The Way Cyber Physical Systems Will Revolutionise Maintenance

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ABSTRACT

The way maintenance is carried out is altering rapidly. The introduction of Cyber Physical Systems (CPS) and cloud technologies are providing new technological possibilities that change dramatically the way it is possible to follow production machinery and the necessity to carry out maintenance. In the near future, the number of machines that can be followed from remoteness will explode. At the same time, it will be conceivable to carry out local diagnosis and prognosis that support the adaptation of Condition Based Maintenance (CBM) i.e. financial optimisation can drive the decision whether a machine needs maintenance or not. Further to this, the cloud technology allows to accumulate relevant data from numerous sources that can be used for further improvement of the maintenance practices. The paper goes through the new technologies that have been mentioned above and how they can be benefitted from in practise.

Keywords: Condition Based Maintenance (CBM), Cyber Physical Systems (CPS), Overall Equipment Effectiveness (OEE), e-maintenance, Internet of Things (IoT)

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1. INTRODUCTION

We are on the verge of a great deal of changes on how machine maintenance is performed, since the era of CPS has come. In fact, embedded devices are now part of every environment, comprising where industrial machinery is located. The online collection of data is able to empower big data algorithms to perform analysis and prediction on many aspects of life, comprising the condition of an industrial machine in the present and in the close future. This can allow for managing maintenance in novel ways. E.g. depending on the business case, it can be reasonable to predict the remaining lifetime of a machine, and buy the correct spare parts in advance to minimize the downtime of the machine. The application of CPS is a consequence of the direction where industrial automation is going. Currently, it is common to organize operations related to industrial automation into a pyramid, e.g. as per ISA-95 standard [1]. Even though there is some difference between ISA-95 compatible formalizations, a coarse definition of its levels can be given: Level 0 (field level), composed of sensor and actuators that interact directly with the process or the machine. Level 1 (direct control) is related to the operations performed by special-purpose hardware, such us PLCs, industrial pcs, DSP processors, as drivers of the actuators and collectors of sensors data. Level 2 (Supervisory Control) acts online with respect to the industrial process, and its major functions are to allow an operator to change set points for the industrial process, and monitor the activity of the machine(s) whose data is collected. Level 3 (Production Control) is targeted to the manufacturing operation as a whole, and includes maintenance, production, quality assurance, inventory management. Level 4 (Enterprise Control) consists mainly of management functions, and it is used to drive the objective of the manufacturing process by scheduling its operations. CPS are located on Level 0, and receive support in the factory up to Level 3, where the process becomes distributed over internet. It can be considered that Production Control involves transporting data over larger distances, and a modern approach is apply the concept of "servitization", where the upper levels are mediated and implemented as services, to maximize scalability and flexibility of the systems. In this context, the two main goals of data communication and processing can be supported by means of a communication middleware the first, and of fog computing the latter. Fog computing is an evolution of cloud computing, where micro-clouds and edge servers are disseminated closer to where the data are collected and used, to allow for data preprocessing and local computation, to parallel the bulk computation performed in the cloud. The acceptance of these new approaches is hindered by a few issues, some of them on the technological side, and some of them on closer to the business. This paper aims to provide an overview of the novel maintenance approaches (section 2), of how embedded systems can support it (section 3), and of the servitization (section 4) of the maintenance-related operations (section 3). Later on, the paper analyzes the issues that must be overcome to reach the technology maturity level needed for the implementation of this technological revolution (section 5), and the business impact that it can provide (section 6). Some conclusions are drawn in section 7.

