MAINTENANCE 4.0 GUIDELINE

EFNMS
COMMITTEE
MAINTENANCE 4.0

EUROPEAN FEDERATION OF NATIONAL MAINTENANCE SOCIETIES VZW

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EUROPEAN FEDERATION OF NATIONAL MAINTENANCE SOCIETIES VSW

1. FOREWORD

This booklet has been written by the Members of EFNMS COMMITTEE MAINTENANCE 4.0 with the aim to provide the basic knowledges and Guidelines of the last advanced model in the scale of Maturity level of Maintenance Function named Maintenance 4.0.Because the Maintenance Function in the incoming and long Industrial Transition time, has and will have a primary role to maintain and improve the characteristics and performances of physical assets in more severe constrains, the Maintenance Management is called to move from Maintenance 3.0 to Maintenance 4.0 with progressive and suitable implementation of Enabling Technology 4.0 and Artificial Intelligence Applications.In this manner the Maintenance Function in more productive way will continue to take care of Equipments, machinery and plants to ensure a better fundamental contribution to the Sustainability,Quality of life,Competitiveness and Growth of company in the framework of Envirorment Social Governance.ESG paradigma.

THE EFNMS COMMITTE MAINTENANCE 4.0 MEMBERS

- **FRANCO SANTINI -AIMAN ITALY**

CHAIRMAN ECM4.0 -KEY NOTE SPEAKER INTENATIONAL CONGRESES

AIMAN PAST PRESIDENT-CEN TECHNICAL COMMITTE 319 MAINTENANCE

EFNMS PAST BOARD MEMBER-MEMBER OF IMA ADVISORY COMMITTEE

20 YEARS AS TECHICAL DIRECTOR IN MULTINATIONALS

CERTIFIED ACCREDIA MAINTENANCE MANAGEMENT EXPERT EQF LEVEL 8

- **PROFESSOR BASIM AL-NAJJAR**

PROF. OF TEROTECHNOLOGY(SYSTEMEKONOMI) PRECOM PRINCIPAL INVESTIGATOR

CHAIR CENTER FOR COSTEFFECTIVE INDUSTRIAL ASSET MANAGEMENT CeIAM

DEPARTMENT MECHANICAL ENGINEERING-SCHOOL OF ENGINEERING

LINNAEUS UNIVERSITY http.//lnu.se/personal/basim.al-najjar

- **EDUARDO CALIXTO –APMI PORTUGAL**

BAC. INDUSTRIAL ENGINEERING- MD SAFETY-RISK MGMT

MEMBER OF EFNMS -ACTIVE IN HSEC- AUTHOR OF MANY BOOKS:GAS& OIL RELIABILITY ENGINEERING

CEO &FOUNDER OF EC CONSULTING SINCE 2015

ENERGY&ENVIRORMENT-CERTIFIED PROFESSIONAL RELIABILITY

AUTHOR OF RAMS&LCC –AI FOR MAINTENANCE 4.0

MEMBER OF EFNMS REPRESENTING AEM

- **GERARDO CUERVO -AEM SPAIN**

MECHANICAL ENGINEER.SPEC INDUSTRIAL ORGANIZATION

MASTER IESE BUSINESS SCHOOL-VICE PRESIDENT AEM

DIRECTOR ENGINEERING & MAINTENANCE LA CORUNA REFINERY

DIRECTOR ORGANIZATION EFFECTIVENESS MODEL OF 5 REFINERIES REPSOL

REFINERY MANAGER OF CARTAGENA-LA CORUNA-PUERTOLLANO

PROFESSOR ISE 1° SPANISH MAINTENANCE AWARD 2007

- **TOBIAS DANK-MFA AUSTRIA**

MAINTENANCE AND FACILITY MANAGEMENT

SOCIETY OF AUSTRIA & MCP DEUTSCHLAND GMBH

MARKETING & CORPORATE COMMUNICATION MFA

SPECIALIZED IN DIGITALIZATION PROJECTS FOR MAINTENANCE & ASSET MANAGEMENT

- **DIEGO GALAR -AEM SPAIN**

PROFESSOR CON. MONITORING OPER.& MAIN. ENGIN. LULEA UNIVERSITY OF TECHNOLOGY

PRINCIPAL RESEARCHER ON MAINTENACE AND RELIABILITY TECNALIA (SPAIN) INDUSTRY

COORDINATOR OF H2020 PROJECTS :CYBER PHISICAL SYSTEMS,INDUSTRY 4.0 IOT BIG DATA

AUTHOR OF MORE THAN FIVE HUNDRED JOURNAL AND CONFERENCE PAPERS

MEMBER NATIONAL - INTERNATIONAL COMMITTEES STANDARIZATION AND R&D IN MAINTENANCE

- **DAVID LOPEZ –AEM SPAIN**

IS EXECUTIVE MBA (EOI SPAIN),MASTER INDUSTRIAL ENGINEERING,

CERTIFIED INVENTORY &PRODUCTION MANAGER(APICS-USA)

INNOVATION DIRECTOR AND PROJECT MANAGEMENT OFFICE MANAGER SISTEPLANT

ENGINEERING & SOFTWARE I 4.0 :CMMS,MES,MACHINE LEARNING SYSTEMS

MEMBER OF AEM AND LEADS OF THE MAINTENANCE 4.0 GROUP

- **RUBEN MORT –MFA AUSTRIA**

ELECRICAL ENGINNERING AND INFORMATION TECHNOLOGY

DIGITAL MAINTENANCE TRANSFORMATION- WIEN ENERGY

PROCESS MINING EXPERT AND DATA ANALYST

- JANNE PEKKA KARTTUNEN-PROMAINT FINLAND

CEO OF DISTENCE IS DRIVEN BY DIGITAL TRANSFORMATIOM

APPLICATIONS OF MAINTENANCE 4.0 WITH REMOTE SERVICE PLATFORMS

ADVISOR IN SEVERAL DIGITALIZATION PROJECTS ON INDUSTRIAL DOMAIN

CLOUD AND EDGE COMPUTING --DIGITAL TWINS-REMAINING USEFUL LIFE

INFLUENCER ON NATIONAL AND INTERNATIONAL SOCIETIES.

- PER SCHJOLBERG -NFV NORVAY

ASSOCIATED PROFESSOR AREA OF RELIABILITY-AVAIABILITY-MAINTENABILITY-SAFETY

AT NORWEGIAN UNIVERSITY SCIENCE & TECHNOLOGY

HEAD DEPARTMENT PRODUCTION&QUALITY ENGINEERING FOR 9 YEAERS

SEVERAL PROJECTS WITHIN MAINTENANCE MANAGEMENT, CMMS,KPIs

MAINTENANCE POLICIES-STRATEGIES,M4.0,SUSTAINABILITY AUDITS,

MEMBER OF BOARD CEN TC 319 ,CONVENOR WG MAINTENANCE ENGINEERING

PAST MEMBER BOARD EFNMS, MEMBER OF IMA ADVISORY COMMETTEE

- GEORGE SCRUBELOS – HMS GREECE

MECHANICAL ENGINEER PHD,HSE/ CRISIS MGMT CONSULTANT

CEO OF RMS GREECE & CRM CYPRUS LTD HSE CONSULTING

EFNMS EHS COMMTTEE CHAIRMAN

- JAAKKO TENNILA - PROMAINT FINLAND

EFNMS BOARD DIRECTOR OF PROJECT COMMITTEES

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2. INTRODUCTION

(adapted from original source reference 27)

Twelve years after the introduction of the fourth industrial revolution, commonly Industry 4.0 at the 2011 Hannover Fair, every type of physical, industrial and service good, including machines, plants, buildings, infrastructures, utilities, factories and social structures, is affected by Information Technology (IT) and digital innovation.

The goal is to improve the production of goods and provide services that are better in every aspect.

In recent years, the change has incorporated the ambitious goals of sustainable and competitive development, made possible by enabling technologies (Technology 4.0) and AI applications.

Maintenance is called upon to use Open Innovation to implement excellent technical-organizational models, achievable through a Strategic Vision that includes four dimensions:

1. Anticipation

By anticipating the future, the criteria and methods of Maintenance Engineering can be revised to offer and implement technologically appropriate innovative solutions in the design, -construction and installation of physical assets, equipping them right from the beginning, with characteristics of intrinsic structural and operational integrity and global monitoring systems, to achieve Sustainable and Competitive Operations for their entire life time.

2. Permanent Education & Field Training

There is a need to define new competences, improve job profiles, general and specific knowledge, expand work experiences, and develop hard and soft skills. The implementation of appropriate education plans will benefit the professional development of maintenance personnel.

3. Assessment of Intensity of Technologies 4.0

Companies need to prepare a Road Map of the innovative applications and the related benefits achievable from the processes and physical assets in place, using SWOT Analysis. (Strengths, Weaknesses, Opportunities, Threats).

4. Performance Assurance.

Technical-organizational models of excellence, will integrate design-operation and maintenance. Companies need to implement effective Preventive Maintenance strategies to ensure compliance with regulations and improve the performance of maintenance and operations. This is complex given the increased emphasis on recovery and resilience. Maintenance management is called on to play an innovative, integrative role and to be farsighted and professional in line with the concept of Environment Social Governance(ESG). In this context, the EFNMS Committee Maintenance 4.0 prepared “Maintenance 4.0 Guidelines” to provide the basic elements that will progressively develop maintenance sustainability in present and future plant configurations. The overarching aim was to achieve value through maintenance.

3. PART I: THE INDUSTRIAL TRANSITION SCENARIO

3.1. The Drivers of Growth

(adapted from original source reference 15)

The drivers of growth- and therefore of the future of companies, rest on the adoption and implementation of four essential pillars:

1. Sustainability: there should be a balanced mix of social, environmental and economic factors.

2. Competitiveness includes both Products and Services.

3. Competences: human Competence should be developed and maximized.

4. Innovation: organizational and technological innovations are on going and companies should take advantages of them.

In all advanced economies, these are constantly evolving drivers, in an industrial infrastructural Transitional Scenario. Maintenance is called upon to contribute to this scenario.

Maintenance, supports the fundamental values of industrial and infrastructural activities, including quality of life, Safety, Operational Integrity and Operational Availability of physical assets. A Culture of Prevention is required to throughout for the entire life cycle, to gain the benefits of enabling technologies, or what we call Technology 4.0.

3.2. Industry 4.0

Industry 4.0 or the fourth industrial revolution, features the application of the new enabling technologies. The term industry 4.0 was used for the first time by Henning Kagermann, Wolf Dieter Lukas and Wolfang Wahester at the Hannover Fair in September 2011. It was reinforced at the2016 World Economic forum and has since become ubiquitous.

The applications of of enabling Technologies 4.0 can transform machines and plants into digitized, automatized, and interconnected assets thus achieving more sustainability and increasing competitiveness.

This, in turn, will generate more value for products, services and lead to economy growth.

The opportunities and benefits enabled by Technologies 4.0 affect almost every activity, including both such as social activities, industrial administration and business.

Benefits are achievable in Research, Design, Engineering, Safety, Environment, Manufacturing, Operations, Maintenance, Logistic, Quality to name only few areas with an appropriate mix of Information and Communication Technology (ICT), Internet of Things (IOT)and artificial intelligence the 4.0 term, in few years has been used to point out an innovative and advanced era by many functions, etc. achievable with an appropriate mix of ICT+IOT and Artificial Intelligence. (AI): ICT+IOT+AI.

3.3. A new paradigm

Industry 4.0 is a new paradigm of industry and business that is supported by the adoption and use of new technologies that enable to develop:

1. Intercommunication between things and things, people and things;
2. Automation of physical and transactional operations;
3. Virtualization of physical things and processes through Digital Tools.
4. Externalization of human decisions to machines.

This new paradigm implies the transformation of other aspects rather than the pure technology only, such as: Human resources model, Strategic business and Organizational models.

3.4. The Global Trend of Technologies 4.0 Applications

A plot of the latest trends in company functions and business adapted from original sources Gartner2020, a leading information technology research and advisory firm is shown in figure 3.1. The figure shows the evolution in companies' application of Technology in the ten years following the introduction of Industry 4.0 at Hannover Fair.

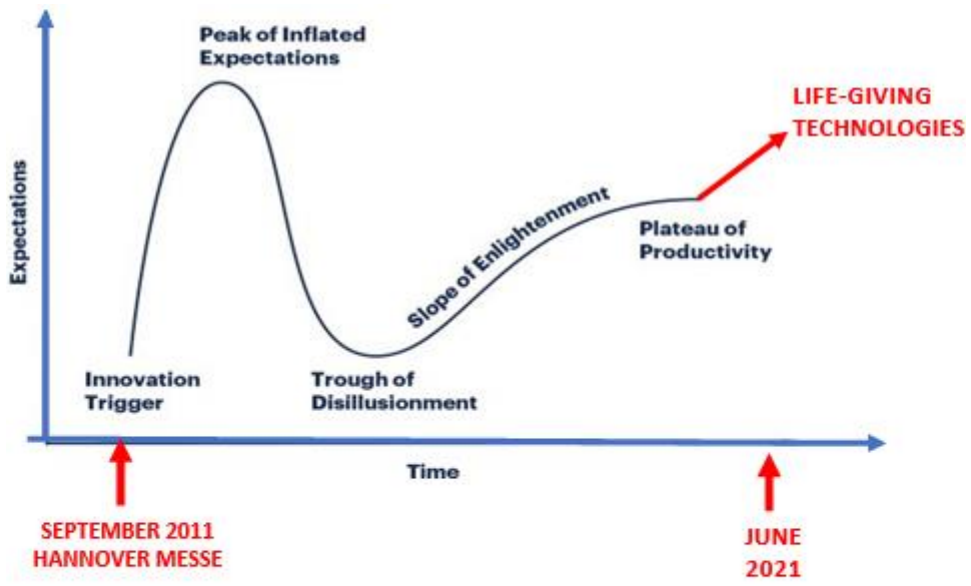


Figure 3.1. Hype cycle innovative technologies 4.0 (adapted from original source gartner research (2020)).

After the initial Hype and subsequent disillusionment, it shows and upward trend and suggests a favourable industrial transition.

3.5. Maintenance 4.0

Maintenance 4.0 is the application of Industry 4.0 paradigm to the maintenance function. The goal is to know in real time the state of health of the critical components of the physical assets, to optimize maintenance resources and increase the value of maintenance services through an integrated digital connection with plants and operations, thus ensuring sustainable and competitive development. It applies the new technologies for the following reasons:

1. To predict failures and prescribe solutions before the failures occur, based on real-time monitoring of current condition of
2. Assets and their systems, subsystems and components.
3. To react and correct the failures, much faster than is possible with conventional means.

In general, by adopting the Maintenance 4.0 paradigm, companies can speed up and optimize the performance of all maintenance operations.

Maintenance 4.0 entails the transformation of the maintenance organization model, as well as the development the performance of all the possible maintenance Operations-It entails maintenance organizational model transformation as well as the development of new technical capabilities of maintenance organization and maintenance engineering to move Maintenance toward new models and above all to achieve excellent performance results from the Physical assets. The main characteristics of Maintenance 4.0 are summed up below.

1. Goals

Maintenance 4.0 It aims to maintain machine quality, by maintaining the asset's technical specifications reducing probability of failures and downtime, easing maintenance actions by facilitating and integrating the application of Augmented Reality (AR), following up on the maintenance impact on company business and enhancing production continuity and company profitability and competitiveness.

2. Performance

Maintenance 4.0 gathers information from all maintenance related areas, such as machines, production, quality, energy, working environment and economy. Maintenance performance is digitalized and automated using a combination of probabilistic and deterministic approaches.

3. Technology

Maintenance 4.0 uses one or more condition monitoring sensors (to detect changes in asset condition), Augmented Reality (AR), Artificial Technology (AT), imbedded and wireless/wired sensors, data gathering boxes, software for automatic diagnosis, prediction and recommendation, modules to detect unhealthy sensors, actuators for conduct automatic actions, communication system, and the Cloud to support integration of maintenance with production processes.

4. Regulation

The measuring frequency needed for monitoring the condition of an asset is likely different for different components, machines, manufacturing/production process, produced products and failure consequences. It should be planned based on several factors, for example failure modes, failure consequences, production/manufacturing processes, nature, anticipate deterioration rate, etc.

3.6. Overview of Technologies 4.0 Applicable to Maintenance

Simply stated, Technologies4.0 refers to the study of machines, materials, technical processes and resources necessary in the application of scientific knowledge to produce objects, perform services and improve the sustainability and competitiveness of physical assets.

This booklet applies the concept of Technologies 4.0 applicable to Maintenance activities in the context and compliances with current regulations. The figure 3.2 shows an overview of the main enabling Technologies operational in Technology 4.0 as these apply to Maintenance 4.0. As the figures suggests Maintenance 4.0 is data driven (adapted from original source Reference 7).

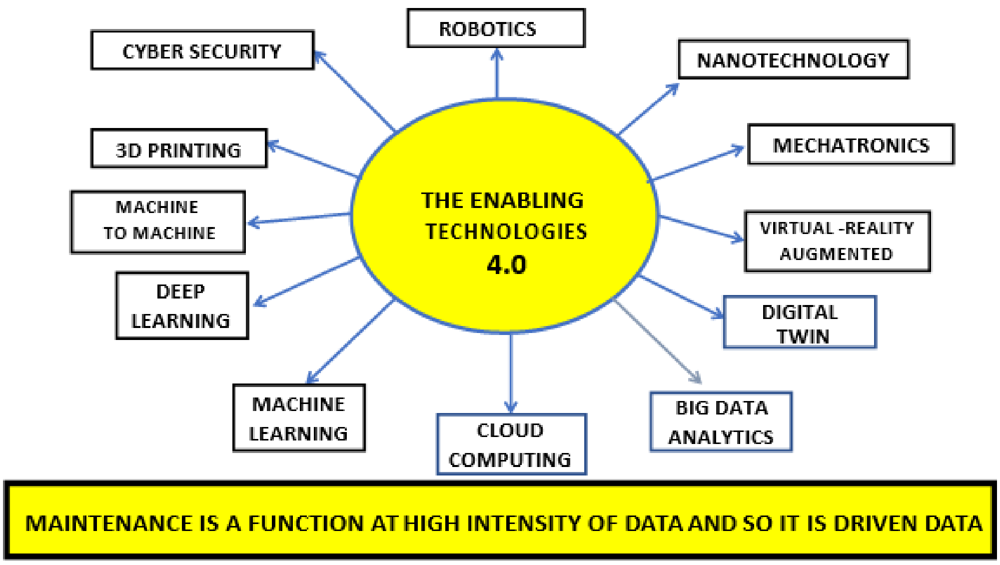


Figure 3.2. The 12 enabling technologies 4.0 for maintenance 4.0 (adopted from original source see original Reference 7).

3.7. Benefits Using Technologies 4.0 In Maintenance

The Figure 3.3 (adapted from original source Reference 16) summarizes the quantitative and qualitative main average values of the benefits that can be obtained with the implementation of 4.0 technologies, as these are found in the literature.

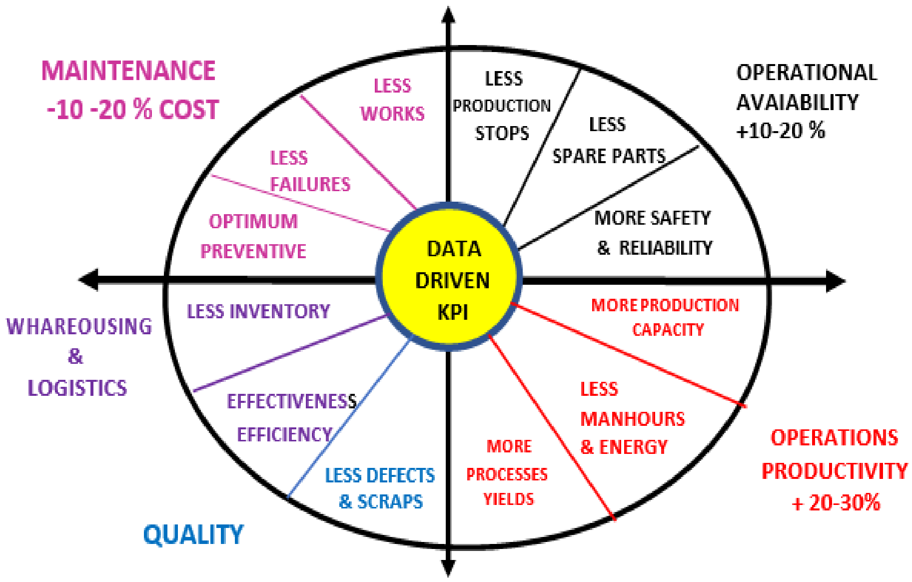


Figure 3.3. Benefits from technologies 4.0 to maintenance-operation-safety-quality- logistic (adapted from original source see reference N° 16).

The benefits relate both to the performance of the physical assets maintained and to the productivity and quality of maintenance services.

3.7.1. Benefits On Maintenance Performance

By adopting technologies 4.0 (see Figure 3.3), It is possible to achieve the following benefits:

1. Advanced Preventive Maintenance strategies based on the systematic use of the Machine, Learning(ML) developed by integrated sensors.

2. A capability to analyse big data in real time and optimize quantitative and qualitative actions using appropriate algorithms. The information related to the characteristics of the physical state and the expected evolution of the degradation of the Components of critical and sub-critical machines and plants is fundamental to implement targets and preventive plans, in relation to descriptive, predictive, prescriptive, prognostic modalities, and thus determine the optimal mix of maintenance actions.

3. An ability to create spare parts using Additive Manufacturing Technology (3 D printing) thus increasing maintainability reducing inventory levels.

4. A consistence maintenance costs reduction by optimizing optimization preventive maintenance and consequent failures reduction saving man-hours materials and spare parts.

3.7.2. Benefits On Operation Performance and Processes

1. Qualitative and quantitative advantages in Safety, Environment, capacity utilization, process yield, productivity, quality, warehousing, inventory reduction, supply chain, logistics, etc.

2. Consequent cost reductions in each operational phase. 3.Significant improvement in quality of products services

3.7.3. Benefits On Maintenance Engineering

In line with the required highest sustainability during the entire life cycle, it is easier to:

1. Identify the weak points of equipment and plants in term of safety and environmental risks, integrity, low operational availability, studies, to choice the most profitable.

2. Carry out studies and choose the most profitable technical improvements.

3.7.4. Benefits to Maintenance Servitization

Maintenance Servitization refers to new modalities whereby maintenance services are offered by the machine providers or specialized contractors.

The aim is to understand and satisfy the customer's needs, in the best possible technical and economical ways, for the interest life of physical assets. These services include maintenance control of physical assets either remotely or in place using technologies encompassed by technologies 4.0, based on a Service Level Agreement between the contractor and the company, and measured by key Performance Indicators (KPI's) (see paragraph 6.7).

3.7.5. Benefits to Circular Economy Projects

To protect the Environment in line with the sustainability Paradigm, Maintenance 4.0 will include useable parts or components of old or obsolete physical asset, using appropriate knowledge of the physical characteristics. Assets may also be repaired or remanufactured. These efforts must be integrated with operations and other company functions.

3.8. From Maintenance 3.0 To Maintenance 4.0

The transition from Maintenance 3.0 to 4.0 includes using and updating the fundamental skills of Maintenance Engineering and Industrial Engineering relevant to the organization, as well as adding new knowledge and hard and soft skills to achieve the necessary competences to define a Road Map progressively and according to priority of benefits obtainable by Technology 4.0 practices (adapted from original sources 2, 3, 7).

Maintenance 4.0 involves a transition through a process of continuous Innovative improvements measured by KPIs. Maintenance 4.0 is no longer simply an opportunity opening a new era for which, in order to be such, must make the transition through Rather, it is a vital requirement to achieve important benefits. Moreover, there are currently strong economic incentives to accelerate the industrial transition and counteract the slowdown caused by the Covid -19 pandemic.

4. PART II: GLOSSARY

This section includes the Terminologies, Concepts and highlights of Maintenance 4.0 Technologies and related enabling factors.

4.1. Additive Manufacturing-3D Printing

Additive manufacturing refers to the capability to create three dimensional physical objects and spare parts from a digitally encoded design through the deposition of materials, usually in layers (see paragraph 5.32).

4.2. Advanced Human Machine Interface (HMI)

Thanks to wearable and new human - machine interfaces (HMI) and conversational interfaces that allow the acquisition and / or transmission of information in voice, visual and tactile format, Human Machine Interface (HMI) is at an advanced stage that includes consolidated systems, such as touch displays, 3D scanners for gesture reading and Augmented Reality (AR) viewers with superimposed and peripheral vision. The Advanced HMI allows the development of performance Support Systems and interactive technical manuals, in the form of solutions that support operational activities and operator training.

4.3. Advanced Materials

Advanced materials, also called Smart Materials, have engineered properties created through the development of specialized processing and synthesis technology through nanotechnologies, producing value-added metals, electronic materials, composites, polymers, and biomaterials.

Self-healing materials are an emerging class of smart materials, capable of autonomous/spontaneous or stimulated repair of their damage under external stimuli, such as mechanical stress, temperature, humidity, ph light, solvents, electric or magnetic field. etc. See paragraph 5.37.

4.4. Artificial Intelligence

Artificial Intelligence (AI) refers to the application of advanced analysis and logic-based techniques to transform data into information that enable HMI and Machine to machine

(M2M) autonomous decisions and actions. The goal is to provide the computer with performance that to a common observer would seem to be an exclusive responsibility of human intelligence. See paragraphs 5.16, 5.17.

4.5. Augmented Reality (AR)

Augmented Reality (AR) refers to the real-time use of information in the form of text, graphic, audio and other virtual enhancements superimposed on real-world objectives. See paragraph 5.26.1.

4.6. Big Data

Big Data refers to the huge amount of data (higher than terabytes) collected, characterized by: high data velocity, large amount of data, data complexity, high variety and high veracity (accuracy). Big Data come from computers networks, sensors, and wearable devices, among others. The data are transformed into intelligent information suitable o improve performances in terms of safety, sustainability, productivity, etc. See paragraph 5.8.

4.7. Big Data Analytics

BIG data analytics refers to the use big data to perform descriptive, predictive and prescriptive analysis in a short time, see paragraph 5.10.

4.8. Building Information Model (BIM)

A Building Information Model (BIM) is important for information management. it is a working method defined in the context of a culture of collaboration and integrated practice through appropriate software, and it represents a profound transformation that affects design, construction operations, maintenance and asset management processes. See paragraph 5.30.

4.9. Cloud Computing

Cloud computing enables the on-demand delivery of IT resources and capabilities over the Internet with pay-as- you-go pricing. Instead of buying, owning, and maintaining physical data centers and servers, company can access technology services, such as computing power, storage, databases, on an as-need basis from a cloud supplier. See paragraph 5.2.

4.10. Collaborative Robots

Collaborative Robots are specifically designed for direct interaction with a human within a defined safeguarded workspace where both (the robot and the human) can perform tasks or processes simultaneously during automatic operations. Unlike autonomous robots, which work largely alone and without supervision, collaborative robots are designed and planned to work with human instruction, or otherwise respond to human behaviours and actions. See paragraph 5.34.

4.11. Computer Vision

Computer Vision is a field of computer science that works on enabling computers to see, identify and process images in the same way as human vision does, and then provide appropriate output. Machines equipped with computer vision will be able to categorize shapes, colours and texture into meaningful groups. For this purpose, the computer must interpret what it sees and then perform appropriate analysis or act accordingly. See paragraph 5.25.

4.12. Cyber Security & Block Chain

Cybersecurity is the combination of people, policies, processes and technologies employed by an enterprise to protect its cyber assets from being stolen, compromised or attacked.

It requires an understanding of powerful information threats, such as viruses and other malicious codes.

Cybersecurity strategies include identity management, risk management and incident management. They are optimized to levels defined by business leaders balancing the resources required with usability/manageability and the amount of acceptable risk.

A block chain is a network of distributed ledgers that provides cryptographically signed, irrevocable transactional records shared by all participants in a network. Each record contains a timestamp and reference links to previous transactions. In this digital register, documents are grouped into blocks set chronological order. Its integrity is guaranteed by the use of cryptography. Once written, its content can no longer be modified or eliminated

without invalidating the entire structure. With this information, anyone with access rights can trace a transactional event belonging to any participant, at any point in its history.

A block chain promotes decentralization, transparency and data integrity. See paragraph 5.35.

4.13. Data Science

Data Science refers to the collective processes, theories, concepts, tools and technologies

That enable the record, store, review, analysis and extraction of valuable knowledge and information from raw data, in order to help people and organizations make better decisions from the stored, consumed, and handled data. See paragraph 5.6.

4.14. Data Mining

Data mining refers to a set of data science techniques and methodologies that extract useful information from large quantities of data through algorithms and advanced technologies, based on artificial neural networks, machine learning and artificial intelligence techniques.

In order to adopt the best strategies, the main models are:

- The Descriptive Model: allows to group historical data of users who have had the same behaviour or physical asset.

- The Predictive Model: grouping the data so that it is possible to estimate/predict future scenarios or results.

4.15. Digitalization

Digitalization refers the use of digital technologies. Digitalization allows companies to change their organizational model and provides opportunities in terms of creating value.

Digitization is the cultural, organizational and operational change of a company, activity or economic ecosystem that occurs through the conscious integration of digital technologies, processes and skills throughout all business processes in a gradual and strategic way.

4.16. Digital Twin (DT)

A digital twin (DT) is a virtual representation of a real-world physical entity or group of interrelated physical assets (machine, plants, buildings).

DT allows real time simulation of behaviours and scenarios via updated real-time data collected from several sources and integrated in a digital model.

It can be used for prognosis (i.e., how the physical object will be having in the real world). AS such, it provides reliable information for optimal decision making, optimize preventive maintenance, enables maintenance improvements and can be used for reverse engineering to maintain optimal operational integrity and extend asset life. See paragraph 8. Digital twin approach for….

4.17. Drones

A Drone (or an "Unmanned Aerial Vehicle": UAV) refers to an unpiloted aircraft or spacecraft. Drones are "remotely piloted aircraft" (APR), i.e. flying devices which, however, have no pilot on board, i.e. they are piloted by an on-board computer or by a pilot who guides them remotely with a radio control. They are also classified as Remotely Piloted Systems (RPS). See paragraph 5.28.

4.18. Edge Computing

Edge computing is an extension of cloud computing technology. While cloud computing involves processing and storing data in centralized data centers, edge computing involves processing data on local devices, such as smartphones, sensors or IoT devices, closer to the data source.

Edge computing is the information processing or other network operations away from centralized and always-connected network segments, and toward individual sources of data capture called edges, that are the physical locations where things and people connect with the digital network (laptops, tablets or smartphones, etc.).

Edge computing is part of a distributed computing topology where information processing is located close to the edge, where things and people produce or use that information.

Edge computing is a distributed computing model in which data processing takes place as close as possible to where the data is requested or on the machine. See paragraphs 5.3, 5.5.

4.19. Fog Computing

Fog is an informatics architecture that uses one or many user devices, or located near the user at the edge of the network, to perform a substantial amount of data storage, communication and management operations. Fog Computing extends the Cloud to be closer to the things that produce and act on IoT data. These devices, called fog nodes, can be deployed anywhere with a network connection: in a factory, on top of a power pole, along a railroad track, in a vehicle, or train. Any device with computing, storage and network connectivity can be a fog node. See paragraphs 5.4 and 5.5.

4.20. Immersive Technologies

Immersion in Virtual Reality (VR) is the perception of being physically in a non-physical world. Perception is created by surrounding the user of the VR system in images, sounds or other stimuli which provide a compelling total environment. It is defined as the subjective feeling of a person to be present in a virtual scenario, within which he will have to operate to carry out work, checks, etc. represented in a virtual scenario before and during the operations. See paragraph 5.26.

4.21. Internet of Every Thing

Indicates "the Internet of the whole", going beyond the topic of interconnected devices; everything from people to objects to processes are connected to each other. We therefore speak of a hyper-connected world, which contains four categories: humans, industrial world, things (data and people) see paragraph 5.1.

4.22. Internet of Humans

It means "Internet of human beings" and refers to the direct or indirect interactions between devices and people, generating a set of information useful for understanding and improving the lives of human being see paragraph 5.18.

4.23. Industrial Internet of Things (IoIT)

It represents an alternative definition to the applicability of technologies inherent to the Internet of Things, applied to the world of industry. Less known and used than the Internet of Things (IOT), it is an application of the latter within the 4.0 industrial context. IOT and IIOT (Industrial Internet of Things) are not interchangeable synonyms, since the second term is related to the physical asset maintenance, operation and business. See paragraph 5.1.

4.24. Internet of Things (IoT)

It is the network of physical entities (objects, mechanical and digital machines) that contain embedded technology to communicate and sense or interact with their internal states or the external environment (other entities, people). All these connected and interrelated things have Unique Identifiers (UIDs) and the ability to transfer data over a network without requiring human to human or human to computer interactions.

