ForeSee

Predictive maintenance technologies for production systems. A roadmap to development and implementation.

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Executive summary

High added-value products manufacturing methods are undergoing a continuous evolution nowadays, aiming to get higher productivity rates, product quality and reduction of defective products. Manufacturing companies increasingly use condition monitoring solutions and Predictive Maintenance (PdM) solutions to guarantee the intended usage of production equipment and to avoid unplanned downtimes. As such, this white paper presents a review of the lessons learned from the point of view of six EU funded H2020 research projects (PRECOM, PROPHESY, PROGRAMS, SERENA, UPTIME and Z-BREAK), funded under the topic "FOF-09-2017 - Novel design and PdM technologies for increased operating life of production systems". These projects were active from 2017 to 2021 and together constituted the ForeSee cluster. Research and technology partners together with industrial end-users worked collaboratively to develop and deploy solutions that advance maintenance practice in industry towards more efficient, sustainable, human-centric and resilient factories. This white paper aims to share knowledge, vision and lessons learnt by ForeSee cluster partners on the topic of PdM, as well as to provide recommendations for advancing PdM in industrial practice. The core target groups of this report are industry practitioners, people in academia and policy makers at the local, national and EU levels.

The technologies that have acted as key-enablers in several of the ForeSee cluster projects (such as Internet of Things, Digital Twin, Proactive Computing, Virtual/Augmented Reality and linked data) are discussed in this document. Furthermore, the skilling of personnel, as well as the use of standardized technologies and processes are cross-cutting issues pertinent to ForeSee projects and their role in PdM projects is presented. The evaluation of these concepts and technologies in ForeSee industrial cases has proven their significance to industrial practice. The validation phase in industrial cases has served the ForeSee cluster with the provision of the following lessons learnt and recommendations for successful adoption of technology and best practices.

Lessons learned:

- ✓ Need for the development of structured data repositories with Industry4.0 and PdM datasets
- ✓ Availability for testbeds for PdM, condition-based maintenance and intelligent asset management
- ✓ Adjustment of AI-based Maintenance and Asset Management Systems to facilitate accessibility by the non-experts
- ✓ Standardization, data and semantics interoperability, as necessary enablers to support the diverse software, hardware as well as business process landscape in asset management.

Recommendations:

- ✓ Business models for Condition Based Maintenance and Intelligent Asset Management should be further investigated
- ✓ Mobile Management - Mobile-First Condition Based Maintenance are important concepts that could benefit the adoption of CBM and PdM strategies
- ✓ Smart and Autonomous Objects should be further considered when it comes to data collection, inspection, data collection and communication.
- ✓ Adequate actions for Training - Education - Lifelong Learning of people working closely with advanced data and Internet of Things technologies should be considered.

Predictive maintenance technologies for Production systems

A roadmap to development and implementation

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Glossary

Term	Description
AI	Artificial Intelligence
AR	Augmented Reality
CPS	Cyber-Physical System
CBM	Condition-based monitoring
CM	Condition Monitoring
DIA	Digital Intelligent Assistant
DT	Digital Twin
IoT	Internet of Things
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes, Effects and Criticality Analysis
KPI	Key Performance Indicator
ML	Machine Learning
MTBF	Mean Time Between Failures
MTTR	Mean Time to Repair
OEE	Overall Equipment Effectiveness
PdM	Predictive Maintenance
RLD	Remaining Life Distribution
RUL	Remaining Useful Life
TCM	Total Cost of Maintenance
VR	Virtual Reality

1 Introduction

High added-value products manufacturing methods are undergoing a continuous evolution nowadays aiming to get higher productivity rates, product quality and reduction of defective products. Achievable production rates in a manufacturing system are significantly affected by the reliability of the equipment (Chryssolouris 2006). The adaption of efficient maintenance strategies is a key element for industries, to provide them with competitive leverage against overseas industries. Manufacturers simply cannot afford to perform corrective maintenance actions only when they have a costly critical failure. Furthermore, they cannot rely on time-based preventive maintenance strategies since the results of such approaches are vulnerable to unexpected variations in process parameters that are related to tool and machine conditions, material quality and human intervention. These factors affect the effectiveness of time-based preventive maintenance, leading to unforeseen costly failures. The problem with conventional preventive maintenance is that schedules and tasks are based primarily on assumption and estimation, rather than data-driven facts. Nowadays manufacturing companies increasingly use condition monitoring solutions and PdM solutions to guarantee the intended usage of production equipment and to avoid unplanned downtimes. Condition-based monitoring (CBM) is the process of monitoring and assessing the status of assets. Based on condition monitoring and taking into account the planned manufacturing processes to be performed, a prediction of the Remaining Useful Life (the error-free operational period of the asset) can be estimated, and the maintenance tasks can be defined and planned accordingly. This process is referred to as “Predictive Maintenance” (PdM). Current solutions deployed on the factory floor are merely based on monitoring the condition of one or more parameters of the assets condition. Popular emerging technologies of recent times, tackling issues of optimizing capital equipment maintenance in manufacturing lines, are said to be the combination of Internet of Things (IoT) and Big Data Analytics. PdM, that is, the analysis of multiple sources of production data for predicting the needs and driving adequate maintenance activities was identified in a recent McKinsey Global Institute report as the most valuable application of the above-mentioned technologies (Snidermann et al., 2016; McKinsey Global Institute, 2015). It is suggested that the use of PdM could save up to $630 billion by 2025, by reducing maintenance costs by up to 40%. Considering the market projections, manufacturers are focusing on the development of integrated systems able to exploit in house production data to extend the production system life span, thus reducing production costs and maintenance downtimes, and consequently improving product quality and profitability.

The purpose of this white paper is to share the ForeSee cluster understanding of future condition monitoring and PdM approaches for the factories of tomorrow and to provide recommendations on how to bring this vision into industrial practice. The white paper is structured as follows: in Chapter 2, the vision for PdM in manufacturing is presented. The chapter describes the ForeSee cluster’s vision of future factory PdM tools. Chapter 3 reports the key enabling technologies that can be utilised to implement the vision for PdM in factories. Chapter 4 provides insight and lessons learned by applying the technologies described in chapter 3 on several ForeSee cluster projects’ industrial pilot cases. The challenges, solutions and impact of industrial pilot cases are described as well. Chapter 5 focuses on standardization challenges. In Chapter 6, recommendations are proposed to industry practitioners, regarding methods and technology adoption and integration of PdM. Chapter 7 provides recommendations for future research directions and innovation policy makers.

2 A vision for predictive maintenance in manufacturing

2.1 Background – Current Trends in Maintenance

The minimization of costs and the maximization of optimal reliability and production efficiency with a low environmental impact, as well as the safety of operations are increasingly important issues for every industry (Bousdekis et al., 2018). The Boston Consulting Group (2013) reports that improvements in maintenance productivity can enable 10-20% savings on labour, repair and maintenance (R&M) of parts and tools which together account for 15% of total costs for a typical organization. This means that improving maintenance can reduce conversion costs by 2-4% (McCarthy et al., 2013). Maintenance should thus be considered a key operation function of manufacturing enterprises (Peng et al., 2010), (Bousdekis et al., 2015). Its strategic position can greatly vary from one company to another – it can either be internalized using dedicated, in-house teams or either fully or partially outsourced to maintenance service providers. Maintenance touches all processes of a manufacturing company. Besides avoiding equipment breakdown, a sound maintenance strategy should be aimed towards improving business performance and maximising profits in terms of productivity, quality, and logistics management (Voision et al., 2010), (Van Horenbeek et al., 2013), (Aboelmaged, 2015).

While industrial maintenance service providers have been used to an average annual growth rate in Europe of more than 6% since the early 2000s, the dynamic has tended to slow down since 2009. Moreover, the growth potential in the petrochemical and steel site maintenance segment, the sector's two main opportunities according to Xerfi (2019), is currently particularly low. Almost all companies have already outsourced these functions, only carrying out the exploitation of their operations. More than the high cost, the main obstacle is confidentiality. Companies do not want their manufacturing secrets to be disclosed by outside parties. The risks of loss, over the years, of technical expertise and know-how, are also put forward as reasons for not using maintenance subcontractors.

As a result, the average outsourcing rate (share of activity outsourced to external companies) in the field of industrial maintenance in Europe has been capped at around 35% since 2010. According to Eurostat (2015), industrial maintenance, repair, and installation in Europe represented approximately 170 billion euros in 2015. The budgetary restrictions imposed by industrial firms have been particularly focused on maintenance, one of the main items of expenditure, which effects are not immediately quantifiable.

Of course, the drivers of growth are less strong today compared to the prosperous periods of the 2000s. However, industrial maintenance professionals will always benefit from a comfortable growth rate. According to Xerfi estimations, the turnover of "unit outage" specialists averages 4.3% per year between 2016 and 2018. It must be said that maintenance contracts run over several years, so operators in the profession benefit from recurring revenues and are therefore less sensitive to economic conditions. Moreover, with the improvement of their business prospects, contractors will have the means to be more aggressive, in particular, to implement new maintenance strategies, in connection with industrial modernization projects.

The maintenance market is gradually maturing with common expertise and technical know-how no longer providing a competitive advantage to maintenance service providers anymore. Faced with market saturation and margins under pressure, subcontractors are easily replaced. In that context, maintenance stakeholders and new actors are seeking to expand their offer towards more remunerative services, particularly predictive maintenance (PdM). PdM is a strategy that has attracted high attention in recent years, leveraged by the introduction of information technologies in production facilities. It is recognised that the real maintenance revolution is the current and ongoing process (Algabroun et al., 2020), however, the involvement of artificial intelligence (AI) analytical models and machine learning (ML) algorithms within the business processes is a nonstop improvement procedure, that will bring the PdM systems in the upcoming few years to its full development potential.

Several market surveys indicate significant growth for the PdM market in the years to come even though the COVID-19 pandemic introduces a considerable degree of uncertainty when looking at prospects. ABI (2014) reported in 2016 that the investments in PdM reached €8.18 billion worldwide where the real growth of the PdM solutions could take charge based on the massification of deployed solutions, data collected as well as the use of sophisticated tools on data processing. Furthermore, the PdM advantage has increased the demand for the systems across the globe, stimulating market growth as reported in recent work by Market Research Future (Market Watch, 2019). Allied Market Research (2019) report estimates that the global PdM market size was valued at $2,804.38 million in 2018, and is projected to reach $23,014.7 million by 2026, growing at a CAGR of 30.20% from 2019 to 2026. Similarly, Fortune Business Inside (2019) estimates that the global PdM market size was valued at $2,387.6 million in 2018, and is projected to reach $18,551 million by 2026, growing at a CAGR of 29,8% from 2019 to 2026. McKinsey Global Institute (2015) reports that PdM could save nearly €630 billion by 2025 with the IoT reducing the equipment downtime by up to 50% and reduce equipment capital investment by 3 to 5% while extending the operating life of the machines.

2.2 Technological Drivers of Maintenance Strategies

Maintenance strategies can be roughly placed into three categories: 1) Reactive (or curative or corrective) maintenance, 2) preventive, time-based maintenance and 3) condition-based, predictive and prescriptive maintenance (Bousdekis et al., 2015). Figure 1 shows an overview of these strategies with increasing optimisation of maintenance and decreasing ease of implementation from top to bottom. Even large companies yet to fully realised sensor-driven, real-time PdM strategies (Bousdekis et al., 2015).

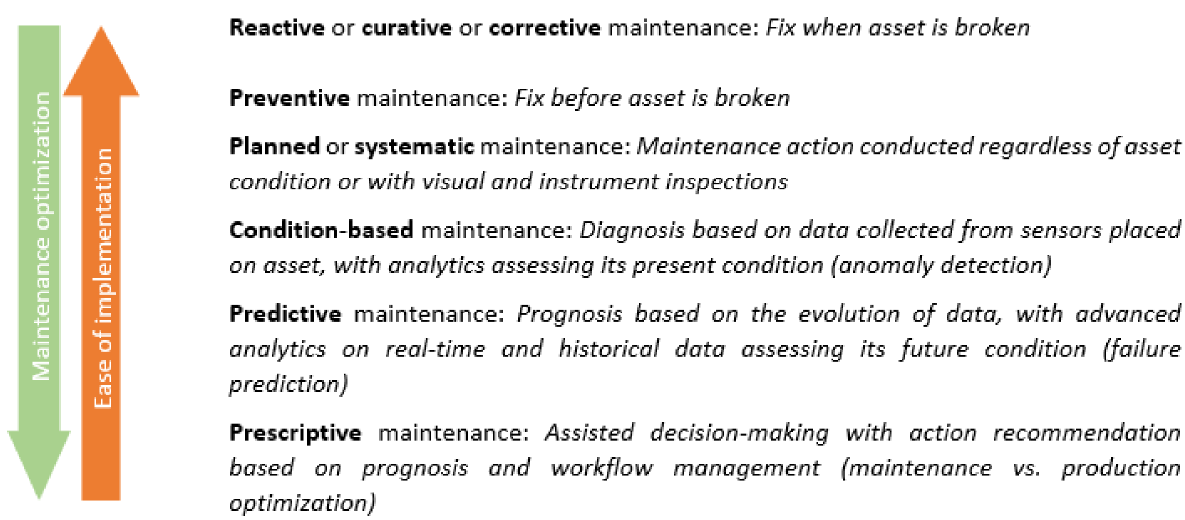

Figure 1: Types of maintenance strategies

However, products are becoming more and more complex and quality and reliability are increasingly critical issues. This has led to an increase in the costs of time-based preventive maintenance, making PdM a more attractive proposition for today’s manufacturing industry (Jardine et al., 2006), with companies increasingly turning towards PdM by utilizing the capabilities of condition monitoring. The main tools needed to implement new maintenance services already exist: sensors, PLCs, big data, IoT, AI, cloud computing. This makes it possible to detect faults before they occur, based on the information recorded by the sensors and the data history.

Condition monitoring is today often achieved using sensors directly integrated into manufacturing equipment. These sensors are capable of measuring a multitude of parameters at a high frequency (Jardine et al., 2006), (I.O. for Standardization - ISO 13372:2012, 2012), (I.O for Standardization - ISO 13379-1:2012, 2012). The cost of manufacturing sensors tends to be reduced thanks to improved production processes and economies of scale. The cost of sensors varies from few cents to thousands of Euros depending on their quality, the type of data they collect, the environment in which they are installed, their potential certification costs, etc. The cost of adding chips for capturing and wirelessly transmitting information from the physical world is becoming so low that any industrial equipment manufacturer may now wonder whether it is worth adding a form of "intelligence" to its products. The communication and storage of the huge amount of Big Data generated by these sensors pose significant challenges to the processing pipeline involved in analysing the data, extracting knowledge from it and finally making decisions (Bousdekis et al., 2015).

Predictive maintenance in the industry has hitherto made use of conventional condition monitoring approaches such as vibration analysis, thermography, acoustic emissions, or tribology (ISO 17359:2011, 2011). Today, data-based approaches are increasingly gaining momentum in the field of maintenance management which provide powerful tools for understanding the useful life of a system through dynamic pattern recognition. These approaches can contribute to determining the Remaining Useful Life (RUL), Remaining Life Distribution (RLD) and other KPIs, and to provide recommendations for maintenance-related processes.

The continuing adoption and evolution of the (Industrial) Internet of Things (IoT/IIoT) are giving the industry the means for enhancing its monitoring capabilities by extensively using physical and virtual sensors. In combination with advanced event monitoring and data processing systems, companies now have the potential to decide and act ahead of time, effectively solving problems before they appear (Engel et al., 2012). This means that failures can be completely avoided, or the consequences of a future failure mitigated before it takes place.

The concept of E-maintenance reflects the convergence of these emerging ICT technology potentials with the systems which deal with management and planning of maintenance resources and services which together can enable proactive decision-making (Aboelmaged, 2015). The E-maintenance vision furthermore takes into consideration the integration of PdM workflows into the wider enterprise process and business landscape, echoing the above sentiment that maintenance should be considered a key operation function of manufacturing enterprises (Aboelmaged, 2015), (El Kadiri et al., 2016). Unlocking the full potential of PdM and its thorough integration into the wider business landscape of a company is a challenging process with many barriers to be overcome.

2.3 Incentives and Barriers to Predictive Maintenance Adoption in Industry

Traditional maintenance value drivers are the most prominent reasons companies plan to adopt PdM solutions according to a 2018 PricewaterhouseCoopers report (see Figure 2). Improving Overall Equipment Efficiency (OEE) is by far the most motivating reason, followed by costs savings, extending the lifetime of ageing assets, reducing health, safety, environment and quality risks, increasing end-customer satisfaction and, only in the last place, capturing new revenue streams.

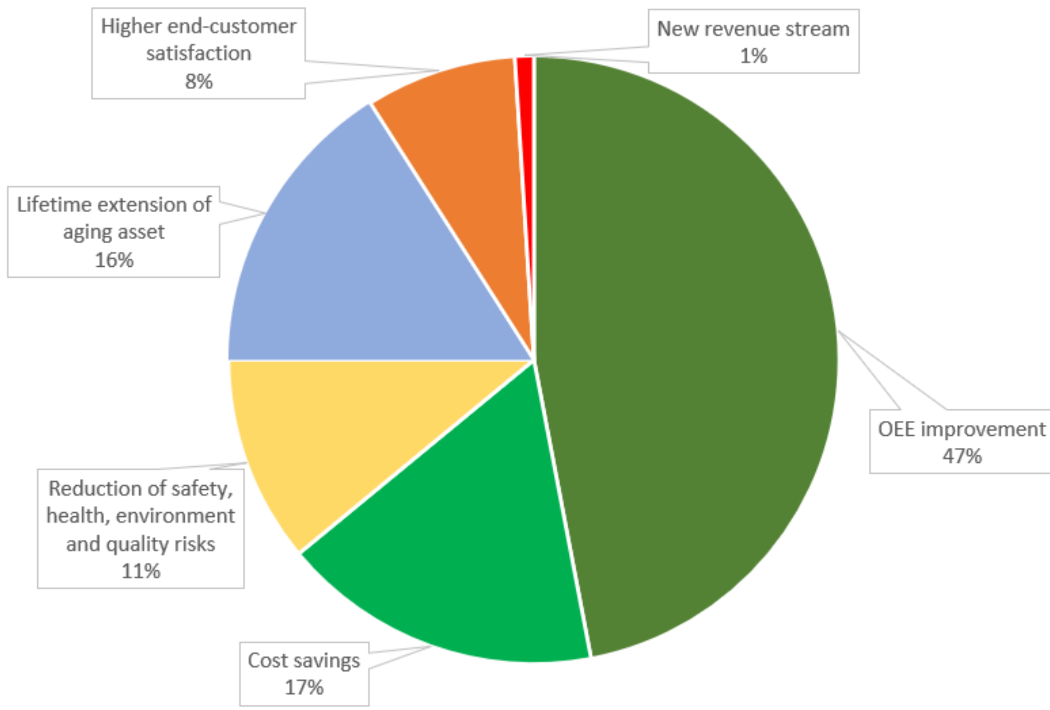

Figure 2: Perceived Benefits of Predictive Maintenance Solutions (Source: PricewaterhouseCoopers BWC, 2018)

The companies' reasons for not adopting PdM are manifold and help understand the barriers that need to be overcome for PdM solutions to be more widely adopted by the industry.

The main factor is the perceived lack of resources and skills required to support deployment. Companies feel that they are already struggling with the level of skill required to support Industry 3.0 practices. Many companies consequently do not feel they are prepared in terms of resources and skills to tackle the problems inherent in a data-driven, Industry 4.0 application such as PdM. They prefer to invest in addressing more pressing issues such as ageing infrastructure, regulatory demands, and commodity pricing pressures – even though PdM could contribute to alleviating some of these issues.

A further intrinsic challenge that hinders industrial adoption of predictive maintenance is the limited availability of data. Whilst current predictive PdM solutions deliver economic benefits when fully up and running, companies often experience that implementing the solutions in the first place can be more difficult and costly than expected. In particular, large companies need a significant amount of time and resources to collect, scrub, and share necessary data than a start-up needs to train the solution itself.

The problem is even more pronounced in industries where data ownership is a concern. This is especially problematic in scenarios in which the operation and maintenance of assets and thus data ownership may be split across different parties. It is also a challenging issue where legacy assets are prevalent, which is often the case. Although sensor and data management technology costs are sinking, and increased connectivity and the adoption of standard platforms are helping to alleviate these challenges, it is still unclear who will eventually own the data and if analytics application providers require access to data to build mature solutions. A related issue is that of data security. The potential lack of guarantees from current cyber security technologies on their effectiveness in data protection in Industry 4.0 applications is a further barrier towards the widespread adoption of PdM solutions (Roda et al., 2018).

Another factor hindering adoption is a disconnect between development and evolution cycles in the IT and the industrial sectors. The IT industry is used to rapid cycles of product evolution, where today's state-of-the-art can be expected to be out of date within three years. In the manufacturing and wider industrial world, these cycles of development can take up to 40 years, especially where critical equipment is involved. As a result, many industrial companies postpone adopting new technologies, because upfront costs are expensive, technologies may not be proven, and leaders may be reluctant to change processes that may have been intact for over 30 years. Ironically, the lure of new features and the dynamic pace of change in predictive maintenance causes many industrial companies to delay decisions until it's too late.

PdM solutions typically require a high degree of vertical customization. Specific models often have to be developed for each use case. This model-driven approach offers a high degree of accuracy, but at a high cost - the lack of horizontal replicability across industries reduces economies of scope and hinders widespread adoption. Furthermore, developing new models for each specific use case is laborious and cost-intensive. This partly explains why condition monitoring – which is largely a horizontal and repeatable solution – is more widely adopted. The industry is changing, however, as a newer generation of solutions driven by artificial intelligence and data-driven machine learning approaches that accelerate deployment and training cycles.

Furthermore, PdM solutions need to address a richer array of business problems and offer actionable decisions and solutions to users, not simply flag failures. We are starting to see this happen as predictive and prescriptive maintenance applications integrate ever-larger sets of input - delivering more useful output not just at the asset level, but for the factory and eventually the enterprise.

Summary of Gaps and Challenges:

- The benefits of PdM need to be better communicated to the industry, especially with regards to opportunities beyond traditional maintenance value drivers.
- The effort required to make data available for PdM needs to be reduced.
- Data ownership and data security issues need to be clarified throughout the PdM and by extension Industry 4.0 data value chains.
- PdM solutions need to be reliable and future-proof to attract industrial customers.
- The speed and efficiency of replicability of PdM solutions across use cases and sectors need to be increased.
- The output of PdM systems must be actionable decisions and solutions on the asset, factory, and enterprise levels.

***Related Key Enablers**:*

- (Industrial) Internet of Things (IoT/IIoT)
- Data-driven analytics
- Proactive Computing
- Augmented and Virtual Reality (AR/VR)
- Linked Data
- Standardisation and Interoperability
- Skilling of Personnel

The following sections provide more detail about the potentials of PdM, as well as the gaps and challenges remaining to be addressed. The sections follow the phases of the proactive computing paradigm adopted by PdM (Bousdekis, et al., 2018), preceded by the generation of data: 1) detect events and situations, 2) predict future undesired events, 3) decide recommendations that are going to be provided, and 4) act by enacting the decision taken to adapt the operating system and by collecting feedback to improve the recommendations. A further section takes a look at the role of interoperability and standardisation in PdM.

2.4 Data Acquisition - Digital Transformation Strategies for Predictive Maintenance

The digital transformation of manufacturing is the foundation upon which condition-based maintenance, and, by extension, PdM is built. Digitalised manufacturing means manufacturing in which the physical world is connected to the virtual world (Lundgren et al., 2020). Assets need to be able to measure their operating parameters and communicate them to software systems able to interpret, analyse and put them into relation with each other, to extract actionable knowledge about maintenance needs and expectations.

On the most fundamental level, this means that assets to be maintained need to be equipped with networked sensors capable of measuring the relevant parameters. Legacy assets need to be retrofitted, or new assets to be procured with integrated sensors. Without an appropriate strategy, the costs for digitizing manufacturing assets run the risk of outweighing the benefits expected from a PdM solution.

The digitization of manufacturing assets requires an appropriate strategy both with regards to the selection and integration of the sensors as well as the downstream IT systems to achieve a maximum return on investment. Although standardised solutions are available, they are seldom used in practice. Rather, vendors pursue the creation of closed ecosystems, to maintain data governance. This approach often does not benefit smaller and midcap manufacturers seeking to digitize their operations. Open and standardised data ecosystems are a more viable approach that needs to be fostered and implemented to allow for data reuse and collaboration on both the acquisition and enrichment of sensor data across multiple stakeholders.

The digital transformation of manufacturing assets for PdM can easily become a chicken-or-egg situation, in which the decision about what comes first – the data or the algorithm – becomes a dilemma. One strategy is to first build an initial data set based on common knowledge and educated guesses to then analyse it and build algorithms around this data set. The opposite approach is to start from the problem at hand and develop an appropriate algorithm, thus determining the necessary measurements and data set, which finally leads to the selection of sensors for retrofitting or specific new digitized assets. The former approach can be more relevant to smaller enterprises who want to implement a solution for very specific problems, whereas the latter approach can be more attractive for large enterprises planning a more comprehensive digital transformation.

A similar dilemma is reflected in the landscape of available solutions. Currently, the industrial state of the art for the acquisition of data both from existing asset systems as well as dedicated sensors is driven by the hardware manufacturers and system integrators on the one hand and IoT platform providers on the other. Both types of drivers have a prejudice for either a data source (i.e. sensors) or data sink (i.e. IoT-Platform). This results in a widespread, heterogeneous landscape of “peninsula” solutions.

The middle ground between these two approaches is currently occupied by consultancies and solution providers who adapt available solutions for specific use cases. At the same time, there are several consortia, mostly community-driven by Open Source, such as the Open Geospatial Consortium (OCG) or The Open Group (TOG), which push the development of unified standards not only for the technical communication layers but also context and meta layers. These consortia are laying the basis for unified data acquisition architectures.

These competing strategies for the digital transformation of manufacturing assets are not exclusive to PdM and can be observed in different sectors with terms like "brownfield VS greenfield" or "cost-push VS demand-pull" development. An exclusive hard decision for either one of the approaches is not mandatory, but in most cases, an iterative combination of both can be a suitable approach.

While several flexible approaches are addressing the shortcomings of choosing either of the two prevailing strategies, the challenge is to involve the established players in them, so that a good adoption rate and market penetration can be achieved. Thus, fostering these approaches and integrating them into the prevailing solutions (both with data sources as well as sinks) is one of the main tasks towards a flexible DAQ landscape. This cannot be achieved merely through the development of technical standards but must be driven by business models which utilise the additional benefits, flexible and vendor-agnostic architecture can offer. Since this will – at least initially – contradict the legacy business models of different stakeholders, a fair and flexible approach for revenue sharing in an increasingly complex structure must be investigated. The complex production and logistics supply chains of the modern world provide a plethora of approaches that should be investigated.

Since the digitization of industrial assets should never be an end on itself, but rather aim towards a higher goal and comprehensive business strategy, the vision for it must be to offer maximum information not only at minimal cost but also with minimal impact on the adjacent systems and with a maximum benefit to the enterprise as a whole. It is therefore of paramount importance that data acquisition systems and architectures do not restrict the choice and configuration of both the systems providing the data and consuming it more than necessary. To this end, vendor lock-in should be avoided, and well documented, open interfaces must be defined and put in operation. This can only succeed if technical standards are accompanied by sound business models which integrate the needs of the prevailing stakeholders. The development and implementation of these business models is consequently a vital aspect.