2. CONDITION BASED MAINTENANCE

CBM is a predictive maintenance strategy that is based on the continuous monitoring of various parameters of an asset to evaluate its health level and future development. The increasing popularity of predictive maintenance strategies is preceded with the necessity of an improved Overall Equipment Efficiency (OEE). The OEE is a term expressed in percentage that evaluates how effectively a manufacturing operation is utilized [2]. The metrics that are taken into account to calculate OEE are *availability*, *performance* and *quality*. The OEE is usually used as to identify the scope for process performance improvement [3]. The CBM approach enables an increase in the availability of the asset, thus, increasing the OEE by reducing the unplanned downtimes of the machines and saving costs in unnecessary repairs. The information gathered by the condition monitoring architecture allows the planning and scheduling of maintenance, while also reducing the storage needs for spare parts. This information can also help to identify failures and determine how to avoid them before occurrence. To be able to implement a CBM system, an initial analysis needs to be done in order to decide which parameters are worth monitoring. Different analytical tools such as Fault Tree Analysis (FTA), Root Cause Analysis (RCA) or Failure Mode and Effects Analysis (FMEA) are useful when identifying the root cause of a failure and the best way to avoid them. These tools allow to decide which parameters to monitor and consequently identify the main failure causes, and to improve future designs. The analysis also considers that its result can be a suggestion not to apply condition monitoring to said equipment. Moreover, there are some cases where the traditional corrective maintenance strategies are also valid, e.g. when a machine can still work when a component breaks down and can wait until the maintenance is scheduled to change the broken component. The Machinery Information Management Open System Alliance (MIMOSA) Open System Architecture for Condition Based Maintenance (OSA-CBM) is a not-for-profit association that develops the open information standards for Operation and Maintenance in manufacturing [4]. The standards that MIMOSA develop are compliant with the ISO-13374 Standard (Condition Monitoring and Diagnostic of Machines), being an implementation of the latter's functional specifications. According to this standard, a CBM system should be composed of various functional blocks: 1) Data Acquisition (DA), 2) Data Manipulation (DM), 3) State Detection (SD), 4) Health Assessment (HA), 5) Prognostics Assessment (PA) 6) Advisory Generator (AG)[5]. One of the main objectives of the MIMOSA OSA-CBM is to standardize the information flow between the various blocks, so that equipment from different vendors could be interoperable. The Data Acquisition block is responsible for picking up the physical phenomenon and converting it to a readable digital signal, by means of a transducer or a sensor. After applying some filters to reduce the noise level and amplify the signal if needed, the analogue signal needs to be converted to a digital signal through an Analog to Digital Converter (ADC) so that a computer or a processing system can manipulate the data and get meaningful information. The data that comes from the ADC is usually referred to as "raw data". This raw data is then sent to the Data Manipulation block. Here, mathematical algorithms such as Fast Fourier Transform, kurtosis or envelope analysis are applied. The outcome of this analysis is stored in the database and, depending on the application, even the raw data could be stored. In the State Detection step, data from the first and second blocks are compared with expected values, to verify if they fit into previously defined limits, generating alerts when they do not [6] [5]. The main objective of a CBM system is to make a diagnostic assessment on the health level of the asset and then do a prediction on how the state is going to degrade. This analysis is done in the Health Assessment and Prognostic Assessment blocks. Usually, the diagnostic is based on the health history trends, operational status and load history while taking into account possible faults. The prediction estimates the Remaining Useful Life (RUL) of the asset and it can be computed with three main approaches: model-based, data-driven and hybrid approach [7]. The model-based approach tries to mathematically describe the physical phenomena of degradation. This method can be very accurate but it gets more complex while being more detailed. The data-driven model is based on a statistical approach, where pattern recognition and machine learning algorithms are implemented. One drawback of this method is that it may be quite time-consuming to get an initial data batch (training data), because usually run-to-fail data is needed. The hybrid approach takes the advantages of both methods and tries to create a model where physical phenomena are described but also uses statistical data to complement it and create more reliable and accurate outcomes. The last step of the chain -Advisory Generation- is to create a report stating the recommended maintenance actions that have to be taken in order to optimize the useful life of the product. These actions could be, e.g., to schedule a replacement of a component at the best possible moment, reduce the speed of a rotating machine to increase its life expectancy, or do nothing if the component is in a healthy state. Other references, such as [8] also state that there could be an extra layer or block, the Presentation Layer, where the information from all the previous step can be accessed from. However, usually only the information of the last three steps is displayed because it ends up being the most useful.