A thing in the internet of things can be: a person with a heart monitor implant, a CNC machining center that has built-in sensors to alert the operator when the cutting tool has reached an inadequate level of wear.

4.25. Interoperability

It is the ability of two or more systems, applications, networks, means or components, to exchange information with each other and then be able to use them. It is applied to different sectors and above all in Machine to Machine (M2M) applications. See paragraph 5.31.

4.26. Machine Learning (ML)

It is an Artificial Intelligence subject that transforms data into information automatically such as cluster data, classification data and data prediction based on mathematical models, mostly supported by computer algorithms. There are several types of learning related to the various kinds of processes, technologies and physical assets in order to optimize the Maintenance Performances. See paragraphs 5.21, 5.23.

4.27. Machine Deep Learning

Deep Learning (also known as deep structured learning or hierarchical learning), is part of learning methods based on the assimilation of data representations, as opposed to algorithms for performing specific tasks.

By applying Deep Learning, we will therefore have a "machine" that is able to autonomously classify data and structure them, hierarchically finding the most relevant and useful ones for solving a problem (exactly as the human mind does), improving its performance with continuous learning. See paragraph 5.23.

4.28. Machine to Machine (M2M)

Machine-to-Machine (M2M) is a process that implies wireless data transmission between two or more physical assets (mechanical or electronic devices) to share information and perform actions without the manual assistance of humans. This system typically consists of embedded wireless sensors that are installed in each device, allowing them to communicate and exchange data with each other automatically or as requested by an application, over long distances, see 4.25 Interoperability

The main components of an M2M system include sensors, RFID, Wi-Fi or cellular communications link, and computing software programmed to help a network device interpret data and make decisions. These M2M applications translate the data, which can trigger pre-planned, automated actions. See paragraph 5.31.

4.29. Mechatronics

Mechatronics is the discipline that studies how to make many disciplines interact as: mechanics robotics, electronics, computer engineering and information technology in order to automate processes, productions and service systems in the best way to increase sustainability and competitiveness. See paragraph 5.36.

4.30. Manufacturing Execution System (MES)

Indicates a computerized system that has the main function of managing and controlling the production functions of a company. The management involves the dispatch of orders, advancements in quantity and time, the payment to the warehouse, as well as the direct connection to the machinery to deduce useful information, to integrate the execution of production and to produce information for the control of production.

4.31. Mixed Reality

It is an immersive technology that enables the integration of physical and virtual worlds that includes both real and computer-generated objects. The two worlds are "mixed" together to create a realistic environment that combines aspects of virtual reality (VR) and augmented reality. See paragraph 5.26.3.

4.32. Nanotechnology

Nanotechnology, also called nanotech, in the contest of computer science, is a type of engineering whose aim is to build electronic components and devices conducted at the nanoscale (1 to 100) nanometers). Nanotechnology facilitates the building of Functional Matter and Systems at the scalar level of an atom or molecule. It incorporates concepts from physics, biology, engineering and many other disciplines (see paragraph 5.37).

4.33. Natural Language Processing

Natural Language Processing (NLP) technology automates the translation processes between computers and humans. It involves the ability to turn text or audio speech into encoded structured information. The ultimate goal of NLP is to build software that will analyse, understand and generate human language naturally, enabling communication with a computer as if it were a human.

4.34. Predictive Maintenance System

It is a system that, thanks to the use of specific hardware, sensors and predictive algorithms and the use of enabling technologies in the IoT field (Big data, Cloud computing, Machine Learning), allows users to maximize effectiveness of preventive maintenance activities, intervening remotely and reducing downtime and maintenance costs. Predictive maintenance combines offline measurement through Predictive technology (vibration, noise, thermometry, oil analysis of line measurements, with continuous measurement named Condition Monitoring Systems on line. See paragraph 5.13.

4.35. Predictive Behavioural Analytics

It allows you to manage real-time analytics relating to user behaviour and to develop business or production actions directly resulting from these analytics. In Industry 4.0, Predictive Behavioural Analytics is used to implement a design method directly linked to user behaviour. The very first result of Predictive Behavioural Analytics is in Predictive Maintenance which analyses the behaviour of means of production and products and the behaviour of operators and consumers in the use of products. Behavioural analysis focuses on understanding the relationship between consumers and products.

4.36. Prognostic Health Management

The Prognostic Health Management (PHM) is a means for making accurate assessments on an on-going basis of the State of Health (SoH), as well as providing high quality estimates of the Remaining Useful Life (RUL) of the system. The PHM is an evolution of the CBM, and performs RUL and SOH prediction for the equipment and components that are being monitored considering extreme stress operating conditions rather than normal operating conditions. See paragraph 5.20.

4.37. Radio Frequency Identification (RFID)

Fore runner of the IoT, it represents a technology for the identification and automatic reading of data associated with certain objectives, persons and products. The RFID provides for the storage of data thanks to tags or real electronic labels (or transponders), that communicate remotely with the Reader, through radio devices that write and read data directly on the labels.

4.38. Servitization

The term Servitization is the transposition of the English word Servitization, composed of “service” and “ization” that means, service and implementation.

The concept behind what is called Servitization is the transition from a product-centric model to a customer-centric model in which service is the cornerstone. In other words, we are witnessing a change in equilibrium at a strategic level in the importance given to the customer with respect to the weight given to the products. See paragraph 6.7.

4.39. Smart Home

It is the application of a set of technologies 4.0, based on computer and electronic engineering, with the aim of integrating a series of devices, capable of automating and simplifying the daily actions of a home or building optimizing the energy consumption, security, operation and maintenance needs.

4.40. Smart IoT Sensors

Internet of Things sensors equipped with computing capacity and in addition to collecting and transmitting data from the physical environment, or from the equipment to which they are associated, they perform calculation functions. It is an IoT capable of returning processed data or with a sort of "pre" processing, can already be used to perform actions on the machines themselves or to transmit more elaborate information to central systems.

4.41. Smart Factory

Manufacturing company that implements digital solutions designed to monitor all production processes, to track both semi-finished and finished products along the Fully Integrated Supply Chain. The Smart Factory is based on IoT and Real-Time Analytics and allows you to increase efficiency and change the relationship with customers and business models.

4.42. Smart Grid

New concept of energy production and management. The smart grid is an intelligent electricity network that, thanks to IoT sensors, measures the energy efficiency of the equipment of users and monitors their consumption, "corrects" their consumption and manages the production of energy according to the quantity actually needed.

4.43. Smart Maintenance

It is the part of Maintenance 4.0 consisting of the digitalization of maintenance activities direct and indirect, through CMMS, IOT, the supporting technologies for remote works, the use of wearables and the predictive advanced technologies, to improve safety, productivity, maintainability and operational availability of physical assets.

4.44. Smart Manufacturing

It is a new interpretation of manufacturing that thanks to digital technologies can increase their competitiveness and efficiency with the digital interconnection of all assets: machines, human resources and supply chain.

4.45. Vertical and Horizontal Integration

Vertical integration is the implementation of specific information and management systems, capable of interacting and exchanging information through those involved in the internal production chain.

Horizontal integration is the implementation of specific information and management systems, capable of interacting with other functions or external companies, distributors and suppliers operating in the supply chain. See paragraphs 6.2, 6.3, 6.4.

4.46. Wearable Technologies

They are wearable devices and sensors. They are an example of IoT since they make part of physical objects (such as watches and smart bracelets) or "things" integrated with electronics, software, sensors and connectivity to allow objects to collect and exchange quantities of data with a manufacturer, an operator or other connected devices without requiring human intervention. This type of technology detects and monitors the body's internal and external biological signals, as well as emotional ones (see paragraphs 6.9., 6.10).

5. PART III: TECHNOLOGIES 4.0 AND ENABLING FACTORS

5.1. Industrial Internet of Things (IIoT)

The term Industrial Internet of Things (IIoT) represents the industrial concept of an Internet of Things (IoT), as opposed to the consumption-oriented IoT concept. The Industrial IoT is a trend that, along with many other IT technologies, serves to improve operational effectiveness and is the networking basis to implement Technologies 4.0 in Industry, Operations, Maintenance, etc.

Industrial internet of things (IIoT) is a subset of the more generic industrial internet of things (IoT). There is a clear difference between use cases in industrial application and the basic idea of connecting a "thing to the internet".

The basis for the IIoT was the invention of programmable logic controllers (PLCs), which made it possible to flexibly control individual elements in the manufacturing chain. With the enforcement of cloud technology in the early 2000s and the development of the OPC/UA protocol, it became possible to store data and transfer it securely between different devices. Thus the IIOT was born.

This refers to digitally networked, intelligent machines or systems in an industrial context, as maintenance. The objective is efficient, self-organized maintenance in which machines, plants, processes and people communicate and cooperate with each other. This networking is intended to optimize the entire value chain of the physical assets during all the life Industrial internet of things, commonly refers to a sensor, instruments and other inter connecter and networked devices that have ability to communicate to achieve a benefit of use.

An IIoT network consists of smart devices that communicate via the Internet data as a service (DaaS The networks and systems made up of them can monitor, collect, exchange and analyse data. The insights gained provide processes control to achieve data to transform in information, to optimize decisions and actions to generate more sustainability and competitiveness during physical assets utilization adding values to the entire Operations-Maintenance chains.

Meanwhile, the concepts of predictive and prognostic maintenance are considered the standard applications of networking par excellence. Machine Learning, self-learning algorithms, deep learning from artificial intelligence based on neural networks, machine to machine are the more utilized technologies 4.0.

The fundamental characteristic of IIOT is improving operational effectiveness through sensors, instruments, interconnected and networked and industrial devices.

The difference with internet of things (IoT) is that with IIoT, computations occur as edge computing at the network edge, where they are generated because the computational effort in the IIoT is higher than in the IoT.

The overall concept of IIoT includes concepts like Edge computing, Additive manufacturing (3D printing) etc. that have separate sections in this booklet. For this It is considered to be relevant to address this concept in context of industrial maintenance. Therefore, we focus on cyber-physical systems and evolution of IIoT emerging from Programmable Logic Controllers (PLC's).

For maintenance function IIoT has meant a vast increase of offering from connectivity services to data visualization, analytics, smart sensors, and on and on.

Cyber-Physical Systems (CPS): the basic technology platform for IoT and IIoT and therefore the main enabler to connect physical machines that were previously disconnected. CPS integrates the dynamics of the physical process with those of software and communication, providing abstractions and modelling, design, and analysis techniques (https://en.wikipedia.org/wiki/Cyber-physicalsystem)

An object of the Industrial Internet finds applications within the "factory", of the corporate reality, in the context of the fourth industrial revolution and in the transition industrial scenario.

5.2. Cloud Computing

It is a form of advanced technological outsourcing in which the user does not buy the product, but the ability to use that product remotely via the Internet, without physically having it.

This technology offers rapid innovation, flexible resources, and economies of scale through the delivery of computational computing services.

Many of the services in Maintenance are moving from local on-site systems to centralized and cloud computing based services. This trend can be observed on several levels of organizations from CMMS systems to more Operations and business systems.

Cloud computing generally is referred to a business model where software-based services are provided with a subscription basis e. g. with a monthly fee or reserving capacity based model over the internet. Acronyms associated to cloud computing are:

1. IaaS = Infrastructure as a Service.
2. PaaS = Platform as a Service.
3. SaaS = Software as a Service.
4. XaaS = Anything as a Service.

These generally refer to generic or specific Services provided on a global scale by remote.

As a technology cloud refers to public, private and hybrid cloud. Public clouds provide service over the public internet to several users e.g. organizations. Private clouds serve by default one organization and are privately organized, built and managed.

Hybrid clouds can hold elements from both of the models e.g. certain parts of the software can use cloud based resources and certain data can be on locally managed databases.

Multicloud is an approach where more than one cloud is used.

A multi-cloud environment can be used to better control sensitive data or provide redundant storage for improved disaster recovery or accidental situations.

As more and more services are moving to cloud integration of cloud services is becoming a standard. It is common to come across integration where common acronyms are API (note that API is only one of many types of integration methods). API is an acronym of Application

Programming Interface. API is a definition that is used to exchange information between systems.

5.3. Edge Computing

Edge Computing is a key technology for the Industrial Internet of Things (IIOT). With stronger networking, the amount of transmitted sensor data increases and with it the demands on IIOT-connected devices, machines and plants. Real-time processing of this data is gaining importance, although this poses further challenges especially with big data.

With edge computing maintenance ensures that captured data does not block processes along the value chain.

Edge is the term used to describe the edge of a technical information network where the virtual and real worlds meet.

In a decentralized IT architecture, big data recovered areas not processed in the data center, but directly at this transition and moved to the cloud if necessary.

Edge computing enables data pre -processing in real time at this point: Collected data is condensed locally according to defined criteria. Initial analysis results can now be fed back directly to the end devices or processed further.

Subsequently, it is possible to transfer only relevant and thus smaller data packages to the cloud, which cannot be used on their own. By reducing the amount of data, stationary servers are relieved, but also the running costs for data transfer and the cloud are reduced. This decentralized processing not only conserves resources, but also reduces the risk of data loss off-site or in the event of cyber-attacks on the cloud.

Edge computing can reduce latency, optimize data flows, and improve production flows and processes.

Edge computing is a method of distributed processing of data at its origin e. g directly from the sensor chip. Close to the term is fog processing that processes data e. g. on gateway level having data transmitted from the sensor to a processing unit.

Edge computing is commonly used in applications where e. g. row sensor data needs to be processed and controlled to this processing pipeline, has relevance processing data close to where it is generated brings considerable benefits in terms of processing latency, reduced data traffic and greater resilience in the event of a data connection failure.

In maintenance these applications can include processing e. g. advanced signal processing in high frequency vibration or electric signals data.

Many IoT applications leverage cloud-based resources for computing power, data storage, and intelligent applications that provide business insights.

However, it is often not optimal to send all data generated by sensors and devices directly to the cloud, as there are generally bandwidth, latency, and regulatory issues to consider.

The 3 main reasons why edge computing is required in IoT applications are as follows:

1. Bandwidth

   The amount of data that some IoT applications generate can be staggering, similar to the costs associated with sending all data to the cloud. This makes local processing more practical and beneficial. This is also a gating factor for any application that requires streaming large amounts of content, including high- definition video, which can be used in oil and gas exploration applications.

2. Latency

   Some applications require extremely low latency. This is the time it takes for a data packet to be transmitted to the destination and back. Any application that involves security, such as driverless cars, healthcare applications, or industrial factory floor applications, requires near instantaneous response times. Cloud services are not optimal in such cases because of the delay involved in transferring to a centralized service.

3. Regulatory Requirements

   In highly regulated industries and regions (such as in Europe with the General Data Protection Regulation DSGVO), the way personal data is processed is strictly controlled, including where it is stored and how it is transferred. This leads to an increased need for local data centers.

In all these cases and more, edge deployments are essential to solving these problems.

5.4. Fog Computing

Fog computing is a network architecture that extends from the "edges," or points where data is generated, to where information is stored. Which is usually a cloud or data center. This distributed network is therefore the link between the transport of data into the cloud and its creation and analysis at the edge.

This means that the network layer Fog Computing, for example, takes care that the data of an autonomous car finds its way to the data center. But there is more going on.

That's because Fog computing can give an organization greater control over where such data should most meaningfully be computed at any given moment. Fog computing frameworks can determine whether the network is fast enough for data transfer, whether a low-latency connection should be created, or whether edge computing should be used instead.

That is, computing on the endpoint, rather than in the data center. Fog and edge computing go hand in hand here to a certain extent, whereby the latter can be described somewhat inaccurately as "many distributed mini-clouds".

Fog computing is commonly used when data collected is cast and needs to be processed e.g. filtered to include only relevant parts from the desired data processing purposes. Common example would be processing industrial process data from an industrial logic controller.

Methods like fog and edge computing enable data efficiency for cloud computing as well as access to applications where latency, network limitations and potential redundancy for connection interruptions are challenges. Some industries, industrial manufacturers or local regulators also have policies that the original data needs to be able to access, replicated and/or primarily stored in certain ways. In this type of use cases technologies like edge and for computing can be applied as follows.

Fog computing and edge computing are both technological approaches to cloud computing, but they can be clearly distinguished from each other.

Cloud computing and fog computing differ in the location where services are offered and data processed.

Fog computing processes data close to its origin at the edge of the network in decentralized "minicomputing centers" and provides for lower latency and reduction of the volume of data to be transmitted in the network by intermediate processing close to the data source.

Fog computing adds another layer, the Fog layer, to the basic architecture of cloud computing. The architecture thus consists of the following three layers:

1. Edge layer
2. Fog layer
3. Cloud layer

The edge level consists of the end devices that collect and provide the data to be processed. They communicate with the next higher level, the Fog level.

In the case of edge computing, the end devices are able to process certain data themselves.

The Fog layer has its own computing power and intelligence. The data transmitted to a Fog node of the Fog layer is pre-processed there. If required, the raw data from the end devices or the pre-processed data from the Fog layer can be transferred to the cloud layer for further processing.

When machines have to react in the microsecond range, there is not enough time to transmit the data to a Data Center in the cloud, analyse it there and send the result back.

It helps if information - for example from position sensors - can be evaluated locally and the resulting reactions triggered directly on site.

5.4.1. Fog Computing Advantages

The Internet of Things networks a wide variety of devices and machines that continuously send and receive data. The volumes of data to be transmitted are increasing, and at the same time there are enormous demands on the processing speed of the data due to the real-time processes in the IoT.

If the processing of the data only takes place in central data centers within the cloud, sometimes large distances have to be overcome.

Since the transmission and computing capacities of the cloud are limited, an increase in end devices and data leads to increasing processing times. The requirements of the real-time applications of the Internet of Things can hardly be met by classic cloud computing.

Fog computing brings computing capacities to the edge of the cloud, shortens the distances to be covered and provides resources that can be used decentralized.

The concept scales well and keeps pace with an increasing number of networked end devices.

Since not all data is transmitted, particularly sensitive information can remain within the company's own infrastructure. Edge or Fog Computing is therefore an alternative, especially for companies that are reluctant to transfer their data to the cloud because they fear that it could be spied on there.

Fog computing provides solutions for numerous applications in the field of the Internet of Things (IoT).

For Maintenance 4.0, Fog Computing is a key technology.

Fog computing is becoming an indispensable building block of a smart factory, where real-time capable processes and applications are in demand. The data supplied by the sensors of the production plants can be processed far and Fog Nodes deliver the required control and regulation information back to the machines within a very short time.

Companies should consider Fog Computing when:

1. Data is collected at the extreme edge: vehicles, ships, factory floors, roadways, railways, etc.
2. Thousands or millions of things across a large geographic area are generating data.
3. It is necessary to analyse and act on the data in less than a second.

Compared to classic cloud computing, Fog computing has numerous advantages.

1. Reduction of transmission and latency times.
2. Faster processing of data.
3. Acceleration of analysis and decision-making processes.
4. Real-time capability of applications.
5. Maintenance of IoT functions even without a connection to central cloud services.
6. Improved availability of IoT applications.
7. Independence from central computing and transmission capacities. 8.Protection of sensitive data through decentralized processing.

However, the advantages of Fog Computing are also countered by some limitations:

1. Higher intelligence at the edge of the network requires additional resources and more complex components.
2. Hardware costs for decentralized components increase.
3. Increased maintenance requirements due to a larger number of decentralized intelligent nodes.
4. Protective measures must be additionally decentralized.

5.5. Edge Versus Cloud Computing

Edge infrastructure can be managed or hosted by communications service providers or other types of service providers. Different use cases require deploying various applications to different sites. In such scenarios, a distributed cloud that can be seen as an execution environment for applications across multiple sites, including managed connectivity as a single solution, is useful.

Key benefits of edge solutions include low latency, high bandwidth, device processing and data offloading, as well as reliable processing and storage.

Cloud Computing is a form of decentralization at the Cloud level for the local processing of data that must manage actions that in turn must take place locally. This solution requires that the data is not sent completely to the cloud but takes advantage of the ability to process locally and communicate with some IoT devices capable of doing so. The classic logic of Cloud computing provides that in the communication between two devices, there is always a sending of data to the cloud itself. Fog or Edge Computing, allows you to keep a certain amount of data for local processing.

These technologies, to work in an integrated way and therefore use shared information, must be connected to a common computer network, which is usually the Internet.

5.6. Data Science

Data Science was recognized as a discipline in its own right (therefore no longer a branch of computer science and statistics) only in 2001, when William Cleveland outlined its fields of expertise, listing different areas of research.

With the advent of big data and the idea of "data value" typical of this paradigm, the very concept of Data Science has evolved, which thus becomes a holistic science, whose founding principle is not the mere data management, but a wider enhancement of the large heterogeneous amount of data coming from different sources (data warehouse sensors, web, etc...).

Data science is as a transversal discipline, which includes both the spheres of computer science, statistics and mathematics, as in the original meaning, and a set of more managerial skills, linked to the most recent need to know how to read, interpret and capitalize big data sustainability and competitiveness. The objective of data science is to understand big data and analyse it, but also to enhance it and ensure that, when properly interrogated and correlated, it generates useful information not only for understanding phenomena, but also for pointing the right direction to generate appropriate application and improvements in each area. Data Science combines multiple fields, including statistics, scientific methods and data analysis, to extract value from Big Data.

Data science is the set of methodological principles, based on the scientific method and multidisciplinary techniques aimed at interpreting and extracting knowledge from data through the related analysis.

The methods of data science (often associated with the concept of data mining) are based on techniques from various disciplines, mainly from mathematics, statistics, information science, computer, engineering and social sciences, especially in the following subdomains: databases and data visualization of artificial intelligence or machine learning through Big Data.

5.7. Data Scientist

Those involved in Data Science are so-called Data Scientist, who combine a wide range of skills to analyse data collected from the web, smart phones, customers, sensors and other sources.

They are experts who apply statistical-mathematical techniques, knowledge and specific software to manage, analyse and use big data to obtain the information that guides the best strategic or critical operational and organizational choices, in the specific realty of existing physical assets and company framework. The Big Data Analytics & BI Observatory of the Milan Polytechnic in 2018 described the Data Scientist as a highly specialized figure who knows mathematical- The difference with the Internet of Things

statistical techniques in depth, knows how to develop and implement Machine Learning algorithms, knows more than one language of programming (especially R or Python) and manages Analytics; can extract data from MySQL databases, use pivot tables in Excel and produce clear and concise views for business users. Since Maintenance is a Data Driven function, the use of 4.0 technologies requires moving from big data through algorithms to information using the most appropriate statistical methodologies. However, taking into account the specificity of the statistical algorithms and the high repetitiveness of the degradation models of the mechanical and electrical components, the Big Data Engineers of Design and Maintenance, after training, can directly use the specific software available on the market to develop the algorithms as Python (see paragraph 20, and reference point 3 and 4).

5.8. Big Data

(Adapted from original sources 19 and 22)

The English term big data generically indicates a collection of information so extensive in terms of volume, speed and variety that specific analytical technologies and methods for the extraction of value or knowledge. The term is therefore used referring to the ability of Data Science to analyse or extrapolate and relate an enormous amount of heterogeneous, structured and unstructured data, using statistical and computer processing methods, in order to discover the links between different phenomena correlations and predict future ones and are considered the Base to develop many kinds of Preventive Maintenance.

There is no pre-established reference threshold in terms of size beyond which it legitimates to speak. In general, we speak of big data when the data set so large and complex that it requires tools and methodologies to extrapolate, manage and process data to achieve suitable information within a reasonable time. In fact, as demonstrated by Moore's law, technological evolution allows storage and management of datasets of continuously increasing size.

Douglas Laney (2001) had defined the three-dimensional the 6V data model:

1. VOLUME: amount of data generated every second from heterogeneous sources.

2. VARIETY: they can be of various types so for accurate analysis more accurate analyses are divided into:

    a. unstructured data
    b. semi-structured data
    c. structured data to finalize them according to specific needs

3. VELOCITY with which data is generated to define the capacity to collect and processit.

   In last years, with the increase in complexity and the large use of Big Data the following other features have been added:

4. VERACITY: considering the variety of data and the velocity at which it is produced, it is necessary to ensure the quality of the data entering the analysis and processing systems in order to achieve a high level of reliability of the released information.

5. VARIABILITY: it must be contained and reduced in order to obtain significant data and consequent information and to appropriately size the processing capacity.

6. VALUE: the choice of big data that will be collected and processed must be carefully predefined as expected information in order to create an effective added value to justify the effort and the resources involved.

5.9. Big Data Engineer

It carries out the technical and organizational task of identifying sources and hardware tools for the collection and storage of big data of production and maintenance processes and software or analysis, structuring, selection and subsequent processing into information to implement the most sustainable and competitive strategies.

Since these activities are part of the tasks entrusted to the maintenance engineering the Big Data Engineer task is part of the Maintenance Engineering Discipline.

5.10. Big Data Analytics

(Adapted from original source reference 29).

Tools and methods for the management of Big Data from Internet of Things equipment, directly connected to the manufacturing and industrial environment or related to the integration of data between IT systems, for planning and synchronization of Production Maintenance and Logistics flows. Industrial Analytics includes Business Intelligence, Data Analytics, Data Visualization, Simulation, Forecasting or the tools needed to support quick decisions from IoT data. It is the systematic computational analysis of data or statistics. It is used for the discovery, interpretation, and communication of meaningful patterns

in data. It also entails applying data patterns towards effective decision making. It can be valuable in rich areas with recorded information; analytics relies on the simultaneous application of statistics, computer programming and operation research to quantify performance.

Organization and data analysis can produce important information to make decisions as well as to define products and services with an ever increasing level of specificity.

Is the field of mathematics that´s performed descriptive, predictive and prescriptive analysis based on collecting data. The descriptive analysis aims to describe the pattern of data (Histogram, probability Density Function, mean, median, quartiles, mode, Min, Max and other statistic parameters)

The prescriptive analysis aims to predict the result of a dependent variable based on one or more dependent variables (Regression Analysis, Correlation Analysis, Supervised Machine Learning prediction model).

The Prescriptive aims to define the best action based on the collected data (Reinforcement Learning).

Data Analytics is a multidisciplinary methodology influenced from some trends:

1. There is a tendency to use the term analytics in business settings text analytics vs. the more generic text mining to emphasize this broader perspective.

2. There is an increasing use of the term advanced analytics, typically used to describe the technical aspects of analytics, especially in the emerging fields such as the use of machine learning techniques like neural networks, decision tree, logistic regression, linear to multiple regression analysis, classification to do predictive modelling.

3. It also includes Unsupervised Machine learning techniques like cluster analysis, Principal Component Analysis, segmentation profile analysis and association analysis.

4. There is extensive use of computer skills, mathematics, statistics, the use of descriptive techniques and predictive models to gain valuable knowledge from data through analytics.

5. The insights from data are used to recommend action or to guide decision making rooted in the business context. Thus, analytics is not so much concerned with individual analyses or analysis steps, but with the entire methodology.

6. In the field of Business Analytics, new analysis and processing models have been created and Big Data Analytics considering their main characteristics:

    6.1. to perform descriptive and prescriptive analysis.

    6.2. to provide information representative of the existing situation, evolutionary forecasts and prognostic projections in relation to the tools and calculation model used for the analysis of the physical state of assets for policy purpose and maintenance strategies.

5.11. Big Data Analysis

It focused on understanding the past; what happened and why it happened and what will happen in the future. There are four types of Big Data Analysis.

5.12. Descriptive Analysis

The set of technical information describing the state of an asset past and actual. The Descriptive analysis is an important first step for conducting statistical analyses. It gives you an idea of the distribution of your data, helps you detect outliers and typos, and enable you identify associations among variables, thus making you ready to conduct further statistical analyses.

There are two types:

1. Descriptive analysis for each single variable
2. Descriptive analysis for combinations of variables

5.13. Predictive Analysis

It is the branch of the advanced analytics which is used to make predictions about unknown future events. Predictive analytics uses many techniques from data mining, statistics, modelling, machine learning, and artificial intelligence to analyse current data to make predictions about future. Measurement tools and IT technologies that perform the analysis of characteristic data of the physical state of an asset to provide information able to predict the evolutionary lines and therefore what could happen in the residual life of the physical assets and related components that is named Predictive Maintenance.

5.14. Prescriptive Analysis

To better understand prescriptive analysis methodologies, it is important to have in mind what an optimization problem is and what it is composed of.

First of all, an optimization problem is the problem that focuses on finding the best solution among all the feasible solutions. Advanced tools that, together with the analysis of data related to the state of a physical asset, specify as Prescription both the actions necessary to achieve the aforementioned results, and the related effects of each in relation to the objectives to be achieved. This approach can help in optimizing decision making, planning, work efficiency and physical assets optimization.

5.15. Prognostic Analysis

Prognostics is the prediction of failures based on certain multi measures of the characteristics of the physical state of the components of a physical asset in correlation with the operating parameters, that are continuously updated during its normal operation with statistically significant cumulative data. The aim is to provide an accurate assessment of the forecast residual useful life.

5.16. Artificial Intelligence (AI)

(Adapted from original sources 1and 2)

5.17. What Is Artificial Intelligence

Artificial intelligence or AI, from the initials of the two words, is a discipline belonging to computer science that studies the theoretical foundations, methodologies and techniques that allow the design of hardware systems and software program systems capable of providing the electronic computer with performance that, to a common observer, would seem to be the exclusive responsibility of human intelligence (see Figure 5.1).

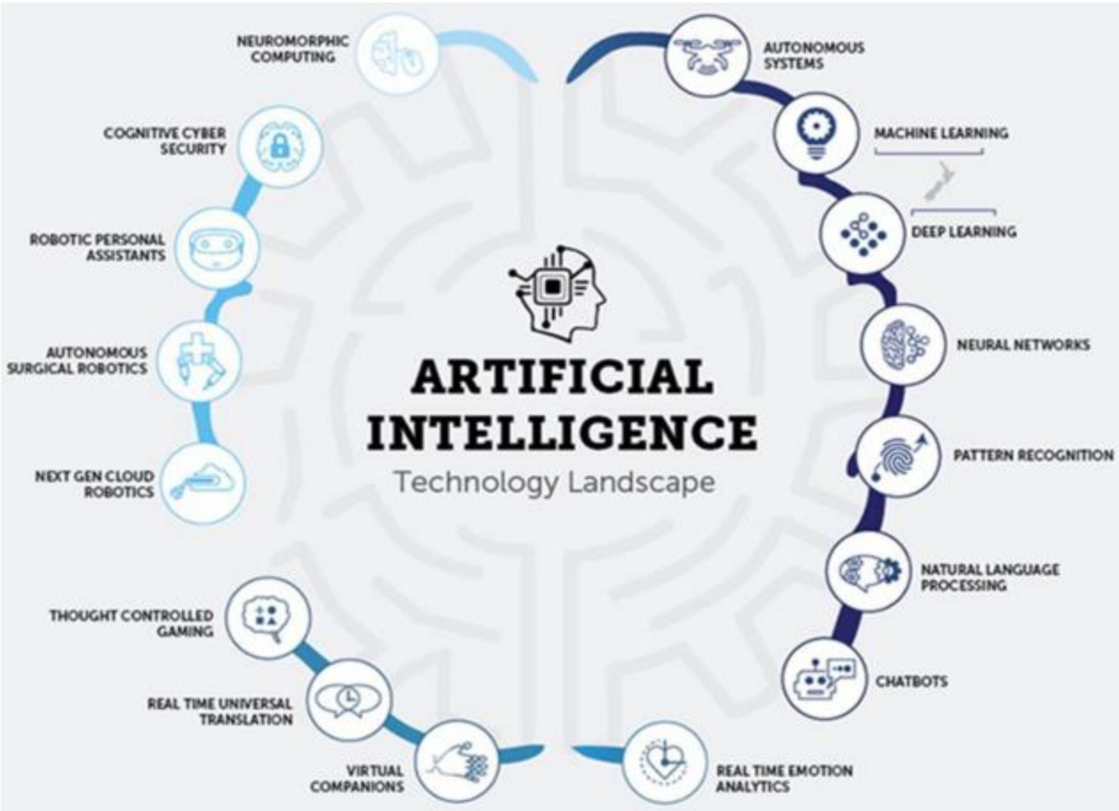


Figure 5.1. What is Artificial Intelligence (Adapted as found in the literature).

Specific definitions can be given by focusing, either on the internal processes of reasoning or. on the external behaviour of the intelligent system and using as a measure of effectiveness or the similarity, with human behaviour or with an ideal behaviour, called rational:

1. ACT HUMANLY: the result of the operation carried out by the intelligent system is indistinguishable from that carried out by a human.

2. THINKING HUMANLY: the process that leads the intelligent system to solve a problem is similar to the human one. This approach is associated with cognitive science.

3. THINKING RATIONALLY: the process that leads the intelligent system to solve a problem is a formal procedure that goes back to logic.