Summary of Gaps and Challenges:

- The current market is dominated by vendor-specific digitization solutions, leading to vendor lock-in and inefficient solutions especially for SMEs
- Open, flexible, and vendor-agnostic architectures need to be fostered to maximise the benefit of digitization for a majority of stakeholders
- Digitization should not be an end in itself, but always be aligned with a comprehensive digital business strategy

Related Key Enablers:

- IoT/IIoT
- Standardisation and Interoperability

2.5 Detection as a Cornerstone of Predictive Maintenance

PdM in general describes strategies and actions to prevent breakdowns of technical equipment by early intervention in degradation processes or failure situations. To do so, PdM strategies may implement regular time-based observations. However, with the increased availability of sensors and embedded computing systems integrated into the assets under maintenance as described in the previous section, PdM is most often understood to be a data-driven strategy that relies on sensor and database condition monitoring. In simple terms, the first objective is to identify abnormal behaviour of technical equipment by preferably continuously observing sensor data streams.

Detection algorithms in data-driven PdM have the task to process raw data to get information about the condition of the components of technical equipment. Different algorithms are available for that purpose with essentially two objectives, namely the detection of the current state of an asset and a prediction of the future state of equipment. Detection borders on diagnosis as it aims not only to detect abnormalities but also to deduce the failure causes from symptoms such as noise, vibration, temperature changes, etc. in the sensor streams. Detection can further be decomposed into several sub-functions: a) the capability to identify abnormalities and recognize relevant patterns in data streams generated by digitized assets, b) the capability to classify patterns according to modes of failure, and c) generating a reliable assumption about the root causes of failure modes.

The next step after the pattern recognition is usually the classification of the pattern according to various categories or classes. As far as maintenance is concerned, this is, in the simplest case, subdivided into "faults" and "in order" or into other previously specified categories. Accordingly, defect classification is often seen as part of pattern recognition but follows with regard to the methodological procedure of extraction of the features (Clarke, 1974). Scientific literature distinguishes between whether algorithms and methods used for classification are discussed on the premise of an existing meaningful feature vector or if its derivation is part of the work. While feature extraction often requires customization, the actual classification algorithms are generally usable.

Classification generally refers to the assignment of objects with certain characteristic values to classes. In the history of science, different approaches to the automated assignment of objects have been developed, which can largely be assigned to artificial intelligence. Artificial neural networks have gained a great deal of attention, which, in the sense of bionics, mimics the processes of nature for the design of neural structures for the classification of objects (Kriesel, 2017). Different classification methods exist, each with its strengths and weaknesses.

After the classification of an object with certain characteristic features, it is usually of interest to interpret this object or the recognized pattern and to obtain an explanation for the symptoms. The aim is to be able to take measures in the medium term to avoid recurring causes. In maintenance, after automated detection, it is also of interest to know the specific causes responsible for the observed symptoms to train the detection process.

For more in-depth causal diagnosis based on various observations, extensive experience and problem-specific specialist knowledge is generally required, which as a rule can only be provided by very experienced staff (Moczulski, 2004). Nevertheless, the idea of an automated root cause analysis or at least a corresponding expert support is not new, so that different methods have been established in different fields of application (Cholewa, 2004). However, due to various technical requirements, these are still rather rare in practical application.

A robust diagnostic approach is vital for PdM since the uncertainties of the estimated system condition affect any future prediction (Jardine et al., 2006; Hess et al., 2006; Patrick et al., 2009). Most challenges towards reliable diagnostic approaches lie in verification and validation (Vogl et al., 2019). Due to the complexity of manufacturing systems, simple diagnostic models are often inadequate. This means that diagnostic methods need to be able to deal with uncertainties resulting from complexity (Vogl et al., 2019). Without robust, verifiable, and validated diagnostics, prognoses and consequently, maintenance decisions made based on PdM can lead to false alarms, diminishing the usefulness of the entire system.

Summary of Gaps and Challenges:

- The quality of the chosen diagnostic approach is fundamental to the quality of predictions generated by a PdM solution
- Robust, verifiable, and validated methods need are required for widespread industry adoption
- In-depth causal diagnostics require in-depth, problem-specific expert knowledge, which means that engineering expertise is required in the definition of diagnostics approaches

Related Key Enablers:

- Data-driven analytics
- Skilling of Personnel

2.6 Prediction – Forecasting the Future State of Assets

PdM strategies that are based on the understanding of processing sensor data to derive information on possible abnormalities and prospective failures may include processing capabilities to estimate trends and Remaining Useful Life (RUL). The category of algorithms used to forecast the future state of assets is accordingly called prediction or prognosis. In simple terms, this builds on the objective described above of diagnosing the state of an asset by identifying abnormal behaviour, predicting possible future conditions by continuously observing sensor data streams and by considering historical data.

Prediction algorithms in data-driven PdM process raw current and historical data in order to provide a sound guess about the future condition of assets or their components. Prognosis is the prediction of conditions and events through the sensor data streams. Broken down into its sub-functions, prediction accordingly consists of a) time-series analysis and prognosis as well as b) the capability to estimate the Remaining Useful Life of the assets or components.

The analysis of time-series and forecasts based thereon take on a decisive role in the automatic condition assessment of technical systems. Based on sensors, which usually supply value pairs consisting of a time stamp and the corresponding measured value, an attempt is made to predict the future trend of the observed time series. In this way, deviations from normal operating conditions can be recognized early and considered in the diagnosis. Another field of application is the analysis and prediction of the degradation of components (Denkena, 2010).

Successful applications of time-series analysis can be found in the financial sector, where the analysis and forecasting of market developments are of interest. The methods used there have been transferred successfully for the analysis and prognosis of machine-related data (Patrick et al., 2009; Volg et al., 2019; Denkena et al., 2010). The methods of time series analysis can be subdivided into frequency and time-related analyses. The former is established in the engineering field for a wide variety of applications, for example for the interpretation of vibration processes. In addition, the methods of time-related analysis of time series are usually based on regression, correlation, and mean calculations (Box et al., 2011).

One objective of predicting a long-term system behaviour is the estimation of a Remaining Useful Life (RUL) for the systems or components as well as the estimation of a confidence interval, which applies to this prediction. The most accurate estimation possible with a small confidence interval is the difficult challenge in the residual lifetime estimation (Xiongzi et al., 2011). RUL describes a period between the current and the future time, which defines the end of the useful lifetime. The concept is based on the fact that the quality of the system decreases with time and thus passes through the phases "OK", "Warning", "Ideal Repair Period" and "Error" (Xiongzi et al., 2011). Different methods are available to estimate RUL (Anagiannis et al., 2020; Bampoula et al., 2021; Aivaliotis et al., 2019; Aivaliotis et al., 2020; Aggogeri et al., 2019).

In addition, outputs or results of the different methods can also serve as input of a further method, which leads to cascaded calculations. From an application-oriented viewpoint, the exact configuration of calculation runs must be provided during the selection of the appropriate methods. Corresponding to this task, therefore, respective instances are to be created and defined which, accordingly parameterized, analyse one or more input data series. Therefore, the combination of several simple procedures, as well as the use of more complex calculation algorithms in a system, must be enabled. These are timed or triggered by an event, for example, a new data record. As a prerequisite, a collection of methods is required, as well as, a platform for their use and configuration with regards to the available data. The challenge here is, however, to aggregate the sometimes-ambivalent results of the methods into a residual lifetime or a relevant business event. In the case of complex technical systems with several modules or components, the status evaluations for the individual components must then be combined with the state evaluation of the entire system.

While promising approaches have been scientifically investigated and developed for various challenges of the state determination of single components, such a discussed integrative approach to the state determination of complex technical systems has so far been considered less frequently. Modular concepts effectively linking different heterogeneous sensors for condition detection and different technologies, methods and algorithms for the condition evaluation are lacking.

Summary of Gaps and Challenges:

- Integrative solutions to determine and forecast the state of complex systems need to be developed
- Modular concepts are required

Related Key Enablers:

- Data-driven analytics
- Proactive Computing
- Skilling of Personnel

2.7 Actionable Decisions on all Levels of Maintenance

As described above, the core functions of PdM solutions lie in identifying the current condition of an asset and accurately forecasting its degradation or potential faults for better planning of maintenance activities. Whilst these functions in themselves offer significant value to manufacturing companies, they can only do so when predictions are translated into actionable maintenance decisions.

One pathway to actionable maintenance decisions lies in the interpretation of predictions by maintenance experts, who can define operative maintenance tasks based on their knowledge and experience. This means that maintenance experts need to be able to understand the outputs of the prediction algorithms to apply their knowledge in the decision-making process. This requires that maintenance experts extend their skill base towards data science.

Another preferable pathway is that the PdM system is capable of not only predicting when a failure is likely to occur but also proactively recommend the best action for completely avoiding or mitigating the impact of the predicted events (Bousdekis et al., 2019; Christou et al., 2020a). Optimally, it should even be capable of automatically issuing the corresponding work order (PricewaterhouseCoopers BWC, 2018). The development of appropriate methods and algorithms for decision-making is driven by the increasing complexity and uncertainty found in today's manufacturing environments. The uncertainty is inherent to predictive analytics and degradation processes as well as the time constraints under which a decision needs to be taken pose challenges in the applicability of decision-making algorithms (Bousdekis et al., 2019). Often, decision-making algorithms for PdM are restricted to specific problems, domains, and industry sections, or only applicable under certain assumptions. They are thus difficult to apply to different production processes.

This means that knowledge about appropriate maintenance actions for individual fault states needs to be introduced to the system, meaning intense cooperation between maintenance experts and system developers or configures needs to take place. However, maintenance decision-making is not an extensively explored area (Bousdekis et al., 2018) and the availability of maintenance decision-making applications is limited, and even experienced engineers in capital intensive and high revenue industries have little experience with such tools. In addition, supervised learning loops may be implemented, allowing maintenance experts to introduce new rules into the system as faults occur or develop. However, continuous learning and improvement of the recommendations have not been thoroughly examined yet (Bousdekis et al., 2018; Ruiz et al., 2014).

Besides the ability of the PdM system to provide accurate and actionable recommendations about maintenance tasks, how the tasks are communicated to the maintenance experts need to be tailored to the needs of the recipients involved in maintenance tasks. These recipients include maintenance managers, maintenance operators and shop-floor staff.

Maintenance managers, who are responsible for maintenance planning and take operative decisions about maintenance tasks, require different levels of information. On the one hand, they require an appropriate overview of the current and predicted condition of all assets under their responsibility. They also need to dig deeper into the data to analyse the detailed condition of individual assets, their maintenance history, and prescribed maintenance tasks. The ability to zoom into different levels of analysis and prediction along with tools that allow the identification of possible relationships between different faults, usage parameters and behaviours are required to assist them in identifying root causes and planning maintenance tasks. Tasks prescribed by the PdM system should be able to be modified or updated based on their expert knowledge and experience, contributing to the system's self-learning loop. Since maintenance managers are often responsible for a large number of assets and often very mobile throughout the company, appropriate means of communicating this information besides advanced visualisation at the desk include multi-channel, mobile devices.

Maintenance operators might require detailed information about how a specific maintenance task should be carried out. This might entail detailed instructions about how a part of a machine needs to be serviced, or how a faulty part should be removed and a new one installed and tested. This specialised information is generally part of the repair or installation manuals. The availability of automatic maintenance task prescriptions by the PdM solution creates the opportunity for a context-aware, digital communication of instructions on the job. However, the lack of skills and abilities of operators with regards to digital technologies presents makes the application of IT in this area challenging (Roda et al., 2018). Digital technologies need to be selected which can be used intuitively, without the need for in-depth IT skills.

Appropriate Key Technical Enablers include Augmented Reality (AR), Virtual Reality (VR) and Digital Intelligent Assistants (DIAs). They can be applied on the job or in training to assist personnel involved in maintenance activities and can be leveraged to provide the relevant to maintenance operators in an intuitive way, accelerating operative maintenance processes and increasing their efficiency and quality.

Shop-floor staff might need information about changes in how a machine should be used when it is faulty, or parts are progressing in degradation. Last but certainly not least, health and safety information concerning faulty equipment needs to be appropriately communicated.

Summary of Gaps and Challenges:

- The interpretation of the results of diagnosis and prognosis algorithms may require maintenance experts to extend their skill base towards data science
- PdM solutions need to provide clear, actionable, and comprehensible maintenance decisions
- (Supervised) self-learning loops for maintenance recommendations need to be thoroughly examined
- Technologies employed in PdM solutions need to cater for different skill groups who are involved both in maintenance decision-making and operative faculties
- Context-aware maintenance instructions should be given at all levels of maintenance, leveraging appropriate human interaction technologies such as AR/VR, AI-driven Digital Intelligent Assistants, and advanced visualisation capabilities

Related Key Enablers:

- Proactive Computing
- AR/VR, DIAs
- Skilling of Personnel

2.8 Standardisation and Interoperability

As discussed above, maintenance processes, and by extension PdM, must be considered a key operation function of manufacturing companies. That means that a PdM solution should not be treated as a stand-alone system but rather seamlessly integrate into the company's manufacturing system and process landscape to optimally contribute to its overall digitization strategy.

The broad adoption of sensor technology in the industry has led to a vast increase in the volume of numerical data. On top of that, additional maintenance-relevant information and knowledge are stored and processed in different types of systems throughout the enterprises, such as CMMS (Computerized Maintenance Management Systems), PPS (Production Planning Systems), MES (Manufacturing Execution Systems), logistics and quality management systems. In many companies, maintenance-relevant information is still captured, processed, and documented with spreadsheet applications or even simply on paper. Stakeholders outside of the company, such as machine vendors or product consumers, can also provide relevant information. Last but not least, the experience of maintenance experts and other stakeholders directly or indirectly involved in maintenance processes should be considered valuable resources of information and knowledge. Many of these sources are not easily integrated into e-maintenance systems. The efficient aggregation, extraction and visualisation of the relevant information and knowledge are thus key technologies for the extraction of maintenance-relevant information.

Standardisation and interoperability are two interrelated topics that can facilitate that integration (Keraron, 2018). On the one hand, some relevant standards are available in the maintenance and manufacturing domains which need to be leveraged to align PdM with existing domain models and knowledge. These standards may be used to inform the fundamental models on which PdM solutions rely to structure data and exchange it with other processes in manufacturing and throughout the company. In addition, relevant standards for the definition of maintenance information system architectures exist, which should be applied in the design of PdM systems and if necessary extended to reflect specific properties of these systems not yet addressed by the standards. For example, data models for PdM system architectures may be appropriately defined following the functional blocks of ISO 13374 Condition Monitoring and Diagnostics of Machines (I.O. for Standardization, 2003) for data processing in combination with the compliant MIMOSA OSA-EAI CM&D (MIMOSA, 2014) information architecture specification.

With regards to inter-process and inter-organisational interoperability, and to ensure the transferability of a PdM solution from one use case or sector to another, PdM data models should furthermore comply with standards on maintenance terminology. Maintenance terminology is currently defined in dedicated standards, including EN 13306 Maintenance Terminology (CEN EN, 2010) or ISO 13372 Condition of machines and Diagnostics of Machines - Vocabulary (I.O. for Standardization, 2012), or in various ISO and IEC standards such as IEC 60812 Failure Modes and Effects Analysis (FMEA and FMECA) (I.E. Commission, 2018). Many other relevant standards exist for the scope of processes, methods and tools involved in a PdM approach, for instance depending on the techniques used for equipment health monitoring.

The second dimension of standardisation and interoperability is influenced by the digital transformation of manufacturing and in particular the rapid evolution of both de-facto and formal standards emerging in the field of the Industrial Internet of Things (IIoT). Here, many new standards, reference models and architectures with the potential for enabling interoperability are being developed. One example is AMQP (AMQP Advanced Message Queuing Protocol – ISO/IEC 19464:2014) (I.O. for Standardization, 2014), which can be used to integrate the functional blocks of a PdM approach. However, the rapid evolution of these standards and their fast proliferation, in conjunction with a lack of experience about how to implement these reference concepts, models and standards currently leave the industry with little solid ground upon which to make decisions. Moreover, competing national and international initiatives such as the US IIoT, the German Industrie 4.0, and the Chinese Cloud Manufacturing approaches complicate matters even further. A recent study on the future of maintenance within Industry 4.0 underlines the industry's current dissatisfaction with the lack of widespread standard solutions for new technologies (Roda et al., 2018). That means that more research and standardisation effort is required to pave the way towards reliable recommendations for industry to ensure future-proof interoperability strategies.

Other advanced means for interoperability are coming up from the semantic web technologies as ontologies, with efforts in the various manufacturing domains including maintenance with the Industry Ontologies Foundry initiative. These efforts are long term efforts of research and need more industrial feedback before implementation in a robust industrial platform. In chapter "5 Standardization " the challenges and experience of the Foresee projects with regards to the standardization are presented.

Summary of Gaps and Challenges:

- PdM solutions need to be seamlessly interoperable with manufacturing processes and systems to ensure maximum benefit throughout the company
- Existing maintenance-relevant standards should be leveraged and, if necessary, extended to ensure process and IT interoperability
- Future-proof, data-driven PdM solutions and strategies require reliable recommendations about technical standards for IIoT ecosystems

- Advanced semantic models for PdM need to be developed to ensure future-proof, cross-domain interoperability

Related Key Enablers:

- Standardisation and Interoperability

2.9 ForeSee Predictive Maintenance System Reference Architecture

Figure 3 below shows the ForeSee Predictive Maintenance System Reference Architecture, which is based on the results of the six projects involved in the ForeSee cluster. It intends to outline mandatory and optional components of a PdM system, whilst abstracting from implementation details. The reference architecture is composed of three vertical sections, from left to right: 1) the manufacturing ecosystem, which contains the physical and virtual components of the system for which PdM is to be implemented; 2) the data acquisition and interoperability slice, which managed the link between the manufacturing ecosystem and the PdM system itself, and 3) the PdM system, which implements data storage, analytics and decision making on streaming and batch data, as well as human user's interactions with the system. The components of the reference architecture are described per slice in more detail in the following.

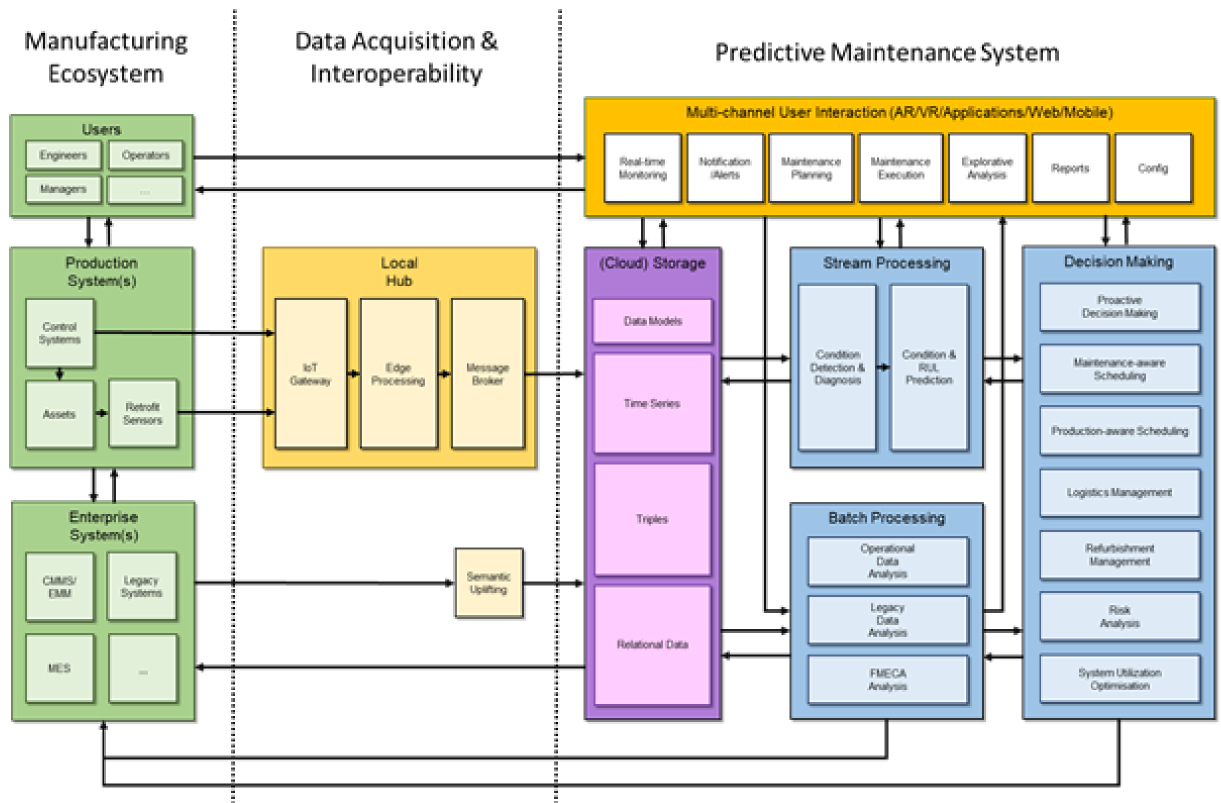

Figure 3: ForeSee Predictive Maintenance Reference Architecture

Manufacturing Ecosystem

The manufacturing ecosystem contains three elements that are relevant to implementing PdM. First are the production system(s) and their respective assets for which the system should provide PdM. This includes control systems and sensors, which may need to be retrofitted, which supply the PdM system with appropriate, preferably real-time streaming which can contribute to an understanding of the systems' and assets' condition. Second, the enterprise systems either contain relevant information about the production system(s) and/or contribute to their management or the execution of production plans. Information stored in these systems (e.g. production plans, maintenance reports) may augment the sensor data in helping understand the historical condition of the systems and assets. Last but not least, the human users involved in processes of production and maintenance management, planning, optimisation and execution, for example, engineers, operators and managers.

Data Acquisition & Interoperability

Both streaming sensor data and batch information made available by the production systems and the enterprise systems need to be accessed by the PdM system, for which they need to be appropriately gathered, pre-processed and forwarded to the system.

For streaming sensor data, this is done via local IoT hubs, which implement IoT gateways to access the sensor data. Streaming sensor data may then be optionally pre-processed on the network edge. Data cleansing, outlier detection, or initial data analytics are examples of pre-processing which can be carried out in an edge processing component. Finally, the streaming sensor data is pushed into the PdM system via a component such as a streaming message broker.

Batch data coming from enterprise systems generally need to be mapped onto the data models of the PdM system before it can be appropriately analysed. For this reason, a component is required for the semantic uplifting of the data before it can be stored in the storage component.

Predictive Maintenance System

The PdM system consists of several sub-elements which are described in the following paragraphs. Each of these components may be implemented on local hardware or hosted on a cloud computing facility.

(Cloud) Storage

The **storage element** is responsible for storing all types of data to be processed or generated by the PdM system. All of these types of data are structured according to data models, which may follow established standards such as MIMOSA and/or reflect FMECA models of the assets under maintenance. Data coming from the manufacturing ecosystem will generally be forwarded to these storage elements, for further processing by the stream and batch processing components respectively.

Three types of data can be differentiated and depending on the PdM system's specific implementation, respective databases will be required: 1) time-series data, which represents streaming sensor data and events detected and predicted by the PdM system; 2) semantic triples resulting from the semantic uplift of legacy data which can be stored in a Triplestore; and 3) relational data for storage in a relational database, comprising all types of information not already handled by the time series DB or Triplestore.

Stream Processing

The stream processing element includes functionalities responsible for analysing stream data typically generated by sensors installed in the end user's assets. This data can be augmented by historical data generated from batch processing components (see below). Stream processing consists of a component for condition detection & diagnosis and one for condition and RUL prediction, providing forecasts for feature values of sensor data. These can be monitored to identify possible outliers that may denote malfunctions or, more generally, abnormal behaviour. Moreover, stream processing provides predictions of future events such as RUL that trigger the processes in the Decision-Making element to provide prescriptions for maintenance plans. Stream processing receives sensor data stored in real-time in the time series storage and generates predictions based on the chosen algorithm. The results of stream analysis, both from the diagnosis and prognosis components, will generally be a time series of events. Both the detection and diagnosis as well as the prediction component may use a streaming message bus as a shared integration point to communicate these events. A typical message from these components contains both the notification of a new event and a payload with the contents of the new event or prediction. Feedback loops to the storage component and the enterprise systems allow direct integration of the results of the PdM system and may be used to implement self-learning loops.

Batch Processing

Batch Processing is responsible for analysing legacy and operational data and providing information about the monitored system, such as clusters of correlated interruptions and/or failure modes, predictions based on past maintenance data, etc. Other platform functionalities depend on the results generated from batch processing to provide more accurate results – decision making and stream processing, for example, may give more accurate recommendations and predictions if results of the historical analysis are included in the relevant models. As with the stream processing component, feedback loops to the storage component and the enterprise systems allow direct integration of the results of the PdM system and may be used to implement self-learning loops.

Decision Making

The proactive decision-making functionality of the ForeSee predictive maintenance reference architecture should implement prescriptive analytics for proactive decision making in PdM. It provides prescriptions about optimal maintenance actions and times based on predictions about future failures, to eliminate or mitigate their impact. The prescriptions deal with sets of actions that are related to sets of predicted failure modes (e.g. when two failure modes usually occur together). Decision methods that can be implemented here include (i) model-based (DM1) Markov Decision Process (MDP); and (ii) model-free (DM2) Reinforcement Learning (RL) with human feedback. Upon user feedback, it formulates and updates the maintenance plan. Users can interact with the decision-making component via appropriate visualisation in the user interaction element. Configurable rules and actions are available to the user. Then, after recommendations about proactive actions, the user is given options to either reject or approve them. This feedback is considered for future prescriptions, while, in case of approval, the recommended actions are inserted into the maintenance plan.

Decision-making in the ForeSee predictive maintenance reference architecture not only relies on the prediction of failures and RUL stemming from the stream processing components; it also (optionally) considers maintenance schedules, production plans, spare parts and resource logistics, and refurbishment plans. The required information can be provided via the analyses carried out in the batch processing component based on information acquired from the respective enterprise and legacy systems.

The risk assessment functionality provides a criticality rating for each component of a system, as well as a rating for each component's failure modes. The risk assessment is data-driven and based on FMECA analysis coupled with the current detected and/or the predicted state of the manufacturing system based on the results of the streaming and batch processing elements.

Feedback loops to the storage component and the enterprise systems allow direct integration of the results of the decision-making component and may be used to implement self-learning loops.

Multi-channel User Interaction

Interaction with the PdM system needs to be tailored to the needs and qualifications of the various human actors involved in maintenance-related activities. It should furthermore be agnostic to the actors' physical locations. The ForeSee reference architecture thus includes multichannel user interaction, via channels such as conventional desktop applications, mobile apps, web applications, and AR and VR interfaces for intuitive maintenance action guidance at the asset-under-maintenance. Appropriate interfaces and visualisation are made available for all underlying elements – real-time monitoring provides easy insight into the current and predicted future status of assets and the whole production system, with alert functionality available to indicate critical issues in real-time. Maintenance engineers and managers can use the maintenance planning functionality to schedule maintenance suggested by the decision-making component. Maintenance execution support, such as repair instructions, can be given to operators on the shop-floor, using AR and VR to implement intuitive and easy-to-understand instructions or visualise existing failures. Explorative analysis tools are provided to help maintenance engineers and managers drill down deep into the data in an intuitive way to better understand the context of complex maintenance issues. Generating reports is a standard functionality which nevertheless is required to document issues and maintenance activities. Last but not least, configuration interfaces are provided for example to design and configure analysis calculation flows by data scientists and engineers, to model assets, and configure all relevant system parameters.

RAMI 4.0 Compatibility

The ForeSee predictive maintenance reference architecture is compatible with the RAMI 4.0 reference architecture. Figure 4 below outlines how the elements of the ForeSee reference architecture map onto the layers of RAMI 4.0.