3. INTERNET OF THINGS AND CYBER-PHYSICAL SYSTEM OF SYSTEMS

CPS pertain to a new discipline – in the field of computer science and communication technologies – that is revolutionizing the way complex systems are designed, implemented and deployed. CPS are the "integrations of computational and physical processes" [9], in the sense they can integrate and merge the physical world and the virtual world. The term CPS was coined in 2006 by Helen Gill at the National Science Foundation in the United States and it naturally emphasizes the necessary link between physical and virtual that is frequently ignored in a world constituted by applications that run only on PCs. As stated in [10], today around 98% of microprocessors are embedded, and hence directly connected to the physical world by various means of sensors and actuators (sensing and acting on the environment) and increasingly connected with one another and the internet. This trend is expected to continue as also confirmed in [11], where the importance of networked distributed systems of embedded computers during the coming years is highlighted. However, as stated in [12], CPS means more than networking and information technology, this concept presupposes that information from the physical world (assets) needs to be integrated and used within the cyber world, while creating sustainable feedback loops, where decisions computed within the cyber world affect the physical world and vice versa. This is the main assumption for CPS and implicitly designates a multidisciplinary knowledge to establish the tight integration of perception, communication, learning, behaviour generation, reasoning for creating CPS-populated systems. As a matter of fact, CPS include a wide variety of systems in the most disparate contexts of application (e.g. aerospace, automotive, manufacturing, white goods, healthcare, telecommunications, power grid, etc.) and domains/fields of engineering (e.g. chemical, electrical, power, mechanical). Besides the domain and the application context, knowledge of the software, communication, control theories, methods, methodologies and tools is also required [13]. By synthesizing all the precedent assertions, the following core elements and/or characteristics can be identified for CPS, extended from [12], [14]: 1) Enhancement of physical entities with cyberspace capabilities; 2) Networked at multiple and extreme scale; 3) Dynamic behaviour (plug and unplug during operation); 4) High degrees of automation, leading typically to closed control loops; 5) High degree of autonomy and collaboration to achieve a higher goal; and 6) Tight integration between devices, processes, machines, humans and other software applications. The above core elements and/or characteristics of CPS spontaneously point to Internet-of-Things (IoT) technologies and System-of-Systems (SoS) approaches, methodologies and/or research initiatives as the backbone for creating Cyber Physical Systems-of-Systems (CPSoS), i.e. large, complex, often spatially distributed CPS that exhibit the features of Systems-of-Systems [15]. IoT solutions can provide the backbone infrastructure to enable seamless integration between the physical and virtual worlds, i.e. to enable the easy and rapid access to the physical world contents and events (e.g. information) by means of computers and networked devices according to the paradigm "anytime, anywhere" [16]. Conceptually, both IoT and CPS are networked systems needing high-degrees of automation that are likely to involve physical sensing and/or embedded devices i.e. both combine aspects of the physical and digital/cyber worlds. However, there is a slight difference between them. In fact, one usually refers to CPS in the case of systems/problems that involve large-scale real-time control (e.g. time critical problems); or problems that involve integrated control of combined organisational and physical assets by profoundly relying on their virtual representation (i.e. the modelled behaviour of cyber entities; conversely). Meanwhile, IoT accounts for situations that collect and process sensor data (including IoT analytics problems) without essentially involving real-time control. CPS here would relate to systems involving collaborative automation of networked embedded systems, and tight human machine interactions; whereas IoT would relate to target systems/applications involving fewer collaborative automation and requiring internet connectivity only. The concept of SoS covers an entire research background constituted by relevant theories, tools, knowledge and approaches to analyse, design, model and control large distributed systems that consist of networked interacting elements [15]. Therefore, CPSoS are essentially ecosystems of CPS and IoT solutions that rely on the effective and efficient collection, provisioning, analysis and visualization of large quantity of data to monitor, diagnose, adapt and optimize (through reconfiguration) the overall behaviour in the environment where they are operating. Therefore, the availability of this large quantity of data immediately triggers the implementation of advanced monitoring strategies for assets management while facilitating – at the same time – the adoption of policies and strategies for maintenance, such as: 1) CBM); and 2) Proactive Maintenance (PrM). As a matter of fact (as deeply explained in [17]), the successful implementation of CBM and PrM strategies thereafter, will be possible as a result of the presence of an efficient and effective monitoring infrastructure that can gather relevant operational data from assets, combine and analyse these data to identify possible breakdowns and their root causes. Consequently, CPSoS have a tremendous potential in promoting the meshing of virtual and physical worlds while leading the interconnection of people, processes and infrastructures within interactive and responsive networks of CPS for fast evaluation of asset performances.

