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Development of digitalised maintenance - A concept

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Table I. The mapping between the maintenance tasks and the problems in the industry

Current maintenance problems	How the problem will be solved
Low status of maintenance within the organisation.	One reason for the low status of maintenance within organisations is the unrealised role and benefit of maintenance activities. The information visualisation subtask could help to realise the impact and role (technical and economic) of maintenance, as it facilitates data accessibility. This will eventually help to improve maintenance status.
Low use of maintenance strategies and limited connection between corporate and maintenance strategies.	In order to make proper maintenance decisions and strategies that are connected to the corporate strategy, a holistic view of the corporate situation is necessary. The information visualisation subtask enables a holistic view of the maintenance and production situation. This facilitates dynamic and strategic decisions and the construction of maintenance strategies that are aligned with corporate strategic goals. Also, this system allows the insertion (through user input update subtask) and selection of plans (through plan selection subtask) with respect to specific goals and strategies. This enables a connection to the corporate strategy to be created.
Low use of information systems in maintenance.	This system is a data-driven one; it utilises digital data to achieve its goals. Collecting data digitally and automatically from sensors and relevant working areas reduces the number of errors in the data and facilitates its utilisation. A simple user interface and integration procedure to encourage the use of IT technologies should be considered at the design stage.
Low use of preventive maintenance, mostly reactive maintenance/firefighting. Low average OEE over 25 years, indicating that maintenance has a very large improvement potential.	The subtasks in the analyse task allow abnormalities to be detected in advance, determining the causes behind these abnormalities and predicting the remaining useful life. This enables the planning to be event-based (using the subtasks belonging to the plan task) and to be made in advance and with respect to the production schedule. Additionally, the execution assistance task will help to conduct maintenance actions properly and efficiently. All of this will support predictive maintenance and increase the OEE average.

Low use of engineering methods (e.g. predictive maintenance), tools, etc.	This system uses and allows the use of sophisticated tools and methods such as predictive maintenance, AR, etc.
Low data quality	The data in this system are collected and updated digitally and automatically, which reduces errors and improves data quality.
Lack of emphasis on system loss (system perspective) and indirect effects of maintenance on production system performance (current theory usually views planned and unplanned downtime as being maintenance-related.)	This maintenance system supports gaining a holistic view of the system level (through the information visualisation subtask) by providing information from relevant working areas to end-users. Therefore, maintenance decisions that reduce system loss could be taken (e.g. the prioritisation of maintenance activities). Additionally, the proposed system in this paper allows direct/indirect profits and losses to be considered and decisions to be made accordingly. This takes place through two subtasks: generation of possible scenarios and plan selection. However, the specific approach is not the scope of this study.

Development of digitalised maintenance - A concept

Abstract:

Purpose – This paper presents a concept for digitalised maintenance (DM), maps the conceptualised DM to maintenance problems in industries and highlights challenges that might be faced when realizing this concept.

Design/methodology/approach – First, maintenance problems that are faced by the industry were presented, followed by a conceptualisation of DM. Next, a typical operational scenario was used as an exemplification to show system dynamics. The characteristics of this conceptualised DM were then mapped to the identified maintenance problems of industry. Then, interesting initiatives in this domain were highlighted, and finally, the challenges to realize this approach were discussed.

Findings –This paper identified a set of problems related to maintenance in industry. In order to solve current industrial problems, exploit emerging digital technologies and elevate future industries, it will be necessary to develop new maintenance approaches. The mapping between the criteria of DM and maintenance problems shows the potential of this concept and gives a reason to examine it empirically in future work.

Originality/value – This paper aims to help maintenance professionals from both academia and industry to understand and reflect on the problems related to maintenance, as well as to comprehend the requirements of a digitalised maintenance and challenges that may arise.

1. Introduction

In today's competitive market, manufacturers strive to adapt new technologies in order to improve their performance and secure their market share. Many studies have highlighted the importance of maintenance in enhancing the performance and the profitability of the production process (Al-Najjar, 2000; Waeyenbergh and Pintelon, 2002; Alsyouf, 2004). According to Djurdjanovica *et al.* (2003), implementing a proper maintenance activity can save a company up to 20% due to the resulting smaller production losses, improved product quality, etc.