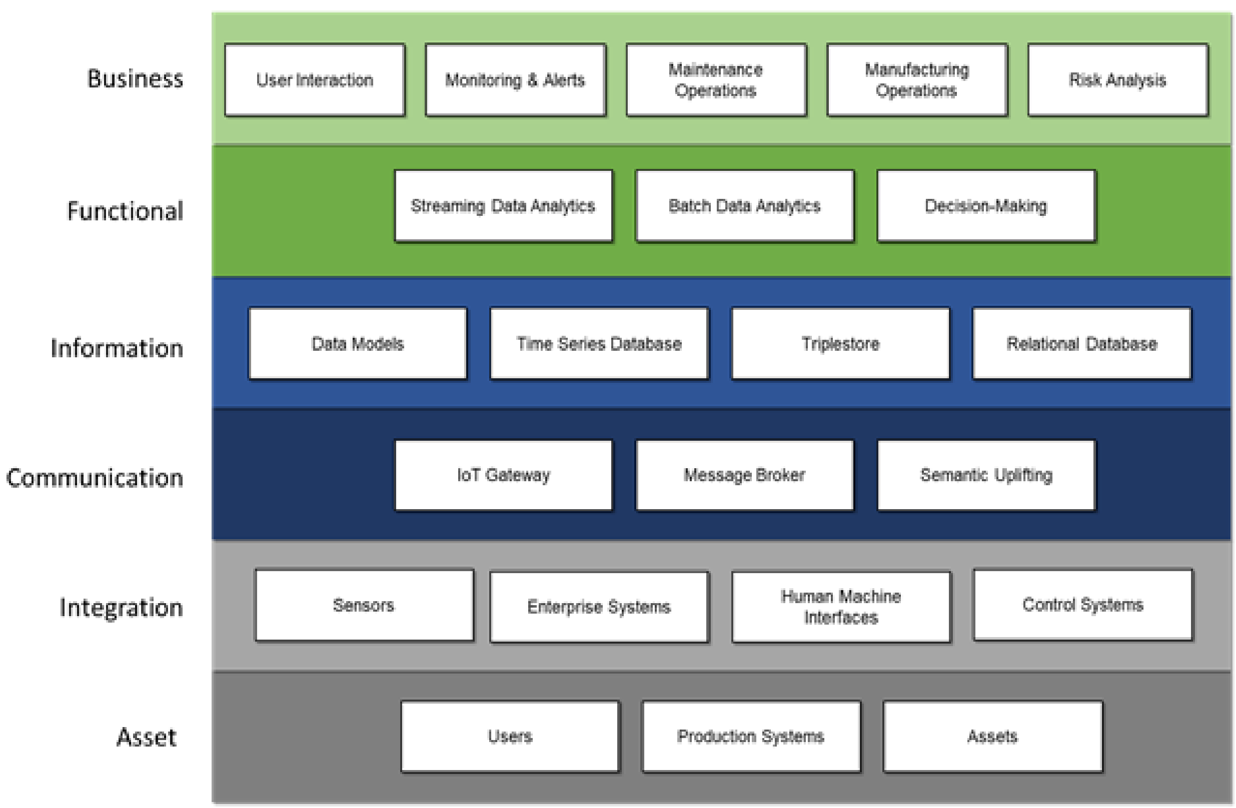

Figure 4: ForeSee Reference Architecture Elements mapped against RAMI4.0 Layers

3 Key-enablers for predictive maintenance in manufacturing

Faced with mounting pressures caused by the shortage of skilled workers, budget cuts and ageing assets, predictive maintenance (PdM) software represents a powerful tool to aid manufacturers in easing their maintenance burdens, by reducing costs and improving the productivity of their production processes. With a wealth of case studies and proof points available in many other analogous industries, attractive potential benefits await the manufacturing sector should it embrace the latest trend in maintenance strategy. Given that Predictive Analytics can help organizations in multiple ways, it is no surprise that organizations are looking for effective ways to build their predictive analytics footprint. However, some enablers are required to ensure efficiency and effectiveness.

First and foremost are the data capture and the required technology environment. Data availability and sufficiency is the biggest precursor to successful model building. There will be times when the relevant data points are not captured, sufficient history is not available, or sufficient granularity is not available. While some techniques may help in the short run, the data capture and sufficiency need to be addressed for an effective long-term solution. This directly leads to the need for a system for capturing these data points to set up the ecosystem for effective future modelling. The solution to this point lies in the correct deployment of IIoT solutions, whether by producing equipment equipped with them since its design or by adequately retrofitting legacy equipment.

Once sufficient data has been captured, the next step lies in the techniques deployed to early detect and predict anomalies on production machines. Thanks to the predictive capabilities offered by the emerging smart data analytics, data-driven approaches for condition monitoring are becoming widely used for the early detection of irregularities on production machines. With proper adjustments, these approaches are even capable of handling situations where the data is even more than expected. Big Data analysts need to quickly sift through a voluminous amount of data to identify the information nuggets. Nowhere are the data quality ramifications more evident than in predictive modelling.

It is not always possible to acquire data from physical equipment in the field under typical fault conditions (MathWorks 2021). Permitting faults to occur in the field may lead to catastrophic failure and result in destroyed equipment. Generating faults intentionally under more controlled circumstances may be time-consuming, costly, or even unfeasible. A solution to this challenge is to create a digital twin of the equipment and generate sensor data for various fault conditions through simulation. This approach enables engineers to generate all sensor data needed for a PdM workflow, including tests with all possible fault combinations and faults of varying severity.

Proactive computing leads to very interesting capabilities for enterprises adopting the related technologies: the capability to reveal insights and extract previously hidden meaningful patterns from structured and unstructured data belonging to a multitude of sources like sensors and actuators, as well as the capability to develop predictions and implement respective actions, e.g. to recognize possible opportunities or threats before these happen and trigger appropriate actions. In the maintenance context, proactive computing is a key enabler since it allows the detection of equipment abnormal behaviours, the prediction of future failure modes and the decision about optimal actions that eliminate or mitigate the impact of future failures.

Once machine faults have been predicted by advanced data analysis techniques, maintenance efforts can be enhanced through the use of Augmented and Virtual Reality. Relevant data with regards to the health and performance of the machines can be transferred without location boundaries, enabling remotely supported maintenance without any degradation in the quality and effectiveness of the maintenance activities. Furthermore, such tools can support machine operators to easily understand and diagnose problems, and thus increase the safety of the maintenance tasks.

Linked Data in the frame of PdM means (mainly but not exclusively) linking and correlating different internal available heterogeneous data sources. Improved sensor technology and wider application of sensors today provide more and more structured numeric data from all kinds of machines in production processes. In addition, considerable information and knowledge are available from internal as well as external sources. Thus, an efficient aggregation, extraction and visualisation of the relevant information are key technologies for information sharing and analysis of anomalies and issue root causes.

The deployment of PdM on a production line is not a straightforward process. Instead, it encompasses a wide set of activities, each of which requires vastly different skills. Such skills cannot be managed by a single person. On the contrary, this involvement is often spread over the components of a dedicated PdM department or, usually, more than one. Albeit the number of companies that started adopting PdM is steadily growing, only a minority of the EU manufacturing companies have personnel skilled in its features. For this reason, the skilling of personnel in the various facets of PdM is a key enabler to be addressed.

3.1 IIoT (Sensors, gateways, platform)[1]

The Industrial Internet of Things can connect everything from individual sensors and machines to whole factories and even networks of factories. Leveraging new technologies like the IIoT can transform every aspect of manufacturing, from maintenance to design. Implementing IIoT capabilities is difficult even in a clean sheet operation but dealing with legacy equipment can magnify the challenge.

A “retrofit” or “wrap-and-extend” solution involves using third-party options to extend the capabilities of legacy equipment. These include IoT platforms, IoT gateways and sensors that measure KPIs and make that data accessible to the IIoT. Most shops won’t find themselves considering all of these options at one time: some equipment may have a sufficient number of sensors but lack an ethernet-compatible control and a platform to handle all the new data. In other cases, instrumenting legacy equipment can just mean adding sensors to connect it to a PLC.

Whatever the case, retrofitting a machine enables the legacy protocols it uses—e.g., PLCs, control applications and embedded sensors—to communicate with modern IoT assets. Turnkey systems that provide out-of-the-box IoT connectivity can be installed with minimal to no interruption to uptime and since they’re built to accommodate a variety of legacy protocols, they can produce results almost immediately.

3.1.1 IoT Sensors and Conditioning Systems

The core element of IIoT systems is the embedded or retrofitted sensor[2]. A survey conducted by engineering.com found that more than half of all production activities are instrumented, if not connected. The survey also revealed a wide range of equipment being reported as instrumented, from actuators and hydraulics to pumps, conveyors and pneumatics. Instrumentation available "as standard" on production equipment is devoted to monitoring the functions that are the core of legacy equipment operation:

[2] Extract from "Research Report: The Argument for Robust Predictive Maintenance Systems for Legacy Equipment" on engineering.com https://www.engineering.com/AdvancedManufacturing/ArticleID/17987/Predictive-Maintenance-Breathes-New-Life-into-Legacy-Equipment.aspx .

position, proximity, pressure, velocity and other fundamental parameters. These are variables that most PLCs and central control systems can already process, and most manufacturing engineering professionals understand, so adding the capability for reliability and maintenance monitoring may be a simple as adding channels to an existing data system and using software to analyse performance data.

However, when using PdM on legacy equipment, integrating new "dedicated" sensors is usually required. While production machinery has featured sensor monitoring for decades, hard-wired sensors feeding analogue signals to PLCs are limited in both the quality and usefulness of the data gathered. A common misconception is that in retrofit applications on legacy equipment, the sensor suite must be hard-wired and run through the machine's original PLC. While this is an option, wireless devices offer much more flexibility at a low cost. Wireless has definite cost and speed advantages in legacy applications and today's systems work in RF environments that would have challenged even wired LAN systems a decade ago. Legacy equipment isn't limited to legacy sensor technology.

Although some sensors can be installed as essentially turnkey solutions, enterprising manufacturers who build custom solutions may require an intermediary between them and the rest of the IoT network. Modern dedicated sensors often have signal conditioning and A/D conversion built-in but retrofit solutions like thermocouples or strain gauges will require at least signal amplification and an A/D converter to transform their low current millivolt output signals to 4-20 mA analogue outputs or digital Fieldbus signals. The electronics are off-the-shelf, but integration in-house is not necessarily a lower-cost option compared to turnkey systems.

3.1.2 IoT Gateways

Connecting control, sensors and servers to the Internet is the logical extension of a fully instrumented factory[1]. It's at this crucial point, between the Edge and the Cloud, where IoT gateways come in. An IoT gateway aggregates sensor data and translates it between sensor protocols before sending it to the Cloud. Some existing equipment can be tied into a network very simply using devices that act as an IoT gateway. Even for older machines that can only be accessed with 24V signals or serial lines, some gateways can convert those into more modern protocols, such as MQTT. With so many different sensors and sensor protocols, an IoT gateway is essential for any PdM program, including those for legacy equipment. While there are numerous options available it's worth noting that some IoT gateways incorporate onboard processing which can filter routine information and only pass on alerts that are worth noticing.

A versatile IoT Gateway should perform the following functions (Open Automation Software, 2021):

- Communication with legacy devices.
- Provide local data caching, buffering, streaming, pre-processing, cleansing, filtering, aggregation, visualization and optimization
- Short term data historian features
- Edge analytics and system diagnostics
- Support machine to machine communication
- Security – manage user access and network security features
- Device configuration management

In edge computing, critical data processing occurs at the data source rather than in a centralized cloud-based location. A versatile IoT Gateway is the essential link in delivering edge computing power to technicians in the field or at the plant floor. IoT Gateways that come equipped with these capabilities are referred to as 'Smart' Gateways. An important thing to keep in mind is the importance of bandwidth and wireless connectivity when it comes to using the IIoT. Even a piece of legacy equipment is capable of generating huge amounts of data when retrofitted, which may entail higher bandwidth costs. Edge-based processing, which moves analytics down from the cloud into the sensors themselves or to a gateway device, can mitigate this issue. For example, a motor or actuator may be configured with sensors that generate a continuous data stream but if the critical maintenance-related issues are only a function of out-of-limit operation, clipping the data set to transients-only or eliminating data reporting under no-load conditions can save bandwidth and simplify the condition monitoring algorithm.

3.1.3 IoT Platforms

An IoT platform is like an operating system (OS) for the IoT which connects all the sensors, equipment and infrastructure necessary for a variety of purposes, including analysis, continuous improvement and, of course, PdM (MathWorks 2021). While an IoT platform is required, few manufacturing companies even think of developing one from scratch and instead relies on the many ones available on the market. The downside is of course the cost of the IoT platform itself, but at least there is no need for dedicated hardware.

With an IoT platform, analytics can be run at the level of individual machines, manufacturing cells, factories, or using a Cloud solution for entire networks of factories. Some IoT platforms are offered as Platform-as-a-service (PaaS) which opens up additional options in terms of scalability and product support. There are trade-offs in terms of pricing at larger scales and reduced control. It’s also worth considering the value of IoT Platforms with open Application Programming Interfaces (APIs) and development tools that allow users to integrate their technology into the platform.

The market for PdM solutions is extremely fragmented and competitive. While many companies highlight their algorithmic capabilities as key differentiators, there is limited differentiation in technology and a lack of adoption by customers. Furthermore, it is currently unclear if any technology differentiator will truly emerge to provide companies with enduring advantages.

Vendors of technology solutions and platforms, in general, fall into one of two groups: 1) maintenance service provides and equipment manufacturers and 2) software companies. These are described in the following.

The first group on the market, maintenance service providers and equipment manufacturers, are not originally computing or software actors. They often rely on cloud computing platforms such as IBM Maximo, Microsoft Azure or Amazon Web Services for the capacity to offer PdM solutions. They have developed a custom, industry-oriented application layers and have the competitive advantage that their solutions are based on their knowledge and expertise of the industrial environment. Against the background of this expertise, they claim to be the best positioned to deploy adapted and integrated PdM strategies. To accelerate the deployment of new technologies in their processes, maintenance service providers have set up partnerships with technological partners. For example, Vinci Energies, through its Actemium brand dedicated to industrials, has partnered with the software editor Augmensys to develop industrial augmented reality solutions.

The second group offering solutions are software vendors, who are currently aggressively pursuing this new market segment. For example, IBM, Microsoft, and SAP have all developed PdM offers based on their expertise in Big Data, IoT and machine learning. Besides these digital giants, start-ups are also entering the market. Both groups threaten to disrupt the competitive environment of PdM by capturing a growing share of the value. The strategy adopted by most software vendors is to provide modular toolkits for the development of applications. Both on-site applications and cloud solutions are on offer. Software vendors also provide a large range of modules on application marketplaces, allowing them to tailor their solutions to customers' expectations. Thus, they can customize applications that meet companies' needs, including user interfaces or application layers above their infrastructure. Their solutions may be more suited for large firms for custom-made applications and large deployments.

3.1.4 Data-driven analytics for predictive maintenance

Predictive maintenance is enabled by Predictive Analytics: this approach can be seen as black-box models that learn systems behaviour directly from collected condition monitoring (CM) data (e.g., vibration, acoustic signal, force, pressure, temperature, current, voltage, etc.). It relies on the assumption that the statistical characteristics of system data remain relatively unchanged unless a malfunctioning occurs. Such a method transforms raw monitoring data into relevant information and behavioural models (including the degradation) of the system. A PdM strategy is mainly composed of two complementary phases. The first step is related to the assessment of the current health state (i.e., severity) of a system, which can also be considered under data-driven diagnostics. The second phase aims at predicting (or forecasting, (also known as data-driven prognostics) degradation trends to estimate the RUL (remaining useful life) of an asset, where time series techniques can be applied.

Pattern recognition techniques such as Machine Learning (ML), can be applied to address the above phases. ML is a method of data analysis that automates analytical model building. It is a branch of Artificial Intelligence based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. Machine learning algorithms build a mathematical model based on sample data, known as "training data", to make predictions or decisions without being explicitly programmed to perform the task. Here below is reported a chart that shows the different groupings of Machine Learning techniques.

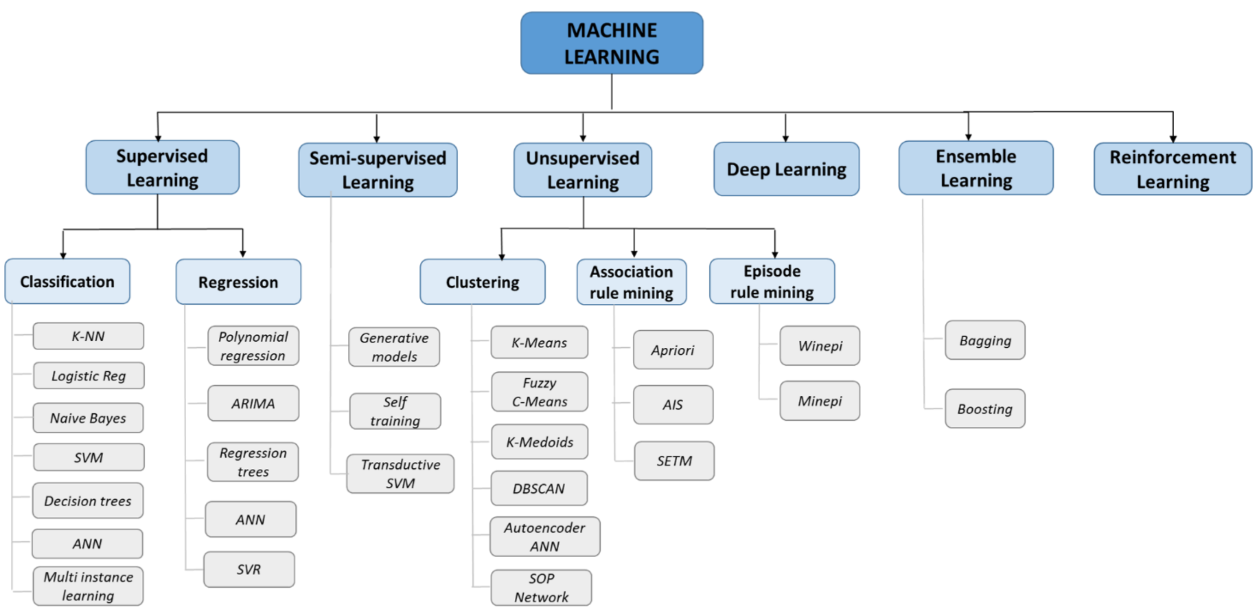

Figure 5: Types of Machine Learning

Basically, for data-driven diagnostics, the supervised classification and/or unsupervised clustering techniques are used, while for data-driven prognostics time-series prediction based on supervised regression and/or unsupervised episode rule mining are used. Here below a summary description of ML techniques (represented in Figure 5) is reported.

Supervised Learning: supervised machine learning algorithms are those algorithms that need external assistance. The input dataset is divided into train and test datasets. The training dataset has an output variable that needs to be predicted or classified. All algorithms learn some kind of patterns from the training dataset and apply them to the test dataset for prediction or classification (Zhu and Goldberg, 2009). Regression and Classification are categorized under the same umbrella of supervised machine learning. Both share the same concept of utilizing known datasets (referred to as training datasets) to make predictions.

Regression in machine learning: in machine learning, regression algorithms attempt to estimate the mapping function (f) from the input variables (x) to numerical or continuous output variables (y). In this case, y is a real value, which can be an integer or a floating-point value. Therefore, regression prediction problems are usually quantities or sizes. Examples of the common regression algorithms include Polynomial regression, Auto-Regressive Integral Moving Average (ARIMA), Support Vector Regression (SVR), Artificial Neural Network (ANN) and regression trees. Regression methods need that Failure Thresholds (FT) to be defined: the FT (assumed or precisely set by an expert) does not necessarily indicate complete failure of the equipment, but a faulty state beyond which there is a risk of functionality loss (e.g., loss of Quality). RUL or other associated KPIs can be defined by the formula RUL = $t_F - t_C$, denoting t_F as a random variable of the time when the next failure occurs, and t_C as the current time (Figure 6).

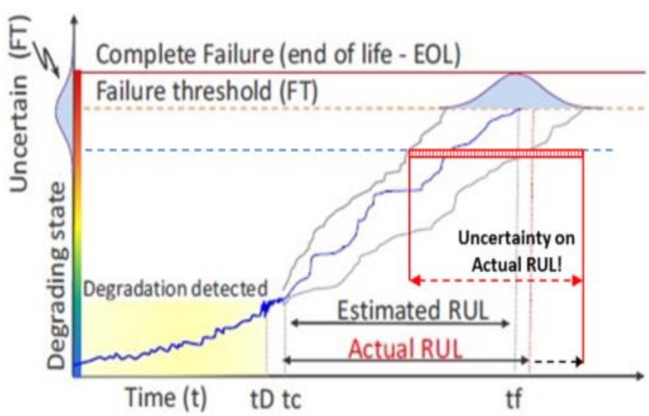

Figure 6: RUL estimation with uncertainties

In this case, the predictions are affected, other than errors associated with the prognostics model, also by errors due to inherent uncertainties of FT.

Classification in machine learning: classification algorithms attempt to estimate the mapping function (f) from the input variables (x) to discrete or categorical output variables (y). In this case, y is a category that the mapping function predicts. If provided with a single or several input variables, a classification model will attempt to predict the value of a single or several conclusions. Examples of the common classification algorithms *include K–NN (Nearest Neighbours), Logistic Regression (LR), Naïve Bayes, decision trees, Support Vector Machine (SVM), ANN and Multi-Instance (learning (MIL).*

Unsupervised Learning: the unsupervised learning algorithms learn few features from the data. When new data is introduced, it uses the previously learned features to recognize the class of the data. It is mainly used for clustering and feature reduction. Unsupervised learning includes *Clustering, Association rule mining* and *Episode rule mining* techniques that are described here below.

Clustering: clustering can be considered the most important unsupervised learning problem; it deals with finding a structure in a collection of 'unlabelled' data. A loose definition of clustering could be "the process of organizing objects into groups whose members are similar in some way". A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. The clustering approach is similar to classification, but the key difference is that it works on an unlabelled training data set.

For instance, when provided with a dataset about sensor signals of a machine/equipment, a classification algorithm can try to predict the health state of a machine (e.g., normal vs anomaly starting, warning, vs incipient failure), Figure 7.

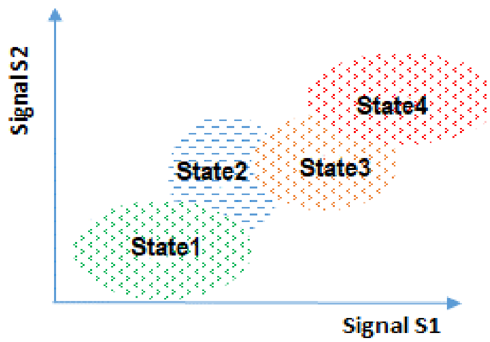

Figure 7: Classification in states of process signals

Examples of the common clustering algorithms include K-Means, Fuzzy C-Means, K-Medoids, Density-Based Scan Clustering (DBSCAN), Autoencoder Artificial Neural Network and Self-Organising Perceptron (SOP) network.

Association rule mining: association rules mining is another key unsupervised data mining method, after clustering, that finds interesting associations (relationships, dependencies) in large sets of data items. Association rule algorithms count the frequency of complimentary occurrences, or associations, across a large collection of items or actions. The goal is to find associations that take place together far more often than you would find in a random sampling of possibilities. An association rule has two parts: an antecedent (if) and a consequent (then). An antecedent is an item found within the data. A consequent is an item found in combination with the antecedent.

Association rules are calculated from item sets, which are made up of two or more items. If rules are built from analysing all the possible items, there could be so many rules that the rules hold little meaning. With that, association rules are typically created from rules well-represented in data. Some application areas of association rules are market-basket data analysis, cross-marketing, loss-leader analysis, data pre-processing, genomics, etc.

In contrast with episode rule mining (see below), association rule learning typically does not consider the order of items either within a transaction or across transactions.

Popular algorithms that use association rules include *Apriori, AIS, SETM* and variations of the latter.

Episode rules mining: association rule mining has been developed for transaction data problems. However, when working with temporal long sequences, the term episode rule mining is mostly employed. The difference between Episode Rules and Association Rules is that the former takes timestamps of events into account and the order does not have to be important (in case of parallel episodes). Association rule mining algorithms, in general, although effective in mining frequent rules, are vulnerable to the rule explosion problem.

Many data mining and machine learning techniques are adapted towards the analysis of unordered collections of data such as transactional databases. However, numerous important applications require the analysed data to be ordered with respect to time, such as data from telecommunication networks, anomalies detection, etc. These datasets are composed of large temporal sequences of events, where each event is described by date of occurrence and an event type.

An episode is a temporal pattern made up of “relatively close” partially ordered items (or events), which often appears throughout the sequence or in a part of it. When the order of items in total, the episode is said to be serial. Similar to the extraction of association rules from item sets, episode rules can be extracted from episodes to predict events.

The main aim behind analysing such sequences is to find episode rules. Informally, an episode rule is a causal relationship reflecting how often a particular group of event types tends to appear close to another group. Once these relationships are found, they can be used to perform an online analysis to better explain the problems that cause a particular event or to predict future events.

Popular algorithms that use association rules include *Minepi, Winepi* and variations of the latter.

The approach *weighted WINEPI* (Sammouri, 2014) has the aim to direct the mining focus to significant episode rules which consider infrequent events, such as failures/anomalies predictions.

Semi-Supervised Learning: semi-supervised learning algorithms is a technique that combines the power of both supervised and unsupervised learning. It can be fruit-full in those areas of machine learning and data mining where the unlabelled data is already present and getting the labelled data is a tedious process (Zhu and Goldberg, 2009). There are many categories of semi-supervised learning (Zhu, 2005), the most important ones include Generative Models, Self-training and Transductive Support Vector Machine (TSVM).

Deep Learning: Deep Learning is part of a broader family of Machine Learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.

The difference between conventional neural networks and Deep Learning lies in the depth of the model (usually Deep Learning includes more than one hidden neurons’ layer). Deep Learning is a phrase used for complex neural networks (Khan et al., 2018). The complexity is attributed to elaborate patterns of how information can flow throughout the model. In the figure below an example of a deep neural network is presented. The architecture has become more complex, but the concept of Deep Learning is still the same: there’s now an increased number of hidden layers and neurons that integrate to estimate the output.

Deep Learning can be then defined as neural networks with a large number of parameters and layers in one of three fundamental network architectures:

- Convolutional Neural Networks
- Recurrent Neural Networks
- Recursive Neural Networks

A Convolutional Neural Network (CNN) is a standard neural network that has been extended across space using shared weights. CNN is designed to recognize images by having convolutions inside, which see the edges of an object recognized on the image. A Recurrent Neural Network (RNN) is a standard neural network that has been extended across time by having edges that feed into the next time step instead of into the next layer in the same time step. RNN is designed to recognize sequences, for example, a speech signal or a text. It has cycles inside that implies the presence of short memory in the net. A Recursive Neural Network is more like a hierarchical network where there is no time aspect to the input sequence, but the input has to be processed hierarchically in a tree fashion.

Reinforcement Learning: reinforcement learning is a type of learning which makes decisions based on which actions to take such that the outcome is more positive. The learner has no knowledge of which actions to take until it's been given a situation. The action which is taken by the learner may affect situations and their actions in the future. Reinforcement learning solely depends on two criteria: trial and error search and delayed outcome (Sutton, 1992).