4. SERVITIZATION BASED ON CPS: THE ROLE OF THE CLOUD AND FOG/EDGE COMPUTING

The wider dissemination of CPS and their aggregation into CPSoS is having disruptive effect on the market structures of enterprises, due to the highly-networked characteristic of most of the systems of today. CPSoS will change existing business models while enabling new suppliers of services for CPS-based systems to enter the market [10]. At the same time, the emergence of cloud computing (and more recently of fog/edge computing) is creating new and exciting opportunities for CPSoS by enabling: 1) The wider consumption of the data generated within the CPSoS ecosystems and the services provided [18]; and 2) The creation of new services as composition of the ones exposed within the CPSoS. As stated in [19], the rise of cloud computing [20] has initially created the foundations for breeding CPSoS by providing: 1) an infrastructure for CPS integration, i.e. services and/or atomic functionalities provided by CPS that are part of the CPSoS ecosystem can potentially be accessed/used over the internet by other CPS or applications; and 2) a huge amount of computational and storage resources that are available within the cloud and can be used "on-demand". Service provisioning both at CPS and at CPSoS level, make maintenance more flexible, enabling remote monitoring and control of processes and tasks. Service management becomes key in this extended context and a number of duties must be addressed: 1) Monitor and control routing of message exchange between services, 2) Resolve contention between communicating service components; 3) Control deployment and versioning of services; 4) Marshal use of redundant services; 5) Cater for commonly needed commodity services like event handling and event choreography, data transformation and mapping, message and event queuing and sequencing, security or exception handling, protocol conversion and enforcing proper quality of communication services. An Enterprise Service Bus (ESB) is a software architecture model used for designing and implementing the interaction and communication between mutually interacting software applications and components in a Service Oriented Architecture (SOA) like the one emerging for CPS in the maintenance context. ESB motivation comes from the need to find a standard, structured and general-purpose concept for describing implementation of loosely coupled services that are expected to be independently deployed, running, heterogeneous and disparate within a network. The main functional areas for an ESB are [21]: 1) Architecture. The main issues covered in this area are support for fault tolerance, scalability and throughput, the ability to federate with other ESBs, the supported topologies, and features supporting extensibility. 2) Connection. The key features in this group include support for a wide range of messaging standards, communications protocols, and connectivity alternatives. 3) Mediation. This group deals with key requirements related to dynamic provisioning of resources, transformation and mapping support, transaction management, policy metamodel features, registry support, and service-level agreement coordination. 4) Orchestration. This layer provides lightweight orchestration of services and more-robust Business Process Execution Language (BPEL) and/or Business Process Modelling Notation (BPMN) support. 5) Change and control. The main components in this group are design tooling, lifecycle management, technical monitoring, and security. The Arrowhead project [22] addresses efficiency and flexibility at the global scale by means of collaborative automation. Arrowhead assumes that a service-based approach will be the feasible technology that enables collaborative automation in an open-network environment connecting many embedded devices and CPS. The multi-billion device/service perspective places a very strong demand on the interoperability and integrity of devices and services provided by the multitude of players in the market place. Thus, Arrowhead's grand challenges are: 1) Enabling the interoperability of services provided by almost any device. 2) Enabling the integrity of services provided by almost any device. Next to cloud computing, fog/edge computing architectural pattern has been recently introduced. This pattern is aimed to extend the cloud computing paradigm to the "edge" of the network for those applications that are latency-sensitive and – thus – have strict delay requirements [23]. Therefore, fog/edge computing is about pushing intelligence, data analytics and knowledge generation into smaller clouds, near to physical devices. Traditional cloud computing data centres are also utilized, however, but moved closer to source of the data [24] while supporting localization, i.e. location awareness and distribution. Actually, fog/edge computing paradigm reflects better the complexity, heterogeneity and distribution of CPS and IoT populated systems and their ecosystems then cloud computing. The combination of cloud and fog/edge computing paradigms and CPSoS is allowing companies to evolve their hierarchical and static configuration into a new one, characterized by agility, openness and peer-to-peer-based interactions. This trend is also confirmed by the manufacturing industry – considered here as the reference sector to show the economic health and welfare of a country – where the combination of ICT and CPSoS is triggering the transformation of the manufacturing value chain patterns from pure manufacturing and selling physical products to the provisioning of sophisticated integrated solutions where physical products are enhanced by functions and services [25]. As explained in [26], this business trend can be designed as "servitization" that means the process of creating value in products and goods by adding services. The term was initially coined by Vandermerewe & Rada [27], and now is widely recognized and adopted to identify a specific competitive manufacturing strategy as pointed in [28]. During the production stage cloud-based CPSoS are facilitating the integration of the data within the enterprise, i.e. from industrial assets at the shop floor level to business applications at management level. In the preproduction and post-condition stages, cloud-based CPSoS can provide relevant data that can be used to support both the Product Lifecycle Management (PLM) and the Service Lifecycle Management (SLM). In this landscape, maintenance assumes a vital role in guaranteeing the perfect working conditions of the industrial assets, and thus the quality of the final product and a resilient service. However, the effective and efficient implementation of manufacturing strategies and procedures strictly depends of the availability of transparent and as much as possible exhaustive insights about industrial assets and products [29]. The creation of cloud-based CPSoS can lead the implementation of maintenance specialized platforms and frameworks to improve industrial assets productivity by relying on the right information at the right time.