5.18. European Code of Ethics of AI Applications

The starting point of the entire document, and of all the legal principles that have emerged from it, is that Artificial Intelligence must have man at the center and must be at the service of the common good to improve well-being and guarantee freedom. First of all, the group of experts identified the legal foundations on which the code should rest by searching for them in the EU Treaties, the Charter of Rights and the International Human Rights law.

From this analysis, those mandatory rights were identified that, in the European Union, must be respected for Artificial Intelligence, namely:

1. Respect for the dignity of man.
2. Freedom of the individual.
3. Respect for democracy and justice.
4. Equality and non-discrimination Citizens rights.

5.19. Artificial Intelligence Applied to The Maintenance 4.0

The Artificial Intelligence (AI) aims to enable the machine to think and take their own decision based on data collected and assessed automatically without any human intervention. The AI has been applied to different fields such as biology studies and research, financial and engineering with successful cases of use of numerical and categorical data, text and images. The vast field of science application of AI for recognition pattern of information collected to take decision has several applications such as natural language processing, virtual personal assistant, visualization, audio analytics, image analytics, internet of things, Robotic & Soft Robotic, Machine translation, Social network analysis, Simulation and modelling, Machine learning and deep earning as shows the Figure 5.1.

Artificial intelligence is the field of science that allows a robot and computer:

1. to imitate the man modelling mental and computational processes to creating algorithms.
2. to carry out computational process through physics, mathematics, computer sciences, engineering disciplines, psychology and linguistics.

With the aim to achieve results that are comparable or better than those obtainable by man with his natural intelligence.

The objective of this chapter is to demonstrate the A.I applied for maintenance 4.0 concerning the Prognostic Health Management (PHM) and Machine Learning Methods.

The aims to predict equipment failures and degradation for preventive intervention, define levels of alert to alarm maintenance technicians when any equipment achieves different levels of degradation and propose a maintenance schedule concerning the real time equipment degradation, to enable maintenance expert focus on the most critical equipment with lowest Remaining Useful Life (RUL) and highest Degradation (DPS).

In addition, the visual recognition based of pattern of failure is the objective of Deep Learning and the definition of the best sequence of action is the main objective of the Reinforcement Machine Learning.

5.20. Prognostic Health Management

(Adapted from original source 2)

5.20.1. Introduction

The main objective of preventive maintenance is to predict the failure occurrence or equipment degradation in order to anticipate such unwanted event that may cause system shutdown, higher operational cost or even accident. Based on the last decades, new technology and the new concept of Maintenance 4.0 has arisen.

The evolution of a preventive maintenance starts with the concept of schedule maintenance based on time, condition-based maintenance, that means, the preventive maintenance based on the condition of the physical asset and the last evolution is the so-called Prognostic Health Management.

The first step of the PHM application starts with a sensor or set of sensors producing data of the equipment or component being monitored, that data being Condition-Based Data (CBD) reflecting the actual deployment and usage of what is being observed.

The second stage being an application-specific data pre-processing tool extracting information out of the sensor data and translating that into Feature Data (FD) that has a relationship to aging and degradation.

The third stage is then consumed by the PHM Algorithm resulting in prognostic information such as Remaining Useful Life (RUL), State of Health (SOH), and Prognostic Horizon (PH) as shows Figure 5.2.

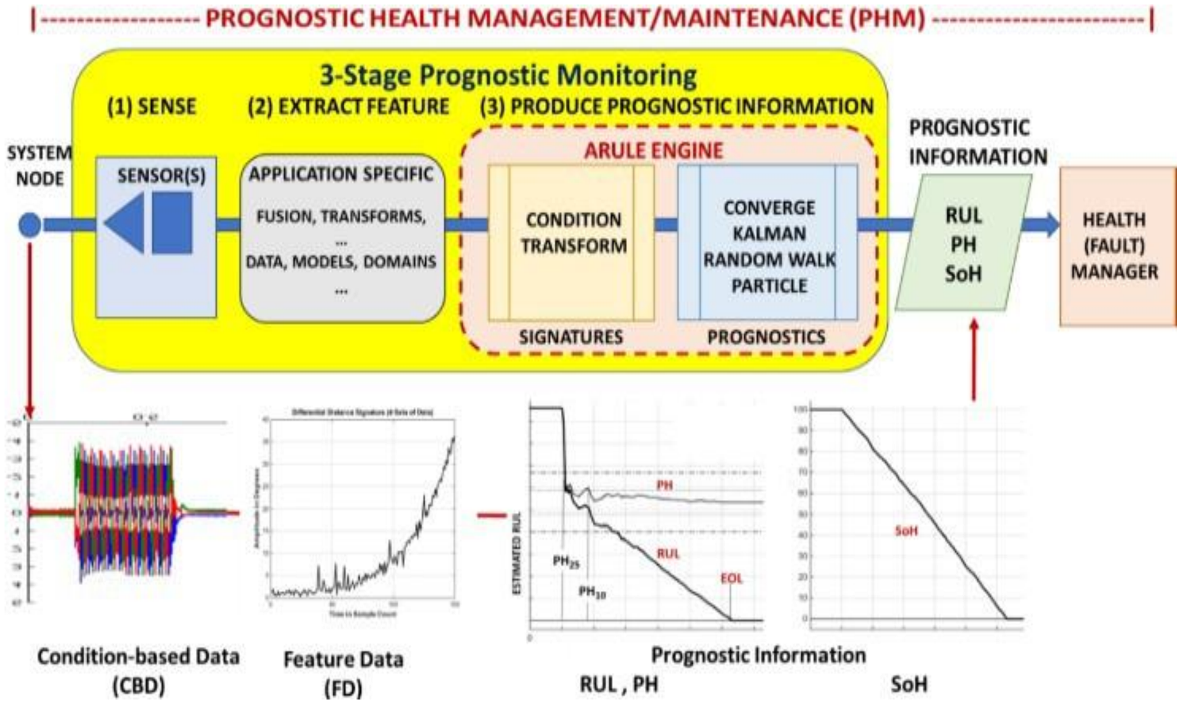


Figure 5.2. Prognostic Health Management Maintenance (PHM) (Original source reference 1-2).

5.20.2. Data Preparation

The data that comes from sensor is so-called the Condition-Based Data (CBD) and such data comprises noise, that need to be extracted to have the feature data. The extraction of noise from CBD is a software task and sometimes performed by the sensors themselves, especially by 'smart' sensors having data-processing capabilities and related firmware. The Feature data is described as:

$$FD = CBD - N \tag{1}$$

Where:

FD = Feature Data
CBD = Conditioned Based data
N = Noise

The next step is to adjust the FD to a smoother shape curves such as Fault Feature progression (FFD) or Degradation Progression Signature (DPS). The FFP is represent as:

$$FFP_i = \frac{FD_i - FD_0}{FD_0} \tag{2}$$

Where:

FD_i = Feature Data in time i
FD_0 = Feature Data in time zero

The Degradation Progression Signature (DPS) is the partial derivate of the Feature data function in each time t that is represented by:

$$DPS_i = \frac{\frac{dg(FD_i)}{dF_0} = FD_i}{FD_0} \qquad (3)$$

The next step is to define the initial Model that will be applied to predict the RUL and SoH. The Kalman Model principle defines three regions of the failure signature with three regions of values in the graph considering the degradation parameter (Axis Y: a1, a2, a3) and time (Axis X: t1, t2, t3) as shows the Figure 5.3. Such regions are selected based on the previous pattern of degradation level and time that can also be defined based on maintenance expert experience. The degradation parameter can be vibration, temperature, humidity. Pressure, rotation, or a combination of different physical parameters.

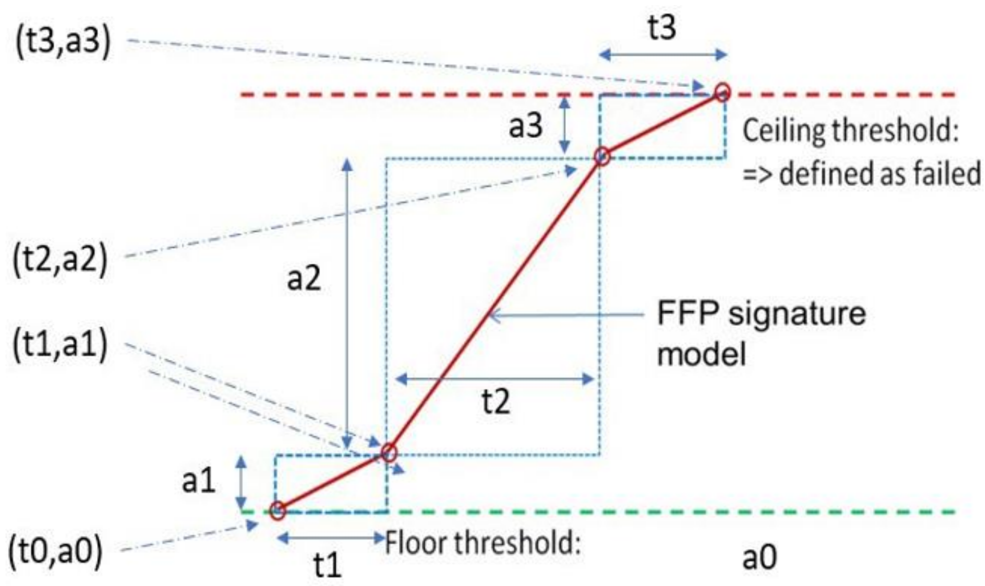


Figure 5.3. Data Space (original source References 1-2).

The next step is to get the sensor data input and chose a model that best fit better on such data. There are different mathematic models such as linear, exponential, power and others that can be used to adjust the FFP or DPS functions as shows the Figure 5.4. The Artificial Intelligence concept is applied for PHM methods whenever the new input data from sensor fulfil the algorithm, then the algorithm chose the best function that fits on the data and perform the RUL and SOH prediction automatically without any human intervention. The Artificial Intelligence algorithm will choose the best function that fit on the data based on accuracy calculation as will be described in the next item.

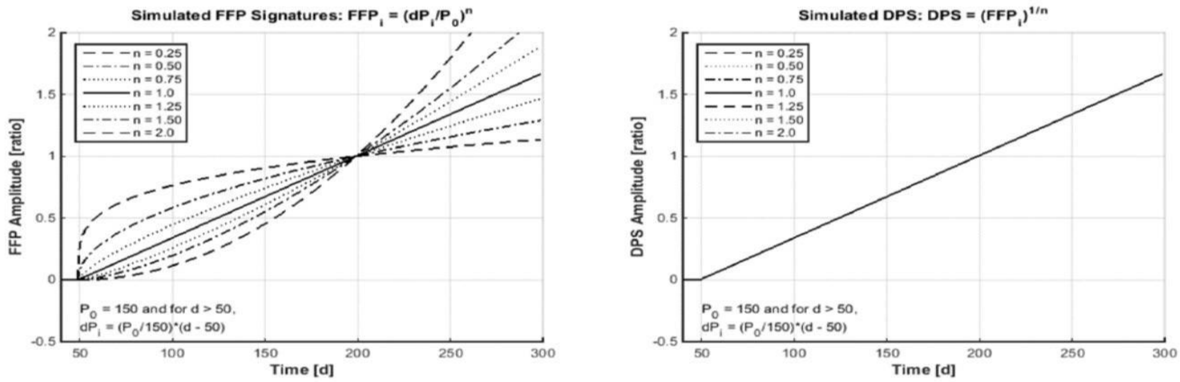


Figure 14. Function set 1, power, model 2: FFP on the left, DPS on the right

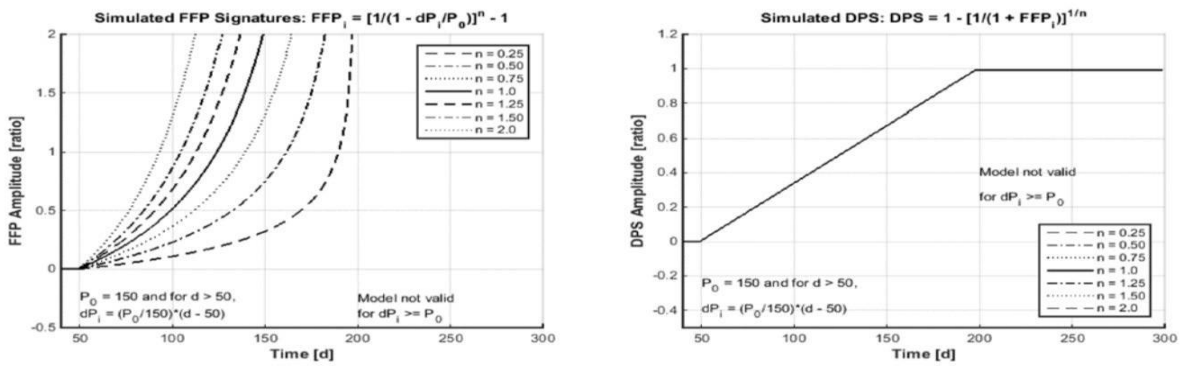


Figure 5.4. FFP and DPS examples (original source reference 1-2).

5.20.3. Remaining Residual Useful Life (RUL) And State of Health (SoH) Estimation

(Adapted from original source reference 2)

After the best function selection, the next step is to predict the RUL and SOH. The RUL is the difference between End of Life (EOL) and the current time (TS) when the data was sampled. The EOL is estimated future time when functional failure is expected to occur. The EOL is usually predicted by reliability engineering studies by using historical data and applying statistical analysis named Lifetime Data Analysis. However, when the equipment/component is operating under high level of stress the EOL will occur shorter on time. That is the main objective of the RUL estimation. The RUL is described as following:

$$RUL_i = EOL_i - TSL_i \tag{4}$$

To produce RUL estimates, a PHM system that uses Condition-Based Data (CBD) is needed to produce degradation signatures that are processed to produce accurate estimates of RUL and SoH for each sampled data as shows the Figure 5.2.

The Figure 5.2 shows an example of linear FFP function that is estimated based on CBD from sensor that measure stress factors parameters such as vibration, temperature, humidity or another parameter. As long as the time past and new CBD comes out from sensors, the RUL is updated.

The Figure 5.5 shows the green line that is represent the usual operation condition where the stress parameter (temperature, vibration, humidity, or another parameter) are under design specification. Above the green line, the stress factor is over the design specification and will reduce the equipment/ component life. The red line is the level of stress that will trigger the equipment/component functional failure. The main objective of the RUL prediction is to alert the maintenance experts about the RUL for the equipment/component achieve the functional failure. That enable them to perform a preventive maintenance action. Despite a great technological solution, whenever multiple equipment has a low RUL its important to maintenance expert to prioritize and plan the most critical equipment to perform a preventive intervention and reduce the System downtime. Such problem will be solved by the Unsupervised Machine Learning models based on cluster data as will be described in the point 6.5.3.

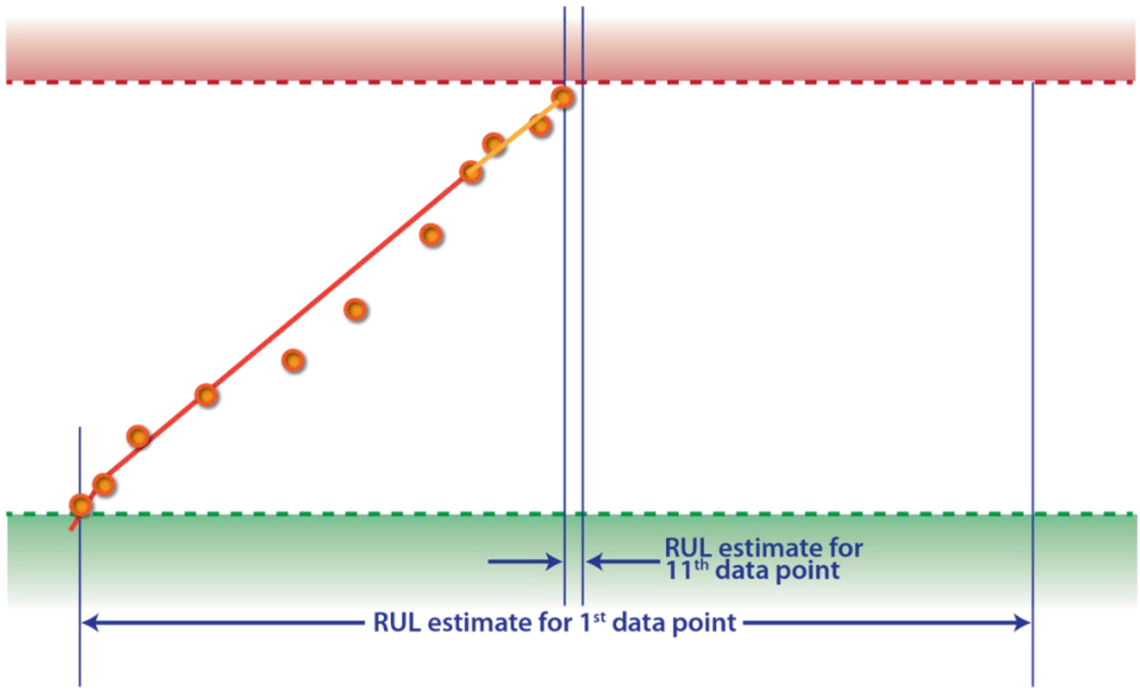


Figure 5.5. Example to produce RUL estimates.

The State of Health (SOH) information is values ranging from 100 % (full health) to 0 % (no health) and is calculated for every data sample as shown in the equation below

The SoH graphic is described in Figure 5.6.

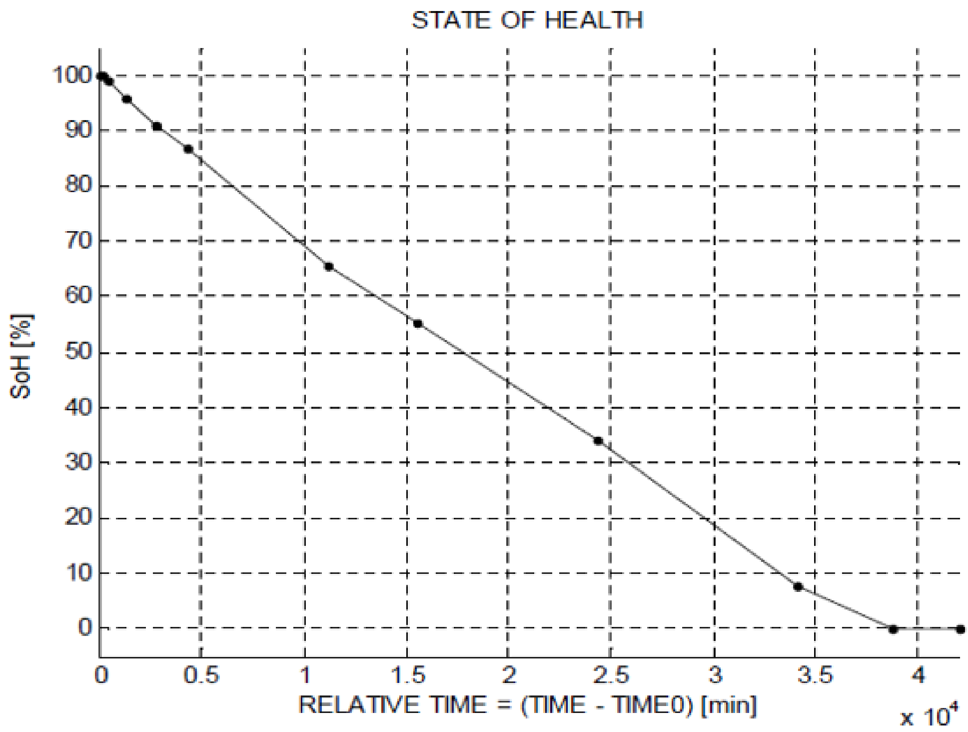


Figure 5.6. State of health prediction (original source reference 2).

The End of Life (EOL) is defined by the equation:

$$EOL_t = PD_t - BD_t * EOL_t = End\ of\ life\ at\ time\ t \tag{5}$$

Where:

PD_t = Prognostic Distance at time t
BD_t = Begining of Degradation at time t

Another important metric that needs to be assessed in PHM is the accuracy of the estimation of RUL. The first metric to be defined is the Differential Non-linearity (DNL). The DNL is a measure of the non-linearity between two adjacent similar values and it is an important specification of the accuracy of data. As applied to RUL and SOH estimates, the DNL at any given time is the difference between the estimated RUL or SOH and the ideal RUL or SOH. Considering the RUL the DNL is described by the equation as.

$$DNL(t) = RUL_{ideal}(t) - RUL_{est}(t) \tag{6}$$

Where:

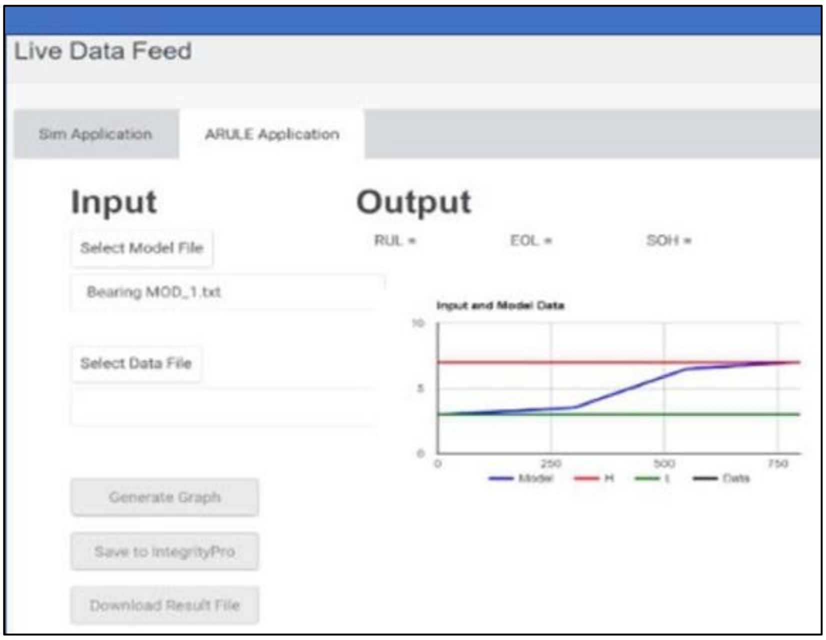
$RUL_{ideal}(t)$ = Initial RUL at time t
$RUL_{est}(t)$ = Estimated RUL at time t

The Accuracy is a measure of how close RUL estimates are to ideal values of RUL that is defined by the table as following:

Table 5.1. *FFP and DSP data from sensor.*

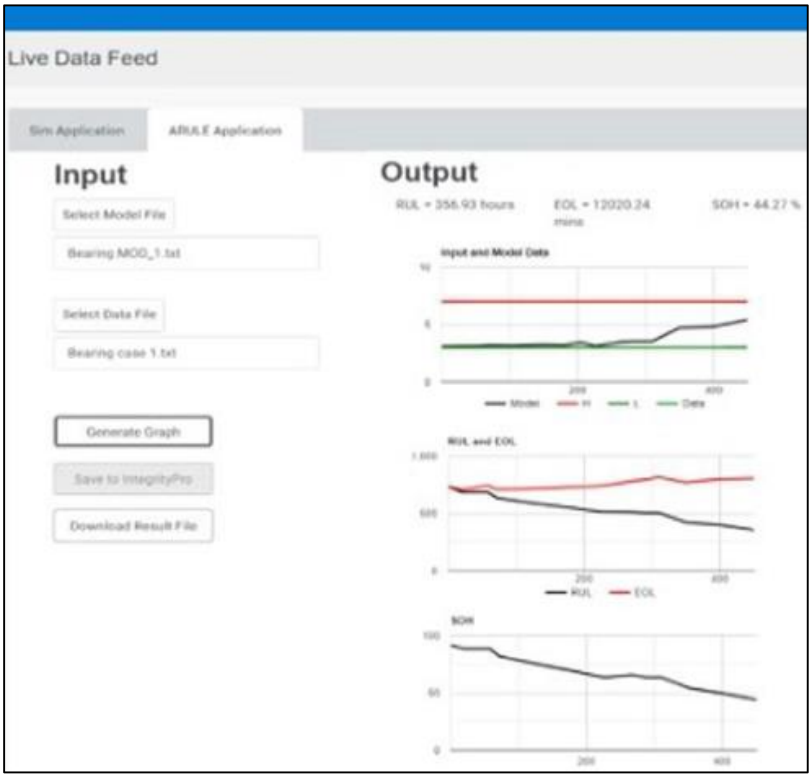
Time	RMS	FFP	DSP
Days	(mm/s)	Ratio	dP/P0
0,7	3,11	0	0,00
20	3,15	0,013	0,03
58	3,16	0,016	0,03
72	3,21	0,031	0,06
106	3,18	0,022	0,04
126	3,22	0,034	0,07
xxx	xxx	xxx	xxx
xxx	xxx	xxx	xxx

The next step is automatic prediction of the RUL, SoH of the pump shaft vibration an automatic updated when new CBD comes from the sensor. The Figure 5.7a shows at first stage, the initial Kalman degradation function based on past historical data. The Figure 5.7b shows the automatic prediction of RUL, SOH and EOL after 500 days. In this time, the RUL is 353 hours, he EOL is 12020 minutes and the SOH is 44.27%. The figure 9C shows the degradation level at 700 days. At this time the RUL is 259 hours, he EOL is 17103 minutes and the SOH is 30.64%. Despite of small reduction on degradation at 700 days the pump´s bearing is close to the functional failure.



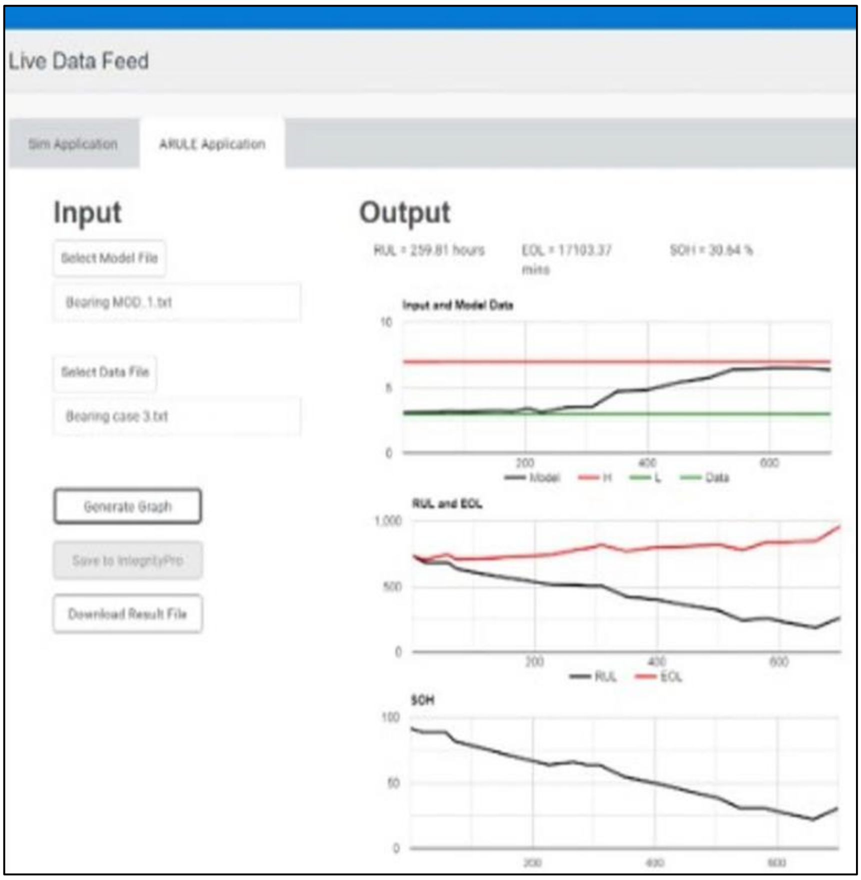
Live Data Feed
Sim Application
ARULE Application
Input
Output
Select Model File
Bearing MOD_1.txt
Select Data File
RUL =
EOL =
SOH =
Input and Model Data
Generate Graph
Save to IntegrityPro
Download Result File

(a)



Live Data Feed
Sim Application
ARULE Application
Input
Output
Select Model File
Bearing MOD_1.txt
Select Data File
Bearing case 1.txt
Generate Graph
Save to IntegrityPro
Download Result File
RUL = 356.93 hours
EOL = 12020.24 mins
SOH = 44.27 %
Input and Model Data
RUL and EOL
SOH

(b)



(c)

Figure 5.7. RUL, SoH, EOL, Real Prediction (Reference 3).

5.21. Machine Learning (ML)

(Adapted from original sources 2 and 4)

The Machine Learning (ML) is an artificial intelligence subject that uses data about individuals' populations, disease, animals and plant samples for research as well as system´s equipment/component and even finance data to perform cluster, classification and prediction based on mathematic models, mostly supported by computer algorithms.

Machine Learning (ML) began to flourish in the 1995 when it changed its focus from achieving artificial intelligence to addressing solvable problems of a practical nature, towards methods and models borrowed from statistics and probability theory as it is the case of Maintenance.

Machine learning is the more utilized technologies on maintenance to transform Big Data in suitable Intelligent Information but can also be applied by using collecting data from predictive maintenance or different source of data an apply different algorithm solution to perform prediction, classification and cluster maintenance data.

Therefore, concerning the maintenance engineering, the machine learning application is applied for the equipment criticality classification, failure regression predictions and the most advanced maintenance strategy, so called Prognostic Health Management, that aims to define equipment Remaining Useful Life (RUL) and State of Health (SoH) based on online monitoring data or non-destructive test by measuring the stressor factors such as vibration, voltage, temperature, humidity and other physical parameter that lead equipment degrade to functional failure. The concepts behind machine learning is about to use the set of knowing the data to cluster, classify or predict future variables response. In order to classify and predict the data response, the machine learning model divides the dataset in the training data (~70% of dataset) and test data (~30% of dataset). The further step is to apply an algorithm to training data for the learning process and then to come out with a model. The model will be applied to the test data and the verification of the result take place. If the result is satisfactory, the new data set can use the same model defined based on the previous dataset to make predictions and if the result is satisfactory the model is validated.

The machine learning can basically be divided into unsupervised machine learning, supervised machine learning, deep learning and reinforcement learning models based on the following definitions.

1. Unsupervised Machine Learning: Aims to define a pattern in the set of data without previous knowledge of data features.

2. Supervised Machine Learning: Aims to classify and predict response based on the known features of the dataset.

The most common Unsupervised Machine Learning models used for clustering are:

1. Principal Component Analysis;
2. Multidimensional Scaling;
3. K-Mean Clustering;
4. Gausian Mixture;
5. Hierarchical Clustering;
6. Neural Network Self-Organized Map

The Supervised Machine Learning is divided in classification and regression models. The Supervised Machine Learning Classification aims to define new data classification (label) based on pre-defined classification knowledge of a previous dataset. The most common example of Supervised Machine Learning Classification methods is the following:

1. K-Nearest Neighbor (KNN);
2. Decision Tree Classification;
3. Naïve Bayes;
4. Linear Discriminant Analysis;
5. Supported Vector Machine Classification;
6. Neural Network Classification;
7. Logistic Regression Classification.

The Supervised Machine Learning Regression model aims to predict the response variable based on predictors considering the pre-defined known dataset. The most common types of Regression Supervised Machine Learning Models are the following:

1. Linear Regression,

2. Ridge & Lasso Regression;
3. Stepwise Linear Regression;
4. Logistic Regression;
5. Decision Tree Regression;
6. Supported Vector Machine Regression;
7. Neural Network Regression.

The Deep Learning methods is a more sophisticated neural network with several hidden layers. The principles of Deep Neural network are the same on the Neural network presented before, but with the complexity to have several hidden networks that will give the final outputs based on the activation functions and weights distributed across the network.

The Deep Learning is applied for image classification that can be very useful for the maintenance application to identify equipment degradation based on image from ultrasound test, radiograph test an infrared test.

The Reinforce Learning is a machine learning method that aims to define the proper sequence of actions based on benefit created by each action. The RL benefit is set up for a pre-defined policy and considering all possible action and constrains under the current and future conditions, where the actions take place. When we apply the reinforce learning to the maintenance context the intention is to define the best sequence of maintenance task considering a group of equipment and their criticality based on classification, RUL, DPS. The maintenance team or maintenance technician is the so-called agent, and the agent will be trained to take the best sequence of maintenance task based on the reward of each action along the simulation. After a period of time, the agent learns the sequence of maintenance tasks that brings the highest reward. The best sequence of maintenance task is defined based on the policy, that is nothing more than subject.

5.21.1. Supervised Machine Learning Regression the Gaussian Model

(Adapted from original source 2, 4.)