3.2 Digital Twins

The first documented mention of the term Digital Twin (DT) was made by Grieves in 2003 during a course on Product Lifecycle Management (PLM) (CoBuilder, 2018) to describe the representation of a physical object as a CAD model (Grieves and Vickers, 2016). The concept has since evolved and today stands for an actionable simulation that not only comprises an object's geometry but also includes its behaviour (Grieves and Vickers, 2016). The first applications of DTs are found in the aerospace sector (Rosen et al., 2015). Here, DTs are used to integrate the models of different sub-systems of space vehicles and their environment by integrating stochastics, sensor data and historical data (Glaessgen and Stargel, 2012). One of the maintenance-related aims of this application was to estimate the remaining useful life of the vehicle (Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013). DTs have since been adopted by the manufacturing sector, especially in the context of Smart Manufacturing (Lee et al., 2013; Lu et al., 2020; Aivaliotis et al., 2019). Although consensus definition of and reference architecture for Digital Twins is still lacking (Lu et al., 2020; Kritzinger et al. 2018), most authors agree that a Digital Twin at least comprises of 1) the (real-time) **reflection of a physical counterpart's state**, 2) the representation of the physical counterpart's **design and configuration** and 3) the ability to reflect and predict the **physical counterpart's behaviour**.

DTs include integrated "ultra-realistic, high-fidelity" (Glaessgen and Stargel, 2012; Shaſto et al., 2012) models describing their physical counterpart's behaviour (Rosen et al., 2015; Glaessgen and Stargel, 2012; Reifsnider and Majumdar, 2013; Lee et al., 2013). Besides multi-physics (Arkouli et al. 2020) and numerical modelling (e.g. 3D modelling) (Aivaliotis et al., 2021) and simulators (e.g. finite element methods) (Makris 2021; Aivaliotis et al., 2018), data-driven analytics is also relevant in this context (Tao et al., 2019).

DTs have already been successfully shown to support (predictive) maintenance scenarios (Glaessgen and Stargel, 2012; Hocchalter et al., 2014; Cimino et al., 2019; Zheng and Sivabalan, 2020; Liu et al., 2018; Aivaliotis et al., 2017; Aivaliotis et al., 2019). Since there is currently no widely accepted definition or reference architecture, most of these DT applications are use case or asset-specific and difficult to transfer to other areas. Nevertheless, DT is highly relevant here since their characteristics - representing a system's design, monitoring its state, and anticipating its behaviour – are all required by PdM systems. The further development of the concept can thus be expected to impact strongly on the field of PdM in the coming years.

Cyber-Physical Systems (CPS) and DTs are interrelated and partly complementary concepts: both consist of a physical component and a digital representation. Whilst CPS focus strongly on processing sensor and actuator data and the control loop between the virtual and physical worlds, Digital Twins focus more strongly on high-resolution data models, simulation, and the system's behaviour. A convergence between the two concepts can be expected, with first efforts being made to integrate Digital Twins into the RAMI 4.0 architecture as the Asset Administration Shell (Anderl et al., 2018; Tantik and Anderl, 2017) and defining DTs as the "cyber" layer of the CPS architecture (Josifovska et al., 2019; Alam and El Saddik, 2017; Lee et al., 2015).

Digital Twins can soon be expected to fully integrate PdM functionality for their physical counterparts. They will become one-stop shops for all maintenance-relevant information about assets and production lines. Digital Twins will be able to show the past, present and predicted future behaviour and condition of assets and production lines, implemented via the Digital Twins' system state and system behaviour components. The use of behavioural models and charts in operation and maintenance could reduce the amount of needed data, thus making data analytics more efficient, less costly and more useful to progressively improve the quality of the models and thus increase the collective knowledge of the actors (Chinesta et al., 2020). Digital Twins promise integrated high-fidelity, multi-physics simulation capabilities which go beyond those commonly used in PdM platforms today. This will make better analyses and predictions possible, increasing the accuracy of PdM based on Digital Twins. Moreover, networked Digital Twins could take autonomous action, for example, to reconfigure production lines taking current and predicted failures or RUL estimations into account, integrating PdM functionality more fully into the control of manufacturing and business operations.

With enough standardisation and commercialisation efforts, Digital Twins of production assets and lines will be sold as integral components of their physical counterpoints as a matter of fact, including modular, plug-and-play PdM capability off-the-shelf. However, many steps still need to be taken to reach this goal. With regards to standardisation, Digital Twins development today suffers from a lack of consistent reference models and integration with existing standards and reference architectures. The Digital Twin concept, along with the corresponding definitions, reference architectures, tools and systems is still evolving rapidly. Whilst efforts are being made to establish Digital Twins as a component of Industrie 4.0 and more specifically CPS, a full integration e.g. with RAMI 4.0 has not yet been achieved. Developments towards the establishment of Digital Twins as the Asset Administration Shell in RAMI 4.0 are, however, progressing quickly (an IEC standard regarding the concept of Asset Administration Shell is under development[3]). If this is successful, it can be expected to accelerate the availability of comprehensive Digital Twins including PdM capabilities. Nevertheless, successful PdM applications are often asset or use-case specific, which means that a "built-in" PdM approach might fail if it is not designed to be flexibly adapted and configured for specific asset deployments and production systems.

3.3 Proactive computing

Proactive computing has been defined by Tennenhouse (2000) as an evolution away from interactive computing, i.e., from classical human-centered workstation settings to human-(un)supervised pervasive computing scenarios. Tennnehouse's two main principles were: getting humans above the loop (instead of in the loop) of computing and responding to human stimuli faster than human abilities. Proactivity refers to the ability to avoid or eliminate the impact of undesired future events, or to exploit future opportunities, by applying predictive models combined with real-time sensor data and automated decision-making technologies (Engel et al., 2012). Consequently, proactivity in terms of information systems is driven by predictions, leading to increased situational awareness and decision-making capabilities ahead of time.

Proactive computing leads to very interesting capabilities for enterprises adopting the related technologies: the capability to reveal insights and extract - previously hidden – meaningful patterns from structured and unstructured data belonging to a multitude of sources like sensors and actuators embedded in objects, customer transactions, social interactions, GPS trails, etc. as well as the capability

[3] IEC/WG 24 Asset Administration Shell for Industrial Applications: https://www.iec.ch/dyn/www/f?p=103:14:5552662393405::::FSP_ORG_ID,FSP_LANG_ID:25623,25.

to develop predictions and implement respective actions, e.g. to recognize possible opportunities or threats before these happen and trigger appropriate actions.

Organizations and companies are currently experiencing a shift from reactive thinking towards proactive thinking, aiming at detecting opportunities and threats affecting their interests ahead of time (Artikis et al., 2014). This shift is also comprised of proactive event-driven computing (Sejdovic et al., 2016). **PricewaterhouseCoopers** (or PwC) in 2016 introduced the concept of "proactive organization", mainly focusing on the services offered to customers. According to PwC, a proactive organization aims to identify and capture digital signals, to identify the right moment to offer services and to identify the right mode of service delivery. Therefore, proactive organisations recognise the critical value of data and are continuously looking for new sources of data and ways of gaining meaningful insights from it. This data treatment should be subjected to privacy and confidentiality regulations and should be used for better decisions. The emergence of the Internet of Things (IoT) paves the way for enhancing the monitoring capabilities of enterprises through extensive use of physical and virtual sensors enabling them to decide and act ahead of time, i.e., to resolve problems before they appear, in a proactive manner. This requires the development of event monitoring and data processing systems that can handle real-time data in complex, dynamic environments to get meaningful insights about potential problems.

Several factors in today's computing infrastructure open the door for the breakthrough of proactive computing: (i) the growing availability of affordable and pervasive sensor technology that in turn generate lots of (big) data, (ii) the spreading of broadband connectivity, and (iii) the developments in predictive analytics technology. The latter highlights a different angle to this process. Analytics has evolved from being merely descriptive (understanding of historical data), to be predictive (providing forecasts of future behaviour). The next step is prescriptive analytics, a term that stands for the use of artificial intelligence, machine learning and optimization algorithms in a probabilistic context to provide adaptive, automated, constrained, time-dependent and optimal decisions. One can view the proactive idea as the event-driven variation of prescriptive analytics; reactive computing, coupled with predictive analytics, yields the ability to react to events before they occur, which is the essence of proactive event-driven computing.

A proactive event-driven architecture combines advanced event processing with dynamic forecasting capabilities leveraged towards online optimisation and decision-making. The decisions are made in real-time and require swift and immediate processing of big data, that is, extremely large amounts of noisy data flooding in from various locations, as well as historical data. Therefore, achieving the vision of proactive computing requires novel research in three different directions:

Dealing with large quantities of data. Massive volumes of historical data and massive streaming data have to be analysed, to forecast events. Most systems are not capable of handling big data in real-time because of scalability problems, the need to cleanse noisy data offline, or the difficulty in fusing different types of data coming from different sources online.

Extending the state-of-the-art in event processing to deal with future events and uncertainty due to incomplete and noisy streaming data. The ability to process past events and forecast future ones make proactive systems a compelling application area. But, the uncertain nature of future events requires a major leap in event processing systems.

Devising methods for making a near-optimal decision within time constraints. The decision about which is the best action to take in proactive computing has three main properties that differ from most contemporary decision support systems: (1) the decision should be taken under real-time constraints; (2) the decision often entails autonomic actions, rather than providing only recommendations for human decision-makers; and (3) the decision models adapt and learn from the actual enterprise operation.

Although the idea of proactive computing appears simple, it is still an emerging area that has not reached maturity in mainstream computing. Proactive applications have been developed in an ad-hoc manner for several years; however, the breakthrough that is required to enable pervasive use of proactive computing is the development of models and tools to express and execute proactive systems along with successful use cases in various application domains. Since manufacturing operations are driven by events, it has identified as one of the promising applications of proactive event processing (Engel et al., 2012; Bousdekis et al., 2015). With the advancements of Industry 4.0, anticipating potential issues during process execution and thereby enabling proactive process management is of utmost importance (Krumeich et al., 2016; Sejdovic, and Kleiner, 2016).

In this context, proactive computing is a key enabler of PdM, enabling the detection of equipment abnormal behaviours, the prediction of future failure modes and the decision about optimal actions that eliminate or mitigate the impact of future failures. The issue of detecting and predicting equipment failures was always considered an essential part of asset performance management. The motivation of PdM is that the vast majority of equipment failures are preceded by certain signs, conditions, or indications that a failure is going to occur. However, the classical industrial view of PdM is mainly focused on the use of condition monitoring techniques such as vibration analysis, thermography, acoustic emission or tribology on a batch mode, according to the equipment supplier's specifications.

In the frame of Industry 4.0, the big data processing technologies in manufacturing environments have brought a new perspective. New practices put failure prediction at the backbone of the maintenance function, facilitated by the continuous advancements of IoT technology and the availability of a multitude of data in manufacturing enterprises. The recent developments lead to a new PdM approach, providing powerful capabilities for a physical understanding of the useful life of a system through dynamic pattern recognition in various available data sources, Remaining Useful Life (RUL) and failure modes predictions as well as proactive decisions. In this direction, proactive computing can take advantage of (deep) machine learning, artificial intelligence and optimization algorithms to perform advanced data analytics (descriptive, predictive, and prescriptive analytics) in streaming and distributed computational environments.

Indeed, early research proves that proactive computing in PdM can significantly reduce long-term costs, extend equipment lifetime, increase in-service efficiency and decrease downtime due to unplanned maintenance comparing to breakdown maintenance and to time-based maintenance that is currently adopted by the majority of manufacturing firms (Bousdekis et al., 2018; Hribernik et al., 2018). However, at the design phase of proactive applications, two main aspects should be taken into account:

Depending on the manufacturing sector, a combination of maintenance strategies, and thus of computing paradigms, may need to be applied to build sustainable solutions. Example factors that affect this balance include the criticality of the equipment or the products, the potential consequences in case of equipment breakdown or product failure (financial, environmental, human), the timescale of operational cycles, the digital maturity of the company.

Proactive computing introduces a new way of thinking, due to its resulting far-reaching change, that may go against engineers' and operators' experiences. Proactive thinking does not require simply a robust digital culture and change management approaches, but also methodologies for bringing together the engineered knowledge of domain experts and the learned knowledge of data analytics. For example, answering questions such as "What would you do, if you knew that a failure is about to occur in approximately X hours?" is very challenging for experts since it indicates a disruptive way of thinking and working.

3.4 VR/AR

Augmented and Virtual Reality (AR/VR) enable the transfer of knowledge without location boundaries. Particularly because of scarce personnel resources or travel restrictions such as the current Corona crisis, these technologies serve as key enablers for a new type of remote maintenance process.

The AR/VR functionalities in the manufacturing maintenance field serve the following main goals:

- enable remotely supported maintenance that could optimize maintenance time and cost without any degradation in the quality and effectiveness of the maintenance activities;
- support machine operators to easily understand and diagnose problems, while at the same time engage in the maintenance process with remote support from machine vendors and other stakeholders;
- increase the safety of the maintenance tasks.

In order to meet these goals, the AR/VR functions should take into consideration the existing maintenance practices in each use case and the current best practices and industry standards on visualization and augmented reality.

Some indicative industrial PdM solutions or approaches which use augmented or/and virtual reality techniques for human involvement in the maintenance loop are briefly presented below.

Innovae is one of the companies focusing on the area of PdM using augmented and virtual reality technologies. They provide a suite of solutions that cover a wide range of PdM cases (Innovae, n.d.), including a solution for a maintenance support system and a solution focusing on remote technical support. Key functionalities of maintenance support solution are the mechanism for asset identification, multi-device environment (tablet, smart glass, PC), guided maintenance process to technicians (using augmented reality technologies) and a digitized knowledge repository (includes resources task plans and statistics). The remote assistant solution also provides a multi-device environment and online guides for the maintenance process. Furthermore, it provides video conferencing system functionality enhanced with augmented reality to support the remote assistant process.

Augmensys includes augmented reality techniques in its solution for PdM (Augmensys, n.d.). The key functionality that provides to technicians using the AR software is location awareness by recognising the absolute position as well as the direction and angle of the targeted point; different views for different users and different places; connection of maintenance workflows (from the central data management system) and real-time update of these workflows; bi-directional communication with technician and central management system; asset recognition through OCR technologies (through barcode or RFIDs or common labels).

Valmet (n.d) proposes an AR solution for PdM that can run on a tablet, smartphone or PC and guides technicians to the exact location of a mechanical component in need of a maintenance check (AR navigation). Also, Valmet suggests that the AR solution should provide the technician data about the maintenance history and access to the online manual for the specific component.

SAP proposed a suite of applications for connected assets with a new dimension of AR and wearable technology in PdM (McMullen, 2019). Initially, the AR application can be used in a portable device (tablet or smart glasses) and through an object recognition mechanism can identify specific material. For every material, a set of healthy or early failure indicators are displayed. These indicators depending on their severity are colored (for example green – yellow – red). Also, a set of instructions (documented or voice-based) is available. Furthermore, AR application is enhanced with voice-video calls for remote assistant and with VR capabilities, so the user can see the 3D shape of the specific material.

Furthermore, the use of AR technologies in maintenance has been investigated in various research efforts. The *Glass@Service* project focuses on the use of AR glasses in the production environment and the provision of the necessary information (FRAUNHOFER FEP, n.d.). The presentation of product defects for quality assurance and repair of electronic flat modules was also considered. As part of the *AcRoSS* project, a service platform of AR software modules was developed so that companies can assemble AR applications according to the modular principle (Schiefelbein and Röltgen, 2018). Technical basics regarding the connectivity of machines were examined in the *SEPIA.PRO* project on the application case of plant optimization (SePiA Pro, n.d.).

3.5 Linked Data

Linking data or "Linked Data" is referred to as structured data which is interlinked with other data through semantic queries so it becomes more useful. Tim Berners-Lee, director of the World Wide Web Consortium (W3C), coined the term in a 2006 design note about the Semantic Web project. Linked Data essentially refers to data published on the Web in such a way that it is machine-readable, its meaning is explicitly defined, it is linked to other external data sets, and can, in turn, be linked to from external data sets (Bizer et al., 2009). The intention was to share and combine data to be able to draw new insights from data and open data sources and their combination called Linked Open Data (LOD). Over the years, turning the Linked Data vision into reality has given new impetus to embrace more lightweight standards and AI and big data technologies.

Linked Data in the frame of PdM means (mainly but not exclusively) linking and correlating different internal available heterogeneous data sources. These data vary from structured to semi-structured and unstructured data. Structured data is data that has a pre-defined data model and is therefore straightforward to analyse like e.g. data stored in a CSV file. Unstructured data is information that either does not have a predefined data model or is not organised in a pre-defined manner. It is typically text-heavy and can contain data such as dates, numbers and free text e.g. description of the conduction of certain maintenance activity. Semi-structured data is a blend of the before mentioned ones in which the data does not conform with the formal structure of data models associated with relational databases or other forms of data tables (e.g. XML files).

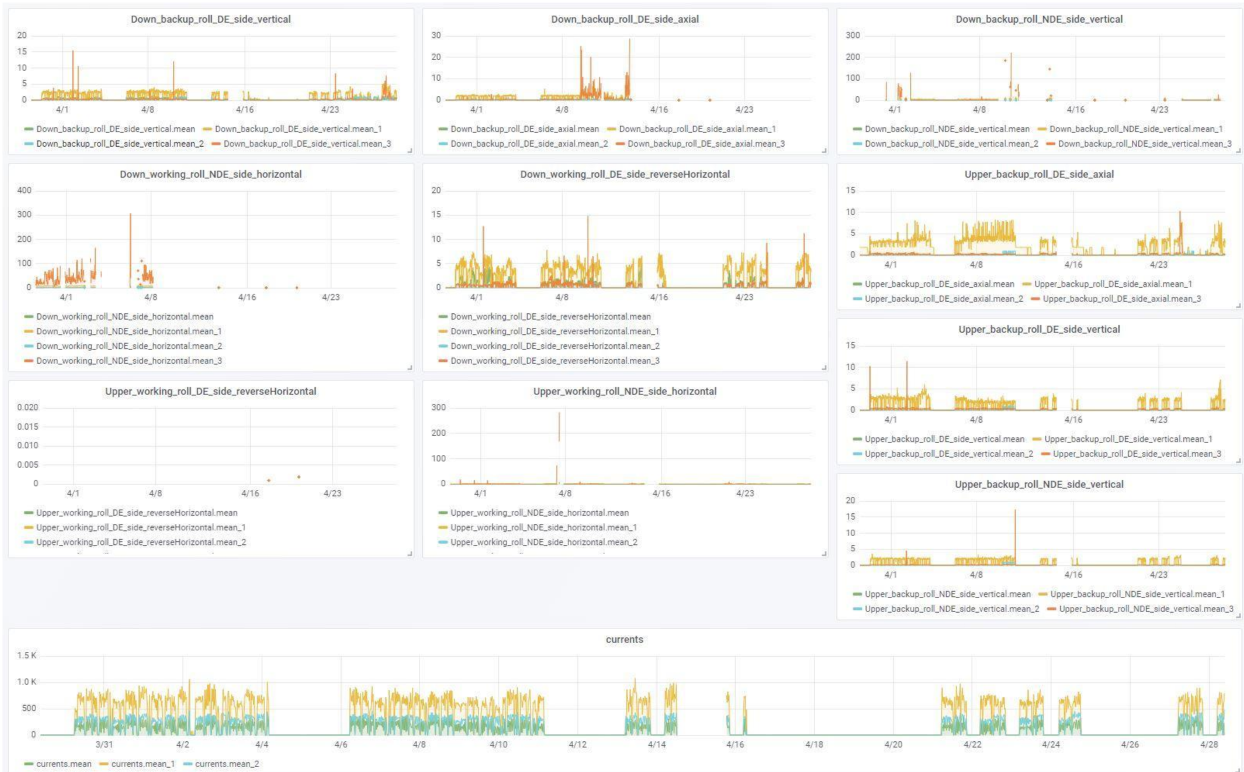

Figure 8: Example of a dashboard implementing explorative search over linked data (UPTIME/Maillis Use Case)

Improved sensor technology and wider application of sensors today provide more and more structured numeric data from all kinds of machines in production processes. In addition, considerable information and knowledge are available from internal as well as external sources. Typical internal sources are related to production planning, logistics and quality management as well as the experience of the maintenance experts. Thus, an efficient aggregation, extraction and visualisation of the relevant information are key technologies for information sharing and analysis of anomalies and issue root causes. Big data-based enterprise applications, like search tools, provide generic aggregation and indexing mechanisms and are available on the market, both as commercial tools (e.g. Dassault Exalead CloudView, IBM Vivisimo Velocity, Coveo Enterprise Search) and as open-source (e.g. Elasticsearch, Solr). In general, most tools target to analyse large volumes of heterogeneous data from high-dynamic distributed sources.

In parallel, the prevalent data deluge that is associated with maintenance processes can be leveraged to create knowledge graphs and semantic data lakes. In this case, big data and graph technologies are put into use to analyze and find useful connections hidden amid huge amounts of data. According to Gartner (2020), graph analytics and graph machine learning are in fact among the top trends in 2020 with the representation of the data in a graph structure to be easily exploited by machine learning models being listed among the core challenges. Manufacturers are expected to be asking increasingly complex questions across structured, semi-structured and unstructured data, often blending data from multiple applications, and increasingly, external data and graph-related technologies will be instrumental in such a quest to timely and accurately predict, prepare and respond to potential failures at the right time.

Different and complementary approaches may be taken to leverage Linked Open Data in the context of a predictive maintenance platform. The first approach deals with explorative visual analytics. Here, an appropriate Human-Machine Interface visualizes data in a customer-oriented way, allowing users to monitor and interact with the data both in real-time, to get insights into developments as they happen, and asynchronously, for detailed batch data analysis of historical data. Individually customisable dashboards are provided to visualise and analyse data in an ad-hoc, intuitive and user-definable way to quickly get deeper insights, support the maintenance decision-making process and investigate new solutions to maintenance problems. This approach allows typical data analysis tasks, such as complex queries or the visualisation of progressions, distributions, and correlations to be conducted even by non-professionals without a deep knowledge of the individual data sources. The second, complementary approach leverages semi-automatic mapping techniques to extract the semantics and the links between maintenance-related data considering an appropriate predictive maintenance data model acting as a taxonomy. In the direction of the linked data principles for inter-connectedness between the data and enabling network effects to add value to data, this approach applies some machine learning models combining and providing further insights into the available maintenance data, for example, related to maintenance logs and OEE.

3.6 Skilling of personnel

The deployment of PdM on a production line is a process that encompasses a wide set of activities. Each of these requires different skills, all of which cannot be managed by a single person. On the contrary, this involvement is often spread over the components of a dedicated PdM department or, usually, more than one.

Broadly speaking three separated steps are required to successfully implement a PdM project into an industrial environment:

- definition of PdM application: includes the selection of the best approach to prediction, the creation and maintaining of PdM models, the definition of which data is required at each stage (for modelling, training, validation), the actual development and deployment of the PdM solution, the validation of the prediction models or algorithms
- collection of the required data: includes activities like the hardware and SW installation of sensors, gateways, and network infrastructure; the inspection, cleaning and formatting of data as well as making the data accessible to relevant stakeholders
- embedding of PdM at all levels of the organisation: this phase is required to scale, operationalise and embed new predictions into day-to-day operations. Associated skills range from the actual process of deciding if, how and when an equipment component, foreseen for failing, should be maintained to the integration of maintenance activities with the current production scheduling, moving through, to the portrayal of maintenance-related information to relevant people in the production/management structure.

While some of the skills required to run these steps are generally already available in a factory environment that does not exploit a PdM approach (e.g. maintenance scheduling or sensors installation and checking), most of them can be considered brand new in the traditional production environment. Consequently, the addition of dedicated PdM actors or the skilling of existing ones is required. The following table provides a list of the required skills.

Skills	Objective	Actor	Available in a traditional factory
Domain/business Knowledge	to formulate the problem correctly	Production manager, maintenance expert	Yes
Failure mode and criticality analysis	to determine the impact of equipment components failure on the equipment, personnel, facility	Production manager, maintenance expert	Yes. If not, the equipment producer might provide support
Analytics tools, Statistical and Machine Learning Techniques, time-series modelling	to select, implement and validate an appropriate methodology to extract insight (equipment condition, RUL) from the data collected	Advanced data analyst, statistical modeller, data miner, data scientist	No
Data engineering, ETL and data warehousing, data quality and data management	to collect, clean, properly format and make available required data to relevant stakeholders	Data analyst	No
Data visualisation	to present collected data into a meaningful and understandable format	GUI designer and developer	No
Programming	to implement data and algorithm workflows/pipelines	Software expert	Yes
Analytics product deployment	to customize commercial solutions to specific PdM implementation	Data analyst	No
Cost evaluation	to determine if it is worthwhile to apply PdM solutions	Business analysts	Only in bigger plants
HW installation	To sensorize and maintain existing equipment, to install gateways	Maintenance Technician, Sensor expert	Yes. If not, the equipment producer might provide support
HW maintenance	to apply maintenance procedures	Maintenance Technician	Yes. If not, the equipment producer might provide support
Activities Scheduling, CMMS/ERP proficiency	to integrate foreseen maintenance activities in the factory production plan	Plant manager	Yes

Table 1: List of the required skills for Predictive Maintenance

Finally, it is worth noting that multi-skilling usually does not sit well with PdM deployment. The PdM skills requirements extend far outside the normal boundaries of competencies usually available in traditional factories. On the converse, such skills are indeed required mostly during the setup of the PdM solution and much less after its validation period. For this reason, SMEs should consider buying a customized PdM solution as a service, as opposed to hiring dedicated personnel. This is not true for maintenance operators that must be actively trained to manage PdM once it has been deployed. These operators have to be aware both of (1) what preventive maintenance to do and (2) how to perform relevant maintenance tasks. Only skilled operators, technically knowledgeable, who understand the engineering of the machines they maintain, and who are proven competent in doing preventive maintenance tasks, should be permitted to maintain relevant machines.

4 Industrial pilots

4.1 SERENA system and industrial pilots

4.1.1 Robotics use case

Motivation: Maintenance operations are currently scheduled by the customer based on the preventive maintenance indications provided by the COMAU manual. The scheduling is contained in a machine ledger, currently in an excel file version. To manage work orders, customers use ERP software. Maintenance operations are planned during production stops to avoid downtime, therefore, machines are over-maintained. Condition-based maintenance can contribute to reduced machine breakdowns resulting in a reduction of maintenance costs and an increase in equipment availability.

Figure 9: Robotic production line

Solution: The COMAU demonstrator includes the local deployment of the SERENA platform and its subsystems, integrating all services as Docker containers in the local ICT infrastructure of COMAU. To better study, the belt tensioning problem, a testbed named RobotBox has been developed replicating the key aspects of an industrial robot (Figure 9). The demonstrator consists of the data acquisition process performed via a local gateway (4G and 5G compatible), predictive analytics as well as the scheduling of maintenance activities and remote operator support to perform the required maintenance activities. In particular, data acquisition is delegated to a REST service on NiFi listening on a specified port for POST requests. Furthermore, the Predictive Analytics service enables the following key tasks:

- Model building triggered by either specific user input or an output of the self-assessment service. It produces as output the prediction model.
- Prediction task triggered by a new robot cycle and generating a prediction label along with a RUL value.
- RUL value triggers the scheduling Service for assigning maintenance tasks to site personnel.

- Real-time visualisation of the monitored equipment superimposing key information is facilitated via a Unity3D engine platform.

Impact: The benefit for the customer is the improvement, in terms of maintainability, of industrial robots exploiting all their components for their entire useful life without over-maintenance activities and with reduced breakdowns. This will in turn facilitate reduced maintenance costs and extension of the robot's operational life. The AR solution may speed up remote support for maintenance and the robot will be able to return faster to its operation.

Lessons learned: Based on the current deployment and integration status, the micro-service architecture gives the possibility to integrate, change or remove a single service with minimal effort. The analytics methods employed in the context of the SERENA project seem promising regarding belt tensioning in industrial robotics instalments supporting predictions both at the edge and on the cloud. Moreover, the adoption of advanced visualisation techniques allows for effective maintenance support.

