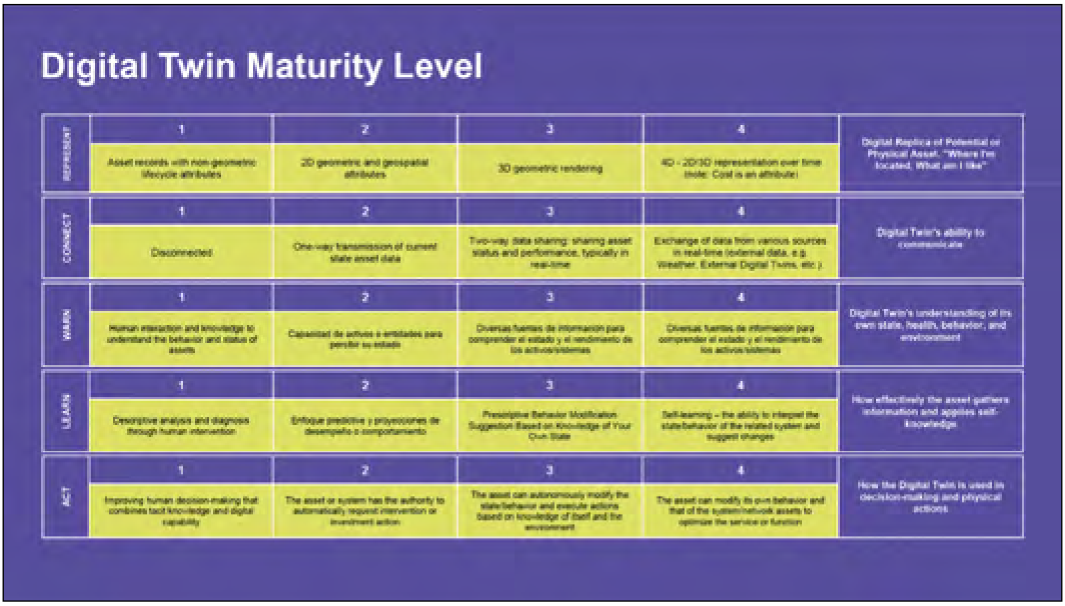

Concepción del CDE
QUANTIA
SHARED
Information approved for sharing with other appropriate task teams and delivery teams or with the appointing party
CHECK/ REVIEW/ APPROVE
WORK IN PROGRESS
Information being developed by its originator or task team, not visible to or accessible by anyone else
Task Team
Task Team
Task Team
REVIEW/ AUTHORIZE
Information authorized for use in more detailed design, for construction or for asset management
ARCHIVE
Journal of information transactions, providing an audit trail of information container development
BS1192:2007 proposes for the first time a conceptual process map of the document repository to ensure effective collaboration during each phase of the project. This scheme has been moved "as is" to the international standard ISO 19650


Digital Twins


Definition
QUANTIA
"A Digital Twin is a dynamic and up-to-date digital representation of a physical civil infrastructure, integrating real-time data, geometric models, and information systems. This virtual model makes it possible to simulate, analyze, visualize and predict the behavior and performance of the infrastructure throughout its life cycle, facilitating informed decisions for its operation, maintenance and adaptation."
In the state of the art we find approaches where they define a DIGITAL TWIN in 5 different areas:
• Physical Entity
• Virtual Entity
• Data
• Connections
• Services / Business Model
Quantia Ingeniería y Consultoría S.L. Todos los derechos reservados.

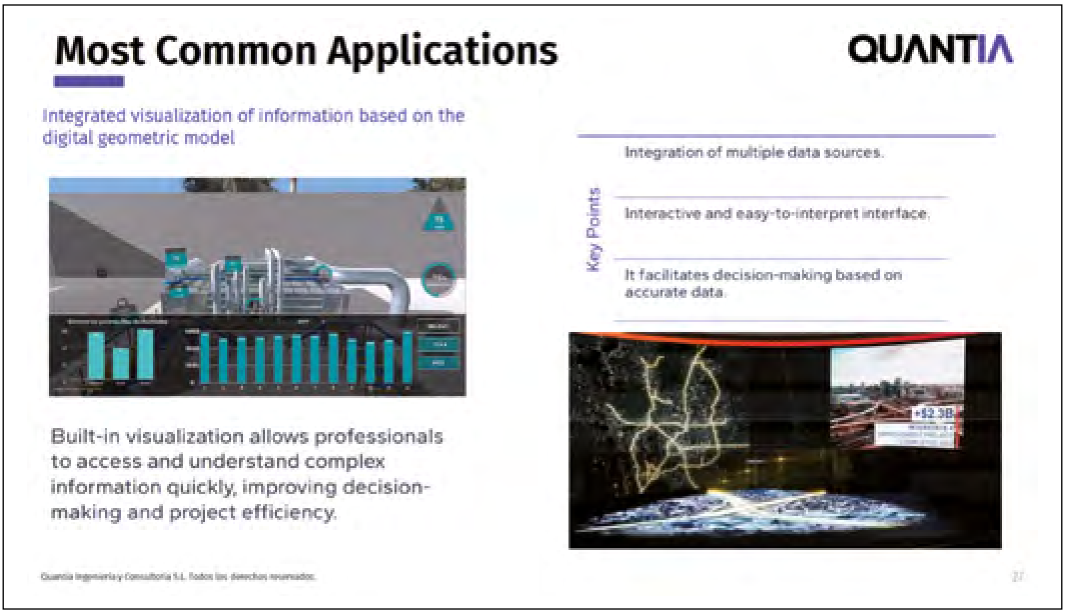

General Concept
QUANTIA
Action on Real Environment
BUSINESS MODEL
SPECIFIC USE CASES
Requirements Specs
IA
PHISICAL TWIN
BIM MODEL
DIGITAL TWIN

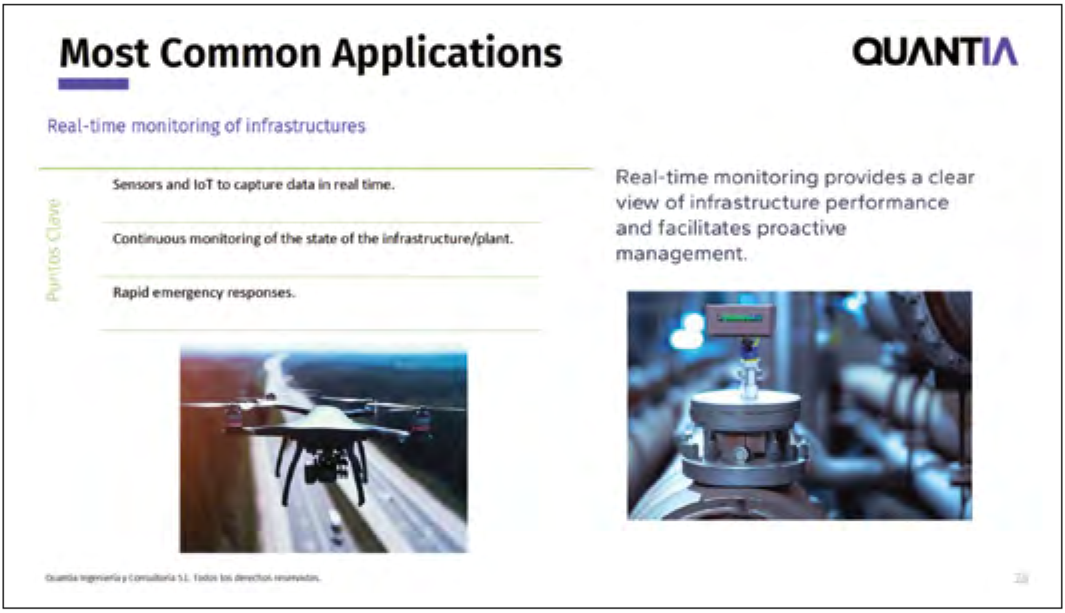




Digital Twin Maturity Level

	1	2	3	4	
REPRESENT	Asset records with non-geometric lifecycle attributes	2D geometric and geospatial attributes	3D geometric rendering	4D - 2D/3D representation over time (note: Cost is an attribute)	Digital Replica of Potential or Physical Asset. "Where I'm located. What am I like"
CONNECT	Disconnected	One-way transmission of current state asset data	Two-way data sharing: sharing asset status and performance, typically in real-time	Exchange of data from various sources in real-time (external data, e.g. Weather, External Digital Twins, etc.)	Digital Twin's ability to communicate
WARN	Human interaction and knowledge to understand the behavior and status of assets	Capacidad de activos o entidades para percibir su estado	Diversas fuentes de información para comprender el estado y el rendimiento de los activos/sistemas	Diversas fuentes de información para comprender el estado y el rendimiento de los activos/sistemas	Digital Twin's understanding of its own state, health, behavior, and environment
LEARN	Descriptive analysis and diagnosis through human intervention	Enfoque predictivo y proyecciones de desempeño o comportamiento	Prescriptive Behavior Modification Suggestion Based on Knowledge of Your Own State	Self-learning – the ability to interpret the state/behavior of the related system and suggest changes	How effectively the asset gathers information and applies self-knowledge
ACT	Improving human decision-making that combines tacit knowledge and digital capability	The asset or system has the authority to automatically request intervention or investment action	The asset can autonomously modify the state/behavior and execute actions based on knowledge of itself and the environment	The asset can modify its own behavior and that of the system/network assets to optimize the service or function	How the Digital Twin is used in decision-making and physical actions





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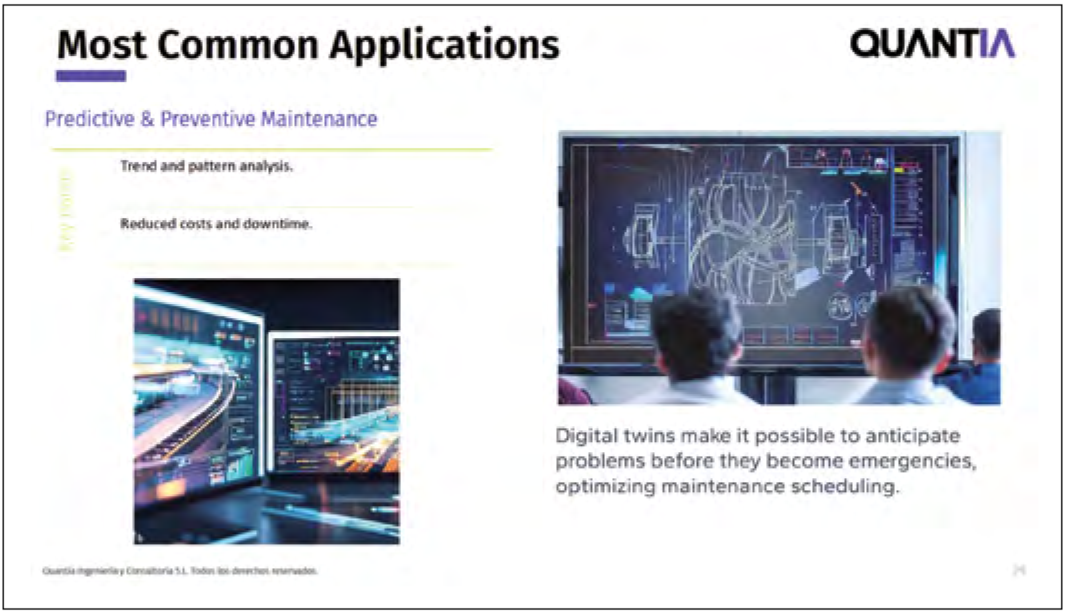

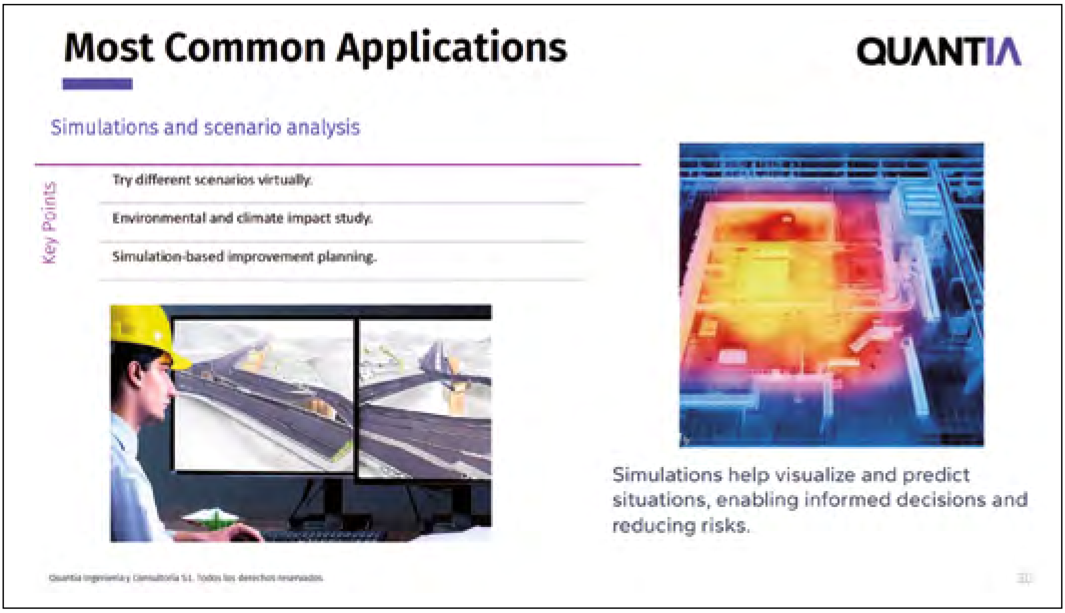

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Other technologies for leveraging virtual models (AR, VR, BIM)

QUANTIA

Differences between Augmented Reality and Virtual Reality

Characteristics	Augmented reality	Virtual reality
Degree of Immersion	It immerses the user in the real world and complements it with the virtual.	It completely envelops the user.
Perception	It helps the user to grasp the information with their own senses.	The perceptual channels are completely controlled by the system.
Capacity	It complements reality.	Try to replace reality
Complementation	Digital or paper-based information.	Not applicable.
Interaction	You can interact with any object in the real world.	You can't interact with real-world objects.