5.21.1.1. Introduction

The Supervised Machine Learning Regression (SMLR) has the main objective to predict and forecast future values of dependent variable data based on the independent variables that are equipment/component features of pre-observed dataset. Therefore, it´s applied to predict process variable's value, Remaining Useful Life (RUL), State of Heath (SoH) and other parameters used in the maintenance field. The main advantage of such approach is to predict the parameter values automatically based on current historical data. Therefore, the SMLR models enable to save the huge amount of time dedicated to such activities as well as to link sensor data to PHM models to predict equipment and component RUL and SoH. The most common SMLR models are the following:

1. Linear Regression;
2. Ridge & Lasso Regression;
3. Stepwise Linear Regression;
4. Gaussian Regression;
5. Decision Tree Regression;
6. Support Vector Machine Regression,

7. Neural Network Regression (NNR).

In order to predict the data response, the machine learning model divides the dataset in the training data (~70% of dataset) and test data (~30% of dataset). The further step is to apply an algorithm to training data for the learning process and then to come out with a model. The model will be applied to the test data and the verification of the result take place. If the result is satisfactory, the new data set can use the same model defined based on the previous dataset to make predictions and if the result is satisfactory the model is validated. The general steps of SMLR process are described in Figure 5.8.

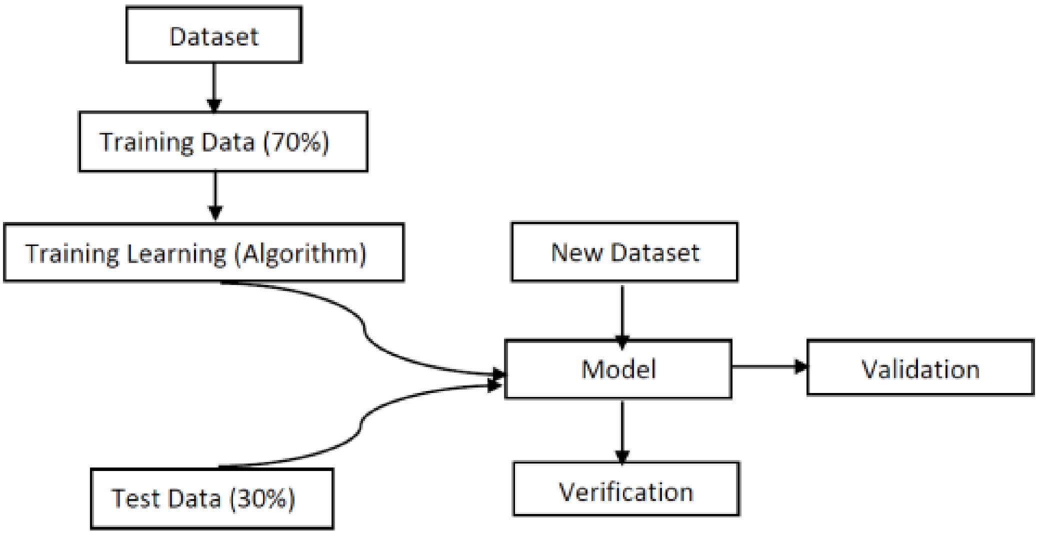


Figure 5.8. General supervised machine learning regression steps.

5.21.1.2. The Gaussian Regression Method

A Gaussian Process regression aims to predict the response value based on the assumption of the dataset belongs to a Gaussian distribution. Therefore, the main assumption of this model is that all data are normal distributed. Concerning the 2D dataset that, $x \in R^n, \sum \in R^{nxn}$.

The Gaussian distribution is defined by the vector with mean and covariance as shown the equation below.

$$f(x\backslash,) = \frac{1}{\sqrt{2|\quad|^{1/2}}} exp\left[-\frac{1}{2}(x-)/\quad{}^{-1}(x-)\right] \tag{7}$$

Where:

x = Reference vector

Escriba aquí la ecuación. = Mean = Covariance vector

Let´s consider now that we need to predict a response variable y given an x predictor value. In this case the equation below will be applied such as:

$$P(y\backslash x,) = \frac{1}{\sqrt{2|\quad|^{1/2}}} exp\left[-\frac{1}{2}(y - \quad ^{*})/ \quad _{*}^{-1}(y - \quad ^{*})\right] \tag{8}$$

Where:

* = Wx

$_{*}$ = Mean = y covariance

$(x, y) = K(x, y) + I \quad _{y}^{2}$

$K(x, y) = \quad ^{2} e^{\frac{-1}{2I^{2}}(x-y)^{2}}$

$K(x, y) = Kernel\ funtion$

I = Control de horizontal length scale

^{2} = Control de vertical length scale

The Gaussian Regression model is the optimization problem that aims to minimize of the horizontal and vertical length scales for infinite vectors defined by their means and covariance while predicting the response y that is defined by:

$$argmax_{I, \quad ^{2}} = P(y\backslash x,) \tag{9}$$

The Figure 5.9 shows the principle of the Gaussian Process Regression model that is applied to predicting the response y given a data points x. Therefore, despite of a measured data point, there is a set of points that produce a Gaussian distribution. It can be understood such as a set of vibration, temperature, humidity, voltage, measured in the same day. Based on such measurements, it's possible to produce a Gaussian Distribution that represents such independent variable. Therefore, the Gaussian Process Regression will produce different of such Gaussian Distribution along time.

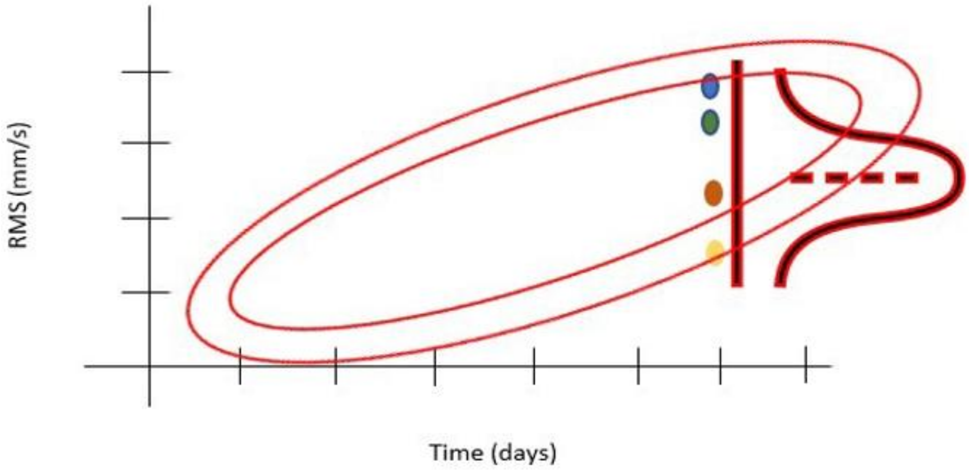


Figure 5.9. Gaussian Regression (Reference 3).

The Figure 5.9 shows an example of Gaussian Process (GP) regression model concept considering the parameter definition values such as vertical and horizontal length as well as the kernel function. The GP regression Model considers the mean, standard deviation and covariance to predict the regression function as described in the Figure 5.10 (A, B, C, D).

Based on the Figure 5.10A to input the data into the GP model the first step is the data collection. Let´s consider as instance, that a measurement of vibration from similar pump´s shafts taking place in different time. Each colour represents the measurement of one specific pump´s shaft vibration. Each pump´s shaft will have one specific regression function based on the measurement taken in different period of time as shown the figure 5.10B.

However, by considering the different pump´s shaft vibration for each measurement time, it´s possible to assume a normal distribution for pump´s shaft vibration, since all such equipment components are similar as shows the Figure 5.10C.

Nevertheless, the final step is to add new pump´s shaft vibration measurement to smooth the regression model standard deviation. By adding new measurement, the shape presented in figure 10c will get a new shape such as presented in Figure 5.10D.

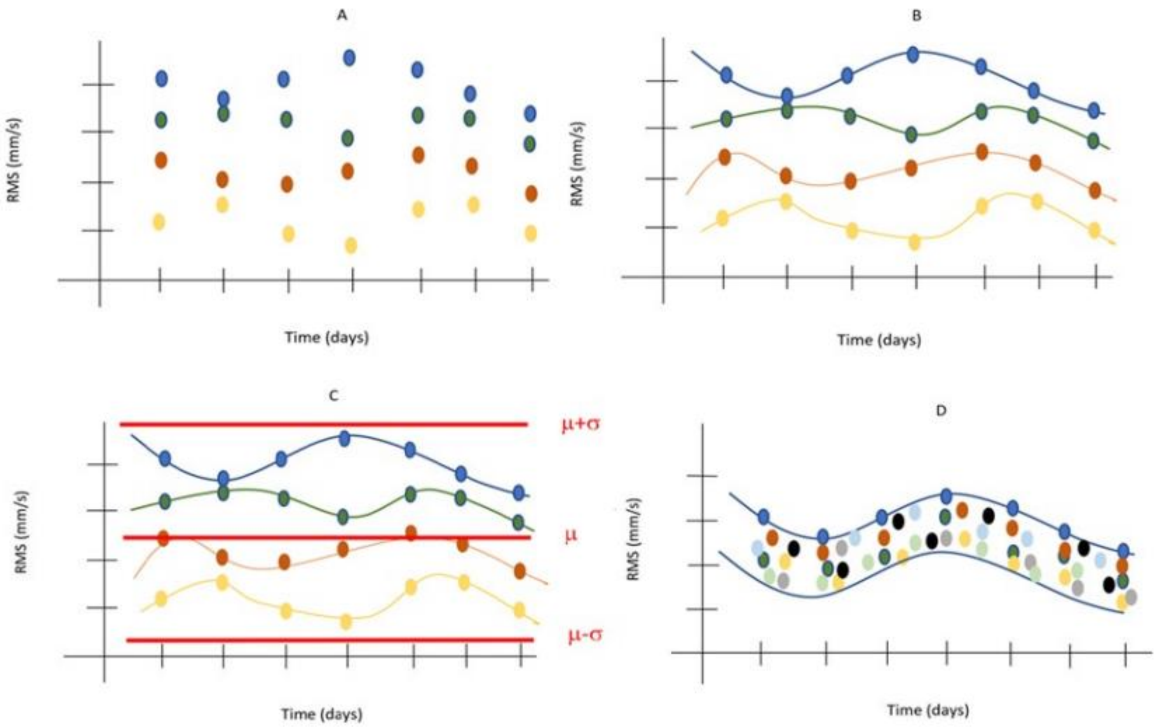


Figure 5.10. Gaussian Process Regression steps (original sources reference 2).

5.21.1.3. The Gaussian Method Applied for RUL Prediction: The Control Room Temperature Case Study

Concerning the maintenance application, the equipment independent variable such as temperature, humidity, rotation, vibration and others variables measured by the sensor as well as degradation measurement such as corrosion, erosion and crack thickness measured by Non-Destructive Test can be used as input for RUL, SOH and other parameter prediction. Therefore, to simplify the understanding about the Gaussian Process regression, let´s consider an example about the computers rooms where high temperature above 50 Celsius can trigger failure in such computer and shutdown the complete database. In order to predict the RUL when the temperature is over than 40 Celsius, sensor capture the temperature in different computers rooms. The Table 5.2 shows on the first and second column, a summary of data from five control rooms where the computer was affected by high temperature and the RUL were calculated based on historical data. The third and fourth columns shows the new.

Table 5.2. *Control Temperature Degradation.*

Old Control Rooms		New Control Room	
Temperature	RUL	Temperature	RUL
43.28	10000	48.78	9504
42.97	9987	48.47	9525
43.03	9974	48.53	9520
42.9	9961	48.4	9530
42.62	9948	48.12	9559
42.64	9935	48.14	9557
42.67	9922	48.17	9555
42.77	9909	48.27	9542
42.95	9896	48.45	9526
43.37	9883	48.87	9499
43.76	9870	49.26	9478
43.91	9857	49.41	9468

The first and second columns values are actually, the set of 99 data of temperature and RUL that are initially used to train the SMLR model that use 70% of such data. The Gaussian Method is chosen based on the comparison of the lowest error (RMSE:256.58) among the other regression methods such as Linear, Tree, SVM, Step Wise and Ridge & Lasso. The Figure 5.11 shows the good fitness of the Gaussian Regression method. The Figure 5.12 shows the prediction of RUL equal to 18 hours (RUL=1064) for the computers functional failure occur at the new computer room.

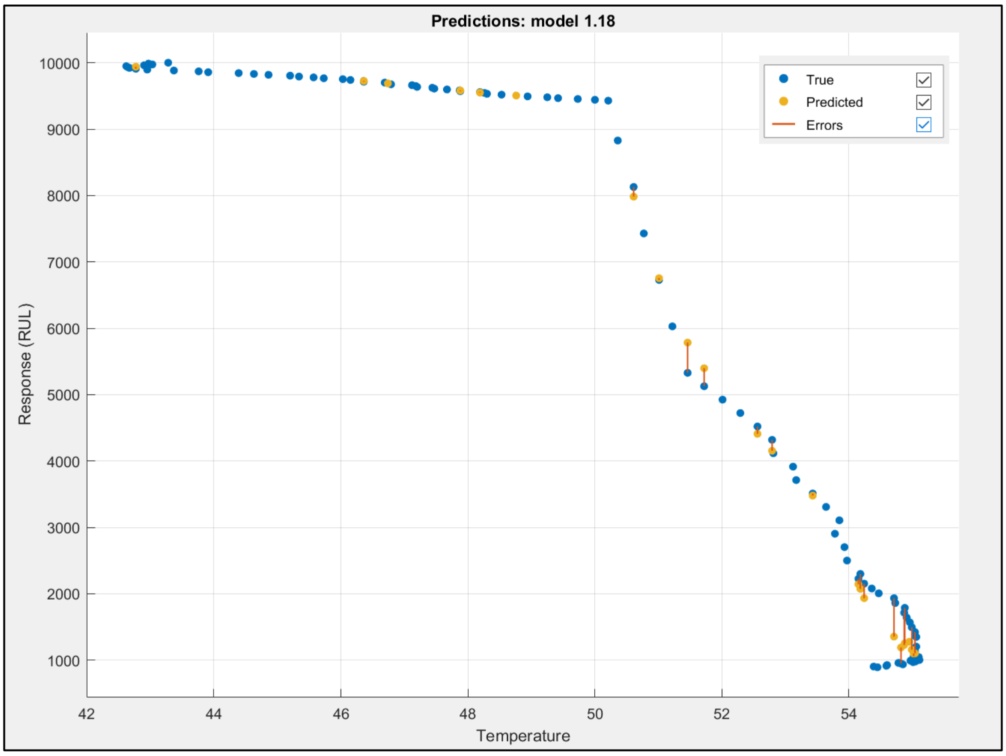


Figure 5.11. Gaussian Regression Training Verification (Reference 3).

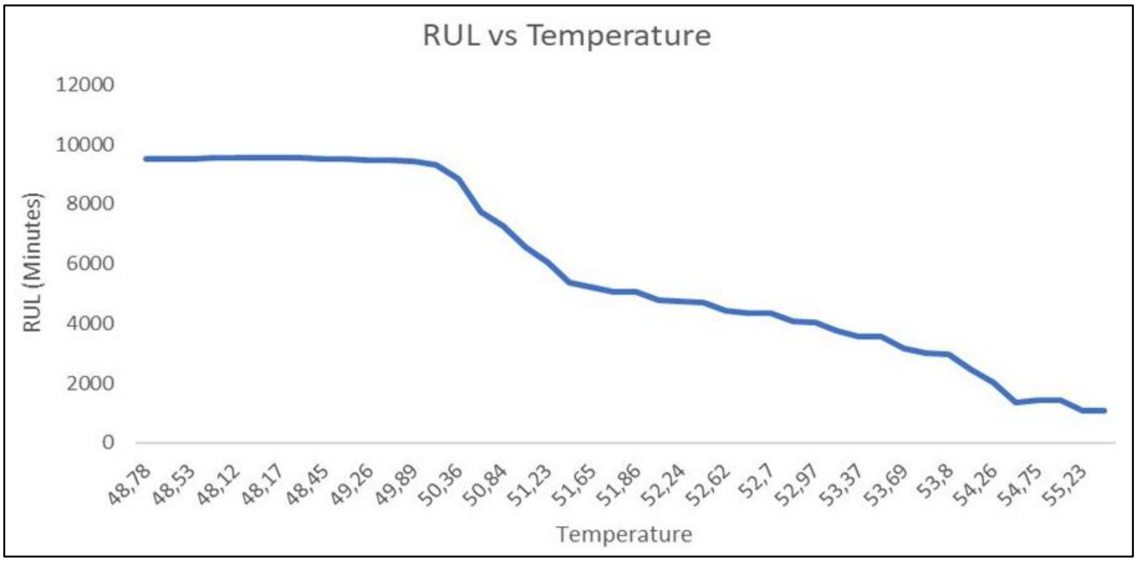


Figure 5.12. Gaussian Process Regression Validation (Original Sources Reference 2).

5.21.2. Supervised Machine Learning Classification: The KNN Model

(Original source reference 2)

5.21.2.1. Introduction

The Supervised Machine Learning Classification (SMLC) has the main objective to classify data based on the features pre-observed in a dataset. Therefore, it´s applied to classify new equipment criticality, risk, high performance, bad actors, and other classification applied in the maintenance field. The main advantage of such approach is to classify a huge number of data based on the SMLC models enable to save the huge amount of time dedicated to such activities as well as to define alarms alert based on equipment and component criticality classification. The most commons SMLC models are the following:

1. K-Nearest Neigh bour (KNN);
2. Decision Tree Classification;
3. Naïve Bayes;
4. Linear Discriminant Analysis;
5. Support Vector Machine;
6. Neural Network Classification;
7. Logistic Regression Classification.

The general steps of Supervised Machine Learning Classification are described in Figure 5.13.

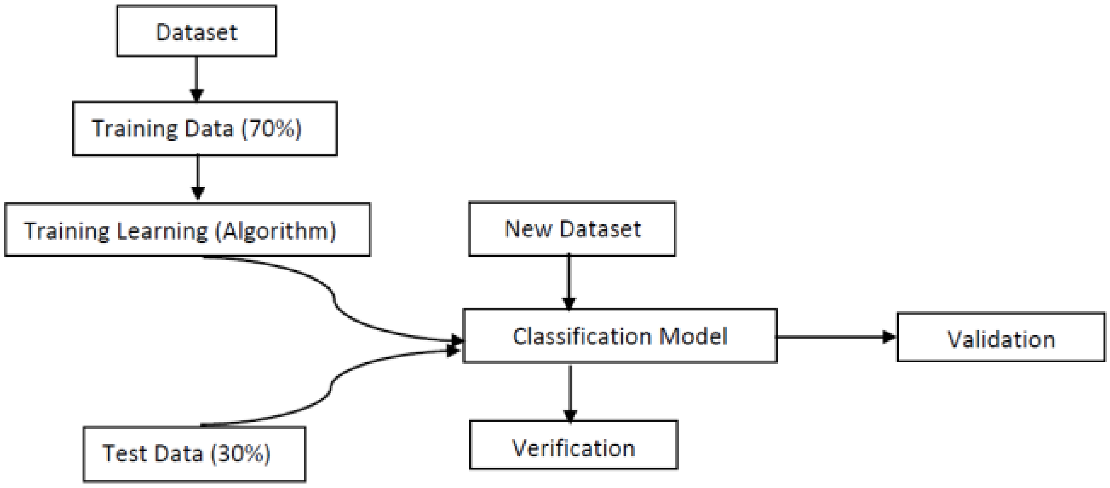


Figure 5.13. General Supervised Machine Learning Classification steps.

Concerning the maintenance application, the equipment characteristic such as criticality, risk, high performance, bad actors, and other classifications enable the maintenance leaders prioritize the equipment. In addition, the SMLC also enable to define alert limit levels to be part of to the PHM program.

5.21.2.2. The KNN Model

The K-Nearest Neighbours (KNN) method is a type of Supervised Machine Learning Classification (SMLC) method, that can be applied to equipment data classification for the maintenance management decision support. The KNN aims to classify a new data considering a set of data already classified based on previous dataset. Therefore, the new data are compared to the K closest point base on the distance between data points. The new data will be classified based on the same class that the closest point belongs.

In order to define the distance among the k Neighbours point, the distance can be calculated based on Euclidian distance, Manhattan Distance or Minlowski distance as the following equations:

$$Euclidian\ Distance = \sqrt{\sum_{i=1}^{K}(X_i - Y_i)^2} \tag{10}$$

Or

$$Manhattan\ Distance = \sqrt{\sum_{i=1}^{K}|X_i - Y_i|} \tag{11}$$

Or

$$Minlowski\ Distance = \left[\sqrt{\sum_{i=1}^{K}(X_i - Y_i)^q}\ \right]^{\frac{1}{q}} \quad (12)$$

Considering a positive integer number K = 1, 2, 3… N, that´s defined the number of nearest points used to classify a new data point. Therefore, the new data point x and a distance metric “d”, the K-NN model are performed based on the following:

1. The distance “d” between the x and each observation of the training data set.
2. The probability of each class that is the fraction of the point in I with that given class label.

The probability is defined by the equation below.

$$P(y = j \backslash X = x) = \frac{1}{K}\sum_{i \in A} I\left(y^{(i)} = j\right) \quad (13)$$

Where, I(x) is the indicator of the function, which evaluates when the argument x is true and 0 otherwise. Then, the new point x is assigned to the class with larger probability.

In order to exemplify the KNN model, let´s consider the list of pumps bearing that are classified as critical medium or low based on the level of DPS and RUL, concerning the bearing vibration, as shows the Table 5.3. In order to demonstrate the K-NN model application for perform automatic classification o criticality of any pump´s bearing, first the model will be trained based on the data provided in Table 3, and after that, the verification and validation will take place considering the accuracy of the KNN model for the provided data.

__Table 5.3.__ Pump´s bearing vibration degradation.

	RMS (mm/s)	DPS (%)	RUL (Months)	Criticality
Pump 1	3.000	0.400	11.000	L
Pump 2	3.500	0.300	12.000	L
Pump 3	4.000	0.350	10.000	L
Pump 1	5.100	0.500	8.000	M
Pump 2	5.500	0.450	7.000	M
Pump 3	5.300	0.400	6.000	M
Pump 1	5.700	0.800	3.000	M
Pump 2	6.500	0.850	2.000	C
Pump 3	6.700	0.900	1.000	C
Pump 1	2.500	0.350	10.500	L
Pump 2	3.000	0.250	11.500	L
Pump 3	3.500	0.300	9.500	L
Pump 1	4.600	0.450	7.500	M
Pump 2	5.000	0.400	6.500	M
Pump 3	4.800	0.350	5.500	M
Pump 1	5.200	0.750	2.500	M
Pump 2	6.000	0.800	1.500	C
Pump 3	6.200	0.850	0.500	C
Pump 1	3.300	0.450	11.500	L
Pump 2	3.800	0.350	12.500	L
Pump 3	4.300	0.400	10.500	L
Pump 1	5.400	0.550	8.500	M
Pump 2	5.800	0.500	7.500	M
Pump 3	5.600	0.450	6.500	M
Pump 1	6.000	0.850	3.500	C
Pump 2	6.800	0.900	2.500	C
Pump 3	7.000	0.950	1.500	C

The Figure 5.14 shows the result of KNN classification defined by the MATLAB software. The Points A1and A2 up on the left side in the graph shows the pump´s with highest criticality (C) based on the highest DPS (85% DPS 90%) and Lowest RUL (0.5 month RUL 1 month). The Points B1 and B2 represent the medium criticality (M) assigned to pump´s bearing with medium DPS (50% DPS 75%) and medium RUL (8 month RUL 9 month), The points C1 and C2 are assigned to the pump´s with lowest DPS (25% DPS 40%) and highest RUL (10 month RUL 12 month).

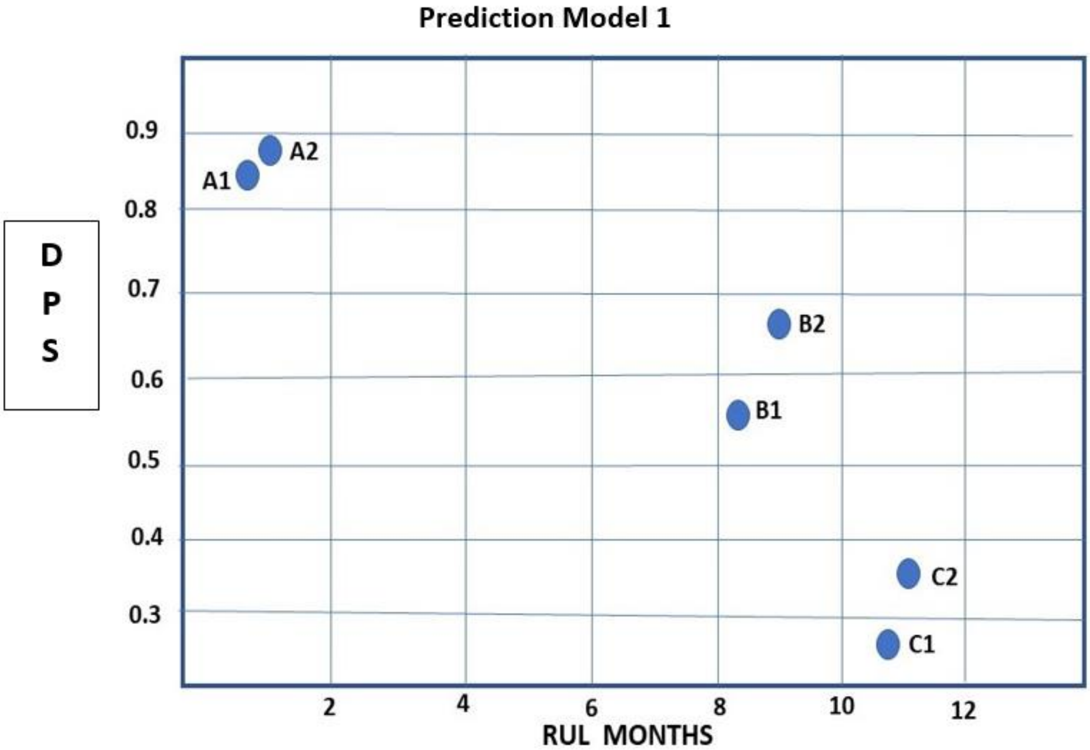


Figure 5.14. K-NN Pump´s bearing Criticality Classification (Reference 3).

In order to verify the K-NN model criticality classification consistence, the SMLC approach has some graph methods to show the adherence of the model result, such as Confusion Matrix and Receiver Operation Characteristic Curve (ROC).

The confusion matrix, or error matrix, shows the percentage of proper classification considering all classification possibilities. The type of classification in the confusion matrix is defined as follows:

1. True positive: The number of predicted positive variables that is positive based on real classification.

2. False positive: The number of predicted positive variables that is negative based on real classification.

3. True negative: The number of predicted negative variables that is negative based on real classification.

4. False negative: The number of predicted negative variables that is positive base on real classification

Depends upon the characteristic of the classification problem, there will not be all types of categories described above in the Confusion Matrix. In the case of pumps´ bearing criticality classification, there are the true positive classification that is the input of the main diagonal in the matrix as shows the Figure 5.14 and one false negative classification. The C (Critical) has 2 true classifications, the L (Low) has 2 true classifications and the M (Medium) had 3 true classifications as shows the Figure 5.15. In addition, there is one false negative that is predicted as M (Medium) but is reality is C (Critical).

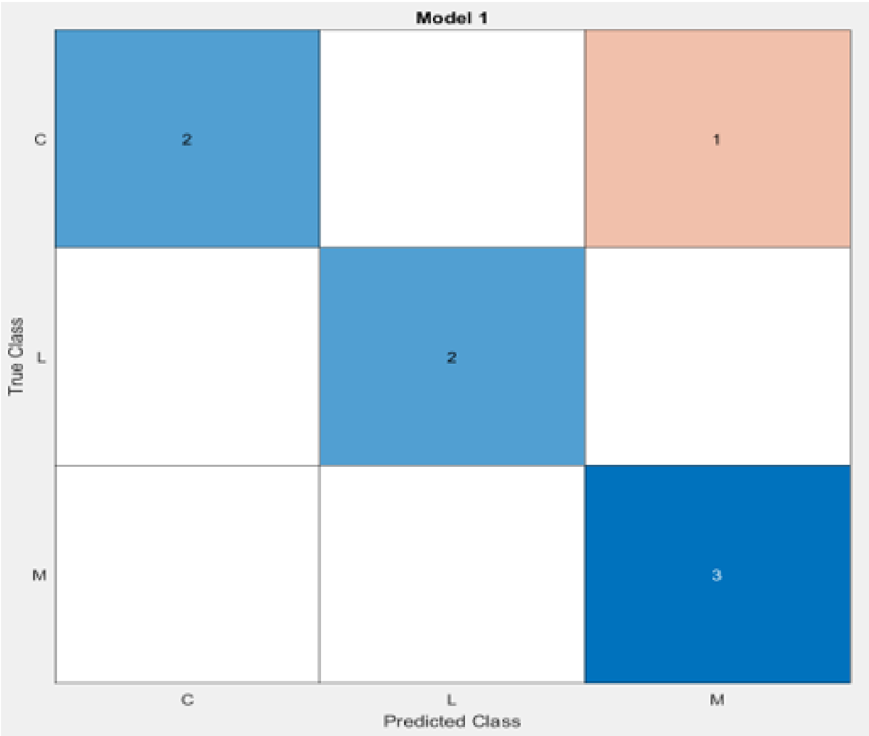


Figure 5.15. Confusion Matrix (Source: Reference 3).

In fact, if thousands or millions of data are applied as training data, there will be a high possibility to have other types of categories in the confusion matrix such as false positive, true negative and false negative.

In order to verify the SMLC performance, the KNN model results some indexes such as accuracy, recall and precision. The accuracy can be defined as the ratio of true prediction (TP+ TN) divided by all classifications (TP + TN + FP + FN) as shows the equation below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

By applying this equation based on the Confusion Matrix result described in the Figure 5.4 we have:

$$Accuracy = \frac{7 + 0}{7 + 0 + 0 + 1} = 87{,}5\%$$

The recall can be defined as the ratio of the total number of true positive divided by the total number of true positive and false negative classified.

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

By applying this equation based on the Confusion Matrix result described in the Figure 5.4 we have:

$$Recall = \frac{7}{7 + 1} = 85{,}7\%$$

Finally, the precision is defined as the ratio of the total number of true positive by the total number of true positive plus false positive.

$$Precision = \frac{TP}{TP + FP} \tag{16}$$

By applying this equation based on the Confusion Matrix result described in the Figure 5.4 we have:

$$Precision = \frac{7}{7 + 0} = 100\%$$

The second verification method is the so-called "Receiver Operation Characteristic Curve (ROC)". This graph shows the performance of the classification model considering True Positive Rate against False Positive rate in different classification threshold limits. The ROC graph is plotted based on true positive rate and False Positive Rate.

True Positive Rate (TPR) is defined as the ratio of the total number of true positive divided by the total number of true positive plus false negative.

$$TPR = \frac{TP}{TP + FN} = \frac{7}{7 + 1} = 85,7\% \tag{17}$$

The False Positive Rate (FPR) is defined as the ratio of the total number of false positive divided by the total number of false positive plus true negative classified.

$$FPR = \frac{FP}{FP + TN} = \frac{0}{0 + 0} = 0\% \tag{18}$$

Therefore, the Area Under ROC curve (AUC) shows the probability that the models predict positive classification higher than negative classification. The AUC ranges from 0 to 1, being 1 the best case (100% correct prediction) and zero the worst case (100% false prediction). The Figure 5.16 shows the ROC applied to the equipment criticality example, with AUC =83%.