4.1.2 Steel industry use case

Motivation: VDL Weweler designs, develops and produces trailing arms, among others, for the manufacturing of trailers, trucks, buses, and cars. The production line of VDL Weweler is fully automated including both machinery and robots. The focus within the SERENA project was to enable and test the developed predictive maintenance (PdM) techniques and scheduling for the proactive maintenance and parts replacement of the rolling milling machine (Figure 10).

Figure 10: Rolling milling machine

Solution: The SERENA deployment on this demonstrator includes a virtual gateway running on local servers overseeing data acquisition from on-site machinery and their communication to the SERENA platform. In the SERENA platform, RUL-based prediction of wear is performed triggering a new maintenance task to compensate for the identified wear, including inspection and if necessary, replacement of a part. The SERENA system aims to support the maintenance operator and possibly guide them on how to perform the inspection and maintenance activities on-site.

Impact: The intended scope of VDL Weweler is to provide to their customers the same products (in terms of quality) but at a lower price, since the downtime for maintenance and part replacement at the rolling milling machine will be reduced along with the production costs while the products produced between consecutive maintenance stops will be increased.

Lessons learned: The SERENA system is very versatile accommodating many different use cases. Prognostics need a deep analysis to model the underlying degradation mechanisms and the phenomena that cause them. However, the analysis of production data revealed useful information regarding the impact of newly introduced products on the existing production line.

4.1.3 Metrology equipment use case

Motivation: Metrological equipment is essential for quality control and in-line inspection in manufacturing processes. To maintain products as competitive as possible, the detection of flaws or maintenance needs must be performed in a cost and time-effective approach, keeping the cost of the final product as low as possible. Furthermore, the early detection of machines' errors would be essential for the customer of TRIMEK and the owner of the measuring equipment, to avoid wrong measurements and loss of efficiency and performance.

Figure 10: Measurement machine

Solution: The testbed aims to monitor the performance of a coordinate measuring machine (Figure 11) to correlate the results of the verification and calibration processes with the values of the operational condition. Data acquisition is performed via the SERENA databox, serving as a gateway and providing data from the edge to the SERENA cloud platform. Moreover, the RUL calculation is performed on the cloud triggering maintenance activities. SERENA AR operator support services are included as well to support the operator during the inspection and maintenance activities. Cloud deployment of the SERENA system is included in this demonstrator.

Impact: The addition of predictive support as a service with the corresponding business model facilitate the reduction of maintenance costs, hardware problems, predictive scheduling of corrective activities, and increased customer satisfaction.

As a result of applying SERENA solutions, machine breakdowns were reduced by 10%, the lifetime of the machine was estimated to be extended by 0.5 years, the cost of repairing and maintenance activities was reduced by 15% while through SERENA enabled the engagement of the correct maintenance personnel to the right customer.

Lessons learned: Tests have demonstrated a reduced number of maintenance visits as well as the time required to resolve occurred issues on the metrology machine. Moreover, the SERENA system provided the means to easily control air unit status via an accessible visualization display of the main operational status information of the machine.

4.1.4 White Goods use case

Figure 11: White goods equipment

Motivation: The Whirlpool testbed is focused on the foaming process, the core process in fabricating refrigerators and one of the most complex fabrication processes in the White Goods industry. The current maintenance of the equipment (Figure 11) is based on a preventive structure that is planned at regular time intervals. However, the predictability of failure is extremely low. The costs associated with maintenance fix are relatively high compared to other breakdowns. Therefore, it is crucial to address the maintenance issues to keep up the availability of the machine and the efficiency of the foaming process. The white goods use case concerns the Foaming Machine and its mixing head. The scope of the experimentation is to monitor the condition of the Mixing Head in terms of 1) General Health Status; 2) Early Warning.

Solution: The White Goods demonstrator includes a SERENA system deployment on the cloud and a virtual gateway in charge of collecting and pushing data to the SERENA cloud platform. The most critical aspect is predictive analytics which includes the offline dynamic and evolvable building and training of the predictive model along with the periodic prediction task evaluating the real-world data and generating a prediction label along with a RUL value.

Impact: Whirlpool aims to reduce the burden on maintenance by ensuring maximum machine availability which will, in turn, reduce unnecessary breakdown thereby extending the life of components. SERENA contributed to an increase to OEE by 5.5%, a 15% reduction of MTTR, an increase of 100% to the MTBF and an estimated reduction of TCM by €8.000.

Lessons learned: The joint work of process experts and data experts identified a promising prediction mechanism that could already be used to influence the preventive maintenance plan, helping to reduce unexpected breaks and optimize maintenance costs. Furthermore, the integration of components proved to be flexible to support both present and future requirements.

4.1.5 Elevators production use case

Motivation: The case concerns the monitoring and support of the KONE automatic metal sheet punching and bending production line (Figure 12). The production line consists mainly of an automatic punching machine, buffer and automatic bending machine including different types of conveyors and turning tables. The testbed provides vibration and sound measures for the project to develop PdM algorithms and models to assess the condition of production equipment. In particular, the goal of condition-based maintenance is to detect bearing faults employing envelope analysis.

Figure 12: Elevators production line

Solution: The testbed development included the installation of data collection devices and software, conveyor bearing vibration sensors and punching tool acoustic emission sensor, vibration sensor and microphone. Raw data analysis is performed first in the SERENA cloud, and in the second phase, the analysis is taken to the edge level to be handled by a Raspberry. The results of these fault indicators are delivered to the SERENA cloud and based on this, MIMOSA schema relations are used to create an alert and estimation of the severity of the failure. Next, the scheduling service plans for maintenance activity. The resulted event is enriched with the required maintenance support information and communicated to a maintenance operator at the pre-determined by the scheduler time.

Impact: The SERENA solutions were able to improve preventive maintenance scheduling and maintenance resource scheduling including spare parts inventory as well as to decrease down time's waiting and repair time based on AR solution and spare parts inventory strategy. In particular, SERENA solutions contributed to an increase of MTBF by 100 minutes and a 10% reduction of maintenance costs.

Lessons learned: In this case edge analytics performed by a low-cost edge device (Raspberry Pi) proved to be easy to install and configure while cost-effective. Moreover, the work in the context of the SERENA project revealed the magnitude of the missing know-how regarding the performance of predictive analytics.

4.2 UPTIME system and industrial pilots

4.2.1 Whirlpool use case: Drum Dryer Production Line

Motivation: The Whirlpool white goods use case deals with an automatic production line, which produces drums for clothes dryers (Figure 13). The drum production equipment is very complex, highly automated and critical from many perspectives. Currently, preventive and reactive maintenance is implemented and although needed, they exhibit many drawbacks. The reactive maintenance is performed during operation time, causing either a stop of the production or a degradation of it. The preventive maintenance is performed to reduce unwanted breakdowns as much as possible, which can improve the Mean Time Between Failures (MTBF). However, it can be very expensive, impacting the Total Cost of Maintenance (TCM). The Whirlpool use case aims to investigate how Whirlpool can make an effective transition from preventive maintenance to predictive maintenance.

Figure 13: Whirlpool drum Dryer production line

Solution: The Whirlpool use case starts with the acquisition of historical and operational data and the analysis of machine failures and maintenance actions to learn from experience and understand maintenance knowledge that relevant data from legacy and operational systems may reveal. The analysis is performed by UPTIME_ANALYZE, combined with the failure modes details detected by UPTIME_FMECA. Accordingly, new additional equipment sensors have been installed into the Whirlpool drum production line, which allows further enrichment of the dataset by UPTIME_SENSE, to continue the evaluation of machine learning algorithms by UPTIME ANALYZE, provide forecasts of future events by UPTIME_DETECT & _PREDICT and build basic rules for establishing health status of the equipment by UPTIME_DECIDE. UPTIME mobile application is available to be used by the factory workers to see generated maintenance recommendations and decide on maintenance actions.

Impact: The capability of the UPTIME system to predict future failures of the drum production line and to give indications about prognostic measures will modify the preventive maintenance plan allowing Whirlpool to anticipate planned intervention on components, thus reduce unexpected breakdowns, delay other interventions, and accordingly save money. The MTBF is expected to increase, since some unforeseen breakdowns will be predicted by the system, allowing maintenance to act before the component breaks. Moreover, the Mean Time to Repair (MTTR) is expected to decrease, due to the maintenance activities that will be planned, and thus optimising equipment downtime. All these effects will also positively impact the Total Cost of Maintenance thanks to optimized management of spare parts, technicians scheduling and improved effectiveness.

Lessons learned: Quantity and quality of data need to be ensured from the beginning of the process. It is important to gather more data than needed and to have a high-quality dataset. Machine learning requires large sets of data to yield accurate results. Data collection needs however to be designed before the real need emerges. Moreover, it is important having a common ground to share information and knowledge between data scientists and process experts since in many cases they still don't talk the same language and it takes significant time and effort from mediators to help them communicate properly.

4.2.2 MAILLIS use case: Cold Rolling Mill

Motivation: The M.J. MAILLIS steel industry use case deals with a cold rolling mill for the production of steel strapping (Figure 14). The demand for changing over the milling rollers comes either from their regular wear or unexpected damage, which can occur due to either defective raw material or an equipment malfunction. When this occurs, rolls are removed from the stand for grinding. This usually happens every eight hours for the work rolls and every week for the backup rolls. Replacement means production downtime which directly impacts costs. The current maintenance is performed frequently at predetermined intervals, which is based on generic performance data or previous experience. It is of utmost importance for MAILLIS to have their machine or a piece of equipment that can tell the machine current health status and the degree to which that status deviates from normal condition along with predictions about its future health state and actions recommendations.

Figure 14: Maillis cold rolling mill

Solution: Health monitoring in the context of MAILLIS use case involves inspection of the state of various components that constitute the milling station. As the physical conditions inside the milling station are extreme, health monitoring cannot be carried out by the traditional methods involving visual inspection during operation. Thus, in UPTIME, a set of appropriate and resistant sensors was set up in the sensor network that monitors the most important operational variables. The UPTIME platform will then acquire and process sensor data (UPTIME_SENSE), to provide information about the current health state of the machines (UPTIME_DETECT), predictions about future failures (UPTIME_PREDICT), criticality assessment (UPTIME_FMECA), proactive recommendations (UPTIME_DECIDE), and generate new maintenance plan. Besides that, an analysis of legacy and Overall Equipment Effectiveness (OEE) data is carried out by UPTIME_ANALYZE showing the prediction of operation interruptions from past behaviour.

Impact: It is expected that MAILLIS will have a machine that reports its current health status along with the appropriate data analytics. UPTIME system will allow predictions about the equipment's future health and provide recommendations for future actions. The ability for machines to perform self-assessment on which basis maintenance decision making can be optimized will allow MAILLIS to reduce its maintenance costs, improve their performance and affect positively the products' entire life cycle.

Lessons learned: Installation of sensor infrastructure: during the initial design to incorporate the new sensors into the existing infrastructure, it is necessary to take into consideration the extreme physical conditions present inside the milling station, which require special actions to avoid sensors being damaged or falling off. A flexible approach is adopted, which involves the combination of internal and external sensors to allow the sensor network prone to less failure. Quantity and quality of data: it is necessary to have a big amount of collected data for the training of algorithms. Moreover, the integration of real-time analytics and batch data analytics is expected to provide a better insight into the ways the milling and support rollers work and behave under various circumstances.

4.2.3 FFT use case: Transportation Logistics

Motivation: The FFT transport logistics (Figure 15) for the aviation industry use case deals with the maintenance of a complex large mobile asset, the wing upper cover transportation jig. The transportation jig consists of a steel structure and a lightweight aluminium cover. It is used to transport large components of aircraft wings over land, water and in the air, thus it is subject to high environmental stress. The current maintenance is based on manual physical checks with limited time and location windows to perform maintenance. Since it is an important resource of the manufacturing/assembly processes, the high availability of the transportation jigs and optimized maintenance process are expected.

Figure 15: FFT transportation equipement

Solution: The FFT use case starts with the implementation of UPTIME_SENSE to acquire sensor data. As a prerequisite for mobile field deployment, mobile sensor nodes to implement a large number of sensors are developed and connected to the UPTIME_SENSE. UPTIME_DETECT takes the sensor data as input and detects anomalies, which is passed as event information to the UPTIME_PREDICT, which estimates a prediction of a certain failure that is expected to happen based on the input event(s) and a user configured set of rules. Besides that, FFT provides some historical datasets from their measurement campaigns and some semi-structured data of manual inputs from the maintenance operator, which customized by UPTIME_VISUALIZE to facilitate qualitative assessments relevant to the Jig status. UPTIME_DECIDE receives predictions about forthcoming failures and generates maintenance recommendations and a new maintenance plan.

Impact: Because both production and logistics schedules can be significantly affected by the availability and plannability of transportation jig, the benefit of having comprehensive condition information about the jig is potentially very high. FFT maintenance service performance can be improved considerably e.g. by ensuring the availability of resources (equipment, spare parts, materials etc.). UPTIME is expected to enable FFT maintenance service to focus more on the primary maintenance processes by automating secondary processes such as data acquisition, processing and reporting, while continuously providing relevant data to improve all processes: planning, execution, reporting, evaluation, improvement.

Lessons learned: Quantity and quality of data: the available data in the FFT use case mainly consists of legacy data from specific measurement campaigns. The campaigns were mainly targeted to obtain insights about the effect of operational loads on the health of the asset, which is therefore quite suitable to establish the range and type of physical parameters to be monitored by the UPTIME system. UPTIME_SENSE is capable of acquiring data of mobile assets in transit using different modes of transport. While this would have been achievable from a technical point of view, the possibility to perform field trials was limited by the operational requirements of the end-user. Therefore, only one field trial in one transport mode (road transport) was performed, which yielded insufficient data to develop useful state detection capability. Due to the limited availability of the jig, a laboratory demonstrator was designed to enable partially representative testing of UPTIME_SENSE under lab conditions, to allow improvement of data quantity and diversity and to establish a causal relationship between acquired data and observed failures to make maintenance recommendations.

4.3 ZBRE4K system and industrial pilots

4.3.1 Philips use case

Motivation: Shopfloor machinery requires periodic preventive maintenance to operate under the predefined industrial protocols and produce the parts within the expected limits. On the other hand, the continuous operation of the machines leads to a degradation of their internal tools. The main goal of the Z-BRE4K solution is to apply algorithms that will be able to predict the remaining useful lifetime of a certain tool between the intervals of scheduled maintenance. The other main motivation of the implementation of the Z-BRE4K solution is to simulate the processes over the complete production chain and monitor, based on sensorial data, the interaction between the tools and the machines in the assembly line and the product family.

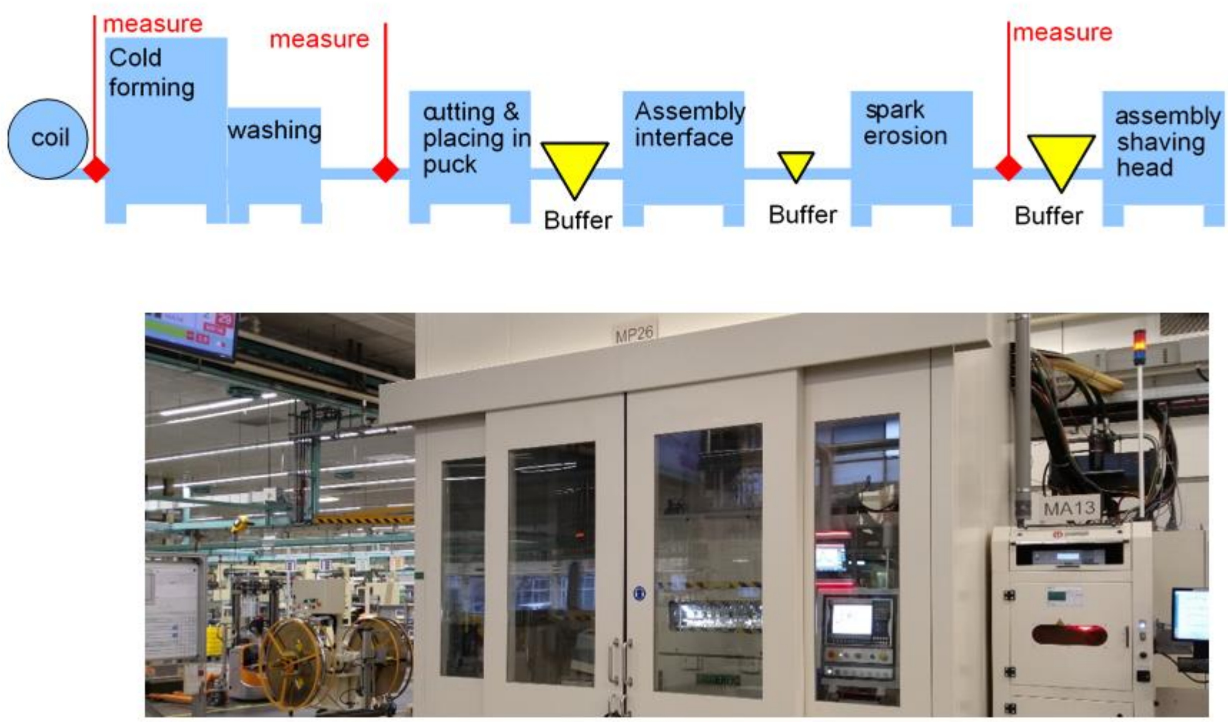

Figure 16: Cutter flow line of PHILIPS use case

Solution: Z-BRE4K combines all separate data and gathers it to the prediction of the remaining useful lifetime component where the component implements algorithms to compute the expected tool life and compare with the results given by the operators, based on their experience. The computed expected tool life is more accurate than the previous one and the prediction outcome is sent to the Decision Support System component which creates a suggestion for the production managers or the tool workshop operators. The suggestions are based on predefined rules by production managers and can create a new Maintenance Plan, which will include new maintenance orders for the tool, based on the prediction of the expected tool life.

Impact: PdM helps this end-user to improve the uptime of their tools in the live production while reducing tooling costs, man-hours and unnecessary tooling parts stock.

Lessons learned: PHILIPS supports the idea of predictive maintenance, "listening to the machines" and understands that the key to success is close contact between technology providers and experts where data integration/architecture and machine learning are both very important projects.

4.3.2 Gestamp use case

Motivation: The use case deals with the complex equipment on the shop floor where the industry will act upon a sudden breakdown. The aim of the Z-BRE4K solution of this use case is to implement cognitive maintenance strategies for full equipment and process production availability while addressing the quality control of instruments on the shop floor and measure it with KPIs.

Figure 17: Automotive Smart Factory for chassis manufacturing of GESTAMP use case.

Solution: The solution exploits the available information by the integrated systems on the shop floor and connects with the shop floor's MES and quality control system for data retrieval that are being sent to the Z-BRE4K Predictive Maintenance Component where the component implements its algorithms to create predictions. Also, data is simulated in the Z-BRE4K solution, creating a digital twin for the system which will be used to predict and reduce failure rates and downtimes. Finally, the Z-BRE4K solution is implemented to optimise the working conditions on the shop floor based on PdM.

Impact: Predictions on the shop floor will reduce breakdowns and downtimes of the machines while readapting the manufacturing procedures on the shop floor to accommodate the most suitable maintenance based on the Z-BRE4K system.

Lessons learned: GESTAMP, besides getting familiar with Z-BRE4K's solution validation and assessment methodology, got a better understanding of internal reflection and readiness to apply predictive maintenance solutions to its plants while new mitigation actions related to process flaws and defects identification were developed during the Z-BRE4K. Also, they have understood the importance of solution validation and assessment methodology defined in Z-BRE4K.

4.3.3 Sacmi/CDS use case:

Motivation: New machinery is equipped with a vast range of sensors, thus making the latter generation of production equipment and advanced CPSs. However, given the high CAPEX of production equipment, the majority of the already deployed machinery in existing shop floors is some years old. This other type of machinery is equipped with a limited number of sensors associated with fixed alarms. In this regard, these systems lack a pervasive condition monitoring system that can detect deterioration trends leading to failures, which some of them cannot be detected with existing alarm configuration and the operation strategy executed by the final user. Hence, an end-to-end PdM suite can provide final users with a solution for improving efficiency and equipment effectiveness.

Figure 18: CCM machine for beverage closure manufacturing and components that are being monitored in Z-BRE4K, source: SACMI

Solution: Sensor data is gathered by additional sensors and a condition monitoring solution in the system and it is distributed in the Predictive Components to create outputs based on dedicated algorithms able to determine the remaining useful life and machine failure.

Impact: Z-BRE4K solution will have a positive impact on plant productivity and also component's management, including inventory costs for spare components.

Lessons learned: SACMI-CDS found out the importance of collaboration not only with a mechanical engineering/maintenance-related professionals but also with different technical background experts that together can improve multi-tasking and combining shopfloor and office-related activities as well as scheduling of activities during the work journey.

In general, after the solution implementation (TRL5), testing the system on the shop floor (TRL6) and validation of the Z-BRE4K solution (TRL7) at end users, the very final lesson learnt can be summarised as follows:

- Live data are gathered by sensors and other systems.
- Data from individual data systems incorporated in a distributed system.
- Quality and maintenance measurements are available.
- Manual maintenance schedules are replaced with PdM procedures and schedules.
- Maintenance experts supported by gathered data and predictions to improve their know-how in the maintenance domain.
- PdM accuracy and performance is established.
- Productivity improved.
- Cost reduction obtained.
- Possibility of Testing a full end-to-end solution for maintenance management including prescriptive and predictive analytics.

4.4 PROGRAMS system and industrial pilots

4.4.1 Milling machine tools use case: Aurrenak pilot line

Figure 19: Aurrenak workshop

Motivation: The Predictive Maintenance (PdM) strategy exploits data coming from sensorized equipment to determine when a processing resource is approaching the point when it will no longer be fit for purpose and, in doing this, allows to reduce the cost associated with corrective maintenance activities up to 50%. However, complex equipment like the FIDIA milling machine tools present in the Aurrenak facility is made up of tens to hundreds of components that must be monitored (depending on the granularity of equipment decomposition).

PROGRAMS DSS analyzed maintenance data from both FIDIA and Aurrenak DBs to decide, for each component of the pilot machine tool, which maintenance strategy should be applied to reduce the overall maintenance cost. The Aurrenak workshop where testing and experimentation took place is presented in Figure 19.

Solution: PROGRAMS combines data coming from machine tool controller, additional sensors installed on it during the project and any available legacy maintenance data to perform an LDA analysis of the components, estimate their life distribution, simulate the overall machine tool availability and LCC under different applied maintenance strategies and finally provide the computation of the RUL for the components for which the PdM was finally selected (spindle, gearboxes, linear guideways). Furthermore, the ideal time for performing preventive maintenance is associated with the RUL information and the production plan, to create a comprehensive activities schedule.

Impact: PROGRAMS solution reduced the overall cost associated with the maintenance of the machine tool by 20%. Furthermore, the machine Life Cycle Cost was lowered by 15%÷20% in the short-medium term and by 25%-30% in the long term.

Lessons learned: correct determination of best maintenance strategies and computation of components RUL requires the collection of a vast amount of data in a format that must be easily accessible and analyzed.

4.4.2 Robot-assisted welding use case: Calpak pilot line

Motivation: In the robot-assisted solar tanks Calpak production environment (Figure 20), maintenance has two main goals:

(1) prevent unexpected breakdowns which will lead to the long delay of the production in a specific period of the year and
(2) determine the remaining time until the welding robots stop granting the required quality level of final products

Figure 20: Calpak workshop

The distinguishing factor is that the time when the second condition is reached is usually shorter than when the first is met. Production equipment components may degrade in condition but keep on working. Nonetheless, the overall quality of their usage will violate quality thresholds.

Solution: Since all the major moving components of the robot concur with the quality of the welding, a PdM strategy has been deployed for each of them by modelling a digital twin for the whole robot. Furthermore, a dedicated vision system has been deployed to monitor the quality of the welding. By proper combining predicted maintenance tasks with the estimated production plans (which are denser during summer), the PROGRAMS solution reduce the possibility of incurring unacceptable quality degradation during the whole year.

Impact: PROGRAMS solution reduced the overall number of unexpected maintenances stops and the length of maintenance activities during summer while still minimizing the overall maintenance costs. The OEE was brought to 95% thanks to the higher Availability (increasing of MTBF and reduction of Mean Down Time)

Lessons learned: robot components show a slow degradation of their performances: data collection must begin as soon as possible.

4.5 PRECOM system and industrial pilots

The PreCoM project uses the same PdM approach for all three use cases as described below. This approach will provide results on the feasibility and impact of applying the PreCoM concept and system in different real industrial scenarios.

4.5.1 Low volume manufacturing: Sakana Production Line

Motivation: SAKANA S. Coop, Spain, is a company that produces cast grey and ductile iron parts. With a total capacity of production of around 30,000 tons per year, Sakana is specialized in the production of very heavy-section parts (20-30 tons) and it is divided into two divisions:

- Wind turbine industry.
- High technology castings (HTC).

The main reason to select this industry is that it is a low volume production industry, where the manufactured products are of high added value. Moreover, the condition of the machine tool could meaningfully affect both the quality of the machined workpiece and the productivity of the machine derided from the unexpected stoppages due to the failure of critical components of the machine. A milling machine at Sakana is presented in Figure 21.

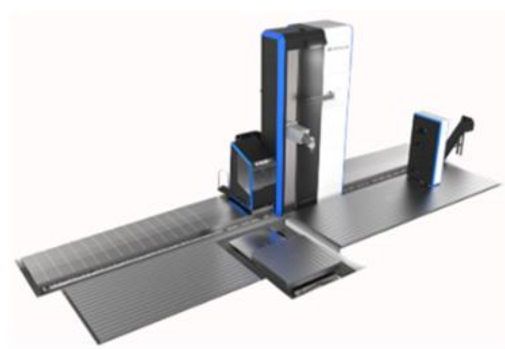

Figure 21: Soraluce's milling machine at Sakana

4.5.2 High volume manufacturing: Spinea Production Line

Motivation: SPINEA is a modern Slovak engineering company, engaged in the development, manufacturing and sales of high-precision reduction gears, which are sold under the trademark TwinSpin (Figure 22). TwinSpin high precision reduction gears are serially manufactured. High precision reduction gear TwinSpin belongs to a category of Hi-tech products and represents a unique technical solution integrating radial-axial bearings with high precision reduction gear into one compact unit.

Figure 22: Overbeck's grinding machine (left) and Lamb's machining centre (right) at Spinea

SPINEA is a high-volume manufacturer and constitutes a different industrial case where it is crucial to avoid stops in the production line and assure product quality. Condition monitoring is a fundamental objective for avoiding losses of money, imperfect products and raw materials due to stoppages and production problems.

4.5.3 Continuous manufacturing: Goma Camps Production Line

Motivation: Gomà-Camps Group manufactures processes and trades tissue paper (Figure 23) and other similar products. It has 2 machines for the production of 100% virgin cellulose tissue and recycled tissue, with a total capacity of 60,000 Mt/per year. Goma Camps is an example of continuous manufacturing, where unnecessary stoppages and breakdowns are highly problematic.