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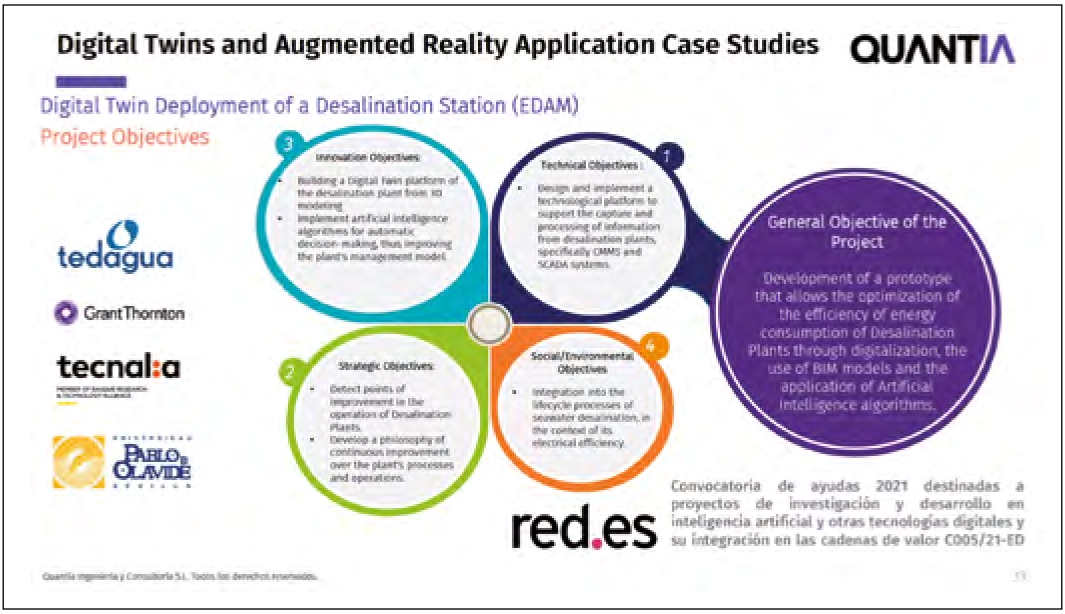
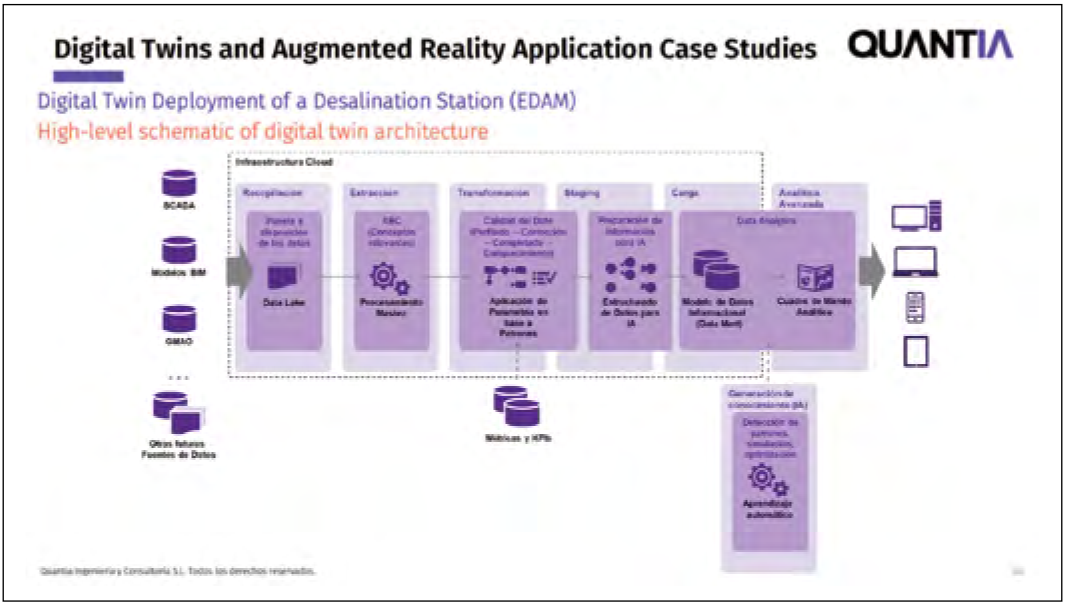
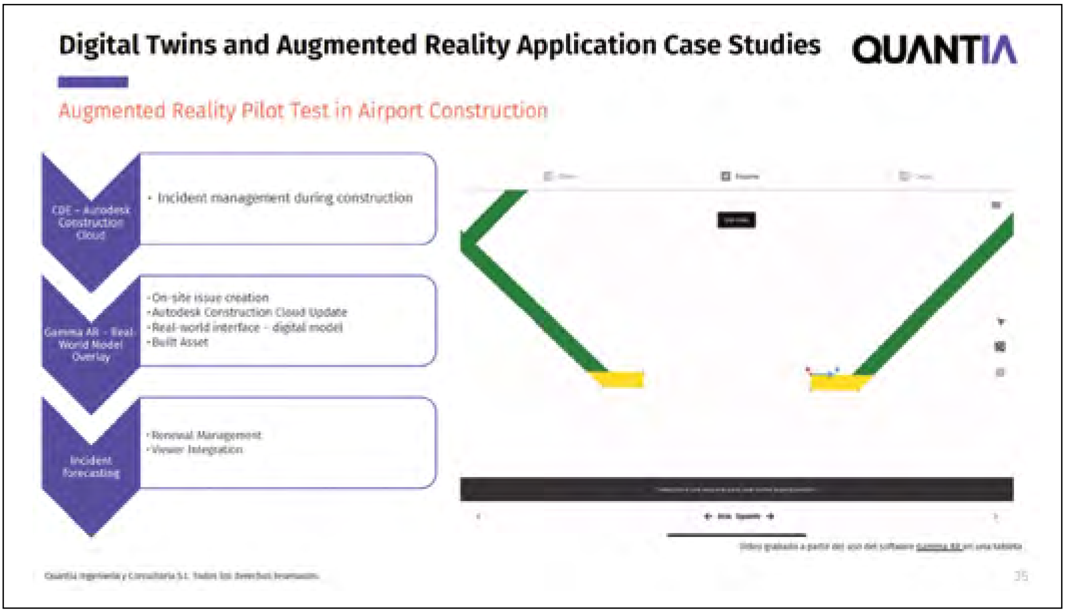

Digital Twins and Augmented Reality Application Case Studies
QUANTIA
Digital Twin Deployment of a Desalination Station (EDAM)
Project Objectives
tedagua
Grant Thornton
tecnalia
Innovation Objectives
Building a Digital Twin platform of the desalination plant from 3D modeling
Implement artificial intelligence algorithms for automatic decision-making, thus improving the plant's management model.
Technical Objectives:
Design and implement a technological platform to support the capture and processing of information from desalination plants, specifically CMMS and SCADA systems.
General Objective of the Project
Development of a prototype that allows the optimization of the efficiency of energy consumption of Desalination Plants through digitalization, the use of BIM models and the application of Artificial Intelligence algorithms.
Strategic Objectives:
Detect points of improvement in the operation of Desalination Plants.
Develop a philosophy of continuous improvement over the plant's processes and operations.
Social/Environmental Objectives
Integration into the lifecycle processes of seawater desalination, in the context of its electrical efficiency.
red.es
Convocatoria de ayudas 2021 destinadas a proyectos de investigación y desarrollo en inteligencia artificial y otras tecnologías digitales y su integración en las cadenas de valor C005/21-ED


Digital Twins and Augmented Reality Application Case Studies
QUANTIA
Digital Twin Deployment of a Desalination Station (EDAM)
High-level schematic of digital twin architecture
Infraestructura Cloud
SCADA
Modelos BIM
GMAO
Otras futuras Fuentes de Datos
Data Lake
Procesamiento Masivo
Aplicación de Parámetros en base a Patrones
Estructurado de Datos para IA
Modelo de Datos Informacional (Data Mart)
Cuadro de Mando Analítico
Data Analytics
Métricas y KPIs
Aprendizaje automático


Digital Twins and Augmented Reality Application Case Studies
QUANTIA
Digital Twin Deployment of a Desalination Station (EDAM)
Platform Deployment


Digital Twins and Augmented Reality Application Case Studies
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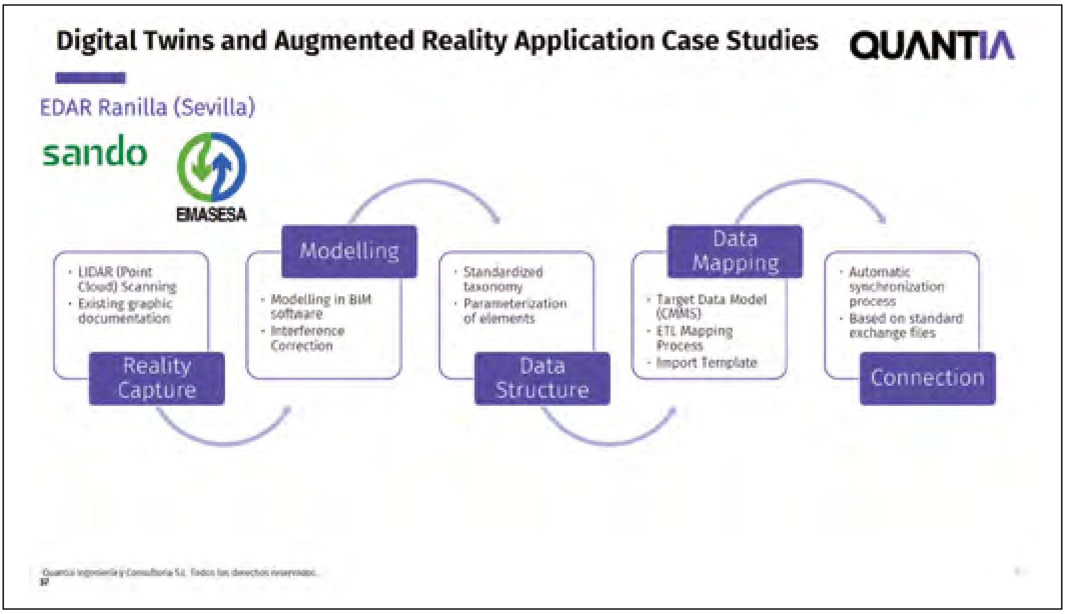
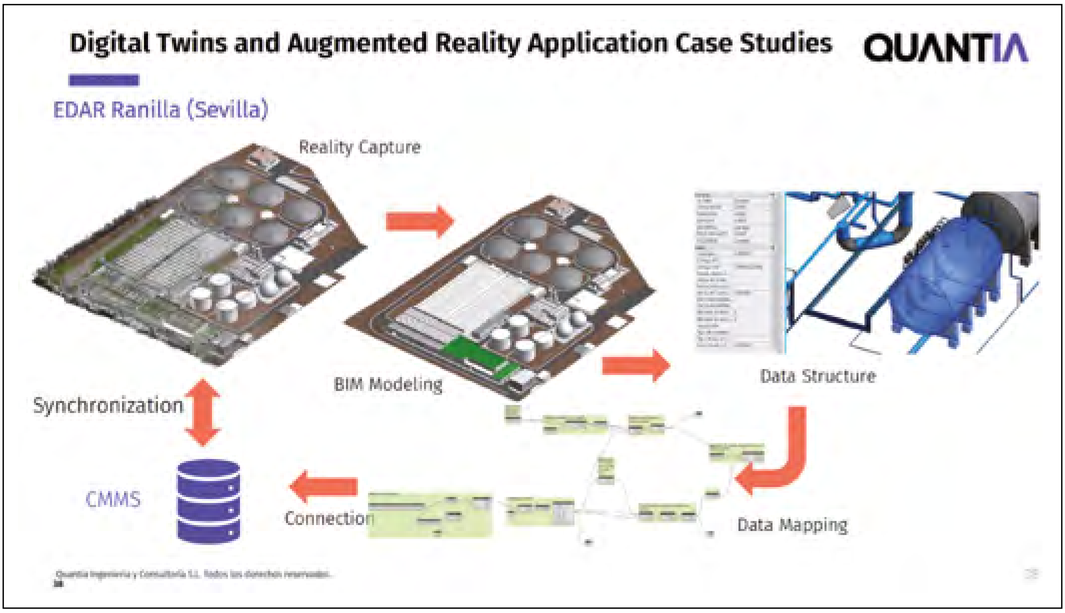
Augmented Reality Pilot Test in Airport Construction
CDE - Autodesk Construction Cloud
• Incident management during construction
Gamma AR - Real World Model Overlay
• On-site issue creation
• Autodesk Construction Cloud Update
• Real-world interface - digital model
• Built Asset
Incident forecasting
• Renewal Management
• Viewer Integration





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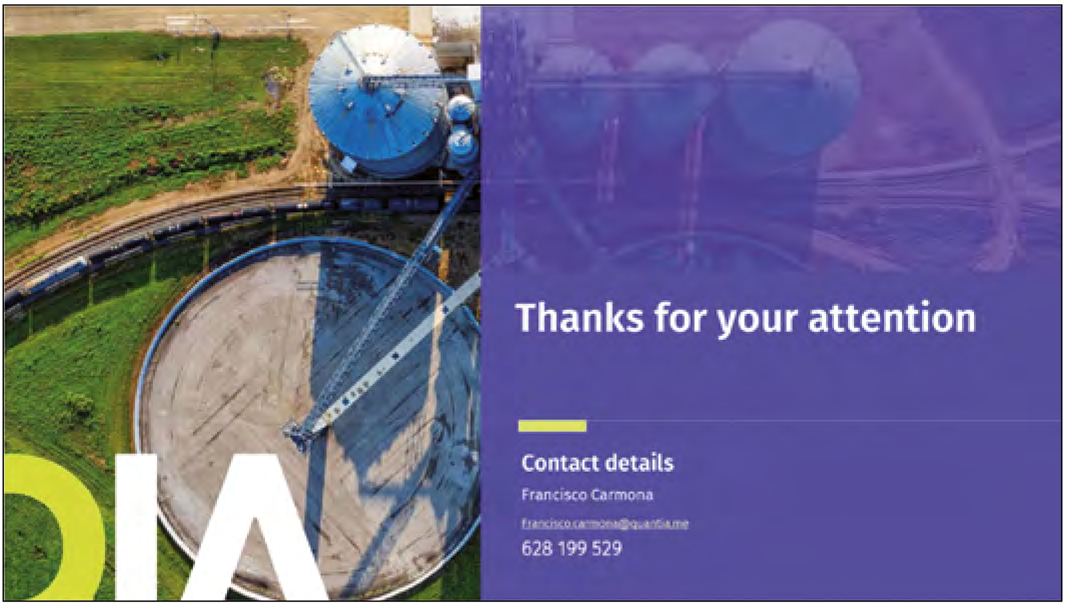

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Digital Transformation in Maintenance & Asset Management

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(Japan Institute of Plant Maintenance)

Abstract

The Project 25 DX document by GFMAM explores the impact of digital transformation (DX) on maintenance and asset management (M&AM). It highlights the role of advanced technologies like AI, data analytics, and IoT in enhancing efficiency, predictive maintenance, and lifecycle management. The document provides sector-specific insights, identifies barriers such as lack of strategy and digital capacity, and offers tailored guidance for different organizational roles and maturity levels. Emphasizing leadership, data governance, and structured practices, it aims to help organizations navigate DX challenges and optimize M&AM processes. The full document is set for release in early 2024.