5. ISSUES TO TACKLE FOR IoT- AND CPSoS-BASED CBM

In this paradigm, data from its sources travel far and might be processed several times before its information is properly extracted and utilized. This can be facilitated by a wide variety of communication protocols, technologies and architectures. How the (mostly sensory) data is then transmitted, virtualized (as per the CPS approach) and used raises higher level issues that might not have been considered previously for condition monitoring scenarios: 1) How to transmit these data from the physical system and to where? 2) How to create interoperable data representation and semantics? 3) What can be the backend that processes this inbound data streams in a scalable manner? 4) How can we still maintain real-time restrictions and abide by communicational constraints? Firstly, the acquired data that might be available with great time and value resolution. However, it is often not practical to be transmitted "as is" from the device or machine for communicational constraints. Therefore, low level pre-processing and local storage might be required. It can include sensor data fusion and filtering, elimination of noise and erroneous data and even could utilize advanced logics (e.g. rule-based notifications). The purpose of this is to only transmit an "extract" of the readouts that still represent the physical process sufficiently for later, higher level processing (within the cloud). It is also of essence that the cloud processing units should still be able to request the raw data streams on demand (if the RUL or RCA algorithms require them), besides the regular bandwidth-friendly messages. This should be facilitated by the sensor nodes, gateways and the employed communication protocol itself. To this end, the traditional client-server architecture is being replaced with bi-directional, persistent (connections are always kept alive) and platform-independent message-oriented middleware (MOM). Basically, there are publishers (data sources) who publish their data in an appropriate virtual channel (topic) at a message broker entity. Data recipients then will subscribe to the appropriate topic at the broker to receive asynchronously the message through it. There are further advantageous features of MOMs that include routing and hence distributed operation (with load balancing between brokers), message queuing or support for transactions. A widely known MOM instance is the Advanced Message Queuing Protocol (AMQP) [30]. It can even be used in pair with its lightweight counterpart, the Message Queue Telemetry Transport (MQTT) [31], the popular IoT sensor node protocol. Secondly, the data representation and the message structures and types used by systems from different origin and vendors might differ completely. Therefore, establishing interactions between these systems and data aggregation from these heterogeneous sources pose a significant impediment for developers. This can be mended e.g. by the usage of the MIMOSA standard and its information metamodel. However, further engineering steps need to be made for resource constrained use cases, where the sensor has limited capability of transmitting its measurement, since the MIMOSA ontology defines a very detailed (and therefore long) descriptor for every measurement location and type. This step involves the analysis of which parts of the MIMOSA ontologies are important for the use case, and the definition of a restricted data model compatible with the full