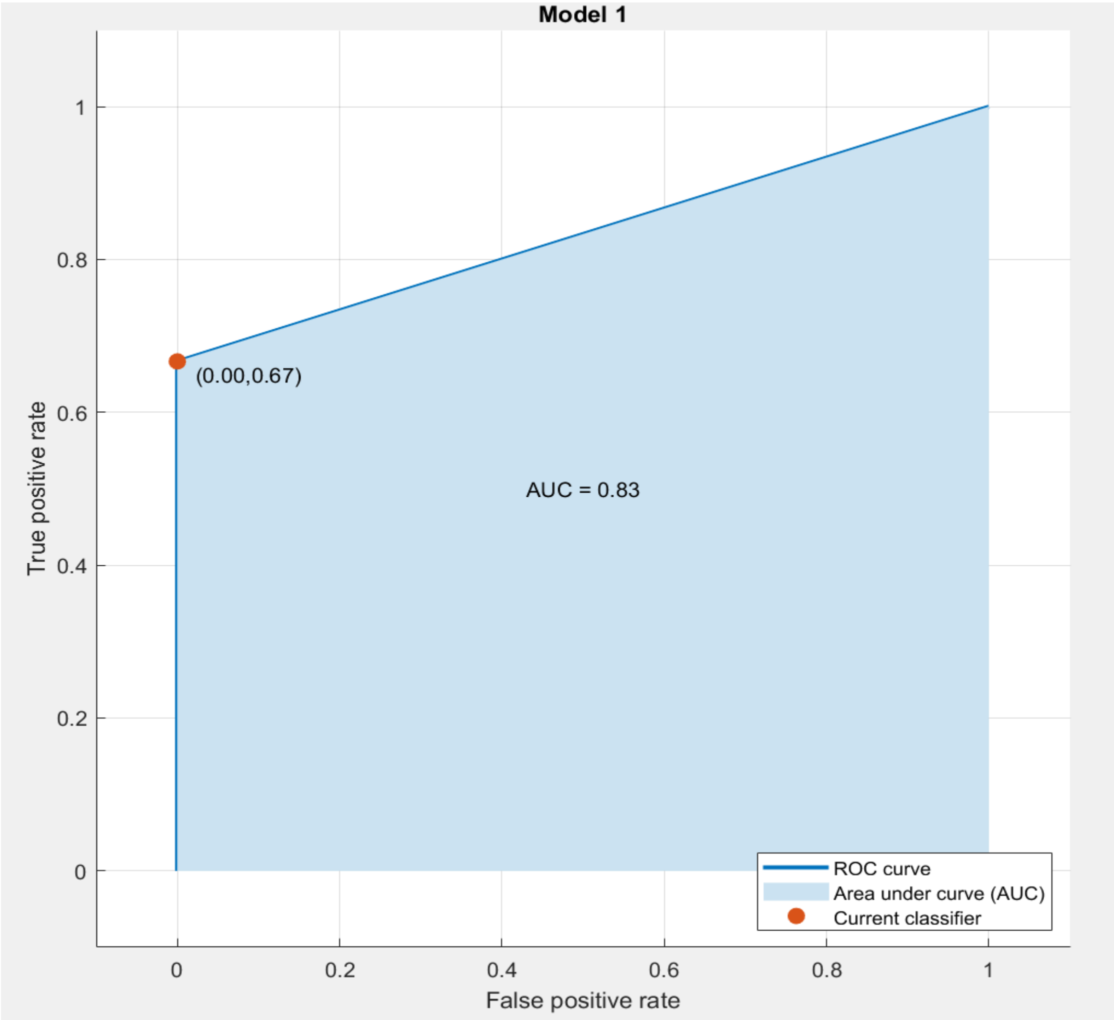


Figure 5.16. Area Under ROC Curve (AUC) (reference 2).

Based on the result of the Confusion Matrix and ROC, that means, accuracy, recall, precision and ROC indexes, it´s possible to compare the K-NN methods result with other methods to define, which are the best SMLC method when considering the same Pump´s bearing input data.

It is important to be aware that the model that achieves 100% accuracy and 100% ROC can be over fitted to the training input data.

That means, if the model is over fitted, probably it will not achieve good accuracy when the other similar Pump bearing data are applied to the SMLC model and that is the challenge of the machine learning models.

The validation of the K-NN model can be demonstrated by applying the algorithm defined in the first pump´s bearing dataset (Training data – Model - Test data – New Data - Validation) to another pump´s bearing dataset from another similar pump.

The K-NN advantages are:

1. Quite simple to implement.
2. Robust regarding the space distribution of the data.
3. Simple classifier update.
4. Only distance metric and k as parameters to adjust.

The K-NN Drawback are:

1. Expensive testing of each new point classification, as we need to compute its distance to all K nearest points.
2. Sensitiveness to noisy or irrelevant attributes.
3. Sensitiveness to very unbalanced datasets.

5.21.3. Unsupervised Machine Learning Cluster: The K Means Mode

(Adapted from original source 2)

5.21.3.1. Introduction

The Unsupervised Machine Learning aims to define a pattern in the set of data without previous knowledge of data features. Therefore, the first understanding of your data set can start by applying the Unsupervised Machine Learning methods to understand the how your dataset can be organized and if there´s a pattern of such dataset based on their independent variable features.

The concepts behind Unsupervised Machine Learning is cluster a set of data without previous knowledge about such dataset. In order to cluster the data, the Unsupervised Machine Learning models the dataset and try to organize it in a cluster. The further step verifies the result based on error and finally, If the result is satisfactory, the new data set can use the model defined based on the previous model and if the result is satisfactory the model is validated.

The general steps of the machine learning process are described in Figure 5.17.

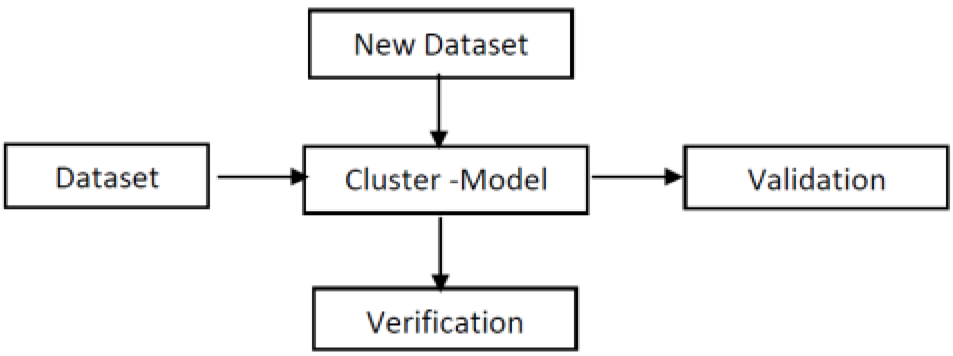


Figure 5.17. General Unsupervised Machine Learning Steps.

Concerning the maintenance engineering, the type of data related to equipment encompasses physical characteristics as well as performance, cost of operations, cost of preventive maintenance, corrective maintenance, spare parts cost. Therefore, by defining some of such variables, it's possible to group equipment with similar characteristics.

5.21.3.2. The K Means Model

The K-Means clustering method is an Unsupervised Machine Learning method for data clustering. The K-Means objective is to organize a set of data point in k different clusters considering the k different centroids and group the data closest to each k centroids. The K means algorithm follows the further steps:

1. To define the value of K, that means, the number of clusters that the data set will be organized.

2. To define a random centroid point to start the clustering process.

3. To calculate the minimum distance between the closest points, close to centroids.

4. To organize the dataset point based on the nearest points closest to each centroid.

5. Update the centroid point based on average positions of each group of data.

6. To define the new centroids and run the process again. Compare the minimum distance between the centroids and the points inside each cluster.

In order to define the distance among the k neighbours point, the distance can be calculated based on Euclidian distance, Manhattan Distance or Minlowski distances the following equations:

$$Euclidian\ Distance = \sqrt{\sum_{i=1}^{K}(X_i - Y_i)^2} \tag{19}$$

Or

$$Manhattan\ Distance = \sqrt{\sum_{i=1}^{K}|X_i - Y_i|} \tag{20}$$

Or

$$Minlowski\ Distance = \left[\sqrt{\sum_{i=1}^{K}(X_i - Y_i)^q}\ \right]^{\frac{1}{q}} \tag{21}$$

To assign n data points (x_1, x_2, x_3 ... x_n) to a j clusters (c_1, c_2, c_3 ... c_j).

By defining the center of the cluster μ_j for the specific j^{th} cluster, where:

$$\mu_j = \frac{1}{\lceil c_j \rceil} \sum_{x_i \in c_j} x_i \tag{22}$$

Then, minimize the distance between the data point and the cluster center represented by the function J,

$$J = \sum_{j=1}^{k} \sum_{x_i \in c_j} \left\| x_i - \mu_j \right\|^2 \tag{23}$$

This process will repeat based on the number of interactions defined or when the center of the cluster does not change significantly anymore.

The best centroid points are the one that the cluster data has the minimum distance to each centroid and chose the centroids with the minimum distance as shows Figure 5.18.

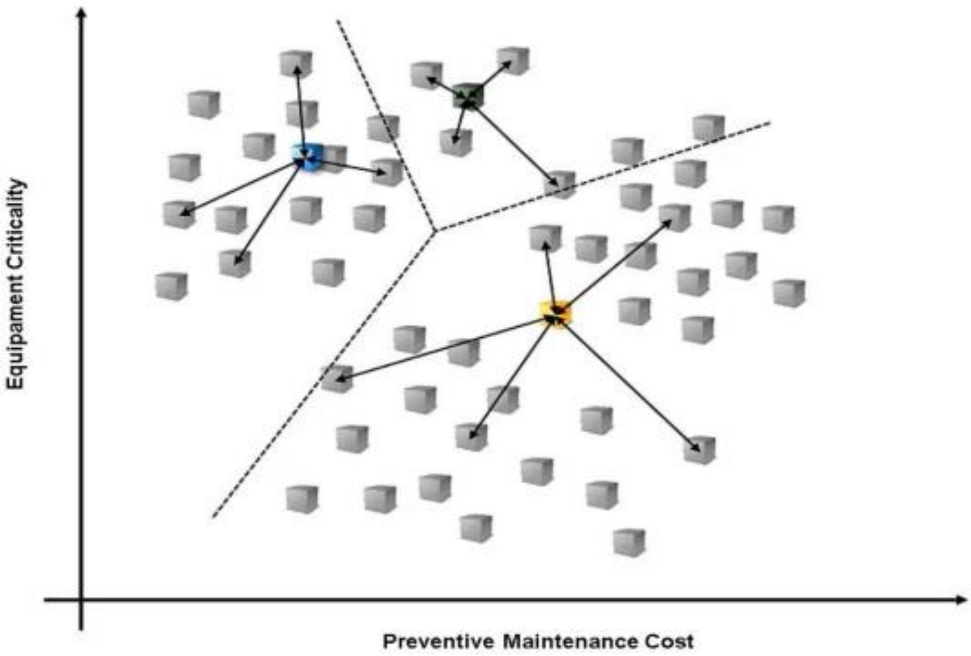


Figure 5.18. K-Means Centroids (Adapted from original sources 2, 3).

In order to practice the K-Means concepts, we can group the equipment of a different clusters based on the variables such as criticality, RUL, DPS, Maintenance Cost and others. Such application is very important for the maintenance domain because enable to define a maintenance schedule agenda based on different criteria defined as data variables.

Concerning the PHM, the K means cluster can be a very good solution for this type of problem, where a group of equipment need to be planned for preventive intervention based on the result of the RUL and DPS prediction as a result of PHM assessment in several equipment. The Table 2 shows the summary of the twenty-four Refineries Coolers Fans bearing with different Degradation Progression Signature (DPS %) based on vibration degradation and Remaining Useful Life (RUL Months). Based On initial PHM result.

Table 5.4. *Heat Exchanger Fan bearing Vibration degradation.*

Time (Days)	DPS (%)	RUL (Months)
Fan 11	0.21	12.6
Fan 12	0.22	11.55
Fan 53	0.22	11.34
Fan 14	0.23	10.11
Fan 63	0.22	9.66
Fan 22	0.26	9.45
Fan 42	0.31	7.41
Fan 24	0.32	7.38
Fan 31	0.29	7.35
Fan 32	0.33	7.32
Fan 62	0.35	7.29
Fan 34	0.36	6.12
Fan 41	0.39	5.88
Fan 23	0.43	4.25
Fan 64	0.44	3.92
Fan 44	0.52	2.32
Fan 51	0.56	2.21
Fan 52	0.78	2.16
Fan 13	0.81	1.72
Fan 54	0.97	1.68
Fan 61	0.97	1.71
Fan 33	0.97	1.66
Fan 21	0.98	1.65
Fan 43	0.98	1.23

In order to implement the K-Means method the MATLAB software is applied as shows the Table 5.5. The K-Means cluster result is demonstrated in the Figure 5.18, where the data is organized is K= 3 clusters.

Table 5.5. *KNN Matlab Code (Adapted from original source reference 4).*

Command Window

```
>> A = Fan;
>> B = table2array(A);
>> grp = kmeans(B,3,'Replicate',5);
>> scatter(B(:,1),B(:,2),5,grp)
fx >>
```

Workspace

Name	Value	Max
A	24x2 table	
B	24x2 double	12.6000
Fan	24x2 table	
grp	24x1 double	3

The K-Means cluster enable a fast and precise cluster of the group of Cooler Fans with different values of DPS and RUL described. The Figure 19 shows the different clusters by different colours such as purple, yellow and blue.

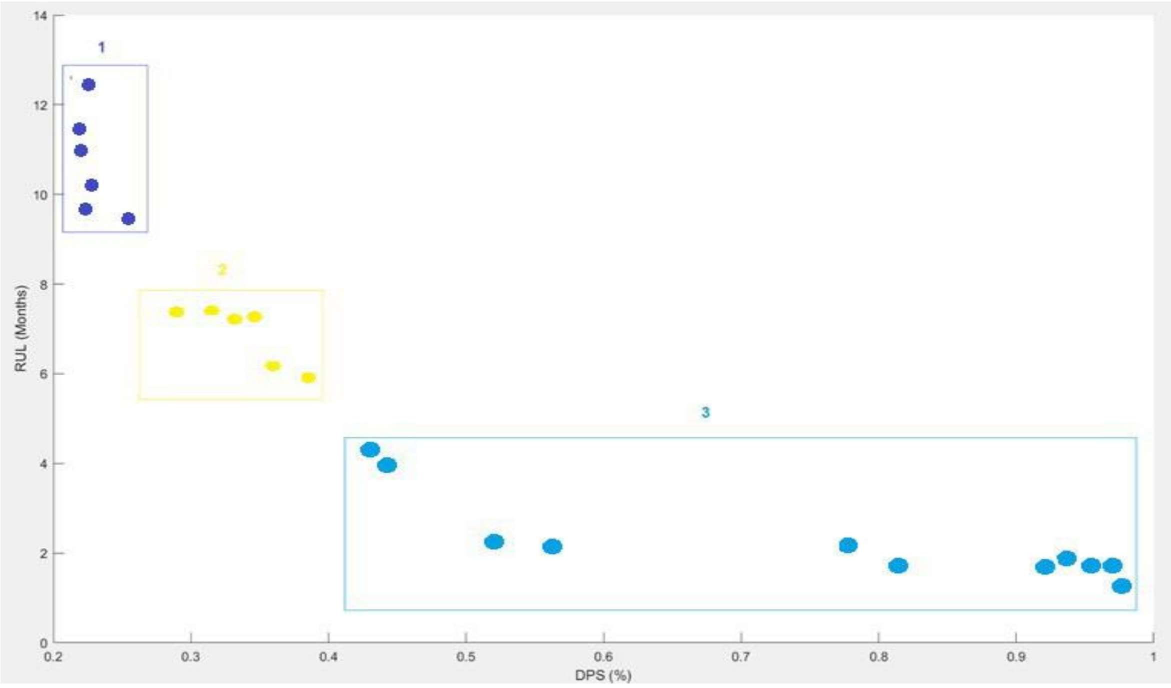


Figure 5.19. K-means cluster results (adapted from original source reference 4).

The cluster 1, on the top on the left side marked by purple colour represents the fan´s bearing with highest RUL (9 months RUL 13 months) and lowest DPS (20% DPS 30%).

The cluster 2, in the middle marked by yellow colour represent the fan´s bearing with medium RUL (5.5 months RUL 6months) and Medium DPS (25% RMS 40%).

The cluster 3, in the left low corner marked by light blue colour represent the fan´s bearing with the lowest RUL (4.5 months RUL 1 month) and medium to high values of DPS (40% RMS 99%). Therefore, the K-means methods, clustering demonstrate that, the most critical fan´s bearing belongs to the cluster 3, and the ones with highest degradation (70%) and lowest RUL (1 month) in the right high low corner of the graph must be the priority for the maintenance team in the current month.

In this case, the K-Means methodology enables to give an automatic response of the group of equipment that needs intervention considering the PS and RUL.

Since the PHM results applied to the Fan´s bearing RUL prediction (or other equipment) is totally dynamic on time, whenever new values of DPS and RUL comes out, the K-Means will cluster the equipment in different groups and set up a new time of preventive interventions for each group of equipment in each cluster. Now imagine how the challenge is for the maintenance team to plan hundreds of equipment under the PHM program that will produce different RUL every day. The K-Means cluster solve this issue and make easier the maintenance team maintenance planning in daily, week and month basis. Therefore, the K- means algorithm in the end need to be integrated with the Asset Management Digital solution. That's what I call Asset Management Intelligence.

The K-Means advantages are:

1. Simple understanding and application.
2. K-means works fine when the cluster data is circular.
3. Good result conversion.
4. Easy to adapt to new examples of the dataset.

The K-Means drawbacks are:

1. The initial K values have a high influence on the clustering result.
2. K-means does not account for variance.
3. K-means does not work fine when the cluster data is not circular.
4. K-means tells us what data point belong to which cluster, but won't provide us with the probability that a given data point belong to each of possible clusters.
5. Centroids can be influenced by outliers.
6. Outliers might get their own cluster instead of being ignored.
7. In higher dimensional space the centroid definition becomes more complex and unclear.

5.22. Deep Learning: Image Classification

(Adopted from original sources reference 3, 4, 9)

The Deep Learning methods is a more sophisticated neural network with several hidden layers. The principles of Deep Neural network are the same on the Neural network presented before, but with the complexity to have several hidden networks that will give the final outputs based on the activation functions and weights distributed across the network. The advantages of Deep Neural network when compared with Neural network are the following:

1. Deep learning models are capable of creating new features by themselves.
2. Deep learning is able to work with unstructured data such as figures and text very well.
3. Deep learning is precise and produce reliable results.

Some current application of deep learning in the real world is speech translation, object detection and identification application used by car in their safety functions.

Despite of all such advantages, the principle of neural network remains the same as described before. However, the evolution of Deep Neural Network is the so called "Convolutional Neural Network (CNN)", which the main objective is to classify images.

The "Convolutional Neural Network (CNN)" is similar to the neural network in principle but has a more robust concept. Since the CNN aims to classify images, the structure of the CNN is quite complex with different types of layer as shown the fig. 21. The elements of CNN are the following:

1. Input Image.
2. Convolution Layer.
3. Pooling Layer.
4. ReLu.
5. Fully Connected.
6. Softmax.
7. Output Classification.

The CCN receive the input image and send the image throughout the different CNN layers to define an image classification in the end. The image is represented initially in pixels matrix and based on filter´s matrixes, such input matrix is transformed in smaller matrix. The next step is to decode the smaller matrix and classify the image. This process is performed step by step by the different CNN layers listed above as shows the Figure 5.20 The Input Image can be the figure of the equipment or product that we want to identify as defected or not or even figures that describe equipment degradation based on graphical representation of SOH or RUL.

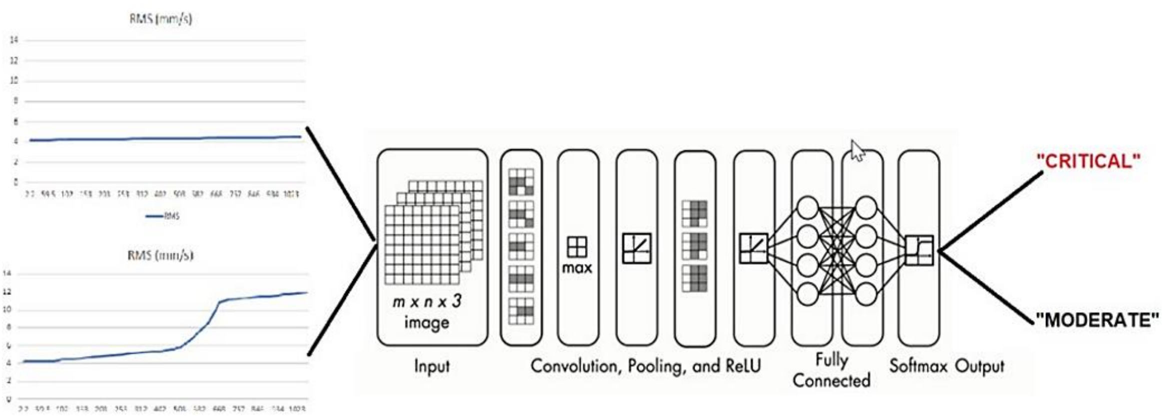


Figure 5.20. CNN Structure (RUL Classification) (adapted from original sources 2, 4).

The picture is loaded and input in the CNN software solution and have its intrinsic characteristic concerning the number of pixels. There´s a different of representation of black and white picture, that is represented by a matrix $n\ x\ m$ or a colour matrix that is represented by $m\ x\ n\ x$ 3. The number 3 means three basic colours such as Red, Blue and Green (RBG), that combined generate the colour of the picture.

5.23. Natural Language Processing

Natural Language Processing is an interdisciplinary research field that embraces computer science, artificial intelligence and linguistics, its aim is to develop algorithms capable of analysing, representing and therefore "understanding" natural language, written or spoken, in a similar or even more performing way than humans.

The deep learning, through the combination of word embedding and convolutional and recurrent networks, represents the most adopted approach to address problems related to the processing and understanding of natural language, in the industrial field, taking the form of products and applications, to better learn the evolution of the physical state of the components in an advanced perspective of prognostics,

5.24. Computer Vision

Computer Vision, or artificial vision, is that interdisciplinary field of study that deals with understanding how computers can reproduce processes and activities, acquire static or moving images, recognize them and extract information through "Digital image Processing."

The artificial vision has many applications:

1. The recognition of environments and objects by remote sensing.

2. Allows remote environment and object monitoring.

3. Safety in the workplace: systems to monitor images of the plant, workers and their actions, in order to identify any risk situations and / or accidents harmful to people or the environment.

4. Scanning of codes in QR Code.

5. Usual serving, which controls the movement of machines, production lines, and operations.

6. Autonomous cars driving thanks to visual sensors.

7. Vision systems that can effectively carry out Predictive Maintenance inspection of components of machines and plants for an assessment of the progressive conditions of degradation.

8. Computer Vision algorithms for monitoring industrial assets - mainly machinery - with a view to evaluate the preventive maintenance actions.

9. Quality control systems and analysis of any product defects, in order to ensure the highest level of customer satisfaction and limit any problems in the post-sales phase.

D modelling; movement tracking and diagnostic analysis in telemedicine; indexing of image databases; it is able to move in the surrounding environment and to "recognize" the road, signs, pedestrians, predictive maintenance, control of production processes and safety support in industrial plants.

5.25. Immersive Technologies

(Adapted from original source reference 18 and 24)

Immersive technologies allow users to expand their audio-visual reception and to interact with a virtual surrounding in real time by means of tools. Growing computing power and the shrinking and mobility of devices in the past decades have increased the importance of these technologies on the market. Depending on the depth of integration, one can distinguish augmented, virtual, or mixed reality.

Based on Paul Milgram's (1994) definition of the "reality-virtuality continuum", mixed reality includes all the facets of a spectrum between absolute reality and absolute virtuality. Augmented reality can therefore be seen as a part of mixed reality close to reality.

All three approaches share the goal to improve the time-to-information ratio and the improvement of the quality of information, whereby the fields of application can be very different.

5.25.1. Augmented Reality (AR)

(Adapted from original source reference 24)

Augmented Reality enhances our real world (e.g. physical objects or places) interactively with data and information. In the simplest implementation, even a basic mobile maintenance app could be considered an augmented reality application, as it delivers information, or data, with pinpoint accuracy. For the most part, however, it involves the visual addition of a simulated plane added onto our view of reality.

Augmented reality applications require basic software and hardware for display, tracking for positioning and adapting to movement and, if necessary, interaction possibilities. The provision of information can be triggered by image recognition like QR codes, GPS locations, radio beacons like NFC or RFID. Hardware is usually furnished by smartphones, tablets, or data glasses. A distinction can be made between see-through displays and displays where computer generated images are added to live videos. Depending on the use case, augmented reality applications can offer real time operating or sensor data, specification sheets, explanatory videos, directions, or 3D-models. It enables the representation of properties beyond the human senses, e. g. infrared radiation, high frequencies etc.

AR Applications can be important in supporting time-critical operations. Where information was previously given in person, in writing or by telephone, it is now possible to transmit it directly and digitally. Another advantage shows in scenarios where objects cannot be physically changed. Systems that are still in operation can be viewed virtually in the smallest detail.

Two of the biggest challenges are data quality and platform usability. On the one hand, it is key to ensure that data is correct and reliable, also to control the safe execution of activities, on the other hand, handling must be facilitated for users to increase acceptance. Furthermore, it cannot be assumed that all data is validated, and interfaces are standardized.

Possible Applications:

- Navigation aid on large terrains or unfamiliar places, e. g. by displaying virtual arrow symbols.

- Display of technical plans and documentation files and component history.

- Display of technical data based on identification markers such as pressure, temperature, throughput, performance. Furthermore, the information whether system parts are de-energized can be relevant for executing units.

- Although the number of providers and possibilities has increased considerably in recent years, one must consider carefully which system to choose. This applies not only to the software but also to the hardware. System integration should also be implemented as openly as possible regarding future use.

- In addition, the time that has to be invested in the preparation and provision of information must not be underestimated. Scaling up to a larger number of employees can also be very expensive (hardware, licenses).

5.25.2. Virtual Reality (VR)

Virtual reality creates a simulated and data-based environment (e. g. a virtual power-plant) in real time, in which the users immerse themselves in a virtual environment by wearing closed head-mounted displays, other helmets or data glasses, often linked to graphic processing computers. The navigation and interaction in the computer-generated environment are accomplished by head and body movements, gestures as well as input devices like keyboards or handheld controllers. While augmented and mixed reality include certain aspects of reality, virtual reality shuts it out completely.

The objective is a realistic and responsive experience, and therefore comes in handy for (a) the simulation of important processes, for which repetition and routine is essential, or (b) the visualization of objects or places, which can't be reached physically by the user. Ideally, videos, data, or 3D models are integrated seamlessly.

Possible Applications are:

- Simulation of an authentic learning surrounding for new employees, in settings which cannot be realized during ongoing operations, or which are virtually guided by retired, not available or expensive experienced colleagues.

- Simulations of safety-critical procedures which can't be trained in real-life: e.g. emergency power up or shut down of a plant. The software not only allows control of the workflow but can also, for example, test response times in order to certify staff for real operations.

- Communication-device: based on the experience of numerous video calls during the Covid19 pandemic, it has become clear that conversations in virtual spaces, without visual and auditory spatial perspective, gestures of the communication partners and independent focus as it happens in real conversations, are tiring in the long run.

This could be facilitated by VR.

The fact that one usually deals with self-contained systems means that the simulated world must be created from scratch. This not only requires timing resources for the design and the preparation of the information but also computing power for a high and realistic level of detail.

Today, however, it is already possible to combine large-scale scans of spaces and buildings with existing 3D models. In this way, factory halls and machines can be shown realistically. Since the applications are not usually used on a daily basis and not every employee needs their own equipment, the focus can also be placed on the quality of the tools and simulations.

It is also important that reality is perceived differently by each person. Colour can be described physically, but the perception itself is a subjective experience and can also lead to greater problems in virtual worlds than in reality due to colour blindness.

5.25.3. Mixed Reality

While augmented reality and mixed reality are often used synonymously, the latter offers a broader spectrum of integration between the physical world and simulated elements. Similar to augmented reality, it would be conceivable to integrate the real world into the virtual one or to merge the two on an equal status.

The two worlds coexist and thereby users can interact with physical and virtual objects alike or both worlds affect each other without user input. Normally the environment adapts through navigation. Mixed reality offers a complementary type of human-technology interaction.

Possible Applications are:

1. Virtual operating panels and control components: by virtually interacting with controls users can operate physical components.

2. Maintenance measures performed by a virtually controlled robot: mixed reality allows maintaining safety-critical limits (only certain actions are allowed), a view enhanced by data (e.g at sensors).

Apart from the progress made, the application of mixed reality in the maintenance sector is still in its early stages. The implementations often relate to individual specific use cases and are therefore associated with a high level of effort. Furthermore, few standards have been able to establish themselves so far and hardware is often a closed system.

5.26. Others Applications

5.26.1. The Telepresence

It is a phenomenon that allows people to interact and feel connected to the world outside their physical body through technology.

5.26.2. Holography

It is the creation of a 3D image in space that can be explored from all angles improving the use of Digital Twin see paragraph 8.

The Immersive technologies, used to create a virtual reality of physical are suitable:

1. for stimulating the maintenance activities to be carried out in the best safe, qualitative and efficient way.

2. for designing maintenance actions and works that are planned or scheduled quantitatively and qualitatively in an efficient way.

3. for designing and improving Good Maintenance Practices.

4. for developing effective training on virtual plants.

5. for implementing the maintenance engineering methods as RCA, FMECA and diagnostic failure analysis. The maintenance by remote is using the various Immersive Applications and software to support the operators through the wearable technologies, using:

5.26.3. Smartphones

They are required to be equipped with a Global Positioning System (GPS) magnetometer, (compass)and internet connections and they must be able to display a video stream in real time. Mobile phones frame the surrounding environment in real time.

5.26.4. Computers

They are based on the use of markers, which are stylized drawings in black and white that are shown to the webcam and that the computer recognizes, and on which multimedia content is superimposed in real time: video, audio, 3D objects, etc.

5.26.5. Chatbot or Chatterbot

It is a software designed to communicate between computers and a person through predefined dialogue systems and schemes.

They are used as support systems in remote maintenance interventions to guide or assist the operator by providing verbal instructions to perform the work in the best possible way or in case of critical situations.

5.27. Drones

Using an unmanned aerial vehicle (UAV) with a camera that wirelessly transmits video feeds to goggles, headphones, a mobile device, or other display The user has a First View Person (FPV) of the environment people, plants and machines in which the drone flies to control the status of machine and plants with appropriate predictive technologies. Using Drones to carry out site and industrial plant inspections brings you resource savings and important technical advantages:

1. It eliminates the costs for securing the operational area.
2. Reduces the risk of workplace accidents.
3. Returns a point of view otherwise inaccessible.
4. It allows a real-time analysis.
5. Speed up and streamline operations.
6. Significantly increase the quantity and quality of data and information in your possession.

7. It allows faithful 3D construction.
8. To control heat radiation from leakages or old pipes.
9. To access narrow ducts with unknown safety risks. 10 .to check Damage or overgrowth of PV panels.
10. To measure 360-degree scan (e.g. thermal imaging) of vents and chimneys.

Being able to observe the structure closely offers you the possibility to find any anomalies, deterioration and damage caused by degradation or meteorological factors, intervening in time thanks to the post-processing that allows you to measure them in a precise and timely manner.

The competence for the regulation of the drones operations is in charge of EASA (European Union Aviation Safety Agency). To make the regulatory process more practical and efficient and understand what requirements are to be met, EASA has established some categories for both operations and drones.

In particular, the first categorization depends on the type of flight that is performed with the drones as follows:

1. Open category.
2. Specific Category.
3. Certified category.

The recommended methodology by EASA is the “Specific Operations Risk Assessment” (SORA) developed by JARUS. This is a new methodology which, through a holistic approach, ensures that all possible risks are assessed and proposes mitigations to keep them under control. The key requirements are the proven competence for the pilot operating from remote.

5.28. The Creation of Digital Twin Trough the Convergence of I.T. & O.T.

Historically, the Information Technology (IT) and Operational Technology (OT/operations) departments within a company have functioned fairly independently. Operations kept the assets running smoothly and in good condition, while IT managed business applications from the front office. But companies are changing. To keep up, the IT/OT relationship must also change.

Industry leaders recognize that the operational data they use to support real-time decision making could create additional value for the company. But these data must be merged with IT data in a meaningful way and made accessible across the organization. With this fusion, IT will help OT align with business systems. At the same time, IT needs to achieve the vision of a connected asset by driving innovation and minimizing downtime. But to get there, IT needs the knowledge and support of OT, as operations departments understand and control the assets.

The technology and operation of industrial assets are complex, but the adoption of IoT and its use with OT platforms enables the use of “digital twins” to manage, monitor, and maintain assets. A digital twin is a virtual representation of a real- world physical entity or group of interrelated physical entities (system), that allows real-time simulation of behaviors and scenarios (as a result of updated real-time data collected from several sources and its utilization within a digital model) in order to prognosticate how the physical object will behave in the real world, providing reliable information for an optimal decision making. The digital twin connects complex assets and their OT systems to an IT environment by capturing data to monitor performance, deterioration and failure, location and safety compliance, and remote monitoring systems for scheduling and asset utilization.

Through data fusion, digital twins become virtual and digital representations of physical entities or systems. However, the clone created with IT and OT convergence to forecast failures, demand, customer behaviour, or degradation of assets is not complete since it lacks engineering knowledge. This happens because the digital engineering models developed during the engineering phase of projects do not typically play a role in the operational phase.

Therefore, digital transformation demands that Engineering Technology (ET) be included in the IT/OT convergence process as the importance of integrating product design increases (see Figure 5.21). For that purpose, digital twins must be complemented by other information to assess the overall condition of the whole fleet/system, including information from design and manufacturing, as this obviously contains the physical knowledge of assets.