1. Introduction

The Global Forum on Maintenance and Asset Management (GFMAM) has undertaken Project 25 DX to examine the evolving landscape of digital transformation in maintenance and asset management. This initiative seeks to address how advanced technologies, data analytics, and artificial intelligence are reshaping traditional practices while maintaining alignment with fundamental principles.

The project explored key findings derived from an international survey conducted among GFMAM member organizations. These insights highlight critical areas such as predictive and prescriptive maintenance strategies, regulatory compliance, servitization, and lifecycle management. Furthermore, the study outlines significant challenges, including investment constraints, workforce skill gaps, and the necessity of structured digital transformation strategies.

The work provides sector-specific insights and maturity-level guidelines, and Project 25 DX offers organizations a strategic framework to navigate digitalization effectively. The findings underscore the importance of leadership alignment, robust data governance, and a comprehensive roadmap to sustain long-term digital transformation efforts.

This document is expected to serve as a valuable resource for industry professionals, enabling them to enhance asset reliability, efficiency, and cost-effectiveness through digital solutions.

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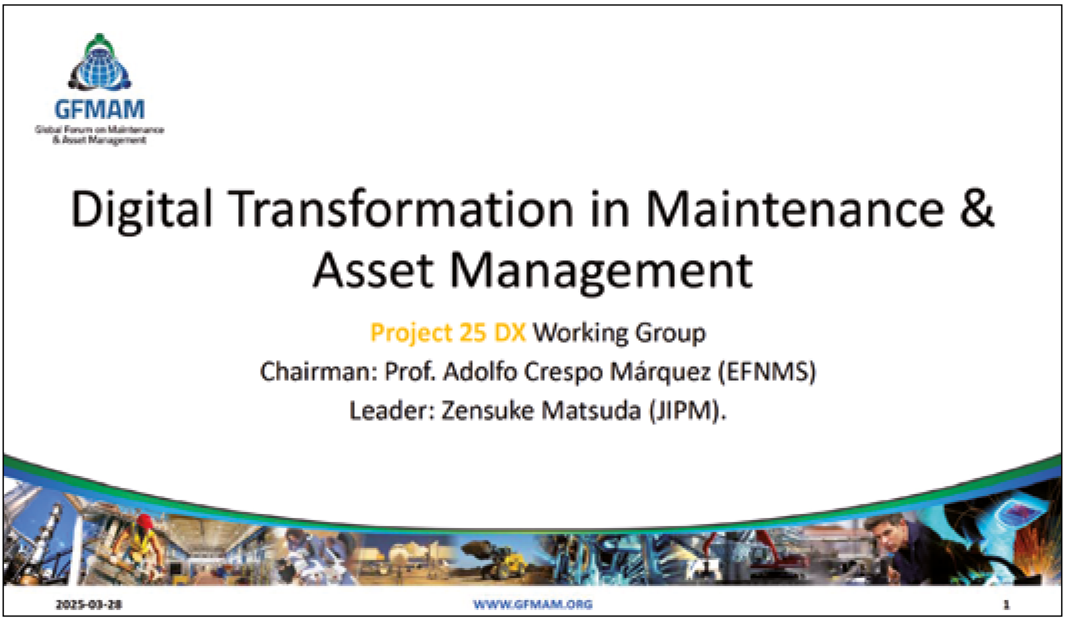
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Global Forum on Maintenance & Asset Management
Digital Transformation in Maintenance & Asset Management
Project 25 DX Working Group
Chairman: Prof. Adolfo Crespo Márquez (EFNMS)
Leader: Zensuke Matsuda (JIPM).
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1


GFMAM
Global Forum on Maintenance & Asset Management
The Global Forum on Maintenance and Asset Management
The Global Forum on Maintenance and Asset Management (GFMAM) has been established with the aim of collaboratively sharing advancements, knowledge, and standards in maintenance and asset management. The enduring objectives of the GFMAM are to:
• Bring together, promote, and strengthen the maintenance and asset management community worldwide.
• Support the establishment and development of associations or institutions whose aims are maintenance and/or asset management focused.
• Facilitate the exchange and alignment of maintenance and asset management knowledge and practices.
• Raise the credibility of member organizations by raising the profile of the Global Forum
More on the Global Forum on Maintenance and Asset Management (GFMAM) can be found on- line at www.gfmam.org
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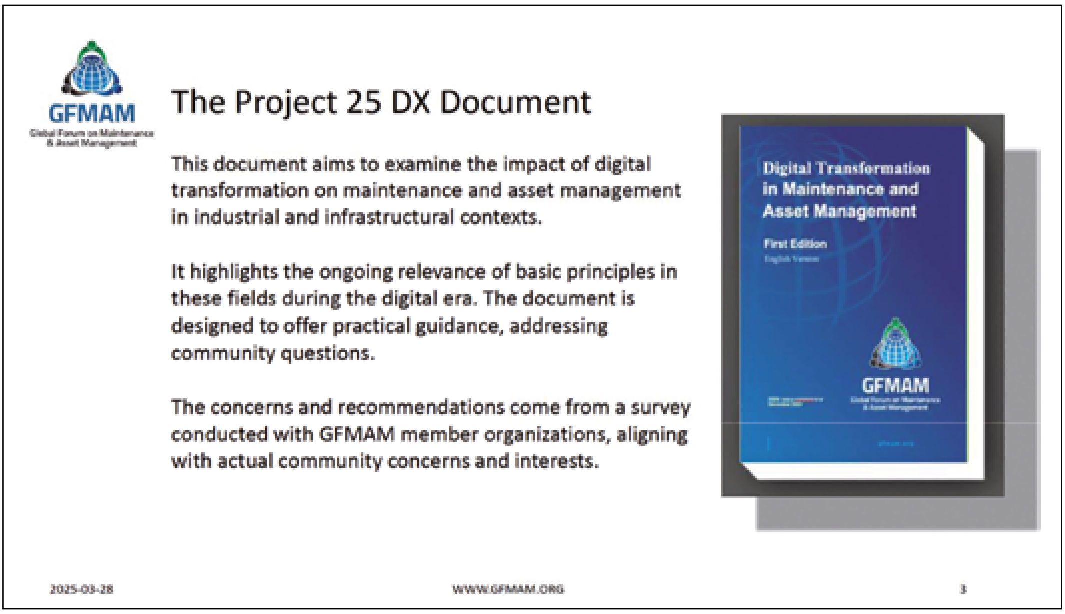

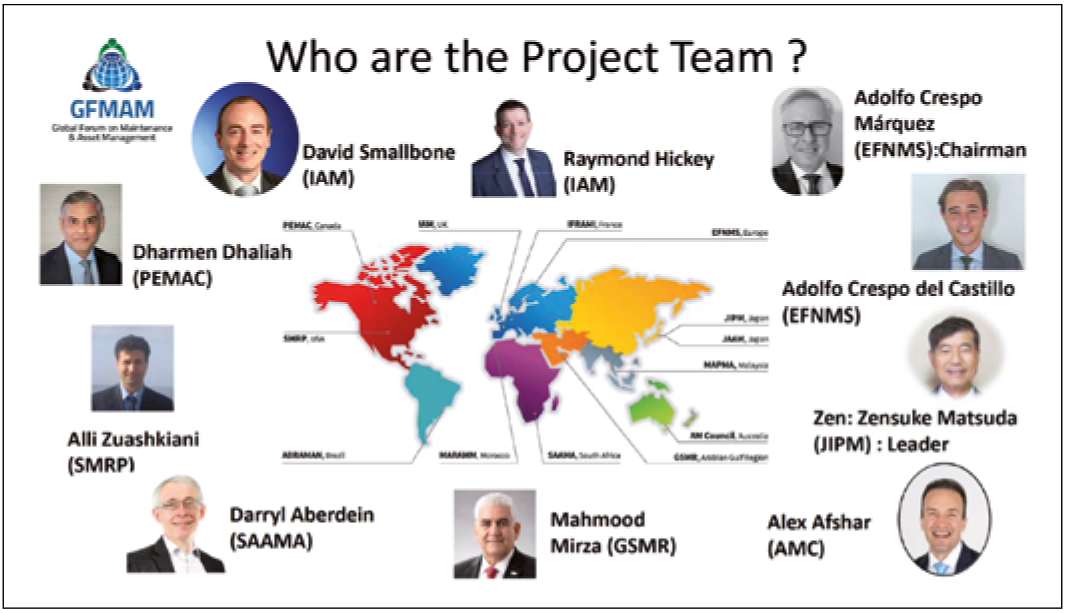

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How was the project developed ?

Figure 1. Document structure & guidance generation process

Findings and implications are coming out of the: "one point information" (findings) and "Telling the story of sectors" (implications). Information provided by team members contributing their knowledge of the current reality and documenting the implications in sectors that are close to them professionally.

Concerns and Guidance are using today's digital tools to: launch an unprecedented international survey, to capture, process, visualize and analyze the survey data, as well as to provide subsequent and immediate guidance coming out of these analyses (oriented to roles in the organization or to different stages in their maturity).

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The Findings

Findings

Digital Transformation and Advanced Technologies

- Rapid advances in digital technologies, data analytics and artificial intelligence, having the potential to radically transform asset management and maintenance.
- Sensing/data-capture solutions, increasing computational power, and advances in statistical techniques to drive machine learning, enable us to manage complex systems better.

Maintenance efficiency and Strategies

- Advanced analytics making CBM a very attractive lever for increasing maintenance efficiency.
- Important efficiency gains by moving, in many cases in an aggressive manner, towards CBM.
- Movements to PdM requiring further investments. Monitoring not only components condition but also the condition of the factors that influence them.
- 'Prescriptive Maintenance' (RxM, with 'Rx' symbolizing 'Prescription' and 'M' 'Maintenance), gaining prominence. RxM leverages the capabilities of data analytics, artificial intelligence, and advanced technologies to dynamically optimize maintenance strategy design.

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The Findings

Findings

Regulatory Compliance and Change Management

- Extra effort for CBM/PdM new strategies to align with existing regulatory requirements.

Optimization and Automation

- The entire M&AM value chain needs to be addressed. Monitoring and analytical capabilities are only a first step.
- Resources management now linked to assets status. New techs like 3D scanning & printing, photogrammetry, etc. are gaining ground to support this.
- Roles changing in M&AM, using technology rather than placing people in hazardous situations.

The human resources

- Maintenance professionals more likely to fill important roles if having data science knowledge and know how to use it.
- Human-based knowledge and experience key drivers for the application of AI to predictive/prescriptive maintenance.

Servitization and complete lifecycle management

- Manufacturers, becoming assets owners, paying more attention to the complete life cycle of the assets.

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The Implications

Implications

Policy Implications

- Legal as an enabling mechanism can safeguard the Digital investment.
- New methodology for procuring services related to data and digital technologies for infrastructure.
- New commercial risk model for digital projects in the organization.
- Utilizing and enhancing data and digital technologies in asset management decision-making.

Business Implications

- New business models.
- New management implications over the asset lifecycle.