There have been three industrial revolutions in the past 200 years, driven by mechanisation, electrical power, and information technology (Deloitte, 2015; Drath & Horch, 2014; Kagermann et al., 2013). Now a fourth industrial revolution is expected as a result of the recent technological advancements in the Internet of Things (IoT), the Internet of Services (IoS) and Cyber Physical Systems (CPS). The fourth industrial revolution is characterised by the vertical integration of systems at different hierarchical levels of the value creation chain and the business process as well as by the horizontal integration of several value networks within and across the factory and end-to-end engineering integration (S. Park, 2016; Thoben et al., 2017).

As such, innovative maintenance paradigms, techniques, tools and systems are necessary in order to fulfil the demands of future industries, as well as, to benefit from the technological advances, which serve as enablers to solve the problems faced by industry (Bokrantz *et al.*, 2017).

With the digital trend in the recent industrial concepts, such as Industry 4.0, Smart Factories, Industrial Internet, etc., several maintenance terminologies are proposed to explain maintenance in digitalised industry, such as Prognostic and health management (PHM), Maintenance 4.0 and Smart Maintenance (Bokrantz *et al.*, 2019). For example, PHM is described as a group of technologies and strategies to promote diagnostic, prognostic and maintenance of a product, machine or process (Qiao and Weiss, 2016; Ayad, Terrissa and Zerhouni, 2018). Maintenance 4.0 is developed to fulfil the demands of Industry 4.0 (Cachada et al., 2018), with an emphasis on maintenance aspects involving data collection, analysis, decision making and visualisation of assets (Kans, Galar and Thaduri, 2016). Smart Maintenance is defined by Bokrantz et al., (2019) as "an organisational design for managing maintenance of manufacturing plants in environments with pervasive digital technologies" (p 11). It is characterised by data-driven decision-making, human capital resource, internal integration and external integration. To engineer such maintenance solutions, it is essential to determine their tasks and features. Several researchers discussed maintenance tasks for digitalised maintenance (DM) (Labib 2006; Lee *et al.* 2011; Al-Najjar and Algabroun 2017; Algabroun *et al.* 2017). However, these tasks should be extracted with a connection to the principal maintenance objectives. Therefore in this paper, we extract these tasks from the principal maintenance objective using established tools in the domain of software engineering, i.e., stepwise refinement in association with the IBM's MAPE-K self-adaptive software architecture (Kephart and Chess, 2003). These software tools are employed as it is expected that software will play a significant role in DM, and hence, a proper software engineering perspective is important.

Demonstrating the potential of such a concept in a case study requires the full development of the maintenance system, as well as, digitalised industry, which is not the case in this study. As such, in this conceptual work, we employ a typical operational scenario as an illustration of this concept. This scenario is derived from an initiative to develop such a concept. Furthermore, we outline maintenance problems faced by industry followed by employing a logical mapping to indicate the potential of DM and reason how the extracted tasks might solve maintenance problems faced by industry. Moreover, we highlight the challenges that are likely to be faced during the development of DM, in order to help developers to consider them properly, as well as, present interesting initiatives to realise such a concept.

Hence, the aims of this study are as follows: 1) to discuss maintenance problems faced by industry; 2) to conceptualise digitalised maintenance, that is determine its tasks, features and input-output, implement them in a realistic scenario, and then, map them to the maintenance problems identified in aim 1; 3) to strengthen the credibility of developing and implementing such a concept by presenting initiatives in this area; and 4) to discuss the challenges that might be faced when realizing such a concept.

2. The problems and needs of industry today

Maintenance research is a subset of Operations Management (OM) (Holweg et al. 2018). The general empirical inquiry within OM is to explain variation in firm activities (i.e. *practices*) and the influence of such activities on business success (i.e. *performance*). That is, understanding what companies do and how that leads to results; an understanding which constitutes the basis for prescribing actions to practitioners by answering the question: if a company does practice X, will performance improve? (Bromiley & Rau, 2014; Ketokivi, 2016). Within maintenance, this can e.g. be to show that continuous improvements and spare part management improve maintenance performance (Gandhare et al. 2018). Therefore, this section presents current industrial problems with respect to maintenance practices and performance, as highlighted in empirical literature. The problems are not intended to be exhaustive, but rather to provide an overview that supports a mapping of the proposed digitalised maintenance concept with the real needs of industrial practice (Section 4).

2.1. Maintenance practices

A practice is defined as an activity or a set of activities that a variety of firms may execute (Bromiley & Rau, 2014). An overview of problems with current industrial maintenance practices that could be positively influenced by the proposed maintenance approach is presented below.