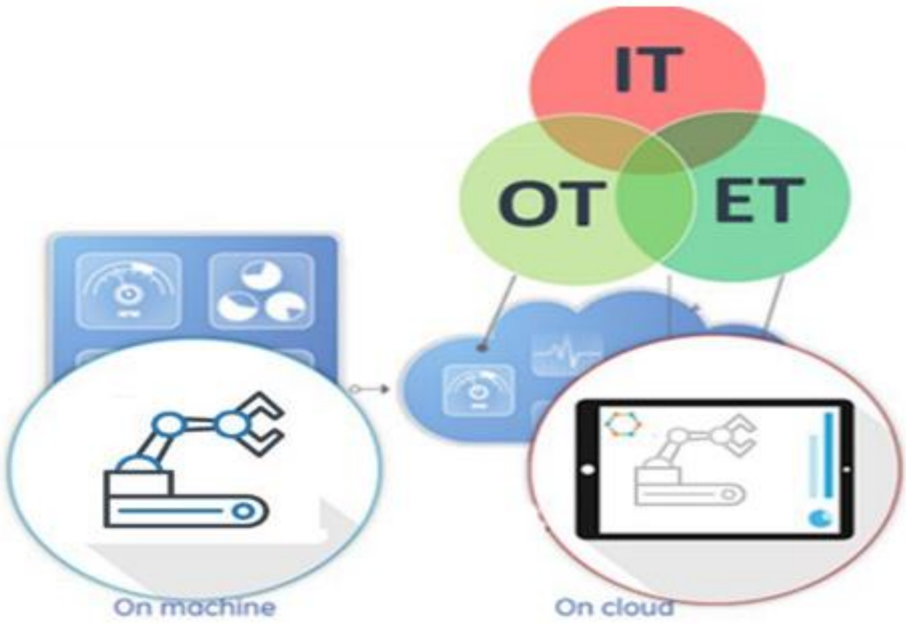


Figure 5.21. Engineering Technology (ET) included in the IT/OT convergence process.

The integration of asset information throughout the entire lifecycle is required to make accurate health assessments, determine the probability of a shutdown or slowdown, and avoid black swans and other unexpected or unknown asset behaviours. Moreover, the lack of data on advanced degradation makes the data- driven approach, where IT and OT are only actors, vulnerable to such situations and ET is slowly gaining entry to the convergence conversation, even though engineering models often remain stranded in information silos, inhibiting the ability to leverage this information to optimize operations.

Despite these challenges, hybrid models comprising engineering knowledge and data collected from the field will soon be part of digitization all over the world. In short, the engineering technology (ET) of an asset, together with IT and OT, will help O&M departments forecast problems, do better planning, and improve performance. Fortunately, it is now possible for companies to merge their IT, OT, and ET to enable asset performance modelling to deliver actionable intelligence for decision support.

5.29. BIM

BIM (Building Information Modelling) is a process that supports document management, coordination and simulation throughout the entire life cycle of the project (planning, design, construction, management and maintenance) starting from the creation of a model Smart 3D.

The information included and recorded in this virtual model is very diverse and increasingly complete. It ranges from the stakeholders involved in the process, the plant model itself, technical, structural and installation aspects, technical data of equipment, economics, materials, execution phases, maintenance, etc.

Each stakeholder involved in the construction, modification, maintenance or operation process is part of the BIM work method, each of them having their own skills and access to the part of information that is relevant to them. That is why it is essential that all of them understand the BIM method and how its tools work.

The information provided in the BIM model comes from different types of software, modeling programs, structural calculation, MEP, budgeting software, energy , analysis, etc. Knowledge of all these tools and the interoperability capacity between them is essential for a correct implementation of BIM.

The advantages of BIM Applications over a traditional work method are:

1. BIM platforms automatically update the information that is edited in any part of the model. This means that if an element is modified in a plant, it is automatically modified in sections, elevations and 3D views, just as if a feature were modified in a list - it changes automatically throughout the project. There is no possibility for human error. The information is always consistent.

2. Given that all stakeholders work on a single model, there is no possibility that information will be lost due to a lack of coordination between versions handled by different professionals.

3. By establishing this method of working in parallel, all stakeholders can from the beginning propose the options they consider most convenient for the project, directly involving the entire organization. The project, throughout its cycle, is developed in real time in a coordinated way in a collaborative environment, and always under the supervision of the client.

BIM allows any required information to be available at all times, in terms of design, technical, costs, execution times, maintenance, etc. It also allows real-time modifications that will automatically update all these parameters, increasing the degree of customization and adaptation of the project to the client's needs.

Facility management tasks and maintenance complex works become much more efficient, with all the asset’s actual information being on demand.

5.30. Machine to Machine (M2M)

(Adapted from original source reference 27)

On M2M, acronym for Machine-to-machine, in general refers to telemetry and telematics technologies and applications that use wireless networks. Machine-to-machine also indicates a set of software and applications that improve the efficiency and quality of the processes typical of ERP, operations and maintenance.

The term M2M is constantly evolving, meanings of M2M include the terms Machine-to-Human (M2H), Machine-to-Enterprise (M2E) and Mobile-to-Mobile describes communications that do not involve landlines.

The primary purpose of machine-to-machine communication is to collect data and transmit it to a network. The main feature of the machine to machine is to create a connection network between different machines: information is collected through sensors, and then sent and received, through a network, which can also use a server to collect and store the data stream.

For this process, which is completely digitized, it is not important how far they actually are, as long as the devices are connected to the Internet to create real communication between machines, even within a closed system.

The more important thing it is that data is changed in real time, the more essential it will be to use a high-performance communication infrastructure, such as optical fiber or the new 5G mobile standard.

Machine-to-machine communication, M2M for short, represents the predominantly automatic exchange of information between technical equipment such as machines, automatic devices, vehicles, measuring features, performance between them or through a central data processing system.

5.30.1. Requirements

The European Institute for Telecommunications Standards (ETSI), pursues the goal of creating international standards for information and communication technologies. ETSI defines the following requirements for machine-to-machine systems:

1. Scalability

   The system must work efficiently even after adding other connected devices.

2. Anonymity

   The system must be able to hide the identity of the devices.

3. Protocol

   M2M systems must be able to record failed installations, anomalies or incorrect data and keep the records for later consultation.

4. The principles of machine-to-machine communication must be respected.

5. Transmission Methods

   The Systems must support different transmission methods, such as Unicast, Anycast, Multicast and Broadcast, and be able to switch between them to reduce the load of M2M data transmission.

6. Information transmission planning:

   The system must be able to define time points for data transmission, as well as manage or delay communications according to their priority.

7. Choice of communication channel:

   The communication channels within the machine-to-machine system must be optimized on the basis of rules relating to transmission errors, delays and network costs.

8. In addition to faster communication channels and the ability to schedule data transmissions over time, machine-to-machine communication offers other benefits:

   - Remote operation and control of devices.
   - Reduced maintenance requirements.
   - Failure prevention and more physical assets availability and costs reduction.
   - Optimiztion of operations, yield process and productivity.

The machine-to-machine also offers new opportunities as machine learning to implement predictive and prognostic maintenance to extend the residual life of physical assets.

5.31. Additive Manufacturing-3D Printing

(Adapted from original source reference 20)

Additive Manufacturing (AM), also referred to as 3D printing, is a layer- by-layer technique of producing three-dimensional (3D) objects directly from a digital model. Unlike conventional subtractive processes that cut away material from a larger work piece, additive manufacturing builds a finished piece in successive layers, each one adhering to the previous.

Since its emergence 25 years ago, additive manufacturing has found applications in industries ranging from aerospace to dentistry and orthodontics. Across all industries, additive manufacturing accounted for $1.3B in worldwide sales of materials, equipment, and services in 2010 and is poised to exceed $3B by 2016 (processes).

The 3D printing technology contrasts with traditional subtractive production techniques and represents a real integration between the real world and the virtual world.

Additive manufacturing is also often used for prototyping as well as for the actual production of limited runs of products. Additive Manufacturing does not require the production of molds and allows highly customized productions.

The objects to be printed are digitally defined by the CAD (Computer- Aided-Design) software used to create files that essentially "divide" the object into ultra-thin layers. This information guides the path of a nozzle or print head as it precisely deposits the material on the previous layer. Or, a laser or electron beam melts or partially melts into a bed of powdered material. When the materials cool or are cured, they fuse together to form a three-dimensional object.

This technology is useful to supply, from remote in short time through IOT, spare parts, and components to restore items and machines, reducing the spare parts inventory level and the supply waiting time.

5.32. Applications of Additive Manufacturing Technologies

The concept of additive manufacturing, over time, has given rise to many technologies, all different from each other, which are used in the most varied scientific and industrial processes.

5.32.1. Photo Polymerization

This is the first additive technology born in the 1990s. It is based on the concept of hardening a polymeric material through photo polymerization. The finished piece is obtained through a process of light radiation or using a laser aiming the lighting on the parts of the layer that we want hard.

5.32.2. Material Extrusion

This technology is based on the softening of a material supplied by the machine in the form of filament and with which the pieces are built. It is particularly popular for amateur and domestic use, especially for the production of niche material (for example, metals).

5.32.3. Material Jetting

It consists in the creation of drops of material that are supplied to the printer in various forms and, subsequently, deposited directly on the piece. Various materials can be used, from polymeric to metallic, even in color.

5.32.4. Bending Jetting

It is very similar to material jetting technology. The difference consists in using a powder bed as a production process. A sequence, that first involves the drafting of the reference layer and then the deposition on it of a material, which serves to glue the previously applied dust particles, is used. This material is called "binder".

5.32.5. Powder Bed Melting

As with bending jetting, this technology also uses a powder bed process. On each layer, the section of the component under construction is exposed by an energy source (laser or electron beam) which liquefies the material. The material then solidifies and the finished piece is obtained.

These processes were previously categorized by a variety of researchers, and have now been Standardized by the ASTM International Committee F42 on Additive Manufacturing

Technologies into the seven classes. The standard presents an overview of process classes, examples of leading companies that make machines for each process, typical materials classes, and the most popular markets for use.

5.33. Corobots -Collaborative Robots

(Adapted from original source reference 25)

Corobotic is part of the Robotic engineering discipline, that studies and develops methods that allow a collaborative robot to perform specific tasks by automatically reproducing human work. Although robotics is a branch of engineering, more precisely of mechatronics, it brings together approaches from many disciplines both of a humanistic, linguistic and scientific nature: biology, physiology, electronics, physics.

The word robotic comes from the Czech robota, which means "hard work" or "forced labor". This term was introduced by the Czech writer Karel Čapek, in 1920. (Rossum's Universal Robots).

The English derivative term robotics, according to the Oxford English Dictionary, appears for the first time in a 1941 science fiction short story by writer Isaac Asimov entitled Liar (1941).

It is a robot specifically designed for direct interaction with a human within a defined safeguarded workspace where both (the robot and the human) can perform tasks or processes simultaneously during automatic operation.

Today there are many types of robots called Cobots (Collaborative Robots) able to support the operators to carry out activities improving safety, ergonomic and productivity.

Maintenance is using Robots as support tools-equipment to improve safety, productivity, quality precision and ergonomics on maintenance works. The Cobots are easy to program, quick to implement and safe to use. Cobots are boosting operation and maintenance activities in many companies of all sizes and sectors, can be quickly integrated into activities that are different from time to time, typical of the maintenance ensure a high level of accuracy and reliability increasing the operational maintainability.

5.34. Cyber Security and Blockchain

(Adapted the original source reference 27)

Information security is the set of means and technologies aimed at protecting IT systems in terms of availability, confidentiality and integrity of any kind of assets and related know-how and properties.

Security involves technical, organizational, legal and human elements. To assess security, it is usually necessary to identify the threats, vulnerabilities and risks associated with IT assets including physical assets, in order to protect them from possible attacks (internal or external) that could cause direct or indirect damage with an impact exceeding a certain tolerability threshold (eg . economic, political- social, reputation, etc.) to an organization.

In addition to the three fundamental properties (availability, confidentiality, integrity) they can also be considered: authenticity, responsibility and reliability.

Physical goods represent an economic value for their installation and operating cost and constitute the technical Capacity to produce products or perform services, they must be protected from

- Direct and indirect sabotage.
- Damage caused by actions external to machines, plants, systems.
- Theft of confidential information such as:

Data production capacity, productivity, process characteristics, research projects, licenses and patents, contracts with customers and suppliers, technological innovations, etc.

It requires an understanding of potential information threats, such as viruses and other malicious codes. Cybersecurity strategies include identity management, risk management, incident management and is optimized to levels that business leaders define, balancing the resources required with usability/manageability and the amount of risk offset.

It is a factor behind the development of industry 4.0 to prevent the interactions and contacts developed within the cyber physical system from being subject to cyber-attacks The protection of technologies, patents, contracts and performances related to industry 4.0 requires the development of adequate IT security tools.

A Blockchain (literally "chain of blocks") is a shared and "immutable" data structure. It is defined as a digital register whose entries are grouped into "blocks", concatenated in chronological order, and whose integrity is guaranteed by the use of cryptography.

Although its size is destined to grow over time, it is immutable since, as a rule, its content once written is no longer modifiable or eliminable, unless the entire structure is invalidated.

These technologies are included in the broader family of Distributed Ledgers, i.e. systems that are based on a distributed ledger, which can be read and modified by multiple nodes on a network. The nodes involved are not required to know each other's identity or trust each other. In fact, to ensure consistency between the various copies, the addition of a new block is globally governed by a shared protocol.

5.35. Mechatronics

(Adapted from publications of Rensselaer institute)

Mechatronics is a branch of Engineering that focuses on the design, manufacture and maintenance of physical assets that have both mechanical and electronic components. The term was coined in 1969 by the Japanese engineer Tetsuro Mori, to describe the synergy that exists between electronic, control systems and the mechanical machine they regulate.

Mechatronics arises from the need to create know-how in the field of modelling, simulation and prototyping of control systems, focusing mainly on Motion Control Systems.

Since then, the meaning of the term has expanded to include the integration of many other disciplines, computer engineering, systems engineering, software and hardware as reported in the logo of Rensselaer Polytechnic Institute founded in 1996 (Troy New York) (see Figure 5.22).

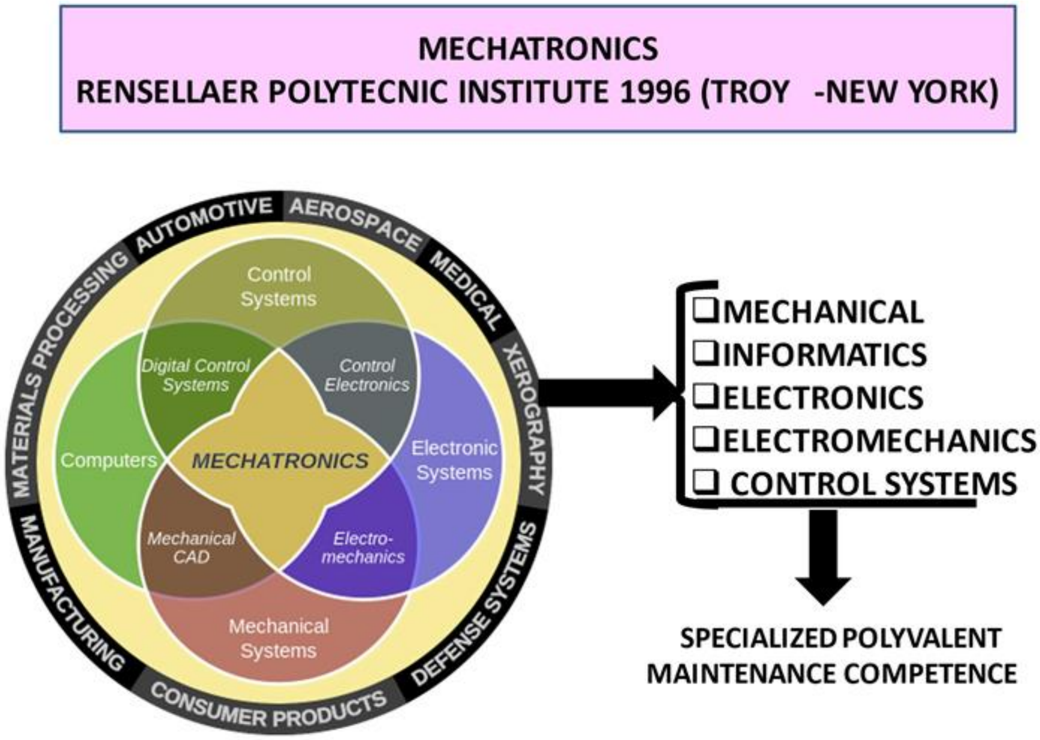


Figure 5.22. What means mechatronics.

The main fields of application are robotics, industrial automation, bio mechatronics, avionics, transportation, and all automatic-electronic mechanical devices installed in any advanced machine and plants. In addition to the technical specializations of traditional maintenance, Mechatronic Maintenance has also been added, particularly involved in the Maintenance 4.0 technologies applied to physical assets.

5.36. Nanotechnologies

Nanotechnologies covers that branch of science that uses, or creates, materials with nanometric dimensions, that is, from ten thousand to one million times smaller than a millimeter.

The continuous technological evolution has made it possible to observe, understand, predict and, finally, build advanced materials and systems belonging to the nano world with new and excellent physical characteristics.

In this way maintenance can achieve better performances and extension life of components reducing the maintenance costs and increasing the physical asset useful life.

A world that follows different laws and properties than those present on higher scales and appreciable by our senses. Quantum mechanics is the master, altering the physical, chemical, optical and electro- magnetic properties of the materials.

Thanks to nanotechnologies, advanced materials and components with mechanical, chemical and electrical characteristics have been developed and continue to be made, which have a longer life and much higher resistance while decreasing the maintenance needs.

There are many innovative materials available as results of research and development of Nanotechnologies as:

1. New composite materials and adhesives with high fire performance.

2. High performance lightweight, multifunctional advanced materials and related components, designed for assembly and disassembly.

3. Coating with better chemical functionality and / or nanostructured materials, with high compatibility with existing technologies.

4. Polymeric materials and related micro and nanocomposites.

5. Nanomaterials and nanometric systems for advanced electronics and optics

6. New materials with high biodegradability and biocompatibility

Above all the Composite materials represent the evolution of science and technology of materials by fusing within them the best characteristics of several materials, produced with innovative technologies that determine their very high physical characteristics. The study of composites is a materials design philosophy that aims to optimize the composition of the material at the same time with the structural optimization project in a convergent and interactive process. As mentioned, thanks to their limited size, the fibers have an extraordinary structural perfection; this feature, combined with the intrinsic properties of the constituent materials, ensures them:

1. High mechanical resistance.
2. Very high elastic modulus.
3. Very low specific weight
4. Linear elastic behaviour up to failure.

The more important example is the Graphene that consists of carbon atoms arranged in a honeycomb lattice. It forms an almost transparent sheet of about one atom thick and is 200 times stronger than steel, but six times lighter.

Almost two-dimensional, it interacts with light and other materials in a unique way, for example, it absorbs only about 2% of light and is impermeable even to lighter gasses such as hydrogen and helium. It is also a highly efficient conductor of both heat and electricity.

The electronics industry has embraced graphene and it is not difficult to see why.

This material is perfect for touchscreens having higher Resistance, Flexibility, Reliability and Maintainability.

Because the major part of failures are coming from the wear of the materials that are representing almost 25-35 % of the maintenance annual cost, the benefits of adoption of innovative and appropriate materials more resistant represent in the medium term a success factor for a sustainable and Competitive Maintenance. Better Materials means less failures, less spare parts, less man hours, less work, less plants shutdown.

6. PART IV: APPLICATIONS OF TECHNOLOGIES 4.0

6.1. Information Technologies & Operational Technologies Integration

In the last time in manufacturing industries, Information Technologies (IT) and Operational Technologies (OT) worked independently of each other. IT technologies were mainly used to support management and administration, while OT controlled machinery and plants on the production floor without processing information from other parts of the organization.

Today, industry 4.0 developments, such as the Internet of Things (IoT), have brought together IT and OT technologies, opening a new era in the sign of intelligent manufacturing and unified business or at least operations and maintenance management.

With industry 4.0 this paradigm is bound to change. Smart machines leverage data from multiple sources to adapt production to ever-changing circumstances, delivering many of the features expected of an intelligent factory: automatic corrections, optimized order routing, complete organizational visibility, predictive maintenance, etc.

The integration between Information Technology and Operational Technology is one of the enabling factors for Industry 4.0, that become fundamental in companies with a high intensity and concentration of physical assets and provides for a radical change of the traditional separation between IT and OT.

In Industry 4.0, digital does not stop at Information technologies, but is structurally and logically integrated with the operational technologies. Consequently, the main objective of industry 4.0 is the convergence and coexistence between the operation technology (OT) and information technology (IT) systems.

6.2. Horizontal and Vertical Integrations

(adapted from original source reference 27)

The adoption of interconnected technologies, both horizontally and

vertically, makes it possible to analyse big data and create open systems for their sharing in real time. This will allow digitization and integration along the entire value chain, in order to create an efficient and effective automated flow.

Horizontal integration supports the management of information between business areas that contribute to the definition of the life cycle of a product and the consequent life cycle of physical assets. Vertical integration allows the company to relate to all members of the value chain, from suppliers to end customers, determining shared working standards and objectives.

In general, time and cost savings are achieved through the production process and an increase in product value for the customer.

To manage this complexity, new solutions are emerging, such as the appropriate operating systems, a cloud-based software and services platforms for the collection and analysis of data from industrial production, from smart buildings which allows you to use 'apps' dedicated to the optimization of assets and processes, and can be used in Platform-as-a-Service.

6.3. Horizontal Integration

From an operational point of view, a horizontally integrated company bases its business around the core competencies it has and establishes partnerships with other companies to build an end- to-and value chain.

The horizontal integration consists in the expansion of the business activity to products, services, production technologies, market policies, processes, manufacturing phases and know how.

To achieve horizontal integration and implement the tools of the Industry4.0 paradigm, it is necessary that all the players in the same supply chain are willing to collaborate.

The aim is to implement a digital transformation process that brings traditional production systems to evolution into cyber-physical production systems that exploit intelligent solutions within an intelligent factory or company.

In general, horizontal integration is articulated on several levels.

Within the same production plant. Machines and production units are always connected and each transform into an object with well-defined properties within the production network. They constantly communicate the performance status using Key Performance Indicators and, together they respond to the needs of dynamic integrated lean and flexible production.

The ultimate goal is that an interconnected production line is able to dynamically respond to the status of each machine to increase efficiency by reducing downtime through learning machine actions implementing appropriate predictive and prognostic actions to improve the Overall Effectiveness Equipment (OEE).

Operations and Maintenance 4.0 technologies promote horizontal integration between production management systems (Manufacturing Execution System).

Horizontal integration is essential when using Full Service, Contracts or Global maintenance services carried out by the manufacturers on machines, because through an integrated Operational Technology and Information technology even remotely it is possible to achieve high levels of service at low cost.

Horizontal integration, on the other hand, supports the management of information between business areas that contribute to define, operate and maintain the entire life cycle of a physical asset.

6.4. Vertical Integration

A vertically integrated company maintains the entire supply chain internally, starting with product development and design and following with production, marketing, sales and distribution.

Vertical integration in Industry 4.0 allows you to connect all logic levels within the factory: production, maintenance, utilities, logistics etc. Data flows freely up and down these levels so that strategic and tactical decisions can be driven by data.

How they are different but complementary to the technological-production chain in which the company operates.

Vertical integration is essential in the operational and organizational processes of manufacturing and maintenance, to measure and control the efficiency and Effectiveness of Each production unit, to verify the maintenance policies adopted and to identify the critical areas and items for improvements.

In this scenario, the data of the production facilities (e.g. unexpected delays) are shared throughout the factory and, where possible, the production activities are automatically moved between other different lines or plants in order to respond quickly and efficiently to production changes and needs.

6.5. BIM for Maintenance Complex Works Planning

The use of BIM methodology is very widespread. Below we have included a description of how we use it to plan large-scale plant maintenance works.

6.5.1. Utilization for Large-Scale Maintenance Works

During large-scale maintenance works, for example a turnaround, it is common to find, at any unexpected moment, that there are incompatibilities between several tasks meaning they cannot be carried out at the same time. This is either because some tasks hinder the performance of others, for example, due to the lack of physical space in the area, or certain tasks are not compatible in the same area, or for safety reasons, for example, it is not possible to carry out work within the safety radius of a crane moving loads.

These incompatibilities, although unforeseen, still represent inefficiencies for maintenance. They represent failures in the planning of the work to be carried out and they cause a loss of time and an increase in maintenance costs. At the same time, they can produce confrontations between the operators involved in these incompatible tasks, even more so if the work is to be carried out by different companies.

Due to all of the above, we have set ourselves the challenge of solving these problems before starting the plant turnaround.

6.5.2. Four Planning of Turnaround Works

Planning shutdown works is a complex activity. The tighter the timetable, the greater the control needed for carrying out the work. We are therefore talking about planning various works to be carried out in a small area of land, at different heights, with different risks and which are carried out by a few hundred people. These are works that are carried out 24 hours a day, 7 days a week, during several weeks. All this translates into managing a mixture of people, machines, scaffolding, different specialties, risks, ... all occupying the same space.

That is why we have work schedules with several thousand activities to be carried out, by many different people in different equipment, and everything must be perfectly coordinated so that the shutdown ends on the scheduled date, and within the budgeted cost.

The usual planning of works takes into account the concatenation of activities, in a logical way, that allows the achievement of the cost and timing objectives in the most efficient way possible.

This is usually achieved by managing three variables that must be minimized, being cost, time and resources. However, we always seem to forget that the works are carried out in a physical space, which is made up of 3 dimensions. If we unite these 3 dimensions, the space where the work is going to be carried out, with the variable time, we are actually talking about 4 dimensions and that is the reason why we are going to call this form 4D PLANNING.

6.6. Corobots Utilization

(Adapted from original source reference 25)

Until now, robots have always been big, strong, robust devices that work on specific tasks which were designed for them. They have been isolated from humans, been kept in cages and surrounded by guards for safety purposes. And it took a lot of programming skills just to set up them and make the work in the right way (see Figure 6.1).

Collaborative robots, on the other hand, are designed to work with humans. Their design and construction include safety features such as force feedback, low-inertia servomotors, elastic actuators, and collision detection technology that limit their power and force capabilities to levels suitable for contact. More compact than conventional robots, cobots generally have lightweight frames with soft, rounded edges and minimized pinch points. In reality, they are "forced limited robots".

Most of the collaborative robots can be easily taught by demonstration, rather than requiring a deep knowledge of programming. The majority can also be moved around the factory floor in order to perform a different task at another station. Being more flexible, they can perform more tasks and even in the future do whatever a human can do.

Figure 6.1. Collaborative robots operating in 3 dimensions.

The ability of collaborative robots to share tasks with humans and flexibly adapt to new requirements can provide high returns on investment in a wide variety of industrial applications:

1. Assembly. Screwdriving, Part Insertion.
2. Dispensing. Gluing, Sealing, Painting.
3. Finishing. Sanding, Polishing.
4. Machine Tending. CNC, Injection Mold, ICT.
5. Material Handling. Packaging, Palletizing, Bin Picking, Kitting.
6. Material Removal.
7. Quality Inspection.
8. Welding.

Cobots have four types of collaboration:

1. Safety Monitored Stop

   This kind of collaborative feature is used when a robot is mostly working on its own, but occasionally a human might need to enter its workspace. For example, when a certain operation must be performed on a part while it is in the robot’s space. Take a heavy part that has to be handled by a robot and a worker needs to do a secondary operation on it while the robot is still handling the part. This way the person can work on the part and still be in the robot’s space. If the human enters the restricted area in the pre-determined safety zone, the robot will stop all movement altogether. The robot is not shut down, but the brakes are on.

2. Hand Guiding

   This type of collaborative application is used for hand guiding or path teaching. It is used to teach paths quickly for pick and place applications for instance, using a Force Torque Sensor that reads forces applied on the robot tool. This type of collaboration only applies to the robot while it is performing this particular function, which means that while the robot is functioning in its other modes, the robot still needs to have safeguarding in place.

3. Speed and Separation Monitoring

   The environment of the robot is monitored by lasers or a vision system that tracks the position of the workers. The robot will act within the functions of the safety zones that have been pre-designed for it. If the human is within a certain safety zone, the robot will respond with designated speeds (generally slow) and stop when the worker comes too close.

4. Power and Force Limiting

   Robots can work alongside humans without any additional safety devices. The robot can feel abnormal forces in its path. In fact, it is programmed to stop when it reads an overload in terms of force. The design is such that it is capable of dissipating forces in case of impact on a wide surface, which is one of the reasons why the cobots are rounder. They also don't have exposed motors.

In summary, the benefits of collaborative robots are:

1. They reduce the accidents and incidents rates.
2. They reduce ergonomic problems for people.
3. They are easy to program and easy to implement.
4. They are capable of performing a wide variety of operation

6.7. Servitization

(Adapted from original source reference 27)

Servitization was created with the aim of understanding and satisfying customer needs in the best possible way. The provision of an offer, which includes both products, machines, plants and services in order to optimize the complete package given to the customer.

With Servitization, the Provider becomes a system capable of delivering to the end customer a range of services integrated with the product, so as to be able to act effectively and in a responsible way in the after-sales period.

The company presents itself to its customers through the services offered, no longer with its product: Anything as a Service (XaaS) as example “Availability as a Service.

There is a change in the strategic value given to the service with respect to the value of the product and this change has a substantial impact on all levels of the organization, operations and above all on Maintenance.

The topic is given by its close relationship with the connection with the enabling Technologies 4.0.

The "invoice", therefore, is not issued for the transfer of ownership, but for the rent of a specific machine or device by the customer paying for the use and performances achieved.

In the new “circular” approach to business activities, for the manufacturer and supplier of machinery, systems and services, the benefits can be different.

The benefits for technology providers are:

1. The market grows with the rental of tools and services.

2. It is possible to build customer loyalty, because the relationship does not end with the purchase of the asset but continues over time in relation with performances and the company growth.

3. The manufacturer maintains greater control over system configurability and development.

4. The manufacturer takes care of the maintenance for all the useful life of the machines.

5. Fault management is centralized.

In the same way, there are also important advantages for those who rent:

1. Can access and use the tool and its service without having to bear the expense of buying it, with immediate and overall costs much lower.

2. Having no ownership, it does not even suffer the obsolescence of the machinery. The newer the technology, and not yet stable and evolved, the more advantageous servitization is, also because there is not the risk of its obsolescence.

3. Can therefore change and renew them with much more ease and flexibility, according to different needs that change overtime.

4. Can try to use machinery and solutions even on an experimental basis, and not definitively with regard to startup, test runs and useful life.

5. It is possible to achieve better performance because the user pays for achieved results.

6. Because the maintenance needs are outsourced; it is possible to reduce the maintenance fixed cost and spare parts inventory.

7. The enabling technologies 4.0 are already installed and updated by the provider because it is his interest to supply an excellent machine.

It is possible to reduce the Capital Expenditures paying the global Contract rent and maintenance services.

The leasing in reality always existed: the striking novelty is that new technologies 4.0 make now the mechanism much more profitable and manageable.

6.8. Cloud Computing Applications

The drastic increase in digitalization of the of everyday Operations and Business activities, produces a higher demands of information systems and a consequent steadily growing need for computing power and storage capacity.

Cloud computing can help to support many activities in operation and maintenance.

6.8.1. Physical Assets Improvements

In discrete industrial environments, physical Asset development involves many complexities. These activities include dealing with iterative design, product testing, installation and implementation works. Cloud computing can help simplify these processes by providing companies with enough computing resources to handle complex tasks.

6.8.2. Maintenance Engineering

The cloud supports Digital Twin or BIM for engineering studies, simulations, communication and collaboration. Cloud computing offers the ability to work remotely through configured devices and the ability for dozens of stakeholders to contribute in real time.

This leads to greater efficiency in project management and in giving, receiving and integrating feedback into projects to do fast and in an effective way.

6.8.3. Technical & Organization Activities of Maintenance

Cloud computing provides an excellent platform for maintaining historical data of failures, lost time, work done, problem solved, safety performance, good maintenance practices, historical and updated technical-organizational- economical KPI, procedure, inventory lists, Planning and Scheduling, etc.

6.8.4. Implementation of Technologies 4.0

The adoption of 4.0 technologies and related implementation requires a high direct computational power that cloud computing provides by accelerating digitalization in a reliable and secure and highly available way.

6.8.5. Improving Automated Processes

Automation relies on data analytics and, in advanced cases, artificial intelligence to function without the constant assistance of humans.

Cloud computing provides an excellent ecosystem for collecting data and integrating it into the applications that drive industrial automation ensuring that automated processes can respond in real time and in appropriate ways.

6.8.6. Achieving Security Measures

Successful data breaches or cyber-attacks can lead to shutdowns in continuous manufacturing processes. Once the data used in deploying industrial automated systems is lost, automation stops. Cloud computing reduces cybersecurity risks associated with Operations and Maintenance and other industrial processes in a variety of ways. Among these ways is the use of firewalls and encryption to protect a company's data from attack. Cloud computing providers also offer risk mitigation packages while providing security patches to ensure the safety of manufacturing data. The cloud also provides a more secure platform for discrete manufacturers to secure sensitive manufacturing data. Cloud service providers are also integrating policies such as the laws of the General Data Protection Regulation (GDPR) into their platforms. This can help companies consistently stay on the right side of the law without having to put in extra effort to integrate such laws.