Technical Implications and Challenges

- Changing the way maintenance activities, by type, are performed.
- New end-to-end technologies for digital maintenance management.
- Many challenges in the adoption of the digital technologies

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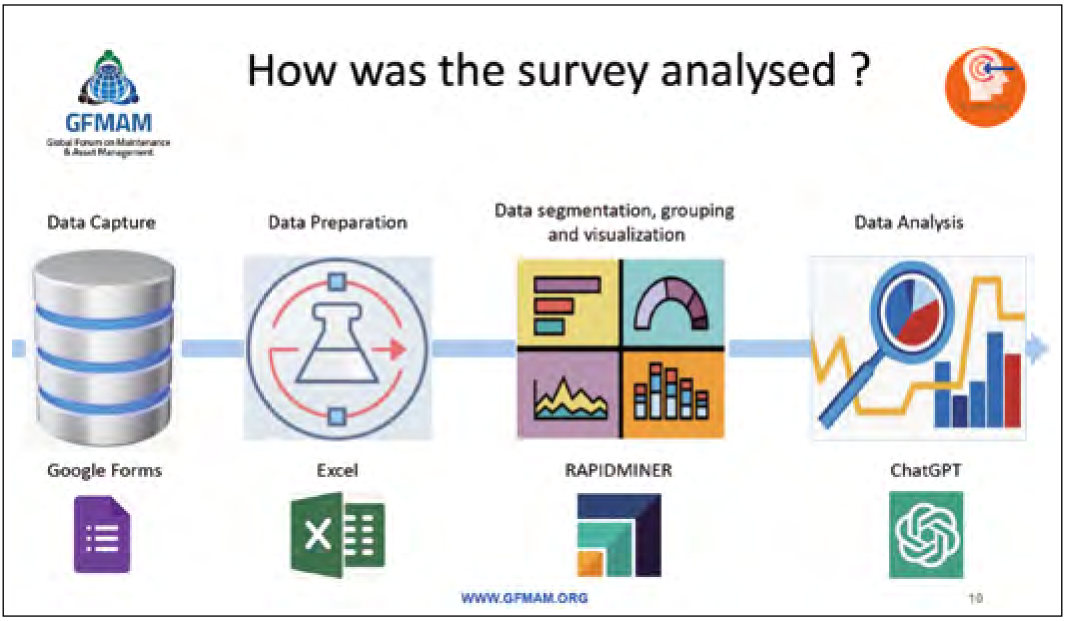

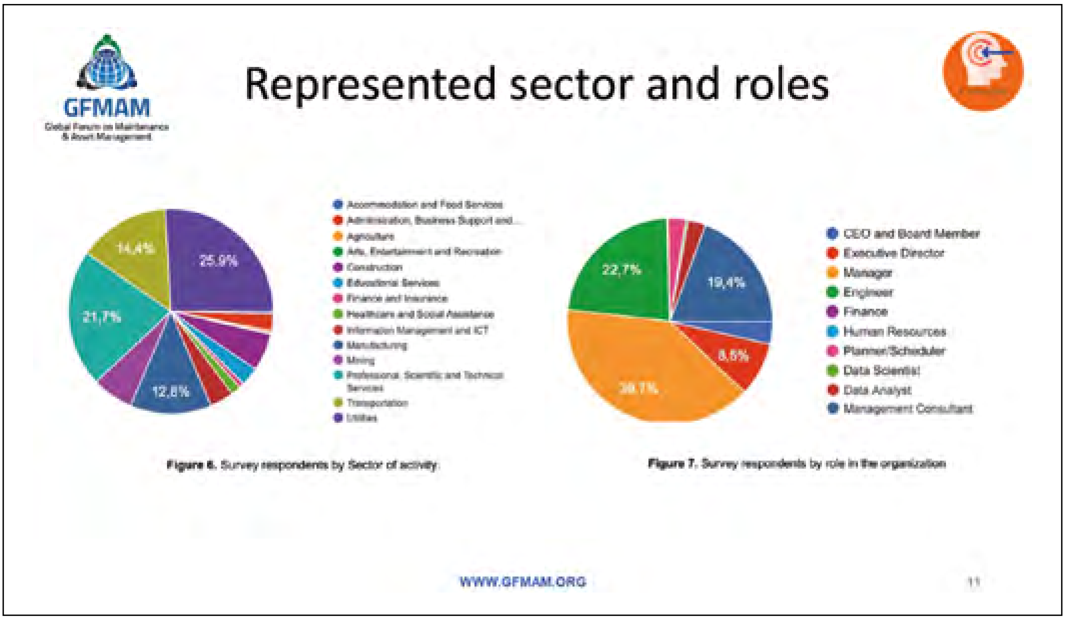

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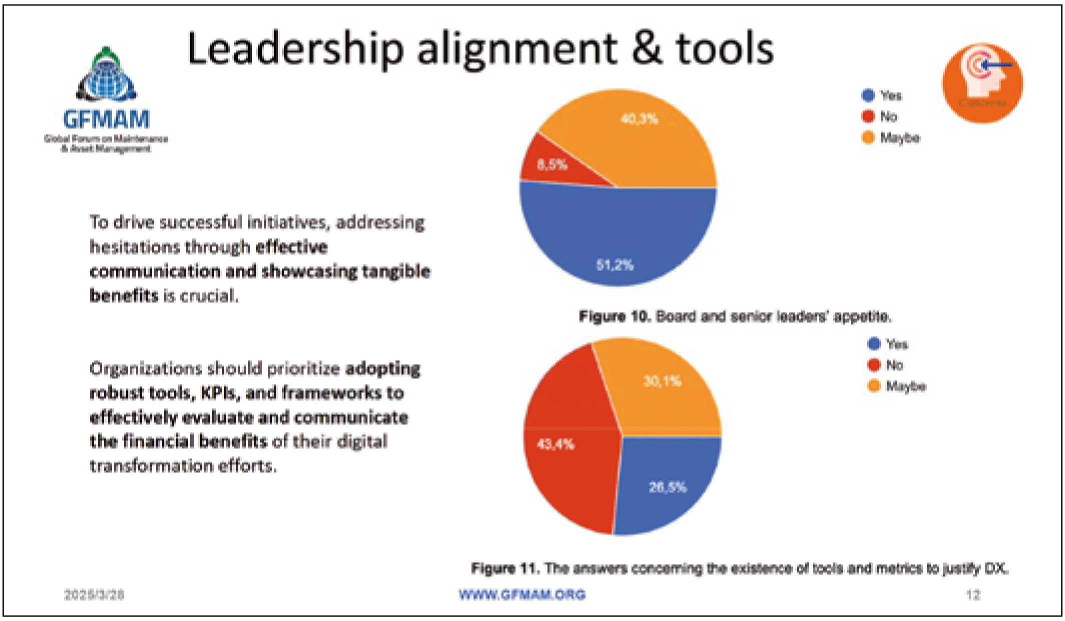
Leadership alignment & tools
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To drive successful initiatives, addressing hesitations through **effective communication and showcasing tangible benefits** is crucial.
Organizations should prioritize **adopting robust tools, KPIs, and frameworks to effectively evaluate and communicate the financial benefits** of their digital transformation efforts.
40,3%
8,5%
51,2%
Yes
No
Maybe
Figure 10. Board and senior leaders' appetite.
30,1%
43,4%
26,5%
Yes
No
Maybe
Figure 11. The answers concerning the existence of tools and metrics to justify DX.
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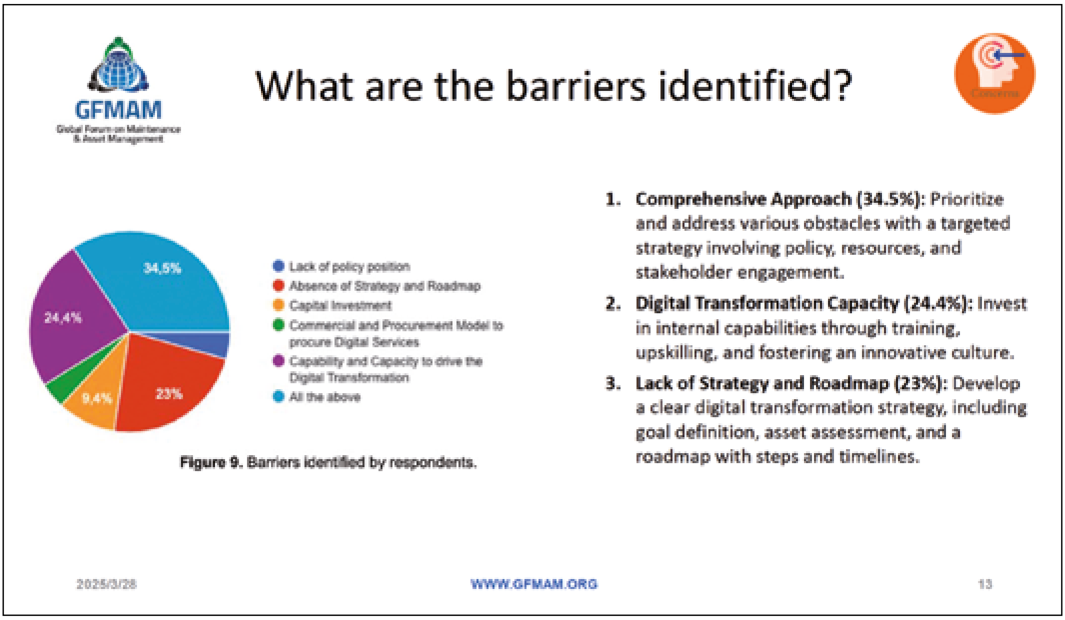
What are the barriers identified?
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34,5%
24,4%
9,4%
23%
Lack of policy position
Absence of Strategy and Roadmap
Capital Investment
Commercial and Procurement Model to procure Digital Services
Capability and Capacity to drive the Digital Transformation
All the above
Figure 9. Barriers identified by respondents.
1. **Comprehensive Approach (34.5%):** Prioritize and address various obstacles with a targeted strategy involving policy, resources, and stakeholder engagement.
2. **Digital Transformation Capacity (24.4%):** Invest in internal capabilities through training, upskilling, and fostering an innovative culture.
3. **Lack of Strategy and Roadmap (23%):** Develop a clear digital transformation strategy, including goal definition, asset assessment, and a roadmap with steps and timelines.
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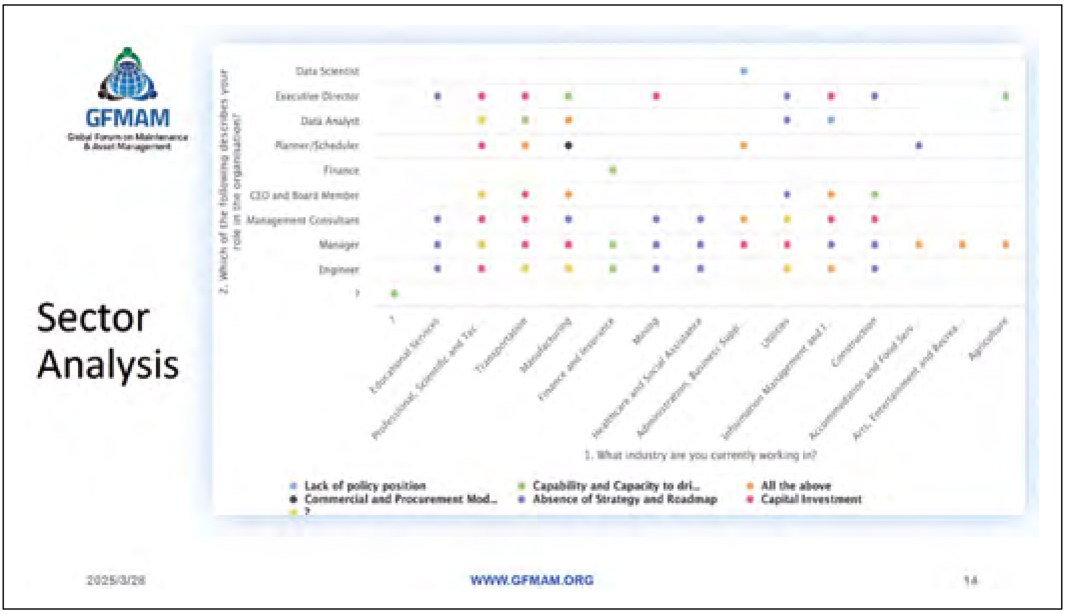
GFMAM
Sector Analysis
Data Scientist
Executive Director
Data Analyst
Planner/Scheduler
Finance
CEO and Board Member
Management Consultant
Manager
Engineer
2. Which of the following describes your role in the organisation?
Educational Services
Professional, Scientific and Tec
Transportation
Manufacturing
Finance and Insurance
Mining
Healthcare and Social Assistance
Administration, Business Supp
Utilities
Information Management and I
Construction
Accommodation and Food Serv
Arts, Entertainment and Recrea
Agriculture
1. What industry are you currently working in?
Lack of policy position
Commercial and Procurement Mod...
Capability and Capacity to dri...
Absence of Strategy and Roadmap
All the above
Capital Investment
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Insights per sector:
• Transportation Sector:
Barrier: "Capital investment" is the main challenge.
Insight: Address financial constraints, explore funding, and prioritize high-return projects.
• Educational Services, Mining, Healthcare Sectors:
Barrier: "Absence of roadmap" hinders digital transformation.
Insight: Clear direction needed; comprehensive roadmaps align stakeholders.
• Arts, Entertainment, Recreation, Agriculture, Accommodation/Food Services Sectors:
Barrier: Diverse barriers indicate unique challenges.
Insight: Holistic strategies required—address financial, planning, resource, and cultural aspects.
Collaborate, share best practices, learn from other industries.
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Sustaining Org DX Efforts

Concerns

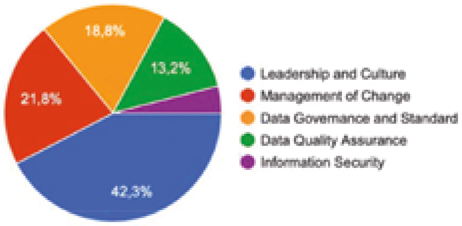

Figure 12. The biggest opportunity to sustain DX.

Key findings to ensure the longevity of digital transformation efforts:

- The significance of **navigating organizational shifts**.
- The importance of **structured data practices**.
- The crucial role of **accurate and reliable data**.

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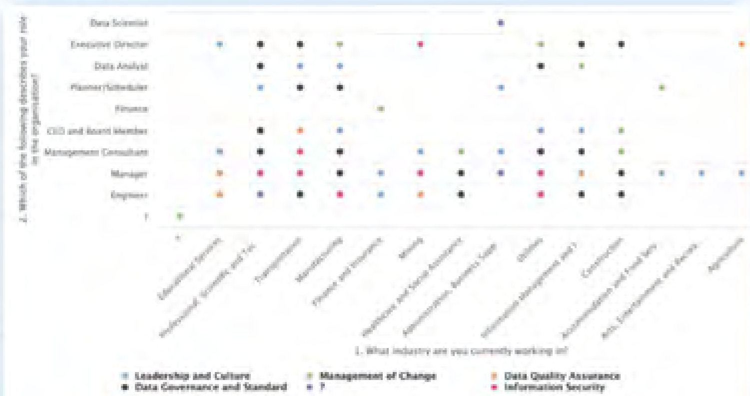

Figure 21. Most common opinion regarding opportunities to sustain DX, found per role and sector.