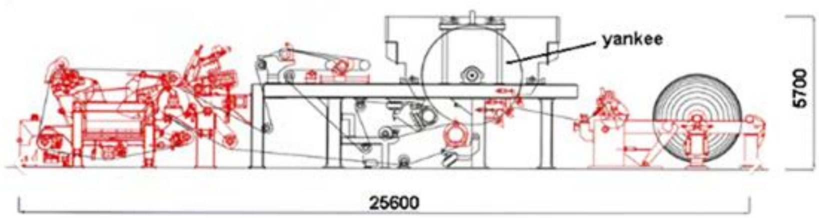

Figure 23: Lantier's paper mill at Goma Camps

Solution: The Predictive Cognitive Maintenance Decision Support System (PreCoM) enables its users to detect damages, estimate damage severity, predict damage development, follow up, optimize maintenance (for reducing unnecessary stoppages) and get recommendations (on what, why, where, how and when to perform maintenance). PreCoM is a cloud-based smart PdM system using vibration as a condition monitoring parameter. Some accelerometers for measuring vibration (of both rotating and non-rotating components), as well as other sensors (i.e. for temperature), have been installed in machines' significant components (i.e. components whose failures either expensive or dangerous). Over 20 hardware and software modules (common to all considered and equivalent use cases) are integrated into a single automatic and digitised system that gathers, stores, processes and securely sends data, providing recommendations necessary for planning and optimizing maintenance and manufacturing schedules. The PreCoM system includes loops and sub-systems for data acquisition, data/sensor quality control, predictive algorithm, scheduling algorithm, follow up tool, self-healing ability for specific problems, and end-user information interface (with the Production Line Information Visualisation, see Figure 24).

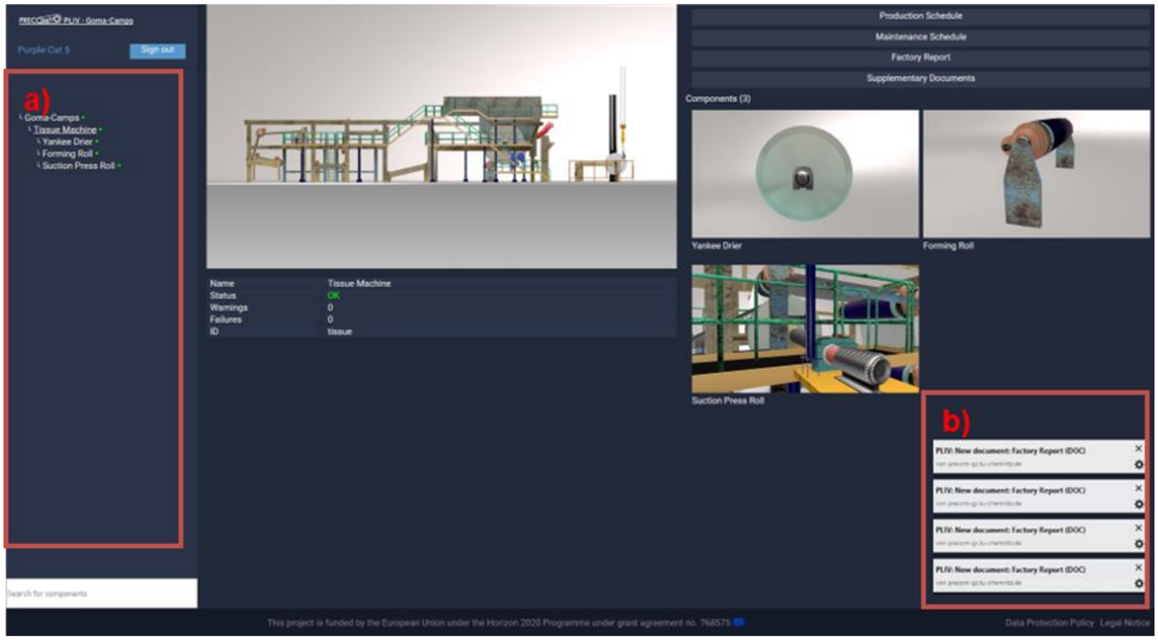

Figure 24: An example of PLIV (dashboard) for Goma-Camps, showing the top hierarchy factory level. a) Provides a comprehensive but detailed overview of the maintenance status of the entire factory. b) Shows the notifications that are popping up immediately after.

Impact: PreCoM impact is introduced below as an average of the impact achieved in the three uses cases: Sakana, Spinea and Goma Campus, based on the components monitored by PreCoM:

- Reduced downtime by about: 88%
- Maintainability (MTTR) improved by about: 24%
- Reduced supervision time in the training for new technicians by about: 76%
- Increased machine overall equipment effectiveness (OEE) by about: 5%
- Applying PdM by company personnel has been increased. From previous level 0 to about 80%
- Energy is rationalized by reduction equivalent to about: 16%
- Material loss is reduced by about: 16%
- Application of PreCoM versus work safety: No accidents previously as well as during PreCoM
- Reduced maintenance hours by about: 16%
- The saving in maintenance hours (at minimum) is about: 92 hours per year

Lessons learned: To develop and apply statistical models for supporting PdM, it is always crucial to have as much as possible failure data, which is not easy to find in the companies' databases. Furthermore, advancing and integrating different technologies in a single automatic and digitised smart PdM system is a challenge that requires close collaboration between research and industry players.

4.6 PROPHESY system and industrial pilots

4.6.1 RUL prediction for production tooling

Motivation: The PROPHESY system and its components were evaluated in a real-life manufacturing environment, in Jaguar Land Rover (JLR) and Phillips factories. Within JLR and Philips, use-cases have been defined around the maintenance of cutting tools and cold forming tooling for high precision metal parts. The evaluation was performed by Philips and JLR employees (shop floor employees, engineers, IT specialists and management) and involve all aspects of the system, technical and economic.

Solution: Data is being collected from several sources (material, machine, product, process and tooling) and fed into a set of PROPHESY-ML algorithms to determine the RUL of the wear parts involved. The PROPHESY-ML algorithms are trained to detect patterns in the data and predict failures without the need for 'feature engineering'.

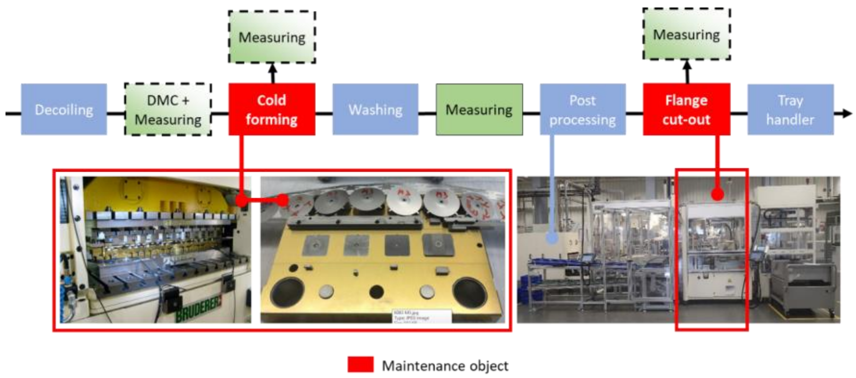

Figure 25: Overview of Philips demonstrator

Impact: The PROPHESY-ML RUL prediction is targeted to move from breakdown maintenance and preventative maintenance to predictive maintenance. The impact evaluation was performed by Philips and JLR employees (shop floor employees, engineers, IT specialists and management) and involve all aspects of the system, technical and economic, resulting in viable business cases for both the JLR and Philips PdM implementation. The techno-economic impact of the PROPHESY PdM instantiations was evaluated by assessing the status of selected KPIs, as defined for both JLR and Philips at the start of the project. Indicatively, at Philips, the MTTR has slightly increased at M36 of the project, with significant improvement of the registered OEE. At JLR achieved consistent improvements in the amount of inventory of cutting tools and a steady improvement of MTTR and Technical Machine Availability.

PROPHESY has also created a valuable portfolio of cost-benefit and optimization tools that is available online through the ecosystem either in the online web form format or through offline Excel spreadsheet downloadable forms-tools (www.pdm4industry.eu). These are offered for free in the online community to any registered member of the ecosystem.

Lessons learned:

- It is challenging to run a development project in a real-life production environment due to high pressure on production output.
- Data collection from legacy systems brings some specific IT challenges.
- Data understanding and data-pre-processing are crucial before starting the data analysis.

- It was proven once more that close collaboration is needed between data scientists and process experts to get reliable results.
- The results of PROPHESY-ML application to the use cases have been reported for both demonstrators in the project's deliverables, achieving RUL prediction with accuracy as little as 4-5% Mean Absolute Percentage error.

4.6.2 AR assisted (remote) maintenance

Motivation:

Newly developed technologies for video-assisted expert support and the advent of Augmented Reality for equipment service, triggered use cases within JLR and Philips. Within JLR, breakage of critical machine components can cause a huge standstill of the equipment if the service engineer needs to fly in from mainland Europe. Within Philips, a use-case was defined to visualize relevant maintenance information for the maintenance technician, at the right moment and connected to live data sources as a visual aid to the right maintenance component.

Solution:

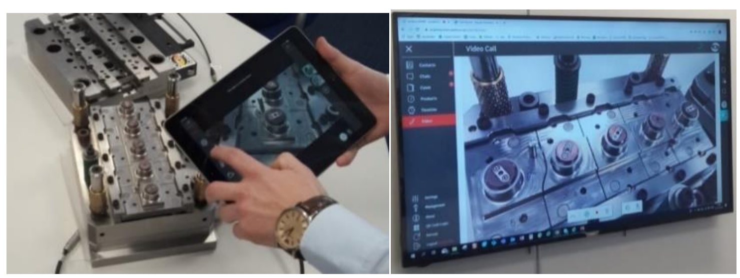

Figure 26: PROPHESY-SHARE AR support

For the JLR use case, a remote service platform, based on the Oculavis SHARE system, has been developed and demonstrated. Equipment experts from abroad can be in contact with the service team of JLR and at the same time, involve a JLR process engineer. The Philips use case resulted in the PROPHESY-AR viewer; a multi-purpose tool for both remote support as well as providing specific work instructions and visualization of (predicted) tooling information to the maintenance mechanic.

Impact: The PROPHESY-SHARE platform, offering both remote service functionality as well as AR assisted tooling maintenance, is bringing various benefits to the maintenance ecosystem. The most important is the time savings in resolving maintenance issues that are directly translated to cost savings. It is estimated that time savings up to 66% can be realized (1 instead of 3 days solution time) and cost savings of up to 90% (based on avoided downtime and travel costs) per remotely solved case.

Lessons learned:

- The PROPHESY-SHARE platform has developed into a multi-purpose tool for both remote support as well as providing specific work instructions and visualization of (predicted) tooling information to the maintenance mechanic. As a result, both industrial partners are considering investments in this technology.
- The end-users are very eager to work with digital support systems that ease their job as it brings a single point of data.

- Quite some hurdles to take in the field of health and safety, IT security, GDPR (e.g. face blurring).
- The development cycle with prototype demonstration v1-feedback from the end-users and other stakeholders-demonstration of an improved prototype v2-feedback from the end-users and inter-departmental stakeholders worked very well.

5 Standardization aspects of PdM

5.1 Standardisation Overview

Industry 4.0, embedded systems, semantic machine-to-machine communication, Internet of Things (IoT) and Cyber-Physical Systems (CPS) technologies are joining the virtual space and the physical world together. Industry 4.0 has the potential of becoming the universal language of production. Each process used in an Industry 4.0 system integrates existing and demonstrated technologies with new technologies and applications to address manufacturing issues. Therefore, the introduction of a harmonised set of industry standards is especially important.

The fast growth and evolution of IoT make standardisation a challenging topic. Standardisation plays a key role in the upcoming development and spread of IoT. Particularly in IoT, standardization mainly aims at improving the interoperability of different applications and systems. Various standards used in IoT (such as communication standards, ontology standards and security standards) might be major drivers for the spread of IoT technologies. Specific issues in IoT standardisation include interoperability issues, radio access level issues, and security and privacy issues.

5.2 Views on Maintenance standards and Predictive Maintenance

Following a research activity developed by *Antoine Despujols* (AFIM) on Maintenance Standards, the standardisation bodies involved in maintenance standards, are classified into three different levels:

- 1st Level: International Level: IEC (International Electronical Commission) and ISO (International Standardisation Organisation);
- 2nd level: European Level: CENELEC (European Electrotechnical Commission) and CEN (European Committee for Standardisation); and
- 3rd level: National Level: National Standardisation Institutes.

Specific Technical Committees (TCs) on Maintenance are presented in Figure 27, including (i) Dependability, (ii) Mechanical vibration, shock and condition monitoring, (iii) Non-destructive examinations, (iv) Asset management, (v) Maintenance and (vi) National Maintenance Committees.

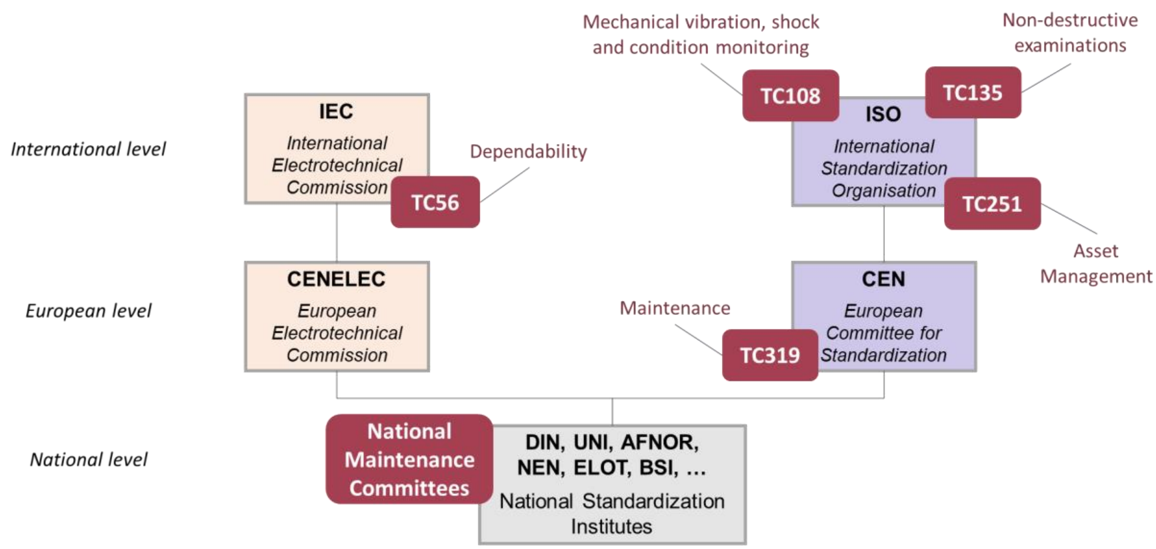

Figure 27: Standardization bodies involved in maintenance standards

The following figure has been developed by Maintenance CEN/TC319 to group the standards into 4 parts.

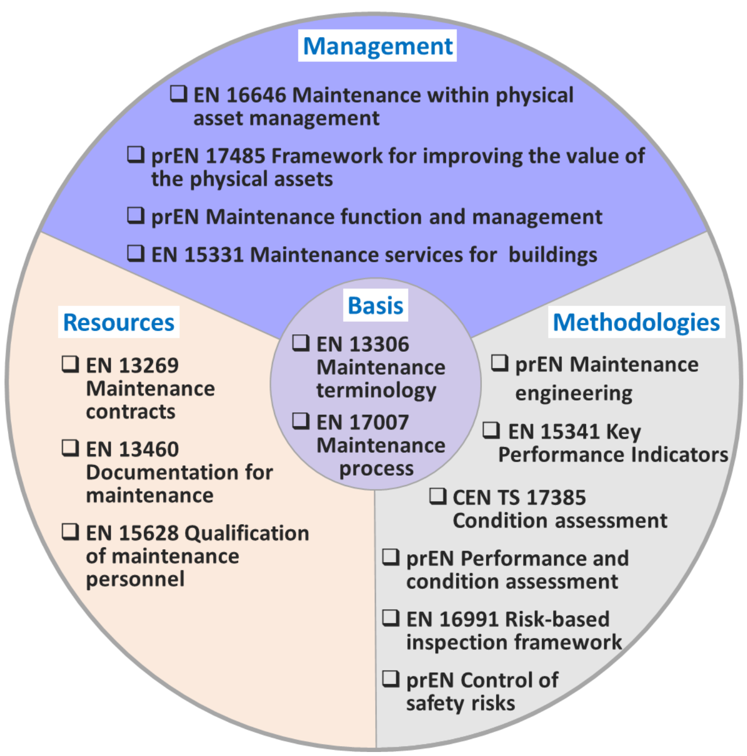

Figure 28: CEN/TC319 maintenance standards

According to the terminology of CEM standards, different types of maintenance tasks can be related to PdM.

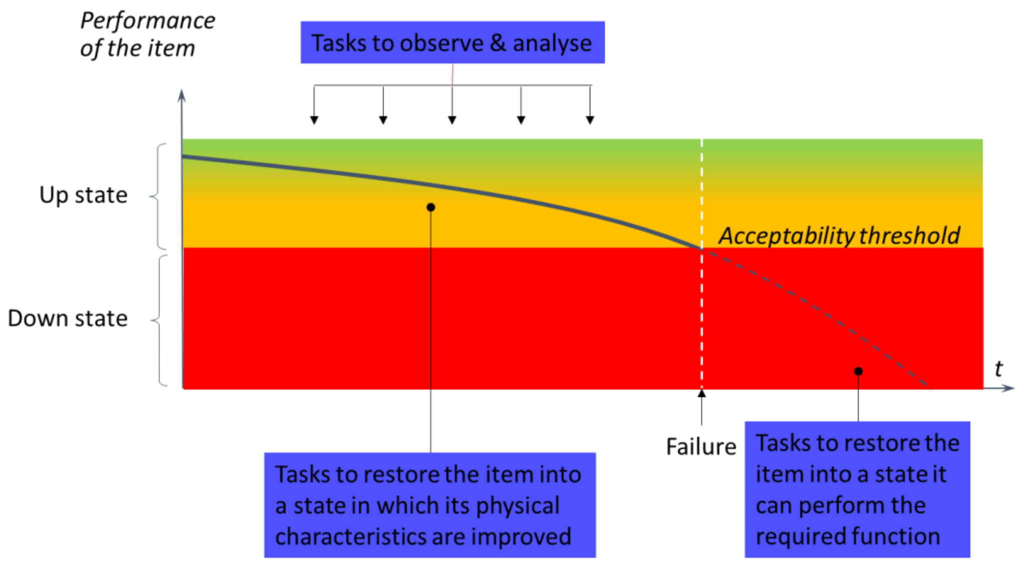

Figure 29: CEN/TC319 maintenance standards Maintenance tasks

Figure 29 shows the evolution in time on the performance of a mechanical component that degrades and, eventually fails with complete degradation.

By defining an acceptability threshold, it is possible to identify two states for the item:

- Before the failure – at upstate – improvement maintenance tasks to restore the item into a state in which its physical characteristics are improved.
- After the failure – at downstate – corrective maintenance tasks to restore the item into a state it can perform the required action.

Failure can be defined as the condition when the curve crosses this threshold. The performance of these maintenance tasks can be based on time or be triggered by observation. Observe and Analyse tasks, which are the third type of tasks, are also directly connected with Predictive Maintenance.

5.3 Maintenance terminology

As maintenance terminology is identified as a need for interoperability (ability to exchange and make use of information), the terminologies used in various ISO, IEC and EN standards have been compared to assess their commonalities and differences. This work has been presented during the workshop "Interoperability for Maintenance" of the I-ESA 2020 conference and published[4]. Regarding maintenance terminology, the I-ESA 2020 workshop participants have concluded that a shared framework will help the stakeholders from different disciplines and with different interests to cooperate consistently on a common system. System engineering principles, methods and tools seem to be the best candidate to build this shared framework. Besides this shared ontological basis, ontologically consistent modules shall be

[4] Maintenance terminology standards: some issues and the need of a shared framework for interoperability KERARON Yves , DESPUJOLS Antoine, I-ESA 2020.

edited by discipline experts. Further work shall address the governance of this set of modules and experiment with the benefit of advanced technological standards to use a set of periodically updated ontological modules for contextualized use cases. Maintenance, responsible for the highest “Upstate” of a system, could be a prime activity to co-develop, complete, deploy and benefit from such a framework.

5.4 Evaluation of Standards

The collaboration within ForeSee Cluster allowed assessing standardisation opportunities and share knowledge and best practices. Relevant activities started in early 2019 and involved all projects of the ForeSee Cluster.

The standardisation elements which were evaluated included interfaces, communication protocols, quality inspection, management systems, performance monitoring and key risk indicators for manufacturing while others will be further addressed in future activities.

The most relevant Data-related standards and Maintenance-related Standards for ForeSee Cluster, representing respectively the Standardisation state of the art from a general point of view and specifically in the maintenance application area are listed in Annex II.

To support the representation of how standards are being applied in the different projects Radar Charts have been adopted, created and periodically re-evaluated. The Radar Chart is a graphical representation of each standard listed in the Annex.

The Radar Chart provides a simple view of the standardisation assessment, illustrating all the elements that may be of relevance to project developments. Furthermore, the Chart highlights the candidate standards for adoption as well as those standards that have been adopted as part of this joint effort.

This chart in Figure 31 is divided into four quadrants, showing the ForeSee strategy for clustering the candidate standards - adoption, monitoring or participation in development, or even in Ecosystem development of standards.

Each standard on the Radar Chart is used to provide visibility of the status and maturity of a standard or initiative. Each standard or initiative are first identified, and further continuously updated to track progress as the standard or initiative evolves. This continuous process of monitoring a standard or initiative includes the current action level (track, candidate or adopted), the quadrant and a link for a full description of the component standards.

The Radar Chart categorized the list of standards into:

- Transversal Standard: coloured in purple;
- Domain/Discipline Standard – coloured in yellow;
- Technological Standard: coloured in greed.

The joint effort lead to the creation of two different radar versions, one for *Data-Related Standards (*Figure 30*)* and one for *Maintenance-Related Standards* (Figure 31).

To distinguish the overall data-related standards – which can be transversal to many different products/solutions – from the maintenance-related standards, it was then decided to perform a separate analysis.

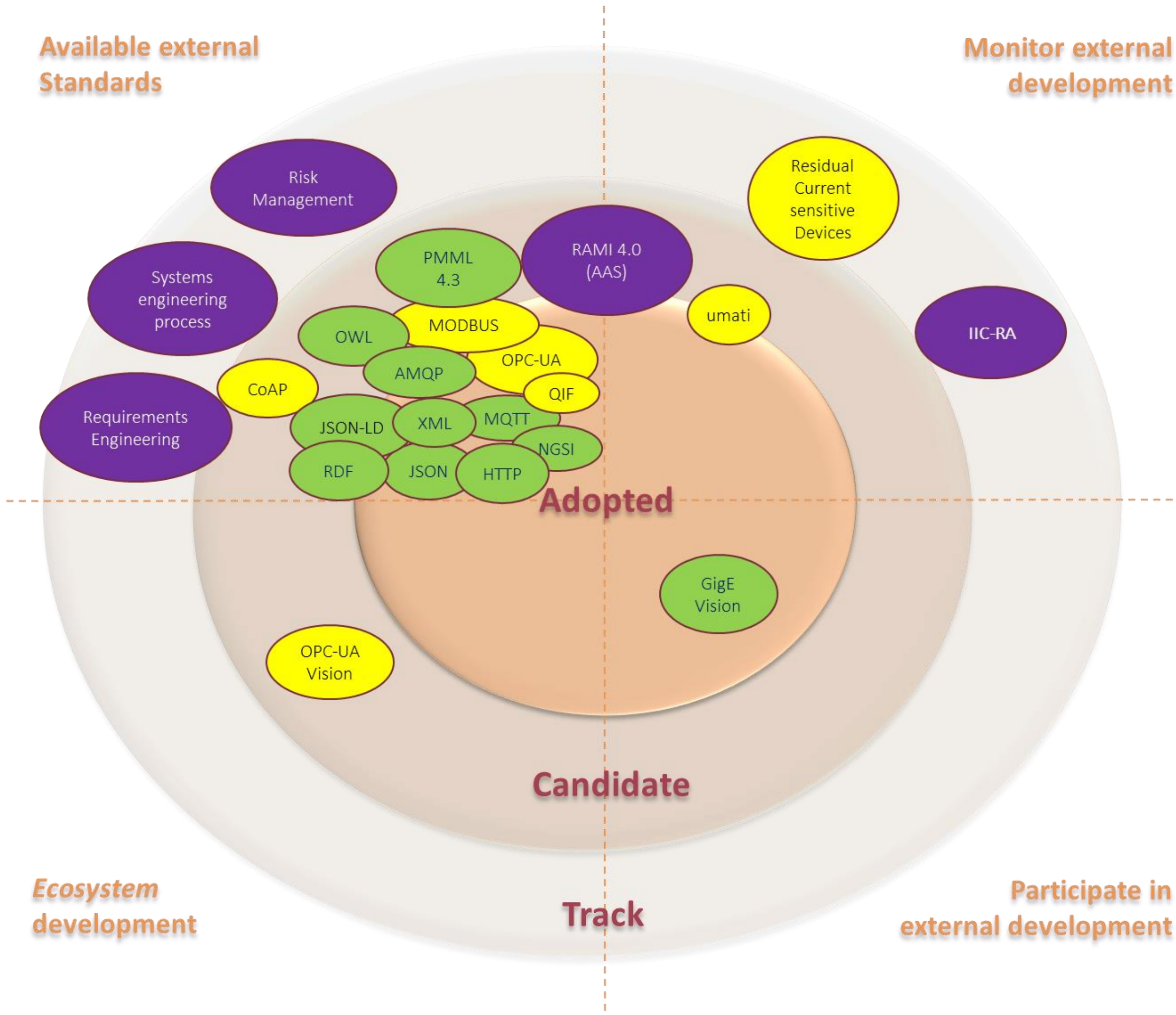

Figure 30: ForeSee Radar Chart – Data-related standards

The first chart highlights that the standards to support the data access, treatment and transfer (such as JSON, HTTP, NGSI, OPC-UA or QIF standards) are the most common. However, not only technological and domain standards are part of this ecosystem, Ontology – which is a broader area – assumes key importance, as well as Risk Management, Systems Engineering Process and Requirements Engineering. Even if these standards were initially developed for maintenance systems, they were clustered under Data-related Standards. Thus, PdM dedicated analysis aimed to promote the awareness on relevant standardisation, resulting from a broader scope on demonstrating the importance and best practices of standardisation in Industry 4.0. The Radar Chart on Maintenance-related standards is presented in the following figure (Figure 31).