6.9. Wearable Devices for Maintenance 4.0

(Adapted from original source reference 24)

The wearables are small electronic devices, which comprise one or more sensors and are associated with clothing or worn accessories such as watches, wristbands, and glasses.

Wearables come with some sort of computational capability, which enables them to capture and process data about the physical world. In several cases, they also provide the means for presenting data in some type of display.

The most common types of wearable devices that are used in the industrial activities include:

- Smartwatches, which are usually connected to the users' smartphones and provide functionalities such as messaging and handling of calls and emails. Some smartwatches are also equipped with sensors that can provide information about the worker and the surrounding environment (e.g., temperature, air quality). Hence, they serve as a useful tool for workers' communication during field service processes, including access to information about the context of the field task.

- Smart Glasses, Clothing and Textiles, which are typically special types of garments that comprise sensors and wireless devices. They resemble regular clothes, but are able to transmit information such as heart rates and stress levels to the user's smartphone.

  This application provides:

  ✓ a non-obtrusive way to obtain information about the workers' status for safety reasons.

  ✓ a host of useful functionalities for field service and maintenance, including Enhanced Cyber-Representations of the task, visual information about the field service or maintenance works at hand in the form of instructions, annotations and recommendations.

Furthermore, field workers can engage in more complex tasks that they could hardly complete before, which reduces the need for on-site service and technicians.

6.10. Wearable Applications

With so many wearable devices and functionalities at hand, there are many possibilities to use wearable technologies to achieve better performance of maintenance processes increasing safety, effectiveness, quality and productivity in many different operative works as for example:

1. Provision of enriched information about the maintenance task takes advantage of virtual and augmented reality information to help workers complete their tasks.

   In most cases, the delivery of enriched information can benefit from the integration with some knowledge management system, which provides information about how to best complete a task from technical and quality point of view within a specific maintenance context.

   - For example, a knowledge management system can classify errors and deliver information about next steps or even navigating in the field.

   - Likewise, the worker's location and asset position can be taken into account in order provide rapid access to the right information in an instruction manual.

   - As another example, workers can be presented with defect reports and documentation for similar errors, through access to a knowledge base.

Overall, wearable devices enable workers to access a wealth of relevant information and documentation in a timely and context- aware fashion. At the same time, this information can be presented in an ergonomic and user-friendly manner via their wearable devices.

2. Improved communication and interaction between workers and devices.

Wearables facilitate communication between maintenance workers, which increases safety and productivity, while reducing service times as well. Field workers can take advantage of wearable devices in order to communicate field information and inquiries to maintenance engineers and other members of the workforce.

Communications are fast and context-aware, as they can include both workers' status and information about the surrounding environment. Information can be transmitted not only in textual form, but in multimedia format (i.e. audio, video) as well.

The combination of the above functionalities can support many different situations, such as:

- Communication between field technicians and remote experts in order to perform service diagnosis in real-time.
- Voice-enabled access to asset management systems and knowledge bases in order to obtain more information about an error.
- Voice and video-enabled logging of service details by the worker.
- Flexible, remote collaboration with technicians and other members of the workforce.
- Automated provision of safety recommendations and alerts to workers.
- Flashlight functionality, which helps technicians to see in dark areas while on job sites. Flashlights take advantage of the screen of the wearable device, which is lightened up to its full capacity.
- Tracking of workers' biometric and contextual data for safety, which keeps track of body temperature, heart rates and other characteristics of workers, in order to make sure that these parameters remain within certain thresholds.

With so many possibilities at hand, the deployment of wearables technologies in maintenance is not simply a matter of selecting and deploying the proper technology. Rather, it is about designing the proper wearables-enabled maintenance process that will optimize safety and productivity in order to meet tight turnaround schedules and operational deadlines.

In most cases, this requires some reengineering of existing maintenance organization and practices, to integrate the wearables with Computerized Maintenance Management System and Manufacturing Execution System.

6.11. Example of Machine Learning Application

6.11.1. Introduction

The Smart Factory is a fab-lab facility created by the Automotive Intelligent Center (AIC) and the Spanish company Siste plant. It is located in Vizcaya (Spain) and its main mission is to develop and test new technologies that allow the hybridization between the physical world and the digital world. One of these technologies is Machine Learning.

6.11.2. The Manufacturing Process

The Smart Factory process is described by the fig.1 below: press, dimensional control,

Welding and final quality control of welding points.

Specific variables that are embedded in the PML parameter can also be monitored:

6.11.2.1. PML Visualization and Forecast

PML values can be monitored in real time and graphically visualized to facilitate the decision making. Moreover, a prediction of the future behaviour of the PML (for a time t: 1 minute, 1 hour, 1 day…) is provided by machine learning software.

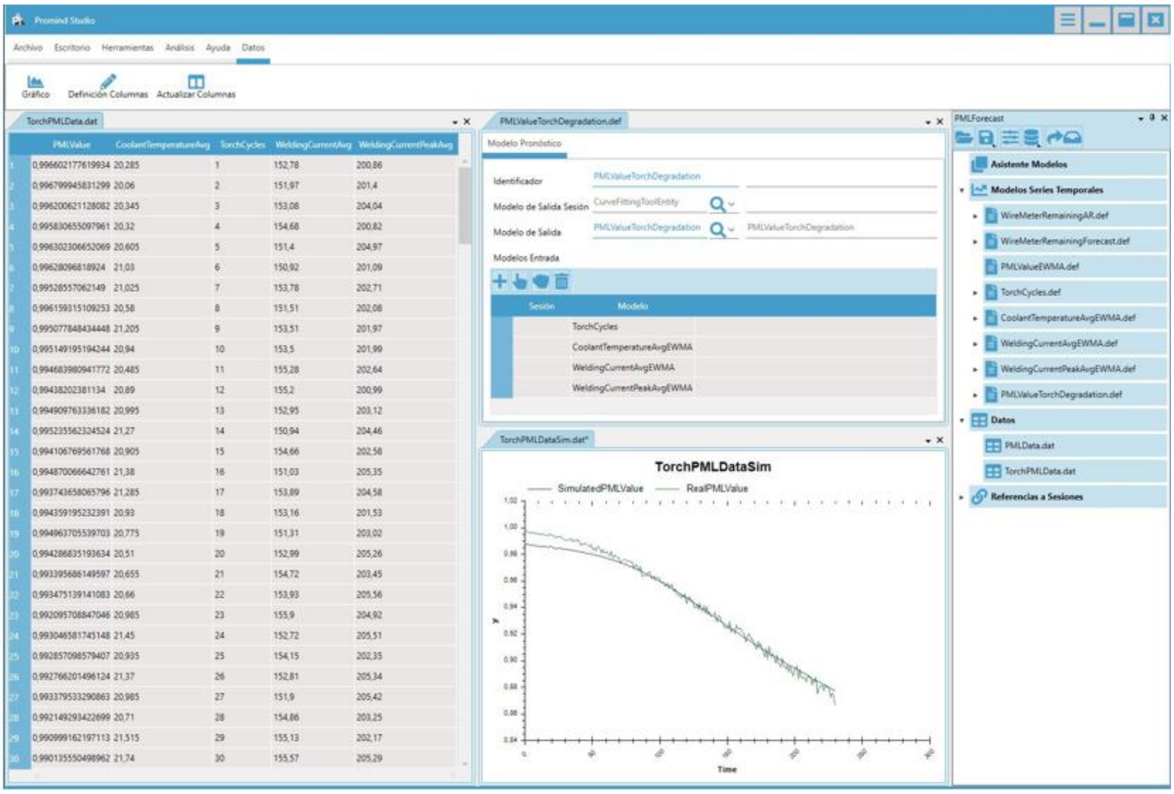


Figure 6.2. PML visualization and forecast.

6.11.2.2. Visual Representation On PML Value

The prognosis is made by applying temporary series and machine learning regression models.

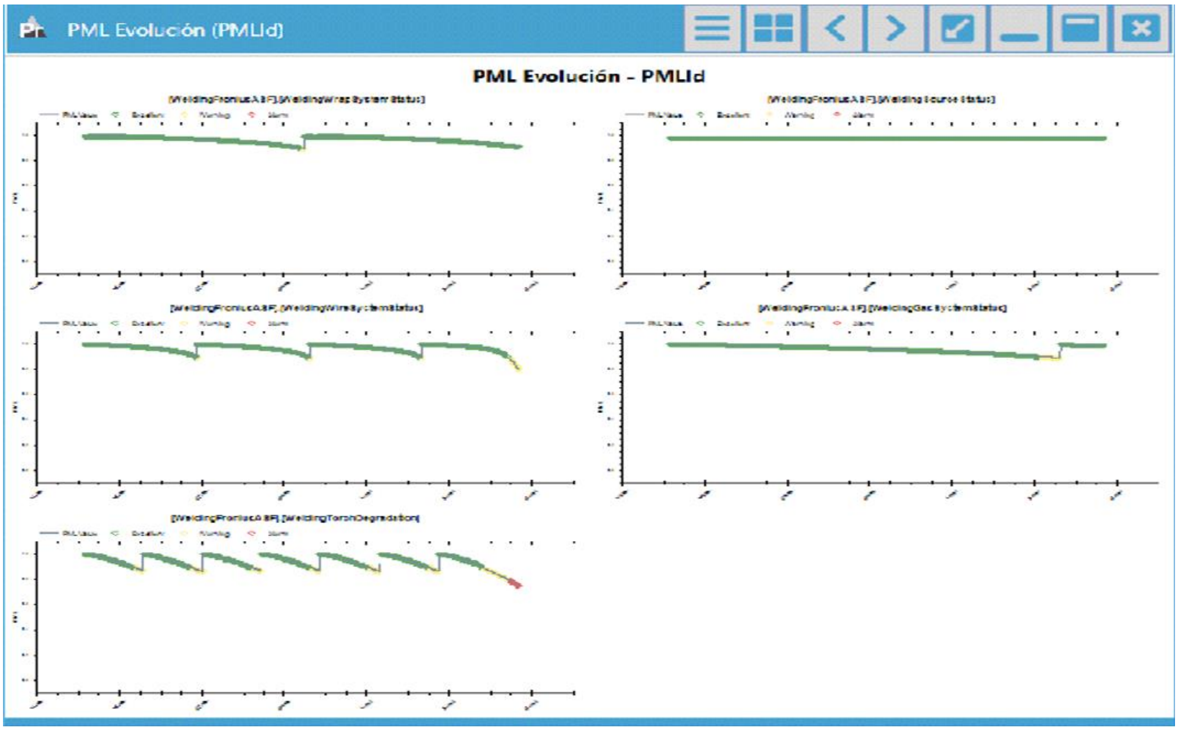


Figure 6.3. Visual representations.

6.11.2.3. Variable Process Real Time Monitoring

Values specific variables that are embedded in the PML parameter can also be monitored...

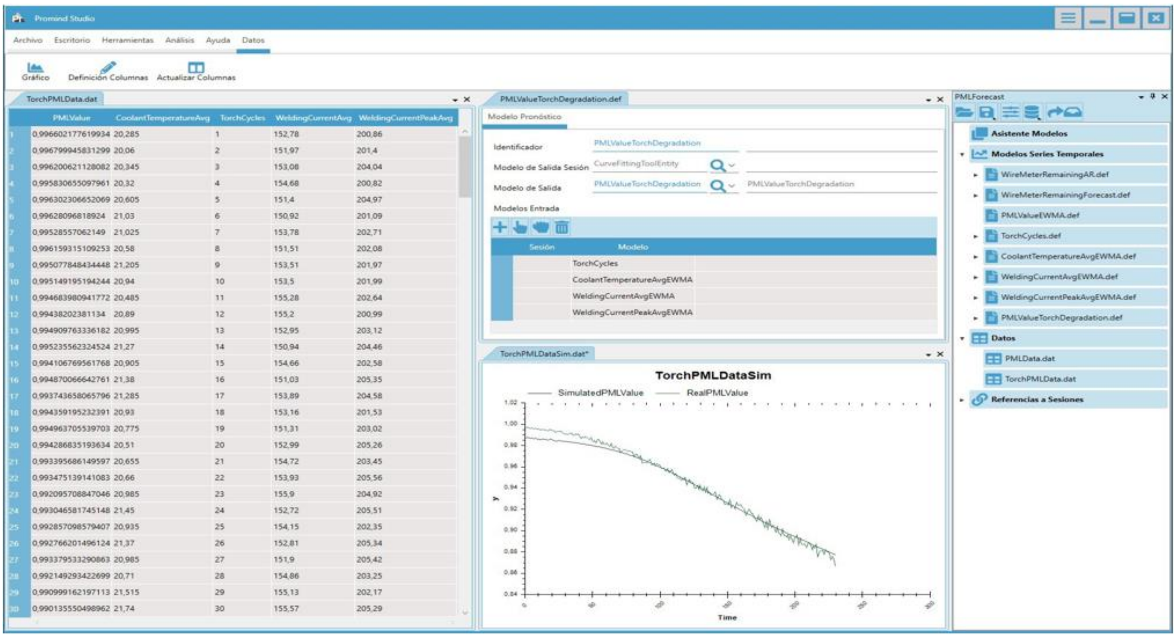


Figure 6.4. Variable process real time monitoring.

6.11.2.4. Optimization Tools

Finally, additional optimization tools are available to perform a deep analysis of the causes of this deviation: impact of inputs on outputs analysis and related r

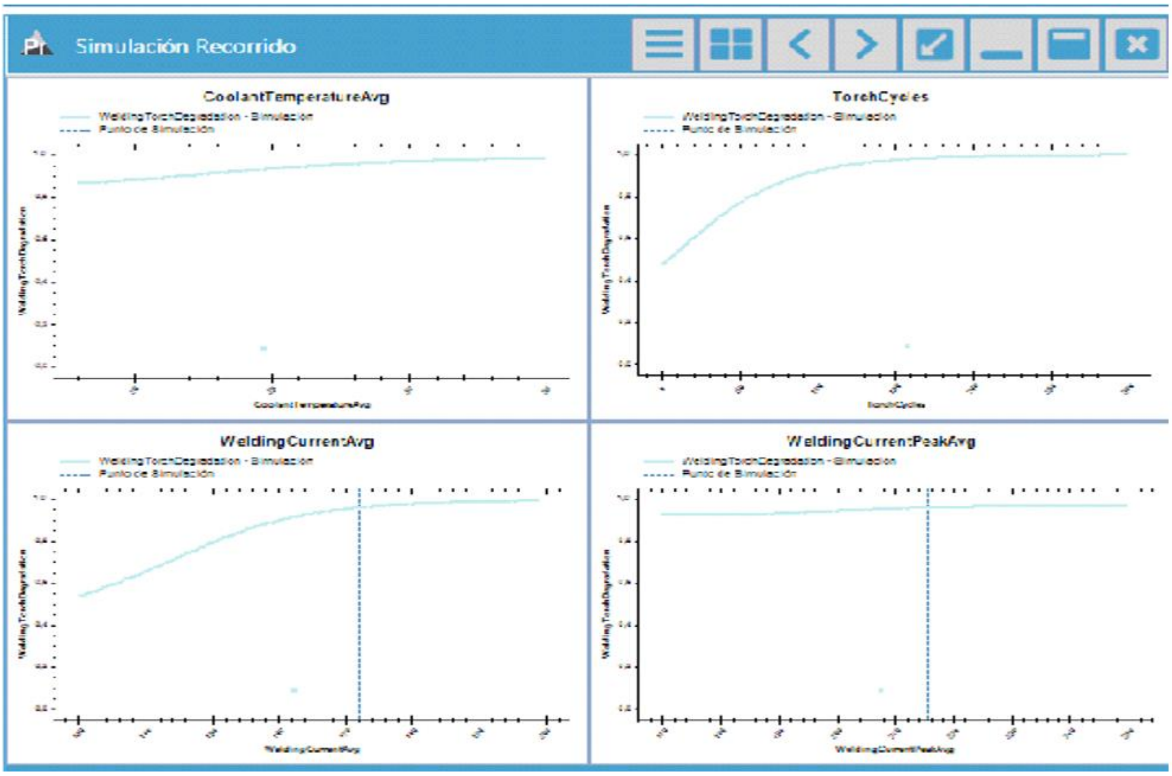


Figure 6.5. Optimization tools.

Metal raw material is pressed to form the main body of the piece, that follows a first quality control to check different dimensions. Next to this, some parts are added by welding and, finally, a quality control to check the robustness of the welding joints is performed.

The manufacturing line is completely automated and the transport of the pieces between the several processes is carried out by an Autonomous Guided Vehicle (AGV). Moreover, there exists unitary traceability, hence every piece that is manufactured has its own and unique history that is digitally recorded.

A photograph of the physical installation and the manufactured pieces are shown in the following Figure 6.6.

Figure 6.6. Smart Factory and manufactured piece.

6.12. Welding Process Health Monitoring

Welding is the critical process of the smart factory. Therefore, a real-time health monitoring system has been implemented by the use of machine learning software.

The first step to implement a real-time Health Monitoring system is to perform an RCM (Reliability Centered Maintenance) analysis in order to define the functional failures, the several failure modes, their causes and the related variables to be measured (see Figure 6.7).

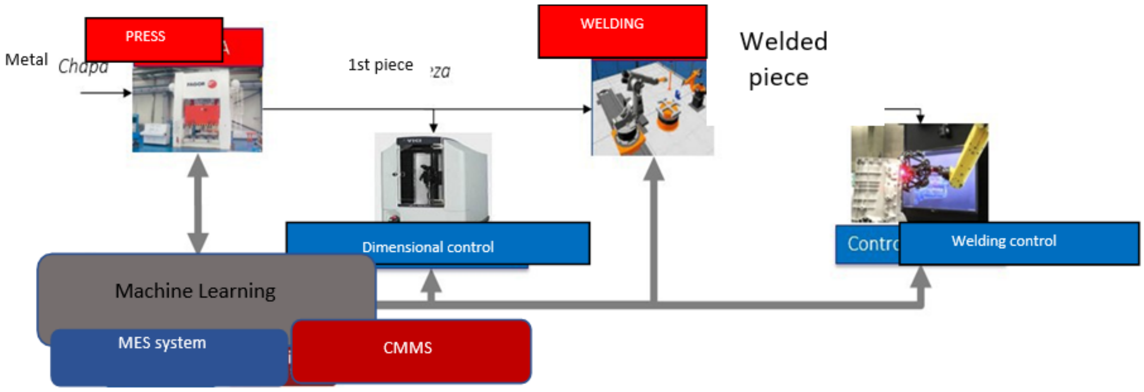


Figure 6.7. Process scheme.

The second step is to define the measurement system to measure the variables related to the failure modes. For this, IoT sensors, MES (Manufacturing Execution System) data capture and CMMS (Computerized Maintenance Management System) parameters are used.

The list of some identified failure modes is shown below in Table 6.1:

Table 6.1. *Sample of failure modes.*

Failure modes
Lack of cooling liquid
Degradation of cooling liquid
Deviation of Electric arc from standard parameter
Lack of atmospheric pressure
Incorrect atmospheric pressure (higher/lower)
Blocked filter
Lack of welding wire
Blocked welding wire
Irregular advance of the welding wire
Strange objects presence
Fixing tools maladjustment
Loss of pressure
Wear of welding torch
Dirt on welding torch

The third step is to define an indicator that represents the global health condition of the welding machine: it is called Process Mastery Level (PML). It is a normalized parameter (values between 0 and 1) that involves the several variables that affect the performance of an asset of its systems and subsystems. The calculation of the global PML of the welding machine is performed by aggregation of the individual PML of each of its systems (see Figure 6.8).

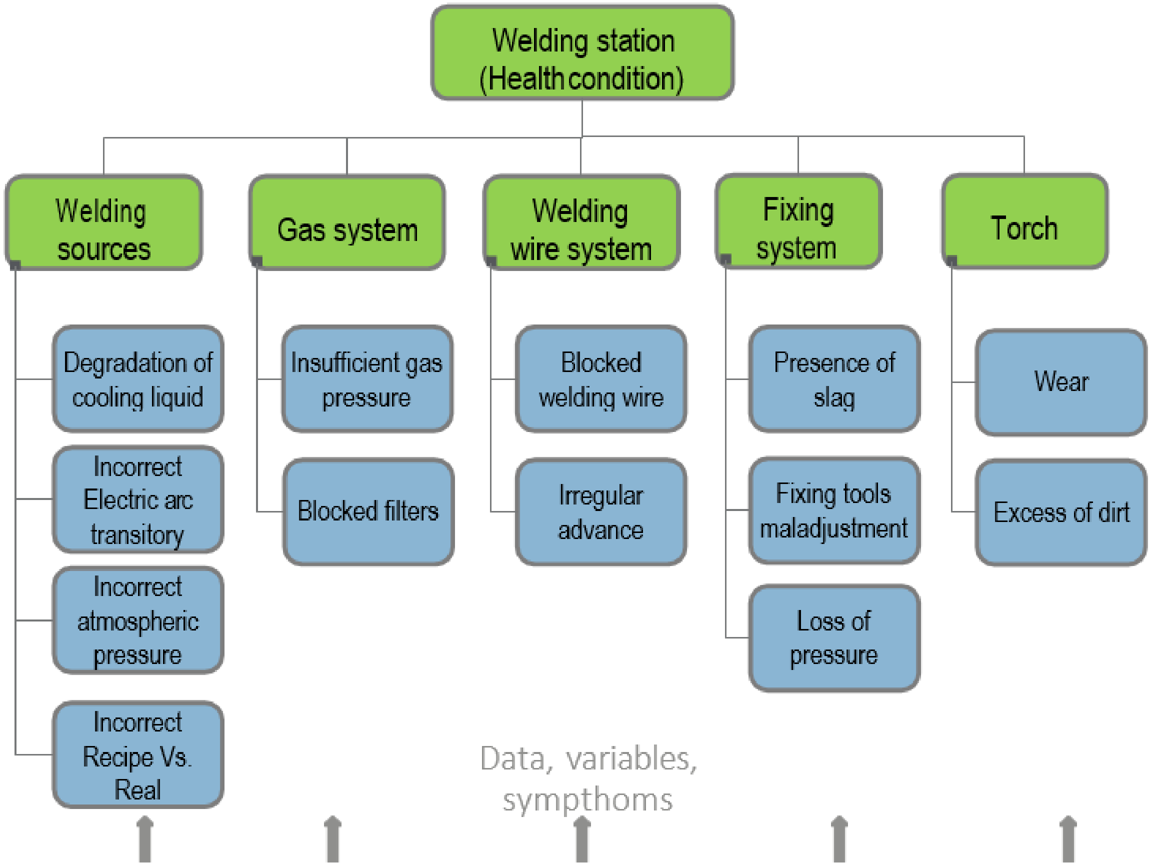


Figure 6.8. PML hierarchy based on assets tree structure.

A PML value equal to 1 means that the health state of the machine is perfect. Values lower than 1 means that there exist some abnormal conditions (see Figure 6.9).

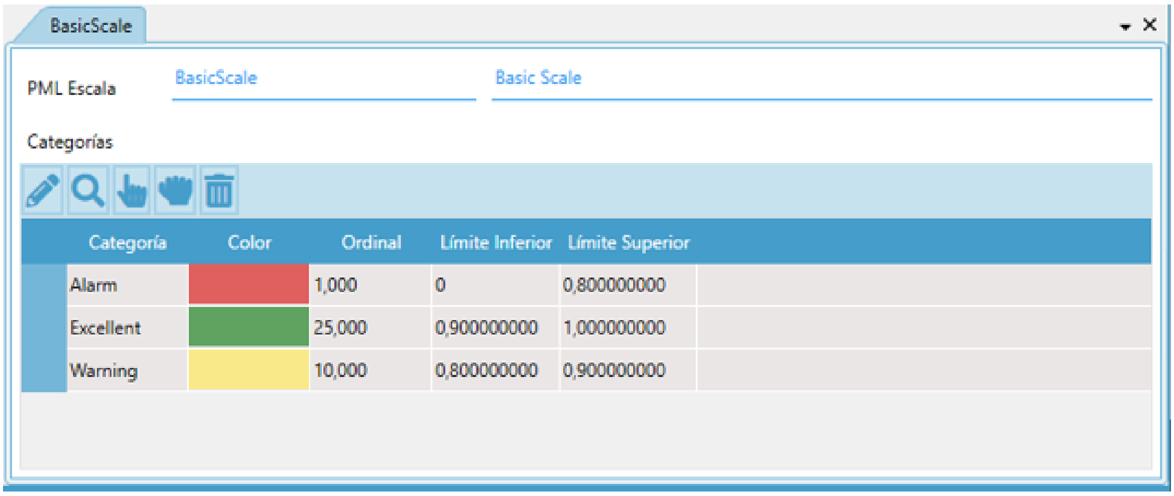


Figure 6.9. PML scales.

The PML calculation is done in real time by the Machine Learning software and data are recorded to perform a historic database (see Figure 6.10).

PML	Activo	Fecha	Valor	Estado
AGVHealthStatus	AGVASF	06/03/2020 8:30:26	1	Invariant
BufferHealthStatus	BufferASF	06/03/2020 8:30:26	0,988513171672821	Invariant
DimInspectionHealthStatus	DimInspectNub3D	06/03/2020 8:30:26	1	Invariant
PressHealthStatus	PressFagorASF	06/03/2020 8:30:26	1	Invariant
WeldingBottlePressure	WeldingFroniusASF	06/03/2020 8:30:26	0,999699413776398	Invariant
WeldingCoolingCycles	WeldingFroniusASF	06/03/2020 8:30:26	0,980771601200104	Invariant
WeldingGasFilter	WeldingFroniusASF	06/03/2020 8:30:26	0,991267085075378	Invariant
WeldingRecipeCompliance	WeldingFroniusASF	06/03/2020 8:30:26	0,999991476535797	Invariant
WeldingSourceTransient	WeldingFroniusASF	06/03/2020 8:30:26	0,977864325046539	Invariant
WeldingTorchDegradation	WeldingFroniusASF	06/03/2020 8:30:26	0,918112874031067	Invariant
WeldingTorchDirty	WeldingFroniusASF	06/03/2020 8:30:26	0,959912240505219	Invariant
WeldingWireJam	WeldingFroniusASF	06/03/2020 8:30:26	1	Invariant
WeldingWireLack	WeldingFroniusASF	06/03/2020 8:30:26	1	Invariant
WeldingWireRemaining	WeldingFroniusASF	06/03/2020 8:30:26	0,973289583206177	Invariant
WeldingWrapCycles	WeldingFroniusASF	06/03/2020 8:30:26	0,940305888652802	Invariant
WeldingWrapPressure	WeldingFroniusASF	06/03/2020 8:30:26	0,990374863147736	Invariant
WeldInspectionHealthStatus	WeldInspectSmartRayASF	06/03/2020 8:30:26	1	Invariant

Figure 6.10. PML database.

PML values can be monitored in real time and graphically visualized to facilitate the decision making. Moreover, a prediction of the future behaviour of the PML (for a time t: 1 minute, 1 hour, 1 day…) is provided by machine learning software.

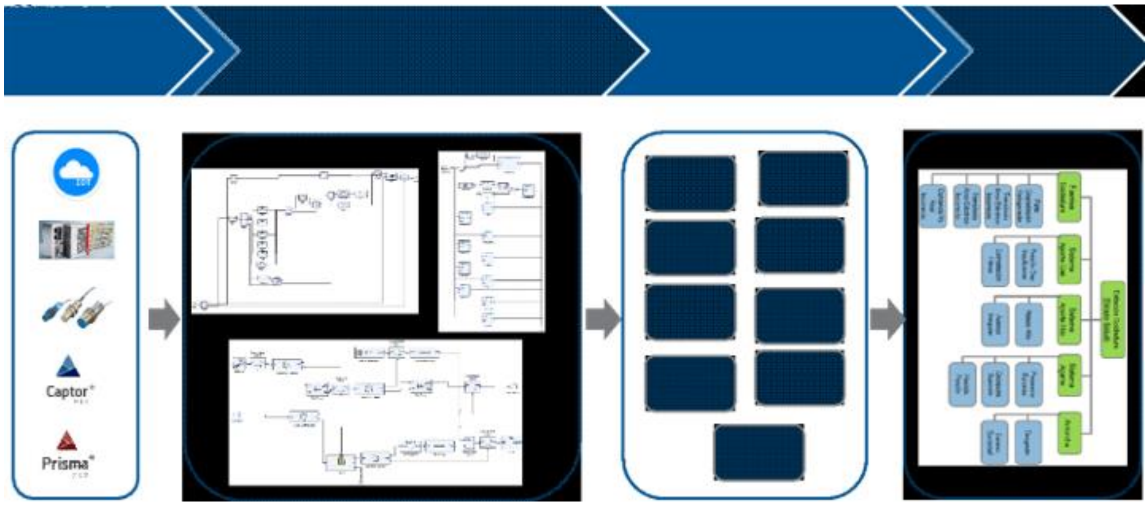


Figure 6.11. Global logic of health monitoring system.

6.13. Integration with CMMS

The health state of the asset is being calculated and real-time monitored. When there is a significant deviation from the standard values of health, a request for work order is automatically triggered and sent to the CMMS, containing specific information for the intervention (PML of each system and subsystem, deviated parameters and related failure modes, standard values, etc.). The request for order is converted into a work order and it is planned in the CMMS for a rapid response to the potential problem.

In conclusion, a complete Health Monitoring application consists of an integrated system where the machine learning tool has a capital importance. But Machine Learning software is not an isolated system, on the contrary, all its potential is achieved only if it is integrated with MES and CMMS systems, as shown in Figure 6.12.

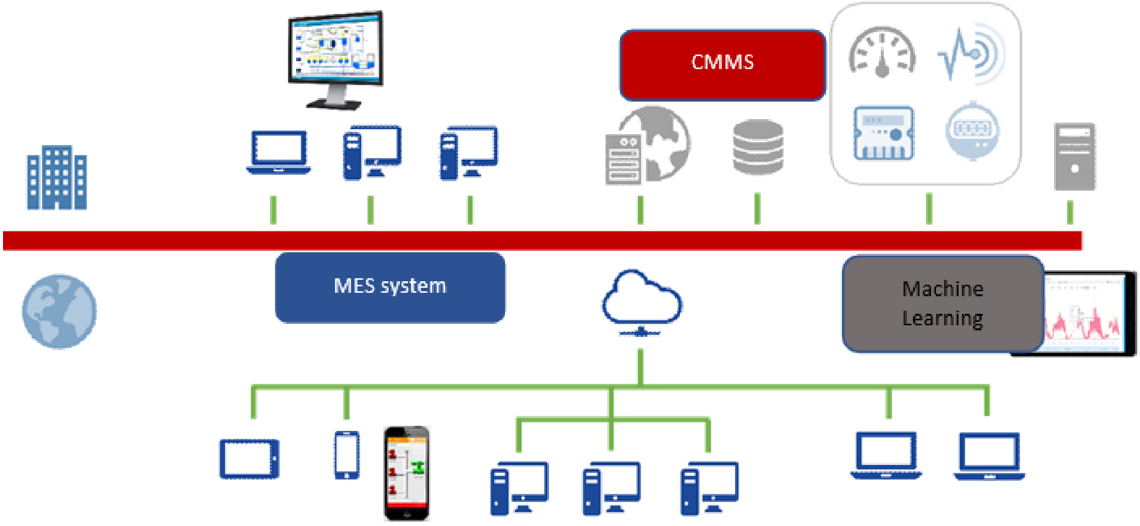


Figure 6.12. Architecture for a complete health monitoring system.

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8. APPENDIX CASE HISTORY WITH PAPER

DIGITAL TWIN APPROACH FOR DURABILITY AND RELIABILITY ASSESSMENT OF BRIDGES

Jan CERVENKA[1], Libor JENDELE[1], Jiri ZALSKY[2], Radomir PUKL[1], Drahomir NOVAK[3]

Cervenka Consulting s.r.o., Prague, Czech Republic.

Klokner's Institute, Czech Technical University, Prague, Czech Republic of Civil Engineering, Technical University of Brno, Brno, Czech Republic Corresponding author email: jan.cervenka@cervenka.cz

Abstract

Digital twin is a modern concept, in which a digital replica of a real product and structure is developed, and a simulation is performed to test the product behavior under service conditions. In the presented paper the digital twin method is used for making assessments of safety, durability and reliability of bridge structures. Although some numerical modelling is often done when an existing bridge is evaluated, it usually does not involve the simulation of real behavior under service and environmental loads including chloride ingress, reinforcement corrosion and assessment of ultimate load carrying capacity. The digital twin concept in addition includes an important aspect of the digital twin calibration and validation using the real monitoring data.