In sectors such as **utilities, manufacturing, transportation, and construction,** managers and engineers consider information security and data governance crucial.

These sectors typically deal with large volumes of sensitive data, complex systems, and regulatory requirements

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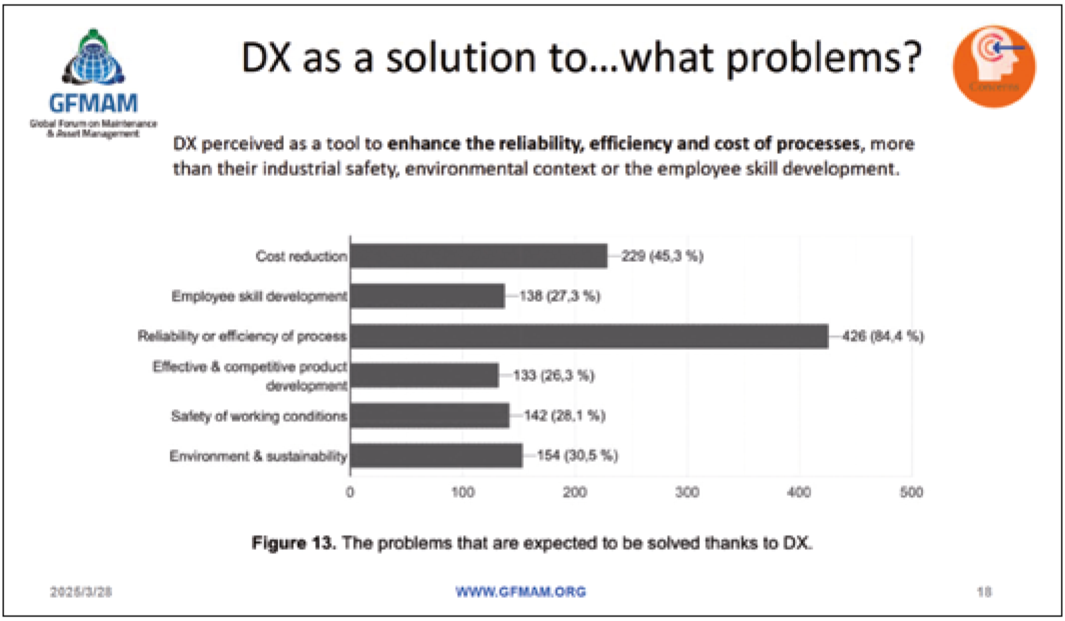

Figure 13. The problems that are expected to be solved thanks to DX.

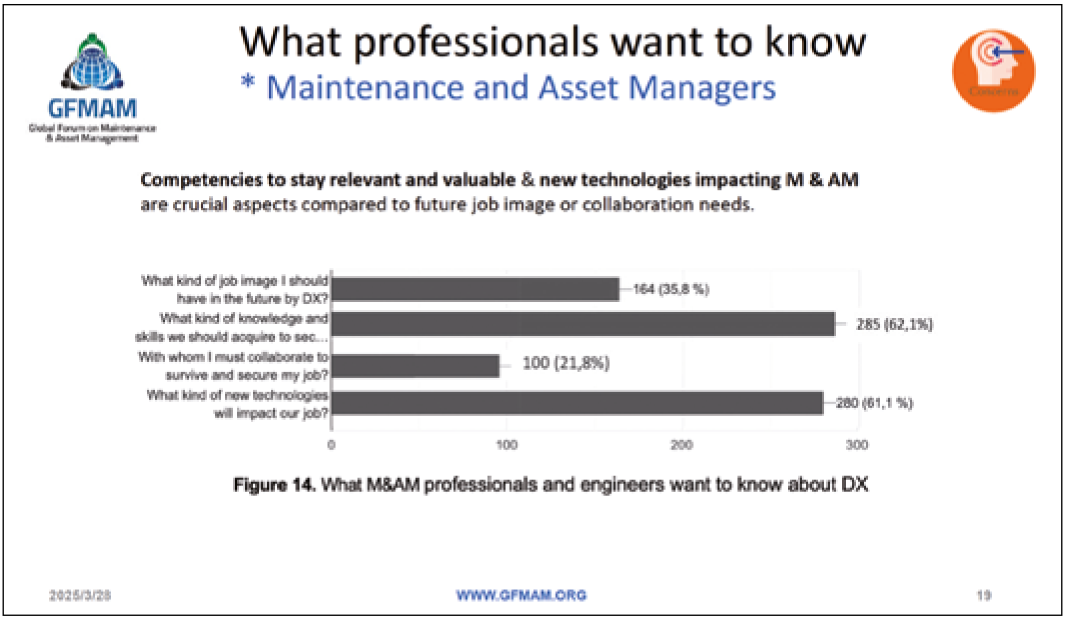

Figure 14. What M&AM professionals and engineers want to know about DX

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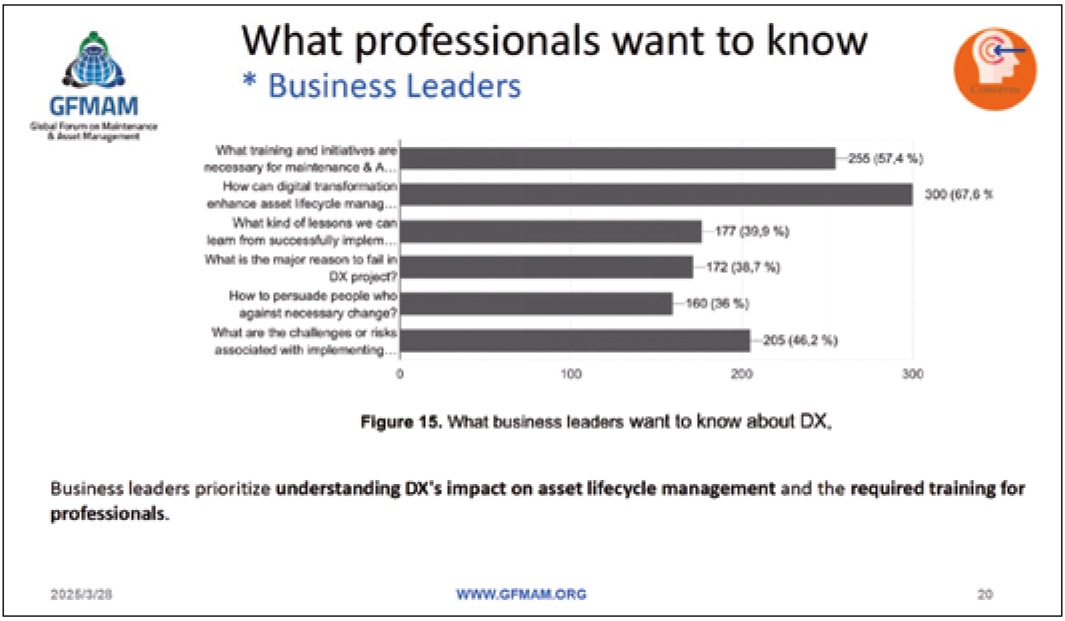

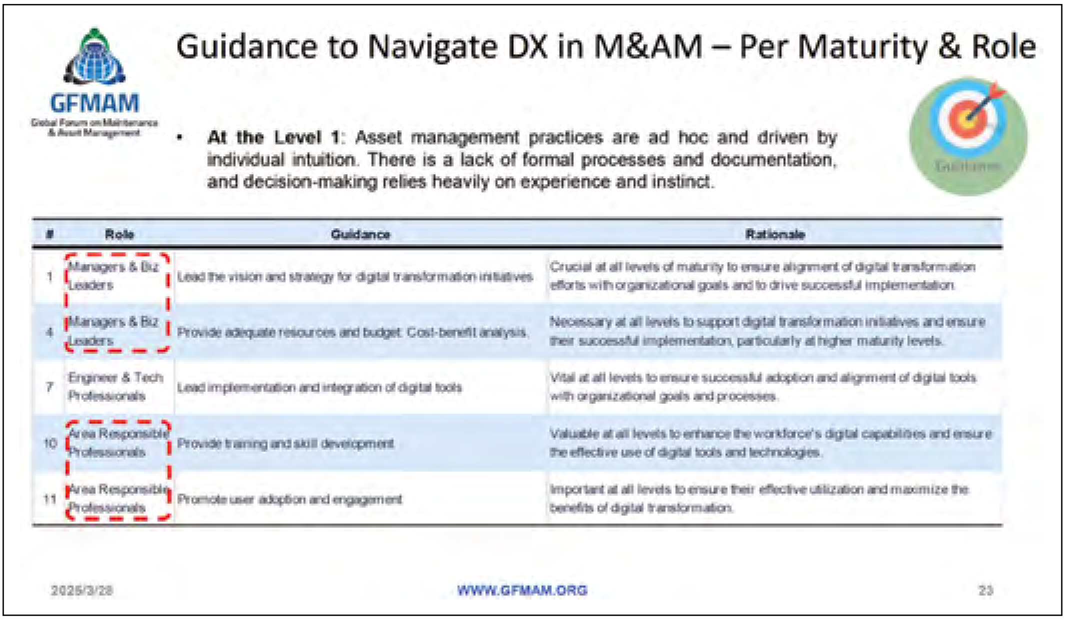

#	Role	Guidance	Rationale
1	Managers & Biz Leaders	Lead the vision and strategy for digital transformation initiatives	Crucial at all levels of maturity to ensure alignment of digital transformation efforts with organizational goals and to drive successful implementation
4	Managers & Biz Leaders	Provide adequate resources and budget. Cost-benefit analysis.	Necessary at all levels to support digital transformation initiatives and ensure their successful implementation, particularly at higher maturity levels.
7	Engineer & Tech Professionals	Lead implementation and integration of digital tools	Vital at all levels to ensure successful adoption and alignment of digital tools with organizational goals and processes.
10	Area Responsible Professionals	Provide training and skill development	Valuable at all levels to enhance the workforce's digital capabilities and ensure the effective use of digital tools and technologies.
11	Area Responsible Professionals	Promote user adoption and engagement	Important at all levels to ensure their effective utilization and maximize the benefits of digital transformation.

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Guidance to Navigate DX in M&AM – Per Maturity & Role

- **At level 2:** asset management practices start to become more structured, but there is still a high reliance on external support and expertise. Processes and procedures are developed, and there is an increasing recognition of the importance of data and information.

Guidance

#	Role	Guidance	Rationale
2	Managers & Biz Leaders	Foster strategic partnerships	Becomes increasingly important as asset management maturity improves to access advanced technologies and expertise for optimization.
5	Engineers and Tech Professionals	Stay updated with the latest advancements	Important at all levels to make informed decisions and leverage new opportunities for optimizing asset management and maintenance.
6	Engineers and Tech Professionals	Collaborate across disciplines	Important at all levels to integrate digital tools effectively, share expertise, and ensure a holistic approach to asset management.
8	Engineers and Tech Professionals	Ensure data integrity and quality	Crucial at all levels to support reliable decision-making, compliance, and accuracy in asset management and maintenance data, becoming more critical at higher maturity levels.

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Guidance to Navigate DX in M&AM – Per Maturity & Role

- **At Level 3:** Asset management practices become self-sufficient and internally driven. The organization develops its own capabilities and expertise, and there is a focus on continuous improvement and optimization of asset performance.

Guidance

#	Role	Guidance	Rationale
3	Managers & Business Leaders	Cultivate a culture of innovation	Becomes more critical at higher maturity levels to drive the adoption of new technologies and best practices for continuous improvement.
9	Area Responsible Professionals	Establish data governance practices and standards	Data governance is essential to maintain consistency and reliability in data, and it becomes more significant as asset management maturity improves to manage complex digital data and systems.
12	Legal Professionals	Stay updated with evolving laws and regulations	Becomes more critical at higher maturity levels to ensure compliance with legal requirements related to digital transformation.
13	Legal Professionals	Provide legal advice and support for digital transformation initiatives	Plays a significant role at higher maturity levels to provide guidance and support in navigating legal aspects and ensuring compliance with regulations during digital transformation.
14	Legal Professionals	Review and negotiate contracts with digital service providers	Essential at higher maturity levels to ensure favorable terms and conditions and align them with the organization's goals.