MIMOSA one, where only a data subset is taken into account. Thirdly, online machine-condition data might be available in very high resolution, and might be aggregated from multiple machines across multiple production sites. Furthermore, machine learning and statistical models can only be properly trained and created the best if the is extremely high amounts of lifetime data for various components and machines. As a consequence, big data approaches and technologies are required and can be used for CBM. It can include the online monitoring of RUL, detection of events and failures, and on-demand root cause analysis of a given failure. This can be supported by distributed stream processors that process the inbound data streams from machines and sensors. If more complex, offline asynchronous algorithms are required, then there are batch processors as well that can pull data from multiple sources (e.g. historical data from various databases). It is also possible to only generate triggers based on events detected by the stream processors. These triggers can be then distributed to the appropriate stakeholders using the message distribution system (MOM), e.g. by contacting the appropriate personnel through a human-machine interface - HMI. Such big data frameworks exist as whole solutions (e.g. offered by Microsoft Azure [32]) or even as open source as well (e.g. the Apache Spark [33] and Storm [34] frameworks). Live data can be stored in non-SQL based, highly scalable and distributed data storage systems as well (e.g. Hadoop [35] or Cassandra [36]). Finally, there can be use cases where the devices measuring and actuating the physical world can directly send their all their data to a central cloud-based backend, where all processing can be done. For these cases, this edge level can consist fully of relatively constrained systems: sensors, actuators and machines connected through a gateway. They can directly communicate with the cloud, and all data can be sent in. However, there are cases, where there can be e.g. security concerns or communication limits, which does not allow for a simple one-way data stream towards “the cloud”. For these cases (and for scalability reasons), multiple level processing is often required as mentioned in section 5. This can be solved by a “miniature” but fully-fledged processing environment that should be established right on site: all CBM related algorithms (i.e. RCA or RUL) need to run locally on dedicated hardware, in a closed and managed network. This can be done for run time, when the appropriate models have been established and deployed (i.e. production-ready machine learning algorithms well-trained for the use case). Nevertheless, since big data and statistics based analytic systems require large amount of data (possibly stemming from multiple production sites, machine types, etc.), these “local condition monitoring clouds” need to sync up parts of their data into a “higher level cloud”. The purpose of this is to feed the most possible amount of data for refinement of the models used for runtime CBM (as indicated in section 2). Currently, this “inter-cloud” synchronization (possibly on-demand, and involving partial historical data) is not solved yet, but might be supported by distributed file systems, such as Hadoop [35]. On a side note, however, the usage of these file systems as storage have not been researched for cases where primarily the MIMOSA standard database is used.