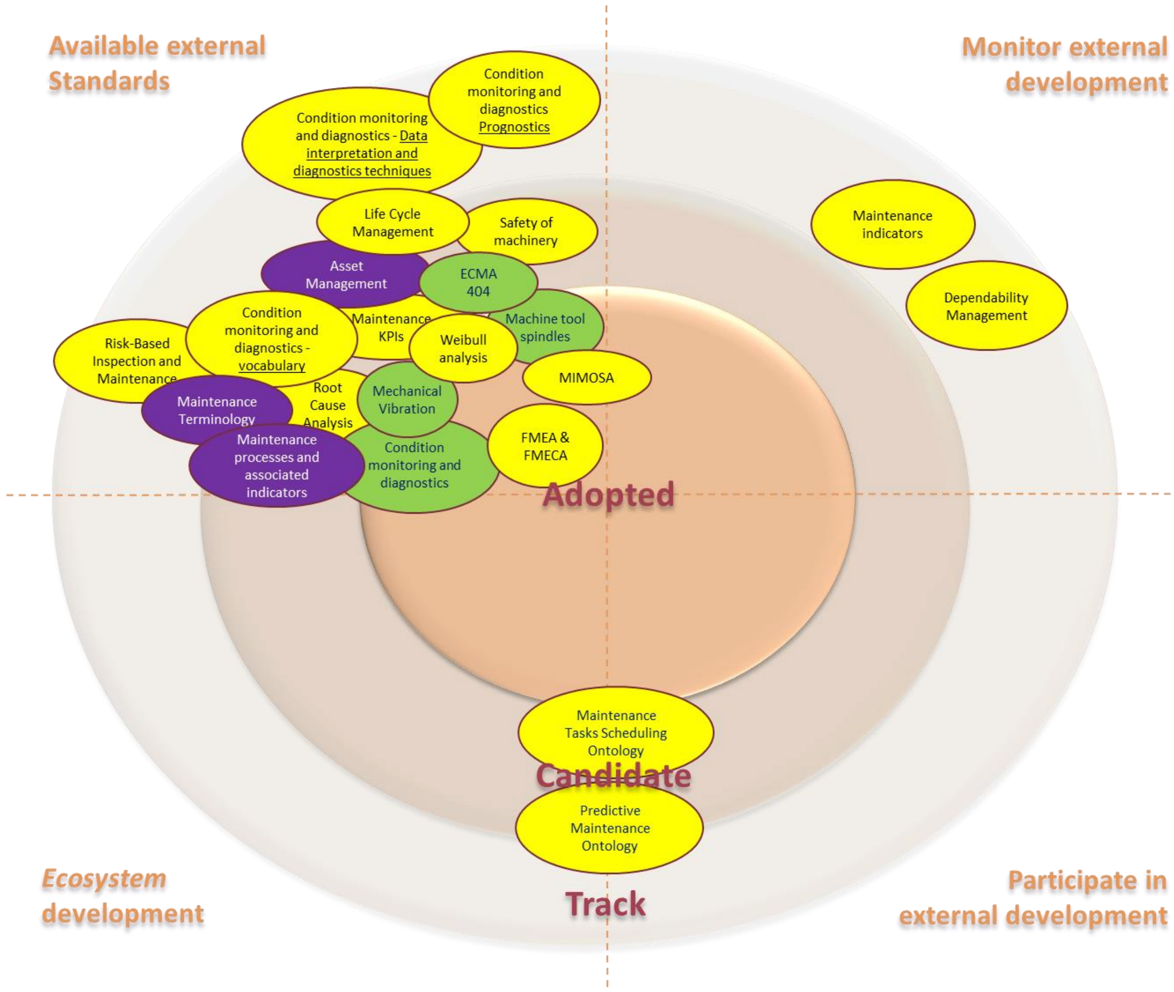

Figure 31: ForeSee Radar Chart – Maintenance-related standards

The Radar Chart on Maintenance-related standards includes two standards adopted by several ForeSee projects: IEC 60-812: Failure Modes and Effects Analysis (FMEA and FMECA) methodologies and MIMOSA. The first one supports the identification of potential failure modes, assessing the risk associated with those failure modes to carry out corrective actions to address the most serious concerns. The second one enables digital-physical asset lifecycle management spanning plants, platforms and facilities, standardising the interface between plant floor systems (including PdM) and EAM systems.

“ANNEX I - Standards application in ForeSee projects” lists application examples of different standards in the Foresee projects. Such examples were presented during the webinar on “Standardisation Challenges for PdM under the ForeSee Cluster”, coordinated by INOVA+, which aimed to develop sustainable PdM solutions for the factory of the future.

5.5 Future Activities

The ForeSee cluster will maintain the activities related to the maintenance terminology and radar charts for PdM. The availability of so-called SMART, Standards Machine Applicable Readable and Transferable, and ontologies or other "industrial commons" will be very helpful to support advanced maintenance strategies as PdM. Legacy data and applications remain an issue because of the lack of standardization, which makes it difficult to map their models to common ontologies. Considering the economic importance of the corresponding assets, alternatives still need to be explored. This is an active research topic with an impact on standardization strategies.

6 Predictive maintenance: An Industrial Perspective

6.1 Introduction

Cheaper and more powerful and well-selected Condition Monitoring (CM) parameters and sensors, statistical and data-driven models, algorithms for specific functions, AI, ML, together with big data analytics, offer an unprecedented opportunity to track machine performance and health condition. As the experience of Foresee cluster projects has indicated the evolution of current maintenance practices from condition-based – to - Smart Predictive Maintenance (Smart PdM) would be an important success factor for manufacturers to reach fewer stoppages, longer production time, higher productivity, stable product quality, reduced defective products and enhanced profitability and competitive advantages.

Reactive and preventive (i.e. regularly time-based planned) maintenance are, in general, still dominating the maintenance implementation in an application does not matter what sector in the industry. However, it is estimated that manufacturers still, in general, spend only 15% of their total maintenance costs on predictive (vs reactive and preventative) maintenance.

6.2 Projects ‘Objectives

The ForeSee cluster projects aimed to deploy, test and demonstrate a Smart PdM decision support system (DSS) able to, for example, identify and localize damages (i.e. in which machines and components), assess damage severity, predict damage evolution, assess remaining asset life, reduce the probability of false alarms, optimize maintenance for production planning, provide more accurate damage detection, issue notices to conduct necessary maintenance actions and ultimately increase in-service efficiency of machines cost-effectively. These notices take the form of recommendations describing what, where, why, how and when latest to conduct a maintenance action, i.e. in transparent notices and not as a recommendation from a black box.

In addition, it allows follow up maintenance and production performances using both technical and economic measurable variables to check whether maintenance generates saving/profits or acquires additional cost.

The focus of the projects has been to develop and apply from different perspectives innovative systems for Smart Predictive Maintenance as new models for sustainable factories and Maintenance 4.0. These systems can also be counted as a predictive, intelligent, digitalized and automated CBM using one or more CM parameters (including the time to failure) to describe and follow up the condition of a machine (and its significant components), assess its current condition and predict its condition development in the near future in a cost-effective way.

The systems gather information from maintenance-related areas, such as machines, production, quality, energy, materials, and economy. Its performance is digitalized and automated using either a probabilistic or deterministic, or a combination of probabilistic and deterministic approaches.

The overall objectives of the projects are to maintain machine quality (i.e. to maintain the machine technical specifications), reduce the probability of failures and shortening downtime, ease conducting maintenance actions through facilitating the integration of additional necessary technologies, such as Augmented Reality (AR) and Virtual Reality (VR), tools/systems to follow up maintenance impact on company business, and secure production planning to enhance production continuity and company profitability and competitiveness.

The cluster projects have been evaluated concerning the direct impact of the platform on, among others, maintainability, availability, work safety, material and energy losses and costs as well as environmental impact, the Smart PdM benefits, pay off possibility and time range of the pay-off. The evaluation of the projects' demonstrations in the industrial use cases highlighted an impressive, positive impact on the key performance indicators (KPIs) and expectations (see chapter 4).

6.3 Development of Smart PdM

To develop a Smart PdM, it is necessary to survey the manufacturing machines in a company to identify critical machines and their significant components (i.e. the components whose failure either expensive or dangerous) to be monitored by the Smart PdM-system. The Smart PdM-system concept and design should properly be defined and determined. The concept shows in an overview plan how it works, what possible functions can be achieved, the type of data necessary and how the data flow will be. The design usually shows how all the elements constructing the system will interact to secure the interoperability and functionality of the system.

This work sequence enabled the consortiums to design concretely Smart PdM-systems and their functionalities in collaboration with use cases. For example in the PRECOM project 24 (hardware and software) modules were connected to a centralised cloud and the overarching intelligence, Brain (i.e. the steering rules to secure data flow, interoperability and right recommendations to the end-user companies).

Second, the projects developed and adapted the selected modules and technologies for making them interoperable for specific applications related to the use case companies involved in the projects.

Third, in some cases, lab tests of individual modules/technologies and the overall system were conducted to verify and validate them.

Finally, the PdM systems were applied in about 12 months of demonstration and validation in the targeted industrial use cases, with continuous monitoring and evaluation of its impact.

The evaluation of the six projects showing the impact achieved in the use cases is summarized in Chapter 4. The project finalised solutions go beyond the state of the art of solutions for predictive maintenance (Maintenance 4.0) currently available in the market.

We demonstrated and validated the developed PdM in an operational environment with important results of economic impact for manufacturing companies which was achieved through, e.g. avoiding unnecessary stoppages, improving production and maintenance planning.

Furthermore, manufacturing and support machines and component builders benefited from the system for better monitoring and identification of weakness in the machine, data describing deterioration and breaks, which can lead (in the medium-/long-term) to improvements in the next generation of machines and components.

In addition, the whole process is based on securing that the data gathered are of high quality and from healthy sensors. Therefore, we developed modules for detecting unhealthy sensors, i.e. to secure data quality. Also, in many cases were not possible to find digitalised data. Therefore, for fully digitalizing and automating Smart-PdM, manually collected data is digitalised and automated.

At the end of the projects, a working and effective Smart PdM system is developed, as well as a set of modules/sub-systems which can be exploited also individually (or in other combinations). The PdM systems showed that they impact positively on the levels of in-service availability, maintainability, quality, economy and worker safety.

6.4 Approaches of PdM

However, industrial experience and applications, and the projects of the ForeSee cluster have demonstrated that PdM can take several shapes based on the concept, objectives, area of application, model(s), data/experience and approaches used to develop it. For example,

1. PdM can be based solely on a statistical model using time-axis (e.g. calendar or age), such as the case in developing statistical models for predicting the residual life (Al-Najjar, 1997), (Jardine et al., 2006).
2. PdM can use several parameters including vibration, shock pulses, temperature monitoring and acoustic emission (De Azevedo, Araújo and Bouchonneau, 2016; Macchi, Roda and Fumagalli, 2017). These parameters can be utilized through converting condition monitoring (CM) values of one or more of CM parameters to the time –axis, e.g. using Proportional hazard Model, to predict the condition of a machine through predicting, e.g. the time to failure (residual life) and assessing the probability of failure (Jardine et al., 1987).
3. It also can be based on using the engineering approach, i.e. deterministic, through applying physical assessment of the deterioration and/or the forces exposed to evaluate the status of equipment/component associated with individual-based experience to predict failure behaviour (prognosis) and subjectively assess the time to maintenance (Al-Najjar, 1997).
4. As it is well-known, it is not always possible to describe reality with the accuracy demanded by industry, such as the time to replacement/action, by using only statistical models or by applying the deterministic approach. Therefore, a combination of the deterministic and probabilistic approaches is recommended (Al-Najjar and Algabroun, 2017). Deterministic/engineering approach is recommended especially when there is enough information/data describing what happened and what is ongoing. The probabilistic approach is recommended to apply when it concerns predicting future damage development depending on what has happened based on facts (CM measurements) (Al-Najjar, 2012). The combination of these two approaches will describe reality and anticipate what may happen with higher accuracy (Anagiannis et al., 2020).

Industrial experience shows that using different approaches in developing PdM may lead to different accuracy in planning maintenance actions, which has a dramatic impact on industrial application i.e. conducting maintenance action too early and losing about 50% of the replaced component effective life (Al-Najjar, 1998) or too late after failures.

Therefore, we claim that PdM can be classified with respect to the approach used in the development, see also Figure 32.

Thus, it is very important for any manufacturing company when selecting a Smart PdM for their assets to consider several factors, for example

1. Whether the Smart PdM system concept and design fit the company infrastructure,
2. The system objectives and accuracy. It is necessary to answer the following questions, such as:
    - Is the system designed for detecting damages at an early stage?
    - does it enable damage to follow up?
    - does it provide enough lead time for conducting maintenance actions when a warning for replacement is activated?
    - what is the accuracy of detection, and recommendation?
3. Whether the areas of applications of the Smart PdM system cover the company´s manufacturing process and environment,
4. Model(s) and approaches used to develop the system and the availability of the data needed. The data needed should be available and in the format demanded by the system and models constructing it.

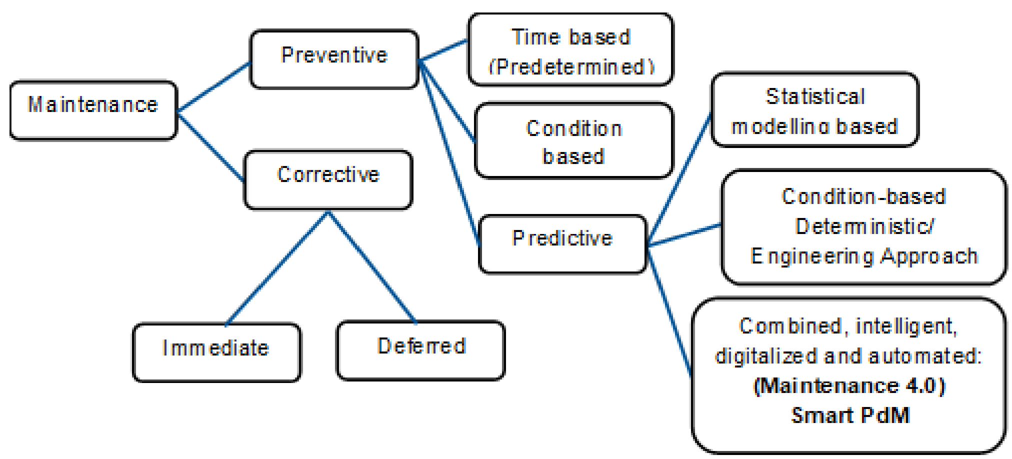

Figure 32: Classification of PdM

When using a combination of deterministic and probabilistic approaches, Smart Predictive Maintenance (Smart PdM) can also be defined as "a Smart, predictive, digitalized, with self-learning and automated Condition-based Maintenance (CBM) using one or more CM parameters, statistical and data-driven models". These CM parameters include even the time to failure. Smart PdM should be able to describe and follow up the condition of a machine (and its significant components), assess its current condition, predict its condition development in the near future and recommend what, when, why and how to act cost-effectively.

Therefore, it has been realised that the major goals of applying Smart PdM are:

- Maintain machine quality (i.e. maintain the machine technical specifications);
- Better control of the condition of manufacturing machines;
- Reduce the probability of failures and unnecessary stoppages and therewith probable failure related accidents, as well as downtime;

- Ease conducting maintenance actions through facilitating and integrating the application of Augmented Reality (AR) and Virtual Reality (VR);
- Reduce losses in energy and material;
- Enhance working environment satisfaction and experience for the human operators, contributing also to their health;
- Reduce environmental effect;
- Enhance production continuity, reduce production and maintenance costs, follow up maintenance impact on company business and consequently increase profitability and competitiveness.
- Smart PdM is to acquire and implement Maintenance 4.0 meeting the demands from Industry 4.0, where the production is mainly digitalized and automated.

6.5 Performance and Technology Necessary for Smart PdM

Smart PdM is considered to gather data/measurements/ information from all maintenance-related areas, such as machines, production, quality, energy, working environment and economy. Smart PdM and its performance is digitalized and automated applying statistical and data-driven models. To achieve the goals above, Smart PdM uses different technologies as it is experienced in several manufacturing companies included in the project, such as:

- One or more of the CM parameters including time should be addressed to monitor a wide range of machine deterioration processes and to enhance the accuracy of diagnosis and prediction, such as the case when using, e.g. temperature and sound, for supporting vibration signal analysis. In addition, using the time (e.g. age and calendar time) is for, for example, statistical modelling and especially for non-rotating components,
- Wireless/wired sensors (even the embedded sensors), PLCs are necessary for data gathering needed to detect changes in the machine condition at an early stage. It is not always possible to use wireless due to disturbances in the manufacturing environment.
- AR, (Mourtzis et al., 2017) and VR: AR has shown very big potential in decreasing the time to repair, i.e. enhancing maintainability, shortening the time for training new technicians and maintaining experience to be utilized by any technician even if she/he was not specialist in the specific task needed to be repaired,
- AI and ML for, for example; controlling data flow, securing communications, preventing streaming of recommendations and warnings, and providing the end-user with the right recommendations. Besides, the self-learning is very significant to enable Smart PdM re-adjusting constants, parameters and warning levels at need, e.g. at failures,
- Cloud/databases are important assets for automatic data gathering, calculations, control and saving. At the same time, manual data gathering analysers can also be considered, because in some cases, as we experienced in the industry, people need to make manual measurements especially when the system detected unhealthy sensor or when there is a warning while the production manager needs the production to continue, or when a measurement is rejected by the system due to a big deviation from the behaviour pattern,
- IIoT, IIoS, IIoT platform, digital twins, gateways, big data analytics software for automatic analysis, diagnosis, prediction, and recommendations are all necessary for conducting activities from data acquisition to the recommendations sent to the end-user,
- Modules for detecting unhealthy sensors to avoid acquiring data of bad quality,

- Automatic maintenance actions using actuators, e.g. for adjusting production speed, changing lubricant amount, start-stop of production,
- Communication system to support the integration of maintenance, with other databases and systems, such as production, quality, economy.

6.6 Return On Investment In Maintenance (ROIIM)

To motivate applying Smart PdM, it is necessary to properly highlight its added values. The goals mentioned above in technical terms, such as fewer failures and unnecessary stoppages, longer production time, lower energy consumption and fewer accidents can always be converted to money (Al-Najjar, 2007) to estimate the amount of savings (or additional cost) being achieved by effective maintenance.

In some cases it is easy to assess the value added by maintenance, for example avoiding any failure (due to detecting damage initiation and follow up its development to amend it when the company wish and not when the machine decided, e.g. at failure) means converting the stoppage time to production time, e.g. when the maintenance action is conducted during production planned stoppages which is possible to arrange, given that every produced item will be sold, the gain is then very easy to assess. The same thing can be said about reducing the downtime, i.e. the time needed to restore a machine after failure or due to condition-based replacement. In a failure situation, the Smart PdM supports the repair process by facilitating the integration of AR to show how a maintenance action should be conducted enabling even a technician who did not do it before to do it effectively. AR aims to shorten the repair time and enhance maintainability, which saves an appreciable amount of production time.

Fewer failures and unnecessary stoppages prolong production time, which can also be assessed and converted to money easily. The energy consumption and the reduction in energy losses are also possible to measure, follow up and improve continuously (Al-Najjar and Algabroun, 2018).

Maintaining machine quality (i.e. maintaining machine technical specifications) means preserving the capital invested in manufacturing assets and prolonging its service beyond the planned time. The benefits of it are not easy to anticipate in advance, but they can be calculated after hand.

The list of the value added by maintenance is much longer, which is motivating investments in maintenance especially when it is possible to follow up investments in maintenance by using Return on Investment In Maintenance (ROIIM) that will be provided by the Smart PdM.

According to our experience and results from Worldwide research and industrial applications, the pay-off of maintenance can be assessed. It is 5-9 times the annual cost of applying effective maintenance (Al-Najjar, 2007). However, this result is impossible to assess, follow up and improve using the currently implemented accountancy system, where the whole maintenance budget is counted as a mere cost.

Therefore, it can be necessary that Smart PdM consist of a special module providing information about the technical and economic impact of maintenance, as well as the ability in estimating the Return on Investment in Maintenance (Al-Najjar, 2009).

Maintenance management skills, as the method on how to lead maintenance, are using planning and scheduling best practices that will bring the work implementation and time-management techniques to improve maintenance productivity. When talking of PdM, we could briefly summarise a few competencies and maintenance management skills from the practitioner point of view (necessary today) as following (Bokrantz, 2017):

- Life cycle value realization activities that are taking place in conducting the cost and benefit analysis for the maintenance operation over the life cycle.
- Operation and maintenance decision making is performed to define and use relevant information for decision making while understanding and practising the asset management objectives and goals.
- Capital investment decision making is involved to understand the consequences of capital investment for the maintenance process while evaluating and analysing the consequences.
- The resourcing strategy is executing the developed work plan to accomplish the maintenance operation about the asset management objectives and plan.
- Asset information strategy is performed ensuring that the maintenance process is acting according to it.
- Technical standards and legislation control, ensuring that relevant technical standards and legislation are followed in the maintenance process
- Systems Engineering that is guaranteeing that the maintenance process operates according to the life cycle balance system, etc.

6.7 Practitioners checklist

In order to identify the key actions, we should consider the big picture of a manufacturing company including the objective stated for maintenance. The major goal of applying Smart PdM described above, is to meet the demands of Industry 4.0 when the production is totally or greatly digitalized and automatized, which is the expected case in factories of the future.

The key actions that are necessary for establishing and implementing Smart PdM can be retrieved by answering the following key questions:

- Is there a clear and written maintenance strategy and policy to specify?
- How is it important to maintain the quality of manufacturing assets?
- how is it important having accurate damage detection, follow up and prediction of the time to maintenance action?
- Is it significant and beneficial for the company to detect, localize and assess damages?
- Is it significant and beneficial for the company to have an automatic recommendation about what, where, why, how and when latest to conduct a maintenance action?
- Is it significant and beneficial for the company to have a knowledge base (which is necessary to document, update and maintain all company-new experience and knowledge developed in maintenance) in addition to the database for historical data?
- Is it significant and beneficial for the company to enhance and complete the available competencies with the application of AR and VR?
- Is it necessary to see over, control and reduce energy and material consumption and their losses?
- Is it demanded to improve the work environment and human health through reducing noise, temperature, and vibration in the surroundings?
- Is it demanded to reduce the environmental effect through more efficient maintenance that reduces the machine effect on the environment?
- Is it considered that maintenance can be utilized to reduce breakdowns and stoppages to enhance company productivity and profitability?
- Is it a competitive advantage to develop and apply a maintenance strategy meeting the needs of Industry 4.0?

Answering these questions provide the underlying information, knowledge, experience, and well-specified expectations necessary to select and implement effectively a Smart PdM.

Practising and implementing new technologies is challenging. Furthermore, applying new technologies to make maintenance more effective, such as implementing Smart PdM as a new paradigm, is more challenging especially if the infrastructure is not ready for these technologies (Algabroun et al., 2020).

The unsuitability of the infrastructure should be considered from different perspectives. For example, those perspectives which are related to one the following:

- juridical definition of the ownership of the technical and economic raw data,
- the willingness of companies to communicate through internet data input and output,
- plans regarding how long time the raw data and analysis results should be stored, where and on whom´ expense,
- besides, investments to implement Smart PdM always demands justifications that is realized by how much and when it will pay back.

In many companies, it is still difficult to find high-velocity internet needed for quick and quality communication, calculations and sending recommendations, which will, in turn, influences the performance reliability of advanced technologies, such as Smart PdM, aimed to enhance e-maintenance efficiency, which will reduce the potential benefits of the application.

7 Recommendation for future research directions and innovation policy

7.1 Development of Structured Data Repositories with Industry4.0 and Predictive Maintenance Datasets

Predictive maintenance (PdM) is a data-intensive task. It involves training Machine Learning (ML) and Artificial Intelligence (AI) algorithms to predict parameters like the RUL (Remaining Useful Life) and the EoL (End of Life) of assets. The development of such algorithms requires appropriate datasets for their training. However, such datasets are not widely and openly available, which is a setback to AI-based deployment and related innovations in the field of maintenance. Likewise, as witnessed by some of the ForeSee cluster projects, manufacturers do not have readily available datasets for ML/AI as their data collection processes record selective data rather than the full range of possible datasets. For example, even if in several cases information about failures and abnormalities tends to be collected in digital form, not all data associated with normal behaviours are recorded. In other cases, it is quite difficult to collect proper datasets for training AI programs, due to the lack of historic data with failures and abnormalities. This is the typical case regarding new machinery that has not suffered enough failures in the past.

Overall, the development of effective AI/ML systems that meet their business and manufacturing maintenance objectives requires rich datasets. It is therefore recommended that:

- Manufacturers and other industrial organizations establish internal data collection processes that will boost their ability to develop, deploy and fully leverage the capabilities of AI systems.
- Industrial organizations and R&D policymakers invest in the collection and structuring of open data repositories to support manufacturers and solution providers (including SMEs) in their efforts to innovate based on ML and AI in enterprise maintenance. The development of such databases will have

to take care of IP (Intellectual Property) issues and to address regulatory requirements (e.g., compliance to mandates of the GDPR (General Data Protection Regulation).

7.2 Testbeds for predictive maintenance, condition-based maintenance and intelligent asset management

The digitalization of the industry entails deploying and testing IT systems in real-life production lines. It's of uttermost importance that this action is performed without disrupting production. This puts certain limitations on the experimentation with PdM and intelligent asset management systems. To accelerate innovation and digital transformation in industrial asset management it's therefore important to establish proper testbeds for PdM, condition-based maintenance and intelligent asset management. Such testbeds could for example be developed in the scope of industrial DIH (Digital Innovation Hubs). They should comprise equipment, algorithms, tools and datasets for innovation and experimentation.

7.3 AI-based Maintenance and Asset Management Systems for the Non-Experts

Many AI and ML systems for PdM (e.g., Deep Learning systems) operate as black boxes that provide limited insights about their operations to maintenance workers and domain experts. This limits the trustworthiness and potential acceptance of these systems by maintenance professionals. Likewise, most AI/ML systems are not easily and flexibly usable by workers and domain practitioners. For example, there is no easy way for retraining models based on new data and applying them on the field, without the involvement of IT experts and integrators of digital automation solutions. To alleviate these limitations, future research should focus on AI/ML systems that can be understood and used by non-tech experts. In this direction, research in the following areas is needed:

- **Explainable AI (XAI)** systems provide insights into the inner workings of AI algorithms and boost the transparency and acceptance of AI systems. For example, systems that identify the dominant features used by a deep neural network to pinpoint possible defects or to predict the need for field service can greatly help maintenance workers to understand how Deep Learning systems work. XAI is currently a very topical research area for AI and its application in the maintenance field could provide value to industrial organizations (Christou et al., 2020b).
- **Automatic ML (AutoML)** systems enable non-tech experts to execute data-driven workflows and pipelines. Coupled with intuitive interfaces like dashboards and AR (Augmented Reality) interfaces AutoML systems can facilitate non-experts in exploiting the power of AI in maintenance and asset management.

7.4 Standardization, data and semantics interoperability

Industry4.0 systems for condition-based maintenance and intelligent asset management are based on the collection, consolidation and processing of datasets from diverse data sources, including sensors, cyber-physical systems, maintenance databases, Computerized Maintenance Management (CMM) systems, as well as business information management systems (like ERP -Enterprise Resource Management- systems). The interoperability of these diverse (in terms of their different semantics and formats) data sources is a key prerequisite for their proper processing. Over the years various standards-based formats for unifying the semantics of these data sources have been produced. Research and standardization in this direction will therefore continue and it will also affect the way Big Data databases and open datasets will be structured. However, some of the projects of the ForeSee cluster have also successfully experimented with alternative approaches that link diverse data sources and datasets, in line with known standards and proposals for linking different systems, such as MIMOSA's common interoperability registry (CIR). Both of the above directions need to be further explored, implemented in real systems and evaluated in terms of their pros and cons.

7.5 Business Modelling for Condition Based Maintenance and Intelligent Asset Management

Despite the proclaimed benefits of CBM (Condition Based Maintenance) and PdM (Predictive Maintenance) (e.g., less unscheduled downtimes, increased value for the assets, improved asset utilization), novel business models associated with these maintenance approaches are still in their infancy. There are still several business questions that remain unanswered when it comes to offering novel services like "Asset-as-a-Service" and "CBM-as-a-Services". Some of these questions include the ownership of the data, as well as how an OEM (Original Equipment Manufacturer) could increase its revenues based on the new approach. Furthermore, there are open questions about how to formulate SLAs (Service Level Agreements) for the above-listed utility-based services.

In this context, there is a need for further research on business modelling, including validation of such business models in practice. To achieve successful business modelling, there is the need for tools and techniques that can calculate techno-economic parameters and resolve relevant trade-offs. Some of the projects of the cluster have successfully dealt with this issue and provided tools and techniques for calculating the most important KPIs (Key Performance Indicators) in this process, such as OEE (Overall Equipment Efficiency), LCC (Life Cycle Cost), RAV (Remaining Asset Value) and ROI (Return On Investment).

7.6 Mobile Management - Mobile-First Condition Based Maintenance

Many enterprises in different sectors are currently implementing "Mobile-first" strategies as part of their digital transformation. This is largely due to the rapid penetration of mobile devices within workers' communities, but mainly to the convenience and value-added features that a mobile-first strategy can offer (e.g., instant access to the status of assets). There is a need for more research on how enterprise maintenance could benefit from mobile-first strategies. This includes studying how mobile devices can be combined with visualization modalities like Augmented Reality (AR) and Virtual Reality (VR) or natural language dialogue-based technologies such as Digital Intelligent Assistants.