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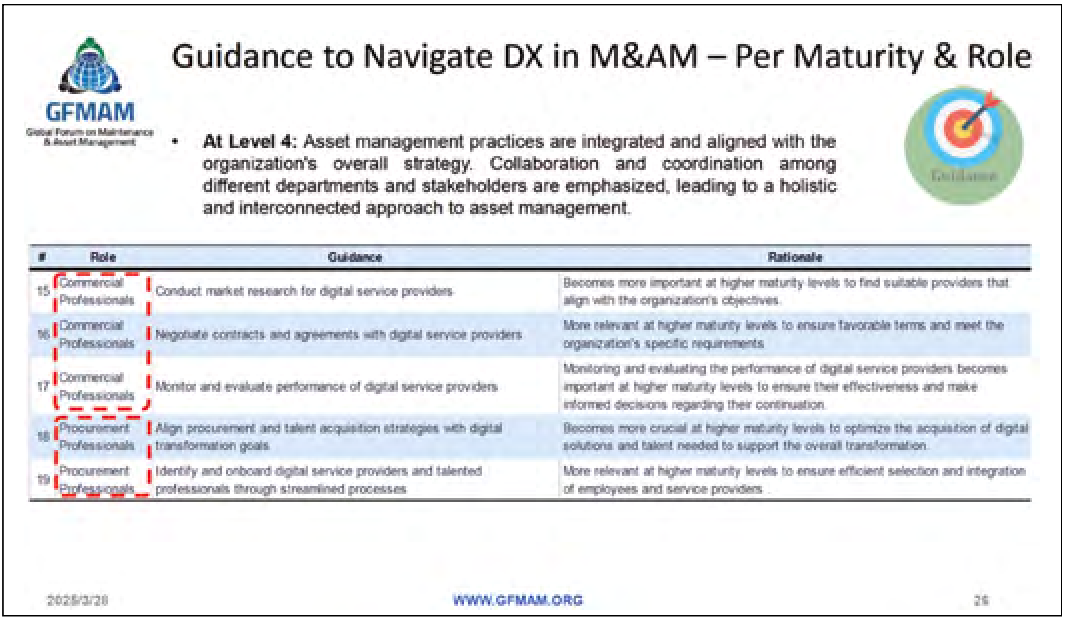
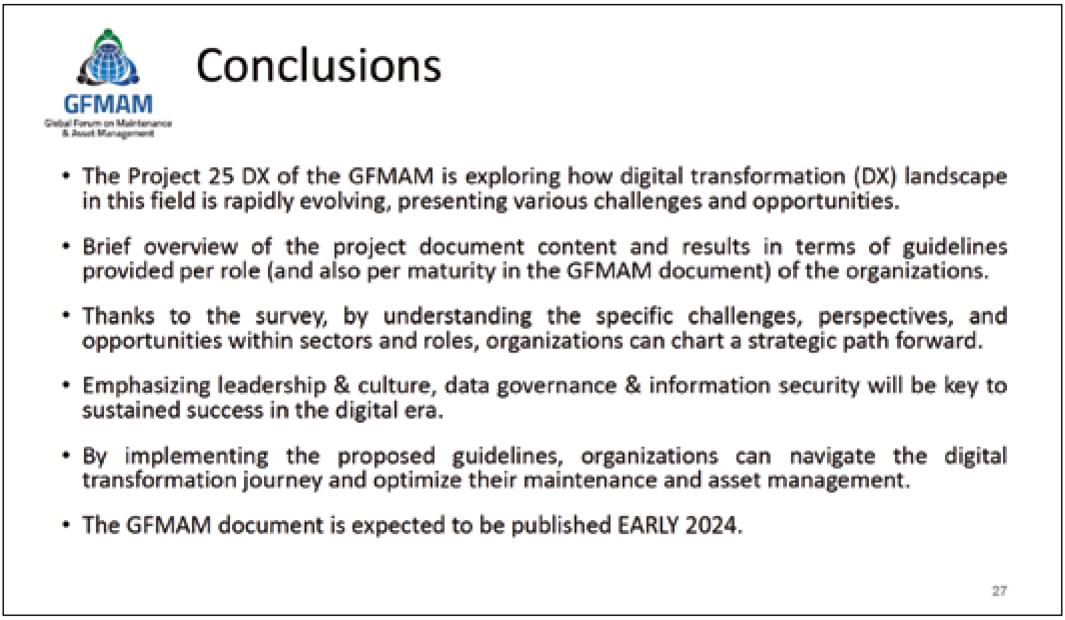


#	Role	Guidance	Rationale
15	Commercial Professionals	Conduct market research for digital service providers	Becomes more important at higher maturity levels to find suitable providers that align with the organization's objectives
16	Commercial Professionals	Negotiate contracts and agreements with digital service providers	More relevant at higher maturity levels to ensure favorable terms and meet the organization's specific requirements
17	Commercial Professionals	Monitor and evaluate performance of digital service providers	Monitoring and evaluating the performance of digital service providers becomes important at higher maturity levels to ensure their effectiveness and make informed decisions regarding their continuation
18	Procurement Professionals	Align procurement and talent acquisition strategies with digital transformation goals	Becomes more crucial at higher maturity levels to optimize the acquisition of digital solutions and talent needed to support the overall transformation
19	Procurement Professionals	Identify and onboard digital service providers and talented professionals through streamlined processes	More relevant at higher maturity levels to ensure efficient selection and integration of employees and service providers



Digital Twin aiding more effective Digital Maintenance

Diego López de Ipiña González de Artaza

University of Deusto

Abstract

This presentation explores the revolutionary impact of Digital Twins in maintenance operations across industries. By creating real-time digital replicas of physical assets, organizations can implement predictive maintenance strategies, conduct remote diagnostics, and optimize operational efficiency. The integration of Digital Twins with maintenance practices enables data-driven decision-making, reduces downtime, and promotes environmental sustainability. Case studies from manufacturing, energy, and transportation sectors demonstrate significant improvements in cost savings and operational performance, highlighting the transformative potential of Digital Maintenance in the Digital Twin Era.

1. Introduction

In the era of digital transformation, the concept of Digital Twins has emerged as a revolutionary approach to managing and optimizing the lifecycle of physical assets, systems, and processes. This talk delves into the transformative potential of Digital Maintenance in the Digital Twin Era, highlighting the seamless integration of digital replicas with real-world operations to foster unprecedented levels of efficiency, predictability, and sustainability in maintenance practices.

We will explore how Digital Twins serve as dynamic, real-time reflections of physical assets, allowing for meticulous monitoring, analysis, and simulation. Through vivid examples, we'll demonstrate the benefits of this paradigm, such as predictive maintenance, which leverages data analytics and machine learning to anticipate failures and optimize maintenance schedules, thereby reducing downtime and extending asset lifespan.

Further, the talk will showcase the role of Digital Twins in facilitating remote maintenance operations. By providing a comprehensive, virtual view of assets, maintenance professionals can perform diagnostics and identify issues without being physically present, enhancing safety and reducing response times.

We'll also explore the environmental benefits of Digital Maintenance within the Digital Twin framework. By optimizing maintenance schedules and operations, organizations can significantly reduce their carbon footprint and resource consumption, contributing to more sustainable industrial practices.

Finally, the presentation will highlight case studies from various industries, including manufacturing, energy, and transportation, where the adoption of Digital Twins has led to substantial cost savings, improved operational efficiency, and enhanced decision-making processes. These examples will illustrate the tangible value and competitive advantage that Digital Maintenance in the Digital Twin Era offers to forward-thinking organizations.

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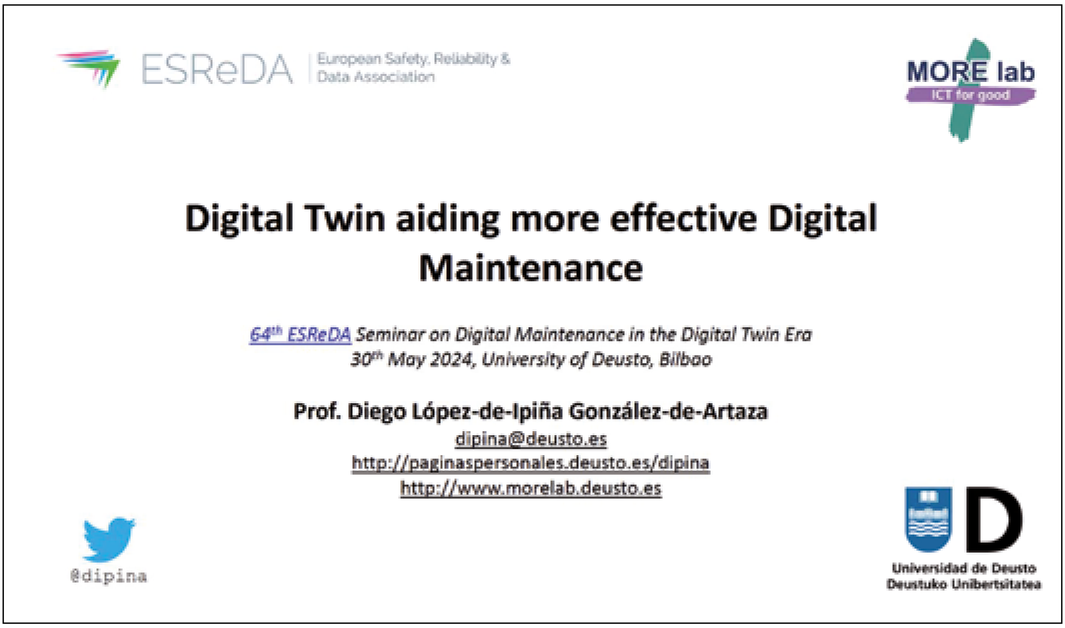
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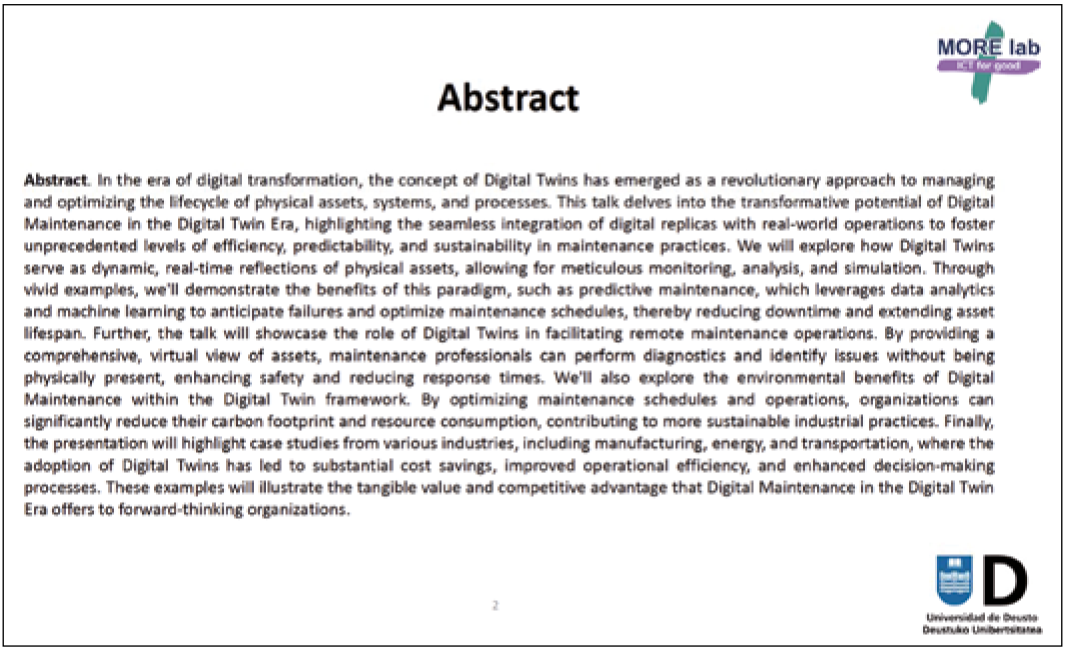
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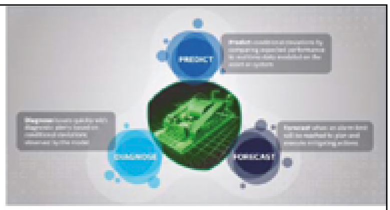
Digital Twin definition



- A digital twin is a virtual **representation of a physical object or system**, integrating IoT sensors, real-time data, and simulations **to mirror and predict the behavior** of its physical counterpart
  - **Real-time Data Synthesis:** Digital twins continuously collect and synthesize data from various sources, including IoT sensors, to update and maintain their accuracy in real-time.
  - **Predictive Maintenance**: They enable predictive maintenance by forecasting potential issues and equipment failures before they occur.
  - **Simulation and Modeling**: By simulating different scenarios and conditions, digital twins help optimize systems and processes without the risks associated with physical testing.
  - **Optimization of Operations:** They assist in refining operational efficiency by providing insights that help minimize downtime and reduce costs.
  - **Lifecycle Management**: Digital twins manage the entire lifecycle of their physical counterparts, from design and manufacturing to operation and decommissioning.
  - **Decision Support**: They offer valuable support for decision-making processes by providing comprehensive insights and outcomes of various hypothetical scenarios.

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Key aspects of a Digital Twin

- **Physical Counterpart:** A digital twin is always linked to a real-world entity, such as a machine, building, product, or even a city.
- **Data Integration:** Sensors attached to the physical entity collect data on its performance, condition, and surrounding environment. This data is then fed into the digital twin, keeping it constantly updated.
- **Digital Model:** The digital twin is a computer-generated model that incorporates data from the physical entity, engineering designs, and other relevant information. This model can be as simple or complex as needed, depending on the application.
- **Analytics and Simulation**: The digital twin can be used to analyze data from the physical entity and run simulations to predict future performance, identify potential problems, and optimize operations.
- **Improved Decision-Making**: By providing insights into the real-world entity, the digital twin can help stakeholders make better decisions about design, maintenance, and overall operations.