The paper presents a chemo-mechanical model covering initiation and propagation of chlorides or carbonation. This model is combined with the nonlinear modelling of cracking, bond failure and reinforcement yielding (Cervenka and Papanikolaou et al., 2008). The paper extents the previously developed model by the authors Hájková et al. (2019), Jendele, Šmilauer and Červenka (2014). The models were implemented in ATENA software and are validated on experimental data. The developed models can be efficiently used in large scale analysis of real engineering problems as demonstrated on applications to an existing bridge structures in Germany. The example simulation using the digital twin concept show time development of reinforcement corrosion due to chloride ingress, and their impact on the evolution of structural safety and reliability (Cervenka et al., 2020(a)).

Keywords: *Durability, Concrete Bridges, Corrosion, Chloride ingress, Finite element analysis.*

8.1. Introduction

In reinforced concrete structures, the reinforcement corrosion due to carbonation and chloride ingress are important damaging mechanisms. They can significantly reduce the service life of reinforced concrete structures (Tang, Utgenannt and Boubitsas 2015). Chloride ingress is usually the consequenceof de-icing, sea water and salts in coastal areas. Ions from chloride penetrate through the concrete binder and their diffusion is governed by several factors such as environmental boundary conditions, concrete cover thickness, cement type, water-to-binder ratio (w/b) (Kwon et al. 2009, Liu and Weyers 1998).

The reinforcement corrosion process is generally divided into two time phases; the initiation (induction) period ti and the propagation period t p (Figure 8.1). The initiation period of the damaging mechanisms was described and validated in the earlier paper by Jendele, Šmilauer and Červenka (2014) and results show strong influence of crack width on the transport properties and on the acceleration of the damaging mechanisms. The cracks of 0.3 mm decrease induction time approximately 6 times for carbonation and approximately 9 times for chloride ingress from sea water. Preventing macro-cracks and designing proper concrete is essential for durable concrete structures (Cervenka et al., 2020(b)).

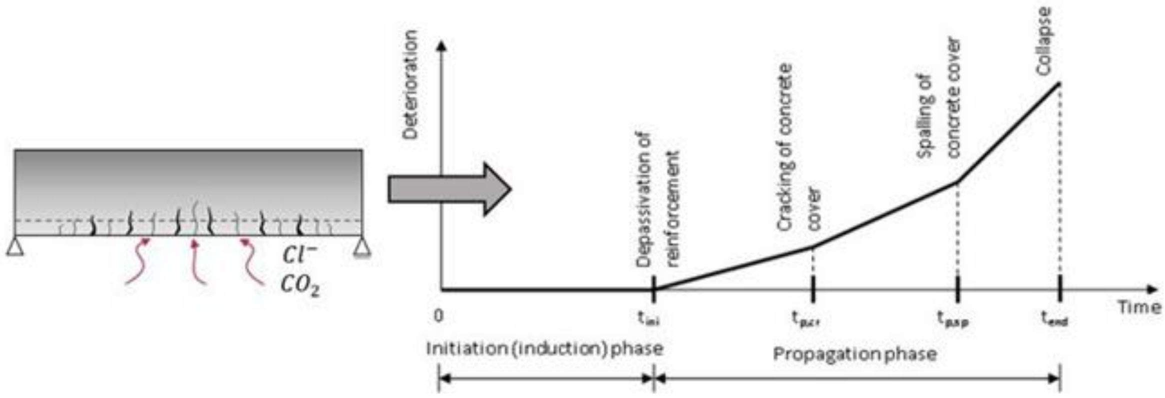

Figure 8.1. Typical phases of the corrosion process (Cervenka et al., 2020(b)).

The presented model covers also the propagation period t p, when reinforcement corrosion takes place. During this period, reinforcement cross-sectional are decreases and is accompanied with growing corrosion products.

The presented approach combines the model by Kwon et al., 2009 for the initiation phase with the effect of crack width by Liu and Weyers (1998) for the propagation period. The presented corrosion model is combined with the mechanical model for concrete nonlinear behavior by Červenka and Papanikolaou (2008).

The validation as well as more details about the individual components of the presented models is described in Hájková et al. (2019) for the corrosion model and in Červenka and Papanikolaou (2008) for the mechanical model. This paper focuses on practical applications of the presented models on a bridge Germany within the digital twin concept and using the global safety formats for nonlinear analysis according to Model Code 2010 (2011).

8.2. Modelling of Structural Strength and Durability

The above models are implemented in ATENA software (Cervenka et al., 2020(c)), using multi-physics approach for mechanics and transport. It predicts induction time and extent of corrosion for chloride ingress, and calculates remaining steel area. The mechanical behavior and concrete cracking is simulated using the fracture-plastic model of Červenka et al., 1998 and Červenka and Papanikolaou et al., 2008. It combines plasticity based model for compressive failure and smeared crack model with tensile softening and crack band approach for tension (Figure 8.2). The reinforcement corrosion is evaluated based on the parameters of the surrounding environment that are specified as a special boundary condition as showing Figure 8.3. Figure 8.3 shows a simple example of a short cantilever whose bottom surface is subjected to chlorides. A mechanical load initiated cracks starting at the bottom surface. For each reinforcement, the closest distance to the surface subjected to chlorides is calculated. The initiation phase as well as the subsequent corrosion phases are evaluated assuming a 1D transport process along this closest distance considering also the width of a possible surface crack. Based on the amount of corrosion, the effective reinforcement area is reduced, which can directly affect the load carrying capacity or the deflections of the numerical model. This approach can simulate the effect of structural degradation in a very effective and efficient way (Cervenka et al., 2020(b)).

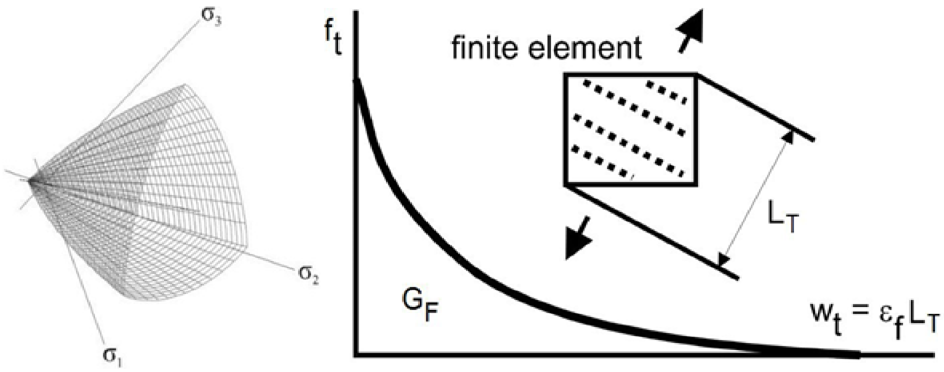

Figure 8.2. (left) three-parameter Menetrey and Willam failure criterion for compression, (right) crack band and tensile softening model for tension (Cervenka et al., 2020(b)).

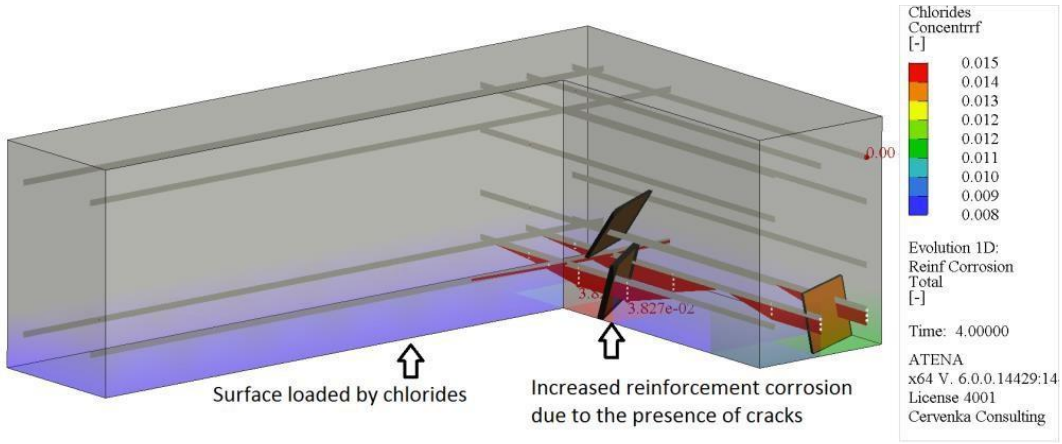

Figure 8.3. Corrosion modelling in finite element nonlinear analysis (Cervenka et al., 2020(b)).

The initiation period covers the time before the concentration of chlorides exceeds a critical value in the place of reinforcement. One dimensional chloride transient ingress into concrete, with an initially zero chloride content can be described according to Kwon et al. (2009) as:

$$C(x,t) = C_S\left[1 - er\,f\left(\frac{x}{2\sqrt{D_M(t)f(w)t}}\right)\right] \tag{8.1}$$

where Cs is the chloride content at surface in [kg/m^3], $D_M(t)$ is the mean (averaged) diffusion coefficient at time t [m^2/s], x is the distance from the surface in [m] and f(w) introduces acceleration by cracking. (equals to one for a crack-free concrete). Cs and C(x,t) can be related to a concrete volume or to a binder mass. The model is in detail described in the previous paper by Hájková et al (2019).

The propagation phase is controlled by the corrosion rate. For chloride ingress it is dependent on the corrosion current density i_{corr} [μA/cm^2] and on chlorides concentration in the concrete. The model predicts the amount of corroded steel during the propagation period t_p, which is governed by Faraday's law according to Liu and Weyers (1998) by the following formula:

$$\dot{x}_{corr}(t) = 0{,}0116\, i_{corr}(t), x_{corr}(t) = \int_{t_{ini}}^{t} 0{,}0116\, i_{corr}(t), R_{corr} dt, d(t) \\ = d_{ini} - \psi 2 x_{corr}(t) \tag{8.2}$$

where $\dot{x}_{corr}$ is the average corrosion rate in the radial direction [μm/year], i_{corr} is corrosion current density [μA/cm^2] and t is calculated time after the end of induction period [years]. By integration of equation (8.2), we obtain the corroded depth for 1D propagation x_{corr}. R_{corr} is a parameter, which depends on the type of corrosion [-], uniform corrosion (carbonation) R_{corr} = 1, pitting corrosion (chlorides) R_{corr} = <2; 4> according to Gonzales et al., 1995 or

R_{corr} = <4; 5.5> according to Darmaw an and Stewart (2007). d(t) is the evolution of a bar diameter in time t, d_{ini} is initial bar diameter [mm], ψ is uncertainty factor of the model [-], mean value ψ = 1 and x_{corr} is the total amount of corroded steel. The corrosion rate for chlorides is affected by concentration of chlorides in the concrete. The calculation of the corrosion current density was formulated by Liu and Weyer's (1998) model:

$$i_{corr} = 0{,}096\, exp\left[7{,}98 + 0{,}7771\, ln(1{,}69C_t) - \frac{3006}{T} - 0{,}000116\, R_C + 2{,}24t^{-0{,}215}\right] \tag{8.3}$$

$$R_C = exp[8{,}03 - 0{,}549\, ln(1 + 1{,}69C_t)] \tag{8.4}$$

where i_{corr} is the corrosion current density [$\mu A/cm_2$], C_t is the total chloride content [kg/m^3 of concrete] at the reinforcement location, which is determined from 1D non-stationary transport, T is temperature at the depth of reinforcement [K], R_C is the ohmic resistance of the concrete cover [Ω] (Liu Y., et al. 1996) and t is the time after the initiation [years] (Cervenka et al., 2020(b)).

8.3. Application Example

The presented model was applied to Vogelsang bridge in Germany as a part of the international Eurostars-2 project E!10925 "cyberBridge". It is a concrete bridge over the Neckar River in the city of Esslingen, Germany. It is a major part of the city's infrastructure with a high impact on the regional traffic. The bridge consists of eight partial structures built in three different construction types. The bridge was built between the years of 1971 and 1973. The total length is approx. 595m and it has a totalarea of 9,744m^2 including ramps. Overview of the structure is shown on the Figure 8.4.

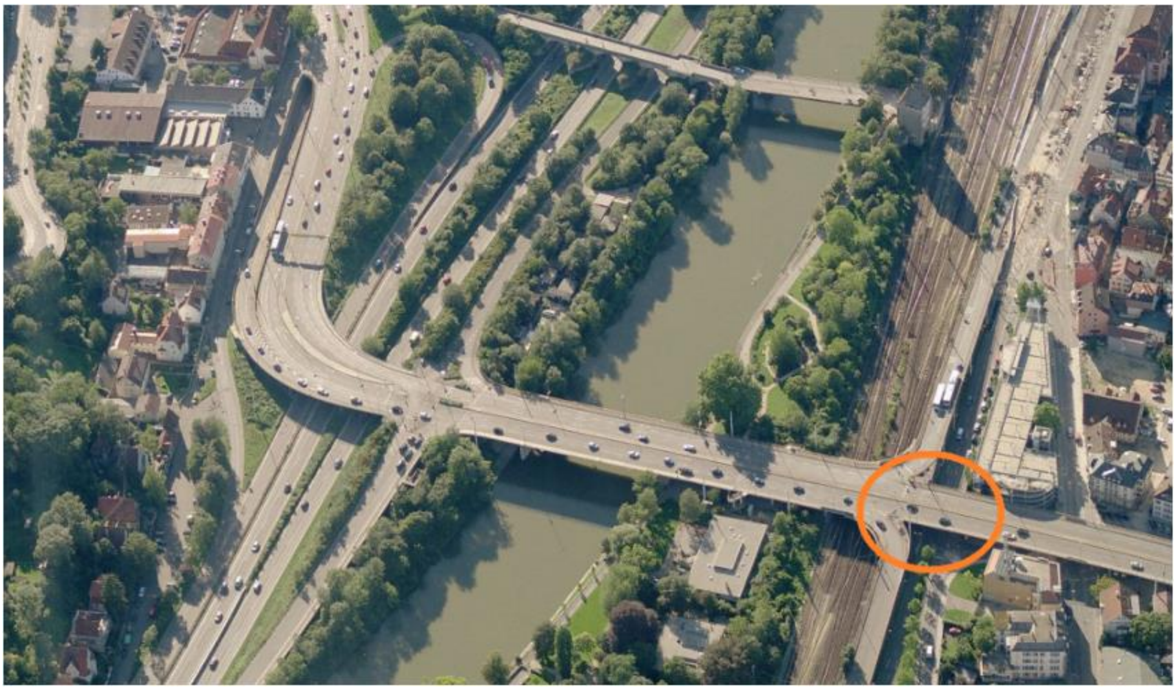

Figure 8.4. Aerial image of Vogelsangbrücke Esslingen, Germany [source: maps.google.com].

During the last major check, many damages have been detected, that influence the structural safety, the safety to traffic and the durability. Due to the damages, refurbishment was urgently needed.

8.4. Monitoring

Monitoring system was placed on "D part" of the bridge as indicated by the red circle in the right bottom corner of Figure 8.4. This part of the bridge was used as a pilot project to evaluate the capabilities of the proposed approach. It is a two-span concrete superstructure with a total length 27 m. Non-prestressed reinforced concrete beam is supported as continuous beam with two spans 13.8 and 13.2 m. Height of the beam is 0.6 m. iBWIM monitoring system was used as developed and further extended and enhanced during the "cyberBridge" project. Monitoring spiders were placed on the bottom side of the slab. Each spider consists of five iBWIM sensors and one data collector. The sensor ensemble consists of one laser rangefinder; five strain gauges arranged in a row transverse to the road; and two strain gauges which are placed on either side of the row. The gauges in the row perform the actual measurement; the two adjacent gauges are used for triggering a measurement and estimating the speed of the vehicle; the laser rangefinder is used to detect and localize the vehicle axles. The group of sensors produce just one average value of micro-strain on each side of the slab. Both measuring spiders are shown on the Figure 8.5 and Figure 8.6 (Cervenka et al., 2020(a)).

Figure 8.5. Position of spiders on the slab (Cervenka et al., 2020(b)).

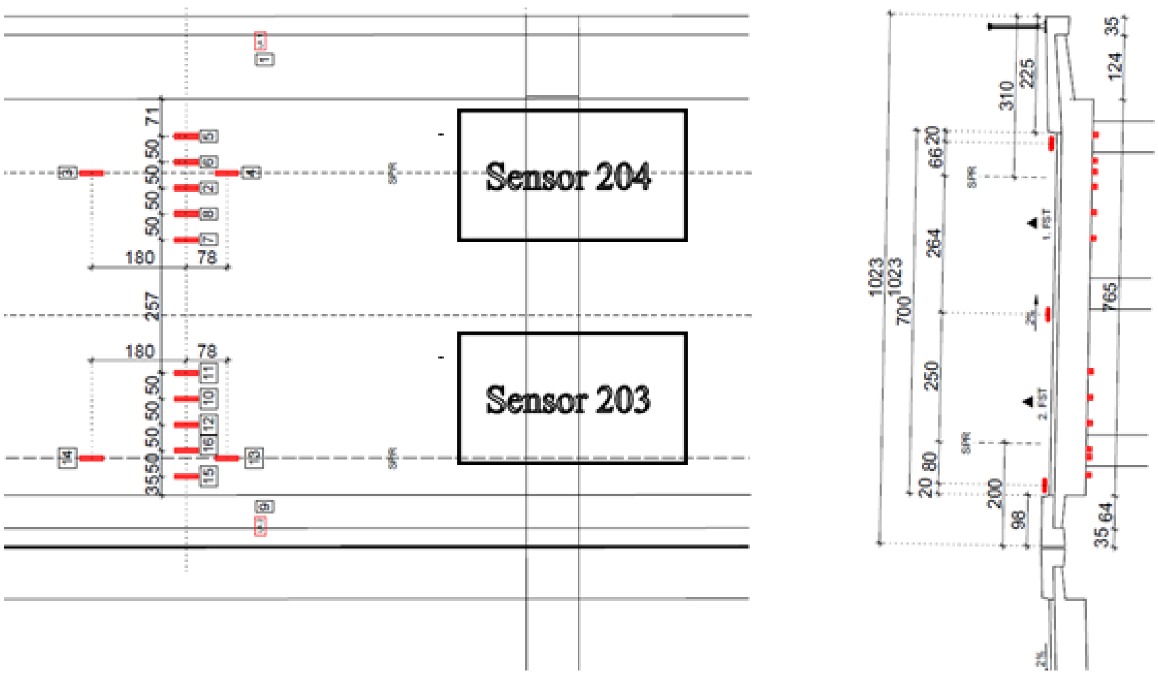

Figure 8.6. Cross-section of the bridge showing the position of the iBWIM sensors (Cervenka et al., 2020(a)).

The monitoring was performed over an uninterrupted period lasting from Jan. 16 – Mar. 17, 2019, i.e. over 61 days. The iBWIM monitoring system provides valuable information for the durability assessment of the entire bridge including the other parts like the main river bridge. Major results like the number of heavy vehicles (trucks) crossing the bridge, the typical gross weight of the trucks, typical length of the trucks and number of axles and their weight were identified as shown in Figure 8.7. Furthermore, the probability distribution of the loading events were calculated (Cervenka et al., 2020(a)).

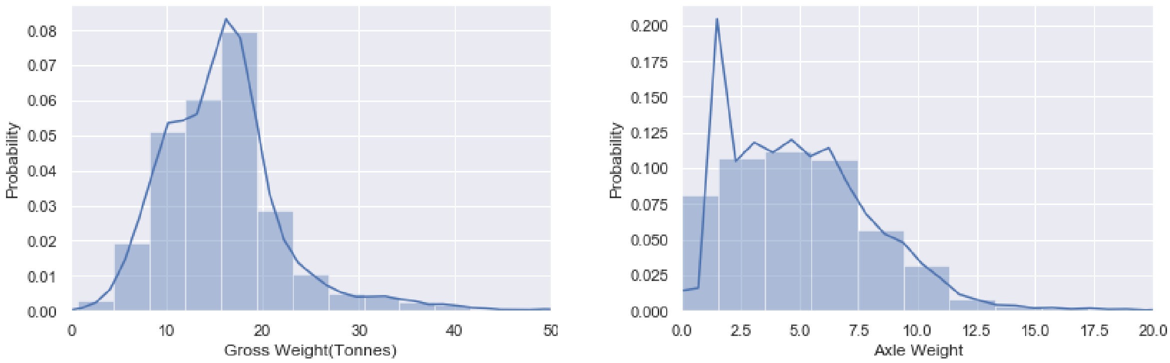

Figure 8.7. Distribution of gross weight and axle weight of vehicles (Cervenka et al., 2020(a)).

8.5. Development and Calibration of the Digital Twin

The data obtained by the monitoring were also used for the calibration of the numerical model that was developed in the software ATENA (Cervenka et al., 2020(b)). Just one half of the bridge was modelled because of symmetry and connecting between two slabs in the middle of the bridge was neglected. The finite element mesh consisted of hexahedra quadratic isoparametric elements with the typical size of about 0,5 m. The bridge is modelled by solid elements reinforced by reinforcing steel bars (shown on Figure 8.8 and Figure 8.9). Figure 8 also shows the model of the passing truck, which was used for the model calibration using the heavies vehicles as detected by the iBWIM monitoring system (Cervenka et al., 2020(a))..

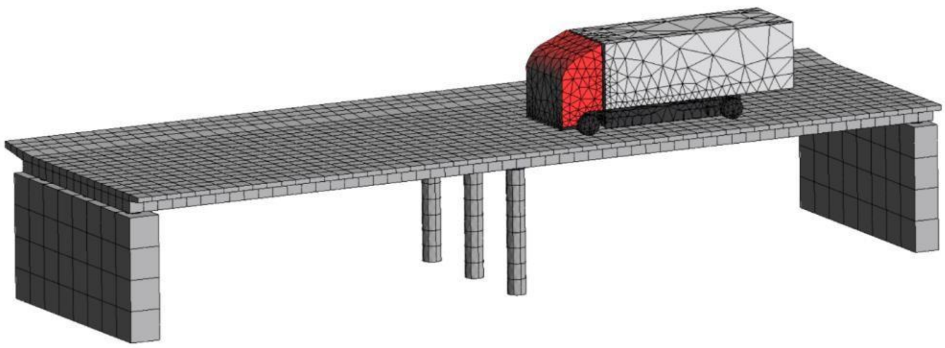

Figure 8.8. Numerical model of the bridge and a passing truck (Cervenka et al., 2020(a)).

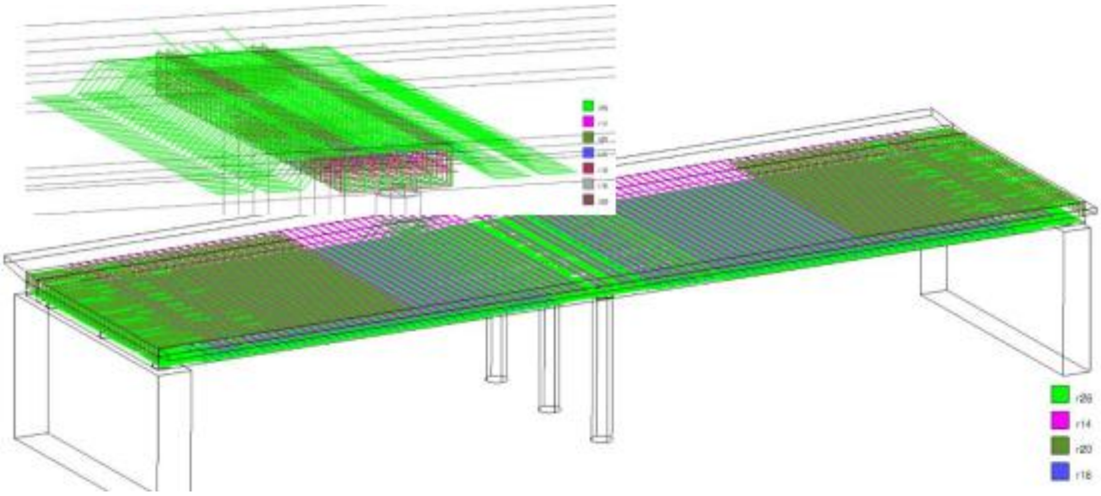

Figure 8.9. Overview on the reinforcement in the concrete slab showing the detail of the reinforcement arrangement above the middle piers (Cervenka et al., 2020(a)).

Initial material parameters were set based on structural diagnostic and on the original bridge design specification. In the original design the concrete B450 was assumed, while the compressive tests on drilled cores show the compressive strength of $f_{c,cyl} = 35{,}5\ MPa$ and elastic modulus $E_c = 33{,}3\ MPa$. These initial parameters were used in a parametric and optimization study to identify the most suitable material parameters for the subsequent durability and bridge life prediction analysis. The optimization was performed using the monitoring data obtained during the monitoring process as described in Section 4. The initial analyses showed that cracks must exists in the bridge in order to match the measured strains, therefore the main optimization parameters were selected to be tensile strength f_t and fracture energy G_F. The final optimized set of parameters is shown in Table 8.1 (Cervenka et al., 2020(a)).

Table 8.1. *Optimized concrete material parameters (Cervenka et al., 2020(a)).*

Material Parameter	Value
Young´s modulus E [GPa]	33.3
Poisson´s ratio ν [-]	0.2
Compressive strength fc [MPa]	-35.5
Tensile strength ft [MPa]	3.24
Fracture energy GF [N/m]	144
Plastic strain at compressive strength εcp [-]	-0.00123
Critical compressive displacement wd [mm]	-0.5
Reduction of compressive strength due to cracks [-]	0.8

Figure 8.10 shows the typical deflection and crack development during the simulation of a two axle truck passing with gross vehicle weight of 27.6 tons. In this case the monitoring system detected the strain of 77 μs trains (group 203) during the truck passing and 30 μs on the neighboring lane (group 204) (see Figure 8.6). In the optimized numerical analysis, the

calculated strains at the location of group 203 sensors was 74 μs and 43 μs at sensor group 204. The average error was about 19% from the monitoring and numerical results for the optimized set of parameters (Cervenka et al., 2020(a)).

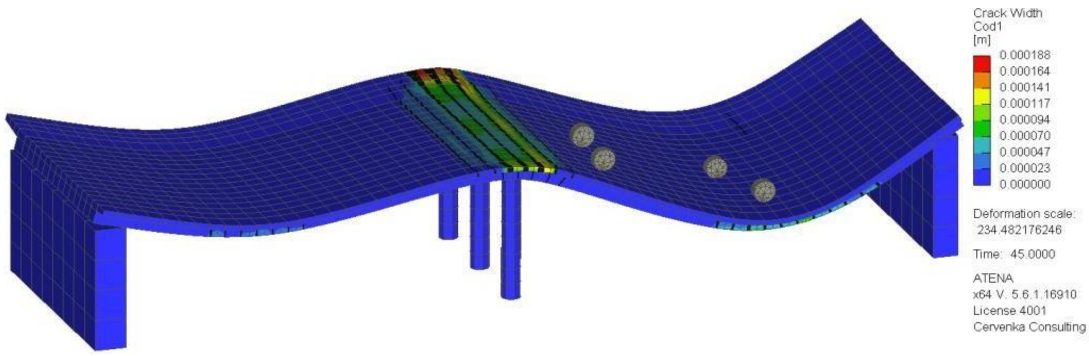

Figure 8.10. Crack width after loading by weight of the truck (Cervenka et al., 2020(a)).

8.6. Prognosis of Structural Durability

The calibrated model according to the Section 2.5 was used for a prognosis of structural service life using the durability model described in Section 2.2. The same numerical model was used as described in Section 5. In the durability assessment, the bridge is loaded by the permanent load and average life/traffic load as determined by the monitoring data in Section 2.4. Then it is subjected to the environmental actions: chlorides: $D_{ref} = 1{,}2e^{-7}\ m^2/day$, $t_{Dref} = 3.650\ days$, $m_{coeff} = 0{,}37$, $t_{mcoeff} = 10.950\ days$, $Cl_{crit} = 0{,}004$, $f_{t,ch} = 3{,}2\ MPa$, $W_d = 0{,}001\ m$, pitting corrosion $R_{corr} = 2$. Chloride surface concentration C_s was applied differently for the top surface C_s = 0.009 and for bottom surface C_s = 0.0055. The corrosion rate after concrete spalling was assumed at 35 μm/year (Cervenka et al., 2020(a)).

The environmental action of chloride ingress was calculated for several duration times: 25, 50, 75, 100 and 150 years. At these times the numerical models are loaded by the most critical ULS load combination. The load is then increased all the way up to failure. This is accomplished by using the Arc-length nonlinear solution methods originally proposed by Crisfield (1983), which allows for automatic reduction of the applied load such that a peak load can be detected in load controlled numerical analysis. All models have been calculated with two sets of material parameters (characteristic and mean) such that it is possible to applied the global resistance method ECOV according to model code 2010 (2011) Section 7.11.3.3.2.

The main results from the durability analysis for the case using mean material properties are shown in Figure 8.11. In this figure, the time development of structural capacity is evaluated using the ECOV method (Model Code 2010, 2011). It shows that the design resistance (solid red line) will drop below the design load level (ULS curve) in 110 years. This number can be interpreted as the service life of the structure. If proper rehabilitation is performed in this period, the service life can be even extended above this time. The current age of the structure was 45 years, so this would mean additional 50-60 years. This was more than the expected life of 15-20 years based mainly on traditional visual observation and expert judgement (Cervenka et al., 2020(b)).

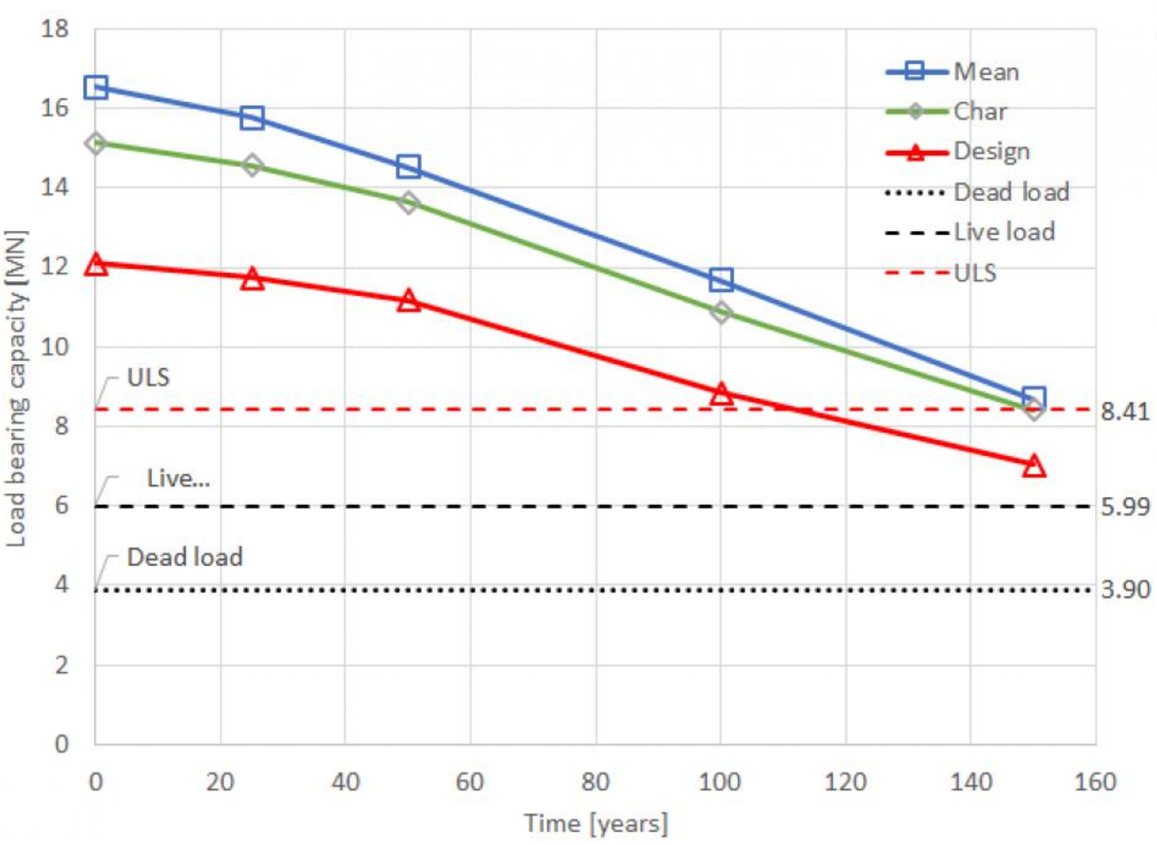

Figure 8.11. Comparison of durability based on reliability of material (Cervenka et al., 2020(b)).

8.7. Conclusion

The paper presents an application of digital twin concept which combines monitoring with numerical simulation to develop a calibrated numerical model of an existing bridge structure. The calibrated numerical model was used to perform durability assessment of the investigated bridge and predict its service life considering the structural degradation due to corrosion. In this pilot investigation is was possible to prove the service life of additional 30-45 years over the initially expected period. In practice it is critical to complement numerical predictions, by extensive on- site investigation and monitoring program.

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