7.7 Smart and Autonomous Objects

In recent years the world is witnessing the rise of smart objects i.e. objects with semi-autonomous behaviour such as robots, drones and automated guided vehicles. In the medium and long term, such smart objects will start taking over enterprise maintenance tasks, such as quality inspections and information gathering about assets. The use of such objects could offer many advantages such as richness in the data collection, inspections in harsh environments, speed, cost-efficiencies, optimization of workers' productivity and more. Robotic cells are already used in quality management tasks (e.g., quality inspection) and their use will be extended in enterprise maintenance. In this context, the collaboration between robots, smart objects and maintenance workers (i.e. co-bots) should be researched. Digital Twin technology is also expected to contribute to this objective as it enables the real-time and two-way mapping between physical objects and digital representation with smart capabilities.

7.8 Training - Education - Lifelong Learning

Currently, there is a proclaimed gap in knowledge associated with CBM/PdM and on the underlying technologies that support these maintenance modalities (e.g., BigData, data collection). As humans remain the most flexible and precious resources on the shopfloor, successful CBM/PdM deployments require properly trained and skilled workers. In this direction, training, education and lifelong learning should be among the most important directions for industrial policymaking. Along with the development of PdM systems, there is a need for structuring knowledge bases/assets and engaging workers in upskilling and “reskilling” processes.

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ANNEX I - Standards application in ForeSee projects

The following section presents examples of the adoption of standards at some of the use cases from the ForeSee projects. The application of standards, protocols and other sets of rules demonstrates the importance in each project and to the overall Industry 4.0.

NGSI (Z-BRE4K)

This example demonstrates the Predictive and preventive analysis of the blade machine in the Philips Production line.

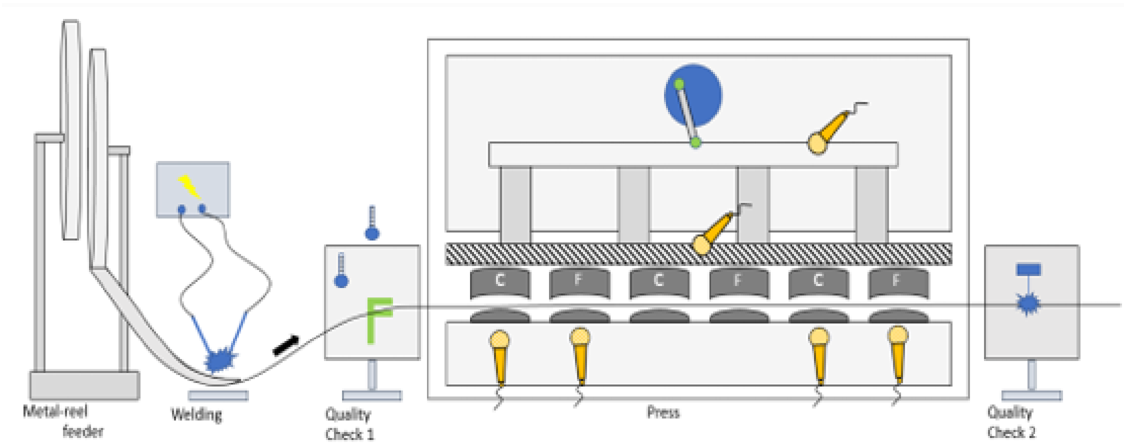

Figure 33: Predictive and preventive analysis on Philips Use Case

The machine production is often interrupted because the Shaving cutter cold forming press stops. The press has 6 dies that operate a cutting or a bending process. These processes are monitored by acoustic emission sensors.

Two critical failure modes within dies: Punch breakage and Fatigue. Based on the number of punches per second, the acoustic emission and quality data predictive monitoring assesses if the usage cycle is as expected and detect wear.

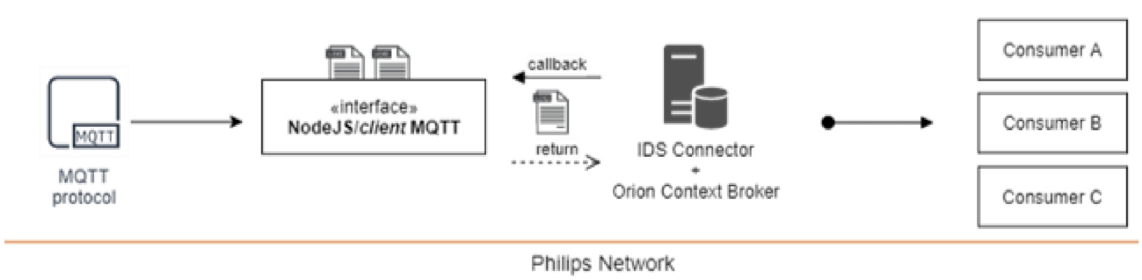

Figure 34: Philips Network

The four stages of the transmission of data in Philips Network are the following:

1) MQTT provides all data by topic;

2) The interface enables in runtime get all data from MQTT and save all data in each file (including Acoustic Emissions – which is a passive method that monitors the transient stress waves generated by the rapid release of energy from located sources, such as a fracture within a material)

3) The exchange of information occurs as IDS-Connector get and convert (NGSI Format) all the data subject to be monitored to be sent to Orion Context Broker.

4) After, all data/entities can be consumed by the existent consumers.

The objective is to assess through alerts if the usage cycle is as expected. The acoustic emissions determine whether there is wear or are anomalies through machine learning.

In this example in the Z-Bre4k project, NGSI format is used for any type of software a large amount of information to make available to customers. The use of this standard facilitates customers (as consumers), as many of them do not have the technical knowledge or are not prepared to consume the information as it is collected. Thus, Z-Bre4k, in the use case of Philips, allows ALWAYS to be made available in the same format and can be consumed through any type of software.

The client-side software must specify which fields the customer demands to access (e.g., temperature), as the information is standardized, the system is available in a default format (data structure). After the technical configuration/implementation on the client, it will be possible to return data (entities) referring to customers' production the values for each machine operating. The client can access the desirable results through a mobile/web application or FIWARE.

The NGSI protocol offers a set of business benefits to Z-Bre4k:

- The platform is widely used – Z-Bre4k benefits from being fed by a large number of customers.
- The Data Analysis process is easier - Z-Bre4k customers and technical providers (Atlantis) will request the data in the same format. The format (of acoustic emissions and the state of the machine for example), is always the same.
- The data structure can be easily replicable through different customers - Z-Bre4k does not have to make a new structure for each customer.
- The platform is prepared for bespoke developments - the customer can filter what wants (or not) to receive. If necessary, the data structure can also receive new fields and be shared with customers in need.

NGSI was selected upon cost-benefit analysis as many other standards could be suitable candidates. The application of this norm enables Z-Bre4k to become more efficient, reducing failures within predictive maintenance. Standardisation is – as demonstrated in this example with NGSI on Z-BRE4K project – a key factor for Industry 4.0.

EN 15341:2019 and PMML (PROGRAMS)

The EN15341:2019 standard has been applied in the PROGRAMS MSO (Maintenance Schedule Optimization) module that identifies, for each equipment component, the optimal maintenance approach – among corrective, preventive, and predictive actions.

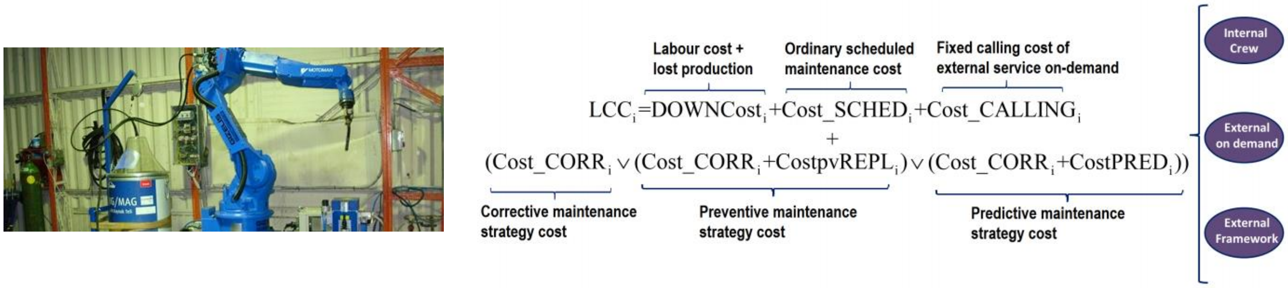

Figure 35: PROGRAMS MSO

As cost is one of the main drivers for the Management of organisations, determining the cost will be a key parameter. By minimising the cost, it will enable the identification of the optimal strategy for maintenance. To develop the cost model, PROGRAMS introduced several KPIs related to maintenance tasks, using those as standards to achieve a common view of what is introduced in the formulas – Figure 35. The Life Cycle Cost could be precisely determined by considering all relevant cost components, allowing to determine how the end users' costs depend on the maintenance strategies and labour policies.

The PROGRAMS MSO was able to determine not only which are the components for which is profitable to deploy a PdM approach, but also the optimal replacement times for applying "traditional" maintenance techniques.

PMML (Predictive Model Markup Language) enables effective Machine Learning (ML) models exchanging between SW modules for data-driven diagnosis and prognosis of machine tools and robots.

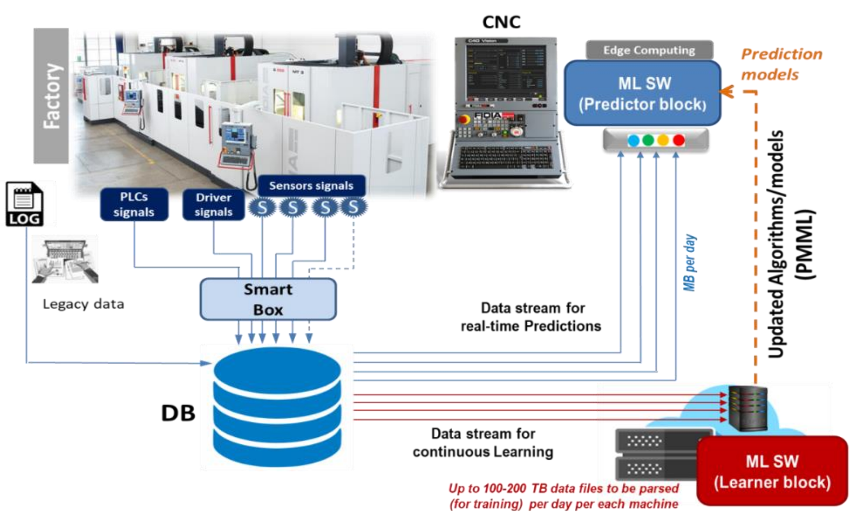

Figure 36: Prediction Models in PROGRAMS project

The key benefits of using PMML are:

- Enabling a modular approach for PdM boosts interoperability, resource efficiency and effectiveness.
- A "Learner" module parses data to generate the AI/ML-based algorithms (TRAINING), while the "Predictor" module uses such algorithms/models (DEPLOYMENT) to assess the status of the components.

- PdM was effectively deployed on Aurrenak and Calpak to determine the machine/robot status, the component responsible for the (eventual) detected anomaly and its RUL (Remaining Useful Life).

MIMOSA (SERENA)

MIMOSA standard provides an information exchange model that allows the description of manufacturing floor assets, provides capability on registering assets in the database and manage the information related to condition monitoring on maintenance – providing the data modelling for predictive maintenance on the SERENA system.

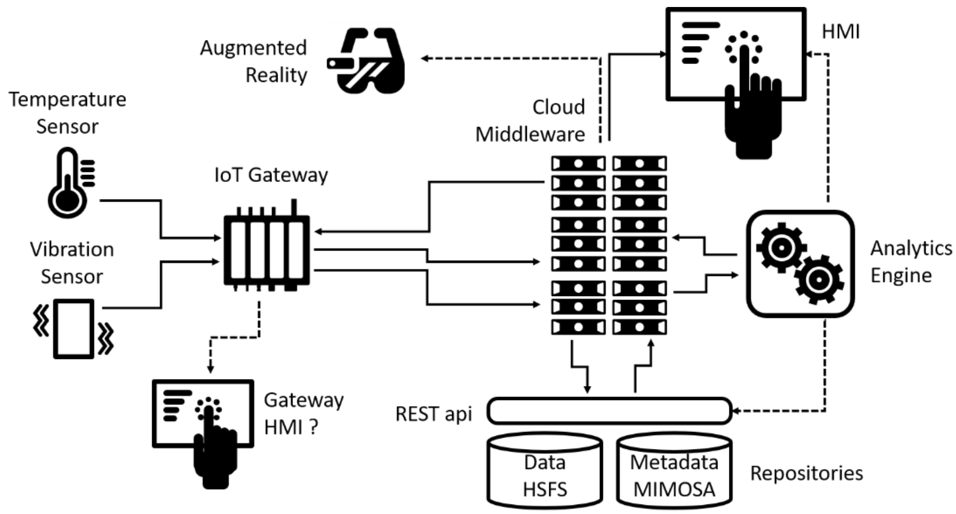

Figure 37: SERENA back-end system

On the VDL WEW use case in SERENA, the predictive maintenance addresses the condition of rolling mills – avoiding becoming corruptive and defective products – on the rolling form machine of this metal parts manufacturer floor. MIMOSA has been applied to the back-end system of SERENA – Figure 37 (where the information of the assets is stored) presenting the following benefits:

- SERENA data model was built on top MIMOSA CRIS 3.2.3 ontology.
- Data stored in JSON format while metadata in MIMOSA CRIS 3.2.3 including the main segment as a hierarchy.
- MIMOSA database generates IDs that the mapped to SERENA IDs accelerating and simplifying the whole process of registering equipment and assets from the shop floor.
- As other technologies/systems can use this standard, it also allows addressing interoperability issues.

RAMI 4.0 (PROPHESY)

In PROPHESY project, a middleware infrastructure has been developed to access and retrieve industrial physical asset data for building PdM solutions. End-users required a well-defined mechanism to enable external systems to gain access to internal PROPHESY-CPS asset-related data.

The solution is an Asset Administration Shell (AAS) that has been developed as a part of the middleware infrastructure. It provides a standardized interface, compliant with RAMI 4.0, to facilitate communication with external systems.

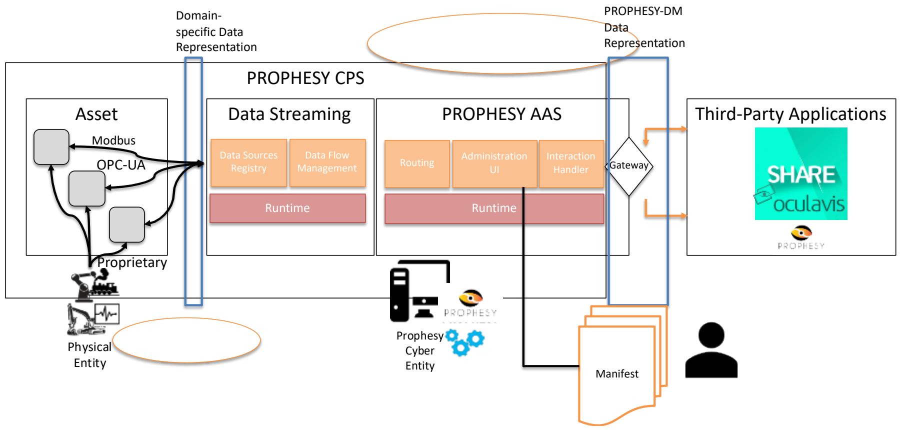

Figure 38: Asset Administration Shell implementation in PROPHESY project

The asset Administration Shell has been deployed between an external application and the PROPHESY middleware application. The rule of the asset Administration Shell is to stream data to a third-party application SHARE – Figure 38. This application uses the PROPHESY application to create augmented reality services. The benefits of the implementation of RAMI 4.0 Administration Shell are:

- Provides standardized digital representation of industrial physical assets (Manifest);
- Establishes the foundation for interoperability within applications managing industrial systems; and
- Allows end-users to more easily expand and improve current solutions with new third-party applications – increase scalability, flexibility, adoption from the industry.

UMATI (PRECOM)

PRECOM project has three use cases, connecting the system with the equipment of the manufacture and its clients. Predictive Maintenance has been analysed on the equipment of the manufactures on the three use cases. With the multi-application of machines and sensors, interoperability and selection of standards become extremely important for PRECOM. The Umati initiative provides the connectivity for a machine tool connection to customer-specific IT infrastructures and ecosystems.

With Umati, PRECOM uses a layer of a transformation engine, working over OPC-UA protocol. Over this layer, a common semantic enables the easier to build an OPC client for data collection.

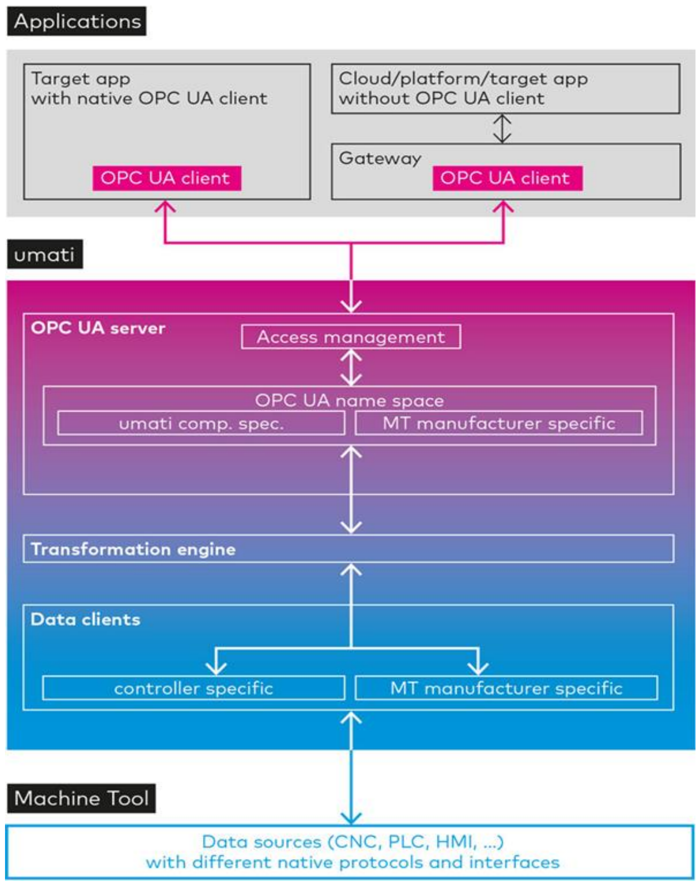

Figure 39: PRECOM data flow for Predictive Maintenance

The main benefits of applying the Umati initiative is:

- Easy connectivity to a variety of machines and suppliers to other systems in the plant (IT, other equipment etc). Open, standardized interfaces based on OPC-UA.
- Umati is jointly supported by VDW and VDMA and is open to participants from industry, research, organisations and networks from all over the world.
- The customer benefits from standardized communication independent of the machine tool manufacturer

AMPQ, MQTT and ISO13374 (UPTIME)

In the UPTIME project, it was defined a set of components to design a predictive maintenance platform – Figure 40.

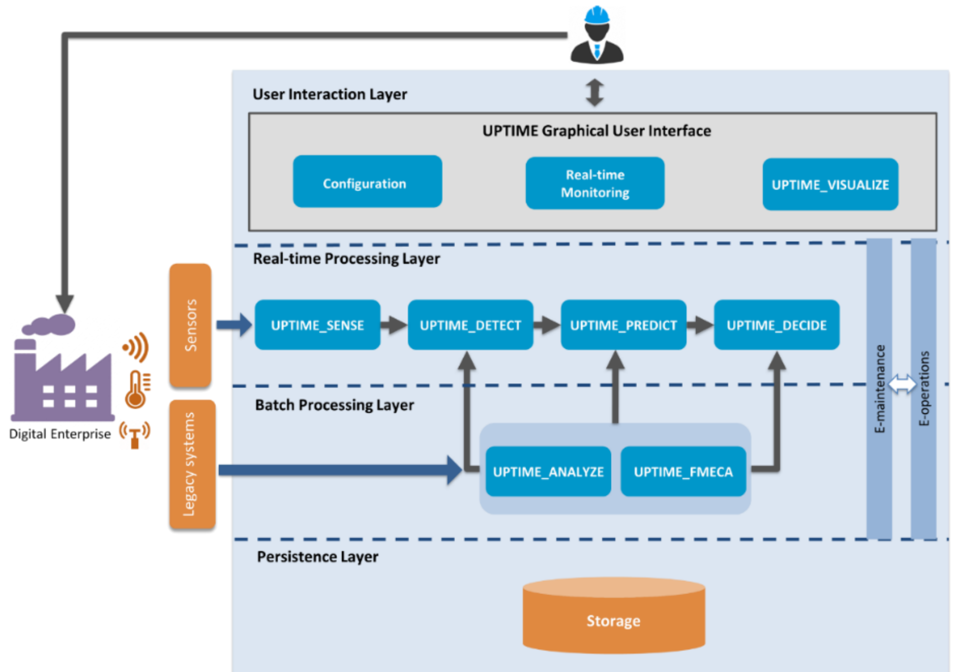

Figure 40: UPTIME Architecture Model

AMPQ (Advanced Message Queuing Protocol) and MQTT (Message Queuing Telemetry Transport) are standards are used to exchange messages between the components of the platform and to facilitate exchange with potential external components.

MQTT is an open OASIS and ISO Standard – ISO/IEC 20922:2016 – is designed for connections with remote locations where a "small code footprint" is required or the network bandwidth is limited. It is used in the FFT use case where data are remotely exchanged.

AMQP – ISO/IEC 19464:2014 – is used for the exchange of messages between components: Detect, Decide and Predict.

The benefits of using these standards are:

- Support to the integration of the components and the interoperability with other components using these standards.
- Enabling the final end-user to integrate the components of the platform in his context and to easily update the solution of predictive maintenance with new components or additional microservices.

Additionally, the standard 13374 – condition monitoring and diagnostics of machines — Data processing, communication, and presentation – is used for the Functional Architecture of UPTIME and uses the associated MIMOSA OSA-CMB standard for implementation OSA-CBM adds data structures and defines interface methods for the function blocks defined by the ISO standard. The benefits of adopting this standard are:

- The UPTIME platform is based on an ISO standard with large application scope and implements it with an Open System Architecture for Condition-Based Maintenance which fits with the modularity and scalability of the platform.

- The MIMOSA OSA-CBM technical specification is maintained and available in new formats. The end-user will save costs and benefit from a solution where changes and extensions will be facilitated.

ANNEX II – Tables of standards cited in the radar charts

Standard Short Name	Name and title/short description
Transversal standards	
Requirements Engineering	ISO/IEC/IEEE 29148:2018, Systems and software engineering - Life cycle processes - Requirements engineering
Systems engineering process	ISO/IEC 26702:2007, Systems engineering - Application and management of the systems engineering process
Risk Management	ISO 31000:2018, Risk management - Guidelines
RAMI 4.0 (AAS)	Reference Architectural Model Industry 4.0 (Asset Administration Shell)
IIC-RA	Industrial Internet Consortium – Reference Architecture
Domain/discipline standards	DOMAIN Standard Description
QIF	ISO 23952:2020, Automation systems and integration - Quality information framework (QIF) - An integrated model for manufacturing quality information
OPC-UA	IEC TR 62541-1:2020 RLV, Redline version, OPC unified architecture - Part 1: Overview and concepts
UMATI	Universal MAchine Technology Interface is a community of the machine building industries and their customers for the promotion and adoption of open, standardized interfaces based on OPC UA.
CoAP	CoAP, Constrained Application Protocol, IETF - RFC 7252
MODBUS	MODBUS is a de facto standard for communication protocol used over serial lines between electronic devices
OPC-UA Vision	OPC-UA for image processing and industrial automation
Residual Current Sensitive Devices	IEC 60755:2017, General safety requirements for residual current operated protective devices
Technological standards	

NGSI	NGSI-LD is an ETSI standard to manage the Context Information about Context Entities
HTTP	HTTP, Hypertext Transfer Protocol, is a W3C standard
MQTT	ISO/IEC 20922:2016 - Message Queuing Telemetry Transport protocol
AMQP	ISO/IEC 19464:2014, Information technology - Advanced Message Queuing Protocol (AMQP) v1.0 specification
XML	XML, Extensible Markup Language
GigE Vision	GigE Vision - True Plug and Play Connectivity (global camera interface standard)
JSON	JSON, JavaScript Object Notation
JSON-LD	JSON-LD, JavaScript Object Notation for Linked Data
RDF	RDF, Resource Description Framework
OWL	OWL, Web Ontology Language
PMML 4.3	PMML 4.3: 2016, Predictive Model Markup Language

Table 2: ForeSee Data-related standards

The following table presents the list of the most relevant maintenance-related standards for ForeSee Cluster, representing the Standardisation state of the art on maintenance-related standards in January 2021.

Standard Short Name	Name and title/short description
Transversal standards	
Maintenance Terminology	EN 13306:2017, Maintenance terminology
Maintenance processes and associated indicators	EN 17007: 2017, Maintenance processes and associated indicators
Asset Management	ISO 55000:2014, Asset management — Overview, principles and terminology
Domain/discipline standard	
MIMOSA	MIMOSA OSA-CBM, Open system architecture for condition-based maintenance. The OSA-CBM specification is a standard architecture for moving information in a condition-based maintenance system.
FMEA & FMECA	IEC 60812:2018, Failure modes and effects analysis (FMEA and FMECA)

Safety of machinery	ISO12100:2010, Safety of machinery — General principles for design — Risk assessment and risk reduction
Maintenance KPIs	EN 15341:2019, Maintenance Key Performance Indicators
Root Cause Analysis	IEC 62740:2015, Root Cause Analysis (RCA).
Condition Monitoring and Diagnostics – Vocabulary	ISO 13372:2012, Condition monitoring and diagnostics of machines — Vocabulary
Maintenance Tasks Scheduling Ontology	-
Predictive Maintenance Ontology	-
Systems and software engineering - Life Cycle Management	ISO/IEC/IEEE 24748:2018, Systems and software engineering - Life cycle management
Dependability Management	IEC 60300:2017, Dependability management
Weibull analysis	EN 61649:2008, Weibull Analysis
Maintenance Indicators (selection and formation)	VDI 2893:2019, Selection and formation of indicators for maintenance
Condition monitoring and diagnostics - Diagnostics	ISO 13379-2:2015, Condition monitoring and diagnostics of machines - Data interpretation and diagnostics techniques - Part 2: Data-driven applications
Condition monitoring and diagnostics - Prognostics	ISO 13381:2015, Condition monitoring and diagnostics of machines - Prognostics
Risk-Based Inspection and Maintenance	EN 16991:2018, Risk Based Inspection Framework
Technological standards	
Machine tool spindles	ISO/TR 17243-1:2014, Machine tool spindles - Evaluation of machine tool spindle vibrations by measurements on spindle housing - Part 1: Spindles with rolling element bearings and integral drives operating at speeds between 600 min-1 and 30 000 min-1
ECMA-404	ECMA- 404, JSON data interchange syntax
Mechanical Vibration	ISO 10816-3:2009, Mechanical vibration - Evaluation of machine vibration by measurements on non-rotating parts - Part 3: Industrial machines with nominal power above 15 kW and nominal speeds between 120 r/min and 15 000 r/min when measured in situ ISO/TR 17243-3:2020, Machine tool spindles — Evaluation of machine tool spindle vibrations by measurements on spindle

	housing — Part 3: Gear-driven spindles with rolling bearings operating at speeds between 600 r/min and 12 000 r/min
Condition monitoring and diagnostics of machines	ISO 13374-1:2003, Condition monitoring and diagnostics of machines - Data processing, communication and presentation

Table 3: ForeSee Maintenance-related standards