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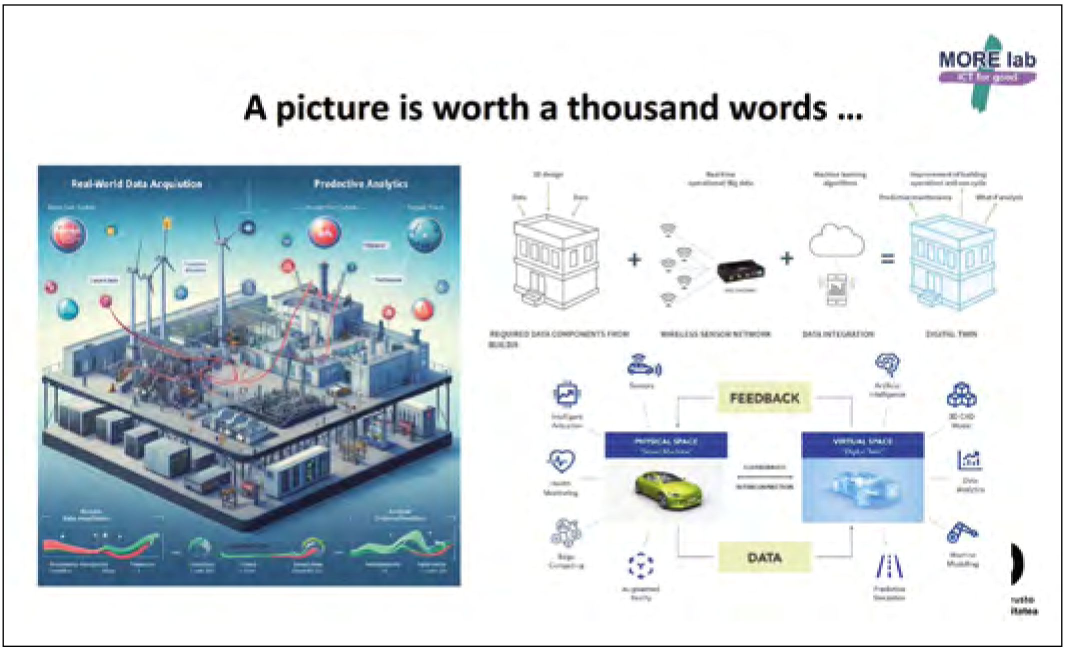
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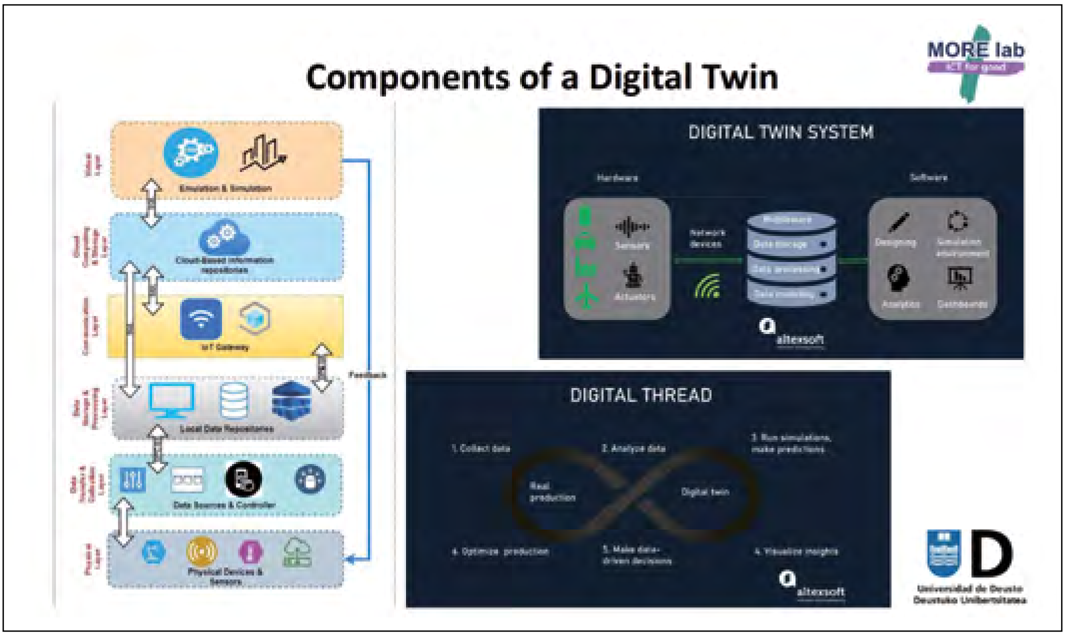
Real-World Data Acquisition
Predictive Analytics
WIRELESS SENSOR NETWORK
DATA INTEGRATION
DIGITAL TWIN
FEEDBACK
PHYSICAL SPACE
VIRTUAL SPACE
DATA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Components of a Digital Twin
Emulation & Simulation
Cloud-Based Information repositories
IoT Gateway
Local Data Repositories
Data Sources & Controller
Physical Devices & Sensors
Feedback
DIGITAL TWIN SYSTEM
Hardware
Software
Sensors
Actuators
Network devices
Middleware
Data storage
Data processing
Data modeling
Designing
Simulation environment
Analytics
Dashboards
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DIGITAL THREAD
1. Collect data
2. Analyze data
3. Run simulations, make predictions
Real production
Digital twin
4. Optimize production
5. Make data-driven decisions
4. Visualize insights
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Landscape of Digital Twin solutions

- **General-purpose platforms**
  - **Microsoft Azure Digital Twins**: This cloud-based platform provides a foundation for building next-generation IoT solutions. It facilitates data-driven workspaces, allowing integration with various Azure services like AI, analytics, and storage. (https://learn.microsoft.com/en-us/azure/digital-twins/overview)
  - **PTC ThingWorx**: A comprehensive suite for building, deploying, and managing digital twins across the entire product lifecycle. It caters to a wide range of industries, particularly manufacturing and industrial operations. ThingWorx offers a low-code development environment for user-friendly customization. (https://www.ptc.com/en/industry-insights/digital-twin)
  - **Siemens MindSphere**: This cloud-based platform focuses on industrial IoT applications. It offers tools for creating digital twins of machines, production lines, and entire factories. MindSphere facilitates remote monitoring, predictive maintenance, and performance optimization. (https://design.mindsphere.io/)
- **Industry specific solutions**
  - **GE Digital Twin Software (Manufacturing)**: GE's solution boasts features tailored for monitoring equipment performance in manufacturing settings. It provides detailed analytics to refine processes and ensure optimal performance. GE's software integrates with platforms like Microsoft, enhancing its usability and expanding its toolkit. (https://www.ge.com/digital/applications/digital-twin)
  - **AVEVA (Oil & Gas, Chemicals)**: This provider offers solutions for industrial asset management, including digital twin capabilities. AVEVA's digital twins focus on monitoring equipment health, optimizing maintenance schedules, and improving overall operational efficiency in process industries. (https://www.aveva.com/en/solutions/digital-transformation/digital-twin/)

Enhancing Maintenance through Digital Twins

- Consider a scenario where "physical equipment on **a factory floor has a digital twin** that's constantly updated and monitored, thus, **allowing for a proactive approach to maintenance**"
- A seamless integration between digital replicas and actual equipment makes this possible:
  - **Real-time Data Flow:** Sensors embedded within the physical equipment collect data on various parameters like temperature, vibration, pressure, and energy consumption. This data is continuously streamed to the digital twin in real-time.
  - **Digital Twin Analysis:** The digital twin receives this sensor data and compares it to historical data, performance benchmarks, and simulation models. This allows for anomaly detection and identification of potential equipment issues.
  - **Predictive Maintenance:** By analyzing trends and patterns in the data, the digital twin can predict when a piece of equipment might be nearing failure. This enables maintenance crews to take action before a breakdown occurs, preventing costly downtime and production delays.
  - **Remote Monitoring and Diagnostics:** The seamless integration allows for remote monitoring of the equipment's health. Technicians can access the digital twin from anywhere to diagnose problems, identify root causes, and order necessary parts even before a physical inspection.
  - **Improved Repair Efficiency:** With the digital twin providing insights into the equipment's condition, maintenance crews can come prepared with the right tools and parts to fix the problem quickly and efficiently. This minimizes repair time and gets the equipment back up and running faster.

Benefits of Proactive Maintenance

- Seamless **integration of digital twins with physical equipment** empowers a **shift from reactive maintenance** (fixing things when they break) **to proactive maintenance** (preventing breakdowns before they happen).
  - This leads to significant cost savings, improved equipment performance, and optimized production processes.
- Digital Twin benefits proactive maintenance by:
  - **Reduced downtime** and improved operational efficiency
  - **Lower maintenance** costs by avoiding major repairs
  - **Extended** equipment **lifespan**
  - **Improved safety** by addressing potential hazards before they occur
  - **Increased productivity** through better equipment reliability

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Digital Twins in Predictive Maintenance (I): Wind Turbine Farms (Energy Industry)

- **Use case**: Imagine a vast wind farm with hundreds of turbines spread across a large area.
  - Traditionally, technicians would rely on scheduled inspections or wait for malfunctions to occur before taking action.
- **Digital Twins** can **enhance maintenance by**:
  - **Sensors**: Each turbine is equipped with sensors monitoring wind speed, blade vibration, gear box temperature, and power generation.
  - **Real-time Data**: This data is streamed to the digital twin, a virtual model of each turbine capturing its unique characteristics and operational history.
  - **Predictive Analytics**: Machine learning algorithms analyze sensor data, historical trends, and weather forecasts to predict potential issues like bearing wear or blade damage.
- **Benefits**:
  - **Early detection of problems** allows for scheduled maintenance before failure, minimizing downtime and costly repairs.
  - Digital twins also help **optimize wind turbine pitch angles and blade rotation** for maximum **power generation** based on real-time wind conditions.
- **Success story:** Siemens Gamesa Renewable Energy, a Spanish-German wind turbine manufacturer, utilizes digital twins to achieve a 40% reduction in maintenance costs and a 15% extension in wind turbine lifespan for their European wind farm projects

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Digital Twins in Predictive Maintenance (II): High-Tech Manufacturing (Manufacturing Industry)

- **Use case:** In a high-tech manufacturing facility, complex machinery operates 24/7. Downtime can be extremely expensive due to lost production and potential product delays.
- **Digital Twins** can **enhance maintenance by:**
  - **Connected Machines:** Production machines are equipped with sensors that track performance metrics like motor current, vibration, and cycle times.
  - **Digital Twin Network:** Each machine has a digital twin linked to a central network, allowing for real-time monitoring and data analysis.
  - **Predictive Maintenance:** The network analyzes data to identify anomalies and predict potential equipment failures. Alerts are generated for proactive maintenance, replacing worn parts before they cause breakdowns..
- **Benefits:**
  - **Reduced downtime** through preventive maintenance ensures production continuity and minimizes disruptions.
  - Digital twins also allow for **remote monitoring and optimization** of machine settings for improved efficiency and quality control.
- **Success story:** Robert Bosch GmbH, a leading German multinational engineering and technology company, implemented a digital twin platform in one of their factories. This resulted in a 25% reduction in unplanned downtime and a 7% increase in production output

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Digital Twins in Predictive Maintenance (III): Smart Buildings (Construction and Facilities Management)

- **Use case:** In a modern construction and facilities management setting, digital twins play a crucial role in optimizing building operations. For instance, in a large commercial building, maintaining optimal conditions is essential for occupant comfort and operational efficiency.
- **Digital Twins** can **enhance maintenance by:**
  - **Building Sensors:** Sensors are deployed throughout the building to monitor various parameters like temperature, humidity, air quality, energy consumption, and the status of equipment such as HVAC systems, elevators, and lighting.
  - **Digital Building Model:** A digital twin is created to replicate the physical building layout and integrate real-time data from sensors, providing a comprehensive view of the building's performance.
  - **Predictive Analytics:** By leveraging predictive analytics, the system can analyze sensor data to predict potential issues such as equipment malfunctions, energy inefficiencies, or maintenance needs, allowing for proactive maintenance strategies
- **Benefits:**
  - **Proactive Maintenance:** Predictive insights enable proactive maintenance of building systems, reducing repair costs, minimizing downtime, and ensuring occupant comfort and safety.
  - **Energy Optimization:** Digital twins identify opportunities for energy optimization by analyzing data on energy consumption patterns, leading to lower utility bills and a more sustainable building operation.
- **Success story:** Schneider Electric, a French multinational specializing in energy management and automation, deployed a digital twin platform for a large office complex in Frankfurt, Germany. This resulted in a 18% reduction in energy consumption and a 12% decrease in maintenance costs

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Some further examples

- Manufacturing Industry: Digital twins have been successfully applied in manufacturing to improve product design, detect problematic areas, forecast machinery performance, and calculate maintenance-related KPIs. By monitoring equipment degradation and simulating maintenance scenarios, manufacturers can optimize operations, prevent breakdowns, and enhance efficiencies. This is exemplified in the article "How to Use Digital Twin for Predictive Maintenance in Manufacturing"
- Healthcare Sector: Digital twins have shown promise in healthcare by enabling real-time monitoring of medical equipment, predicting failures, and optimizing maintenance strategies. By leveraging data analytics and machine learning, healthcare facilities can enhance patient care, reduce downtime, and ensure equipment reliability. Success cases in healthcare can be found in literature reviews like "Predictive maintenance using digital twins: A systematic literature review"
- Logistics and Supply Chain Management: Digital twins have revolutionized predictive maintenance in logistics by providing real-time insights, optimizing maintenance schedules, and reducing operational disruptions. By simulating different scenarios and monitoring asset health, companies can minimize downtime, improve safety, and innovate faster. Success stories in logistics can be explored in articles like "Overview of predictive maintenance based on digital twin technology"

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Empowering Maintenance Professionals

- Digital Twins empower maintenance professionals with the tools and information they need to be more proactive and efficient:
  - **From Reactive to Proactive**: Traditionally, maintenance professionals relied on inspections or waited for breakdowns to occur.
    - Digital twins enable a shift towards proactive maintenance.
    - Sensor data and real-time insights from the digital twin allow them to predict potential issues before they escalate into major problems
  - **Improved Decision-Making**: The constant stream of data and analytics from the digital twin empowers maintenance professionals to make data-driven decisions.
    - They can prioritize tasks, identify root causes of failures, and optimize maintenance schedules for maximum efficiency.
  - **Enhanced Remote Monitoring**: Digital twins enable remote monitoring of equipment health.
    - Technicians can access the digital twin from anywhere to diagnose problems, identify necessary parts, and even prepare for repairs before physically reaching the equipment.
    - This saves time and improves response times.
  - **Streamlined Workflows**: Digital twins can integrate with maintenance management systems, streamlining workflows.
    - Work orders can be automatically generated based on predicted issues, and technicians can access relevant information and historical data directly within the digital twin platform.

Benefits for Companies Adopting Digital Twins

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- Digital Twins offer a pathway to significant cost savings, improved operational performance, and a more sustainable approach to asset management:
  - **Reduced Downtime**: Predictive maintenance sayesinde (German for "thanks to predictive maintenance"), companies can identify and address equipment issues before they cause breakdowns. This significantly reduces downtime, leading to increased production output and improved operational efficiency.
  - **Lower Maintenance Costs**: By preventing major repairs and optimizing maintenance schedules, digital twins can help companies save on maintenance costs. Early detection of problems allows for replacing parts before they fail completely, reducing the need for expensive repairs or replacements.
  - **Extended Asset Lifespan**: Proactive maintenance based on digital twin insights helps to extend the lifespan of equipment. By addressing issues before they cause significant wear and tear, companies can get more value out of their assets.
  - **Improved Safety**: Digital twins can help identify potential safety hazards before they occur. By monitoring equipment health and predicting failures, companies can take proactive steps to prevent accidents and ensure a safe working environment.
  - **Data-Driven Optimization**: The data collected by digital twins provides valuable insights into equipment performance. This data can be used to optimize maintenance strategies, improve machine design, and develop more efficient production processes.