6. THE PROACTIVE MONITORING AND MAINTENANCE BUSINESS LANDSCAPE

In order to survive and thrive in a globalised market, companies are being forced to develop intelligent maintenance solutions and move towards a balanced mix of product- and client-focused approaches. Hence, companies will benefit from high service gross margins, much less adjusted than product traditional ones: 1) Traditional pay-per-use services are common practice, and also services that are included within the asset's price or warranty. 2) To this day, PMM services are not independent businesses nor have their own operating account. They are integrated within the company’s global maintenance services. 3) Other monetisation methods (pay-per-use, availability pay, payment by results) and risk sharing between the customer and the vendor are not as usual but they are expected to become more popular. This paper has emphasised the need for acquiring certain technology capabilities in order to be able to offer PMM products and/or services. This means investing in technical, human and financial resources. For this purpose, there are different strategies: in-house development, technology vendor acquisitions, and diverse collaboration and partnership efforts. PMM implies adding intelligence and connectivity to the end product, and it also requires to promote service based business models in contrast of traditional product centric models. The reasons behind this shift are many and varied: to meet customer needs, to leverage asset’s characteristics, to implement technology innovations, etc. As stated by Brisk Insights market analysis, the global operational predictive maintenance market will grow at a CAGR (Compound Annual Growth Rate) of 26.6 % within 2016 – 2022, foreseeing a total market value of EUR2.900 million by the end of such period. This will be certainly boosted by the IIoT market rise, which is growing at a CAGR of 42 %, and will act as an enabler for its rapid industrial penetration. One of the key sectors (among all industries), in which predictive maintenance will make a huge difference will be manufacturing. The European manufacturing sector accounts for 2 million companies and 33 million jobs, representing the 15% of the total EU GDP. With the aim of increasing this contribution to 20% by 2020, European manufacturing industry faces a huge but promising challenge, given industry's potential in jobs & growth creation. However, industry's share in the EU GDP has declined during the last years, mainly due to a deceleration of global investments, market uncertainty and production offshoring to low-cost countries. This applies to all actors of the manufacturing value chain, involving production asset end users, asset manufacturers and asset service providers. In order to cope with that, the full digitisation of European industrial ecosystems has been stated as the foundation upon which competitiveness goals will be achieved. Within this framework, predictive maintenance accounts for a huge improvement potential to all actors mentioned: relevant productivity increase (asset end users), new revenue streams with higher profit margins (asset manufacturers) and new business opportunities based on analytics (asset service providers). According to McKinsey, predictive maintenance in factories could cut maintenance costs down by 10 to 40 percent, leading to manufacturer's savings of 215 to 580 billion euros in 2025, resulting from reduced downtimes and minimised manufacturing defects among others. Despite this clear potential, maintenance strategies in place still rely on ineffective corrective and preventive maintenance actions, which have a high impact on productivity (higher production costs, delays on delivery, customer dissatisfaction, etc. Not only available shop floor data and production assets' behaviour knowledge is underutilised, but also new businesses generation along the value chain is completely hampered. Regarding technology, there are several reasons behind the lack of adoption of predictive maintenance across EU industries: 1) Production systems complexity: the majority of EU industrial facilities is shaped by very heterogeneous assets, being the asset end user unable to gather deep knowledge about the behaviour of each asset (expertise often retained by the asset manufacturer). Heterogeneous data needs to be collected in an efficient way. 2) Lack of interoperability among different assets: afraid of the possibility of having a 3rd party providing services on their production assets, asset manufacturers often apply vendor lock-in solutions to their products. This results in a huge IT integration work required to connect them, usually preventing end users from implementing predictive maintenance solutions. 3) Non-reliable prognostics estimates at system level: even though successful prognostics applications have been deployed at component and sub-system level, asset end users' interest focuses on increasing the availability of the whole system, which has a direct impact on competitiveness. Thus, the lack of real prognostics & health management systems demonstrated at industrial level derives in a reluctance in early adopters. In order to overcome those limiting factors, there is a clear need of bringing together all value chain actors (gathering real time data, asset behaviour knowledge and analytics expertise); as well as taking advantage of advanced analytics technologies already applied in a wide range of sectors. This will enable to match predictive management system capabilities with real industrial needs, achieving downtime minimisation and OEE maximisation at system level. Besides all above, several non-technological challenges (such as corporate culture) prevent the penetration of predictive maintenance technologies across industries. This applies especially to SMEs, being the most relevant the following ones: 1) Uncertain Return on Investment (ROI): industrial CAPEX plans are fully subject to their expected profitability, usually in a short term (depending on the company's balance sheet, often 2-3 years). Since the implementation of such a predictive maintenance systems may imply investing in data acquisition, industrial communications & advanced analysis technologies (mainly regarding old production assets), companies often opt for more profitable investments (e-g purchasing new machinery, which leads to a direct productivity improvement). 2) Required skills: despite the high level of automation in place in most of European industrial companies, the implementation of Industry 4.0 (within which predictive maintenance is located) is currently requiring a shift from classical operator to highly analytical profiles. Industrial HMIs usually do not take advantage of available technologies such as adaptability, self-learning features, etc., resulting in workers' frustration by not showing the right information to the right people. With this in mind, it is fundamental that each company defines clearly their core business and performs a strategic planning to achieve the goal they seek. In any case, PMM opens the possibility to define and develop new business models where more companies will be involved throughout the product's value chain.

7. CONCLUSION

Proactive monitoring and maintenance enabled new business models shall address the optimized value proposition for each organisation. Personalized identification of a Canvas model element, such as key partners, key activities, key resources, customer segments, customer relationships and channels, derive a revenue stream that should definitely strength financial outcome.

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