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Environmental benefits of Digital Twin aided Maintenance

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- The integration of digital twin technology into maintenance practices offers a pathway to more sustainable industrial operations, leveraging precise data and analytics to enhance environmental performance across multiple fronts:
  - **Reduced Resource Consumption**: Digital twins can simulate various operational scenarios and predict outcomes with high accuracy, enabling companies to optimize the use of energy and raw materials. By fine-tuning processes before implementing them in the real world, industries can minimize waste and reduce their resource consumption.
  - **Enhanced Energy Efficiency**: By creating a virtual replica of physical systems, digital twins allow for the monitoring and analysis of energy usage in real-time. This helps in identifying inefficiencies and potential improvements, leading to more energy-efficient operations and lower carbon footprints.
  - **Optimized Equipment Lifespan**: Maintenance powered by digital twins can predict when a piece of equipment will fail or when its performance will degrade. This predictive maintenance means that parts are replaced only when necessary, extending the lifespan of equipment, reducing waste, and decreasing the frequency of manufacturing new parts.
  - **Decreased Emissions**: Optimizing operations and maintenance with digital twins can lead to smoother, more efficient processes that emit fewer pollutants. For industries like manufacturing, transportation, and energy, this can contribute significantly to reducing overall emissions.
  - **Lower Transportation Costs and Impact**: Digital twins can simulate logistics and supply chain scenarios, helping to optimize routes and loads. This not only cuts costs but also reduces the environmental impact of transportation by minimizing fuel consumption and associated emissions.
  - **Remote Monitoring and Control**: With digital twins, it's possible to monitor and control systems remotely, reducing the need for physical travel and inspections. This decreases the carbon emissions associated with travel and transportation of maintenance crews and equipment.
  - **Training and Simulation**: Digital twins provide a platform for training personnel in a virtual environment. This reduces the need for physical resources during training and helps in avoiding errors that could lead to inefficient resource use or environmental harm.

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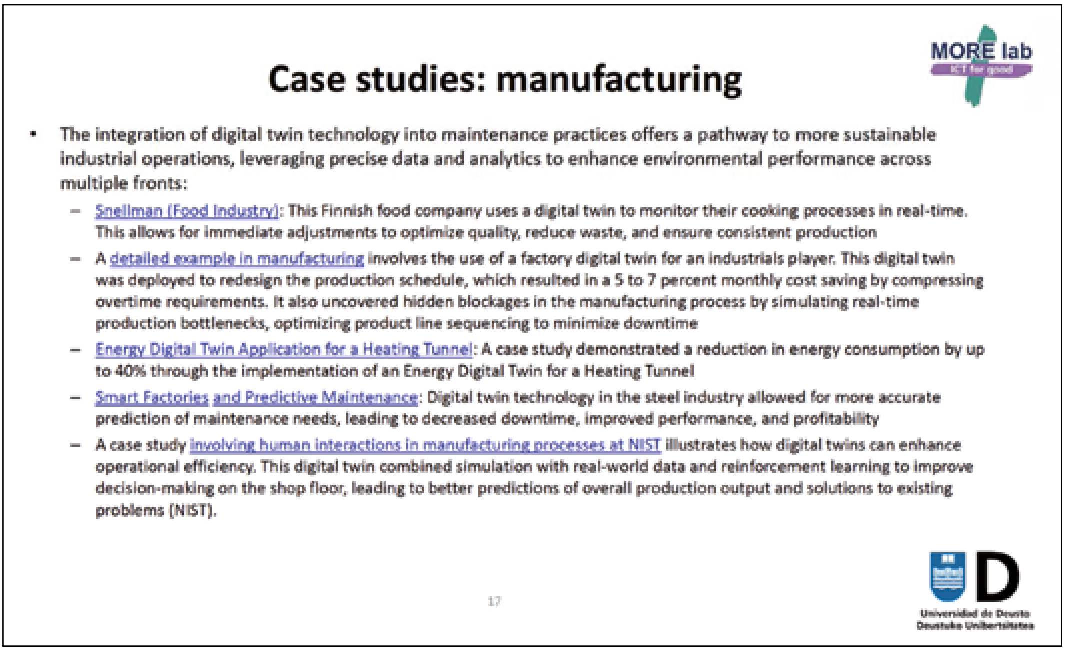
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Case studies: manufacturing
• The integration of digital twin technology into maintenance practices offers a pathway to more sustainable industrial operations, leveraging precise data and analytics to enhance environmental performance across multiple fronts:
– Snellman (Food Industry): This Finnish food company uses a digital twin to monitor their cooking processes in real-time. This allows for immediate adjustments to optimize quality, reduce waste, and ensure consistent production
– A detailed example in manufacturing involves the use of a factory digital twin for an industrials player. This digital twin was deployed to redesign the production schedule, which resulted in a 5 to 7 percent monthly cost saving by compressing overtime requirements. It also uncovered hidden blockages in the manufacturing process by simulating real-time production bottlenecks, optimizing product line sequencing to minimize downtime
– Energy Digital Twin Application for a Heating Tunnel: A case study demonstrated a reduction in energy consumption by up to 40% through the implementation of an Energy Digital Twin for a Heating Tunnel
– Smart Factories and Predictive Maintenance: Digital twin technology in the steel industry allowed for more accurate prediction of maintenance needs, leading to decreased downtime, improved performance, and profitability
– A case study involving human interactions in manufacturing processes at NIST illustrates how digital twins can enhance operational efficiency. This digital twin combined simulation with real-world data and reinforcement learning to improve decision-making on the shop floor, leading to better predictions of overall production output and solutions to existing problems (NIST).
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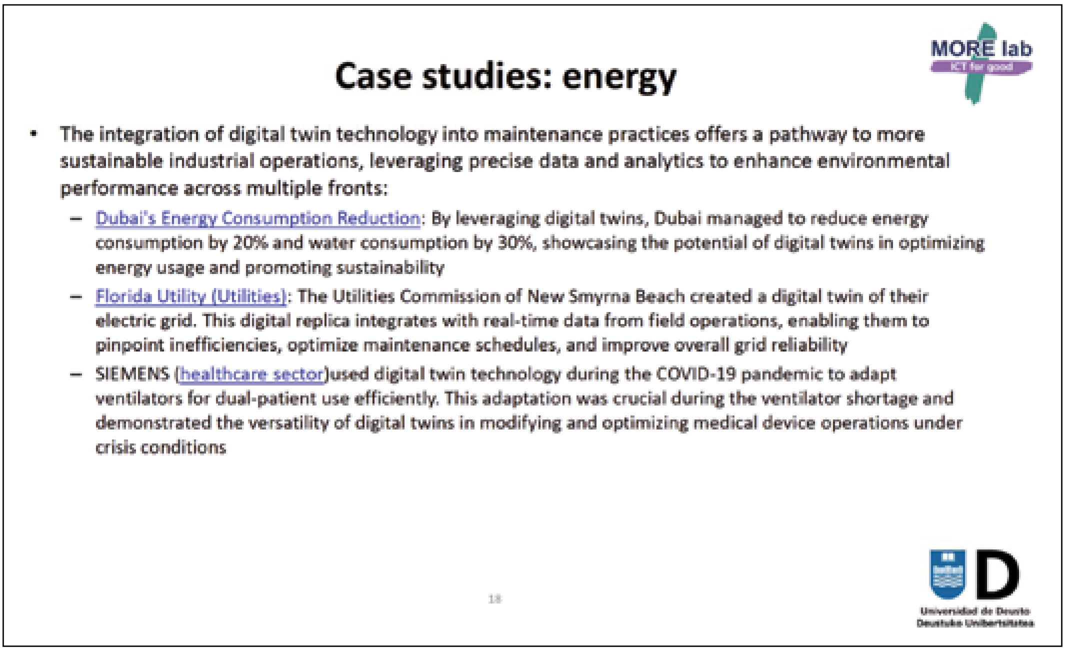
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Case studies: energy
• The integration of digital twin technology into maintenance practices offers a pathway to more sustainable industrial operations, leveraging precise data and analytics to enhance environmental performance across multiple fronts:
– Dubai's Energy Consumption Reduction: By leveraging digital twins, Dubai managed to reduce energy consumption by 20% and water consumption by 30%, showcasing the potential of digital twins in optimizing energy usage and promoting sustainability
– Florida Utility (Utilities): The Utilities Commission of New Smyrna Beach created a digital twin of their electric grid. This digital replica integrates with real-time data from field operations, enabling them to pinpoint inefficiencies, optimize maintenance schedules, and improve overall grid reliability
– SIEMENS (healthcare sector)used digital twin technology during the COVID-19 pandemic to adapt ventilators for dual-patient use efficiently. This adaptation was crucial during the ventilator shortage and demonstrated the versatility of digital twins in modifying and optimizing medical device operations under crisis conditions
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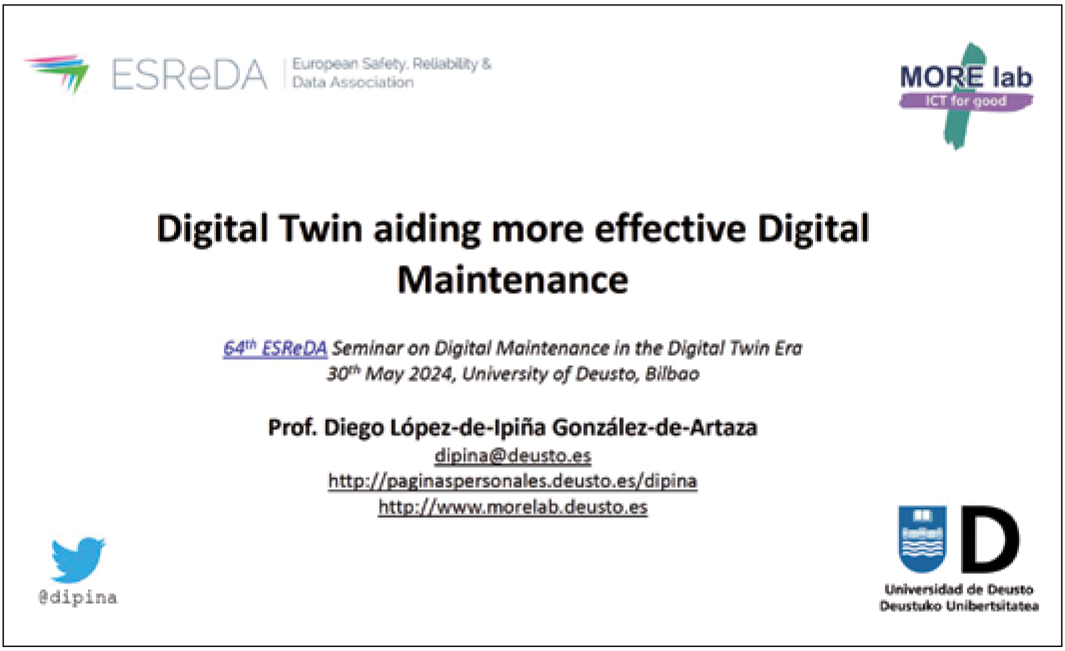
Case studies: transportation

- The integration of digital twin technology into maintenance practices offers a pathway to more sustainable industrial operations, leveraging precise data and analytics to enhance environmental performance across multiple fronts:
  - Predictive Maintenance in Transportation: The use of digital twins in transportation enables predictive maintenance, resulting in reduced maintenance costs by up to 40% and increased equipment uptime by up to 20%
  - Volvo (Automotive): Volvo leverages digital twins to virtually test new car designs. This allows for simulations of various materials and aerodynamic configurations. By optimizing designs virtually, Volvo reduces the need for physical prototypes, saving time and development costs
  - Singapore Land Transport Authority (Transportation): This government agency implemented a digital twin of their entire transportation network, encompassing roads, trains, and bus services. The digital model integrates real-time data from traffic sensors and fare collection systems. This empowers them to analyze traffic patterns, predict congestion risks, and optimize transportation operations for efficiency

Conclusions

- **Digital Twin** approach offers clear benefits for enhancing maintenance in a wide range of industrial domains.
  - A successful digitalization of maintenance hinges on a collaborative effort, where individuals with different roles must work together to leverage technology for improved decision-making, optimized maintenance strategies, and enhanced overall equipment effectiveness
    - **Management**: Leaders need to champion the digitalization initiative, securing resources, fostering a data-driven culture, and promoting collaboration between departments like IT, maintenance, and operations.
    - **Maintenance Technicians**: Experienced technicians possess valuable domain knowledge about the physical assets. They can provide crucial insights into historical maintenance data, failure patterns, and best practices. Their buy-in and active participation are essential for a successful transition.
    - **Data Analysts**: These individuals are responsible for collecting, cleaning, and structuring vast amounts of maintenance data from various sources like sensors, CMMS (Computerized Maintenance Management System), and historical records. Their analysis skills are vital for identifying trends, predicting equipment failures, and optimizing maintenance schedules.
    - **IT Specialists**: IT plays a critical role in integrating digital twin platforms with existing IT infrastructure, ensuring data security, and providing ongoing technical support.
    - **Maintenance Technicians**: As maintenance becomes more data-driven, technicians will need training in new skillsets like data interpretation, using diagnostic tools, and working with digital twin interfaces. This empowers them to leverage the data for more effective troubleshooting and preventive maintenance.
    - **New Roles**: Digitalization may create new job opportunities for individuals with expertise in data visualization, machine learning, and integrating domain knowledge with advanced analytics.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This book contains the proceedings of the 64th ESReDA Seminar & Doctoral Workshop, hosted by the University of Deusto in Bilbao in 2025.

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