Most simply, the role of the maintenance organization is to maintain plant equipment according to the company policy. That is, to ensure that all equipment is up and running and in healthy condition, not to repair them after failure. However, a long range of studies have consistently shown that reactive maintenance dominates industrial practice and that too little time and effort are spent on preventive actions (Lee Cooke, 2003; Chinese and Ghirardo, 2010; Jin *et al.* 2016; Ylipää *et al.* 2017). These findings are alarming in light of the empirical evidence which shows that reactive maintenance is negatively associated with performance (Swanson, 2001).

To move from reactive to preventive practices and thus meet their objectives, maintenance organizations need to utilise supportive digital technologies and adopt more sophisticated engineering approaches. However, studies point towards that the awareness and adoption of such approaches are limited in industry. For example, very few predictive maintenance practices are utilised in industry (Jin *et al.* 2016), maintenance is rarely involved in the engineering work in early phases of plant design and development (Sandberg, 2013; Bokrantz *et al.* 2016a), and even the most common maintenance concepts Total Productive Maintenance (TPM), Reliability-centered Maintenance (RCM) and Condition-based Maintenance (CBM) are not extensively used (Alsyouf 2008; Bokrantz *et al.* 2016a). Moreover, many theoretical assumptions about how practitioners actually use CBM do not hold against empirical evidence (Veldman et al. 2011), and using CBM in practice is much more complex and time-consuming compared to what is being described in literature (Akkermans et al, 2018). Although, CBM was introduced in the middle of the last century (Prajapati, Bechtel and Ganesan, 2012; Ruiz-Sarmiento et al., 2020), and since then, numerous techniques for condition monitoring were developed, including shock pulses, temperature monitoring, vibration, and acoustic emission (Prajapati, Bechtel and Ganesan, 2012; De Azevedo, Araújo and Bouchonneau, 2016), in industry however, CBM implementation is yet limited to significant components. The costs of its life cycle and its complex technology could be some of the reasons behind its limited applications (Guillén et al., 2016). Furthermore, companies also face a variety of organizational and human implementation challenges that prevents them from extensively using CBM and other data-driven maintenance practices (van de Kerkhof et al., 2016; Gopalakrishnan et al. 2019).

Since the introduction of Information Technology (IT) within the maintenance realm, e.g. Computerised Maintenance Management Systems (CMMS), the use of IT to improve maintenance practices has been a major interest among researchers (Muller *et al.* 2008). The expanding data amount in maintenance departments has motivated the needs for CMMS to manage and access data in real time. However, utilising the stored data to provide instructions and guidelines to engineers, as well as, to mangers to provide appropriate decision remains a challenge (Rastegari and Mobin, 2016). Furthermore, CMMS lacks the decision analysis capabilities and it is mainly used as an administrative tool (Kans, 2008; Rastegari and Mobin, 2016). Today, data-driven decision-making is a core dimension of modernised maintenance management (Bokrantz, 2019a; 2019b). However, CMMS and company-wide IT solutions are still not completely diffused in industry (Kans, 2013), and maintenance information systems are often decoupled from the rest of the plant (Sandberg, 2013), which can be a barrier in collecting data from working areas which are relevant to maintenance such as economy, quality and production. Therefore, management of information systems within maintenance often represents a weak link for improving performance (Naji et al. 2019). To increase the use of data-driven maintenance practices, a clearly expressed industrial need is simple and user-friendly decision support systems (Bokrantz *et al.* 2017a). However, user-friendly industrial applications of predictive maintenance are still scarce (Vogl *et al.* 2016) and maintenance organizations often lack the relevant data to drive decision making (Jin *et al.* 2016). In addition, lack of quality data is a common and critical concern for maintenance decision making (Lin *et al.,* 2007; Bokrantz *et al.* 2017b; Kumar et al. 2014), and it is one of the reasons for the low use of advanced analytics in maintenance practice (Zio, 2009). Extensive data management challenges are further corroborated by the case study in Razmi-Farooji et al. (2019). Hence, neither data with sufficient quality nor user-friendly systems for advanced maintenance analytics is readily accessible to the manufacturing industry.

On a strategic level, there is often limited connection between the maintenance strategy and the corporate strategy (Lee Cooke, 2003), and many companies do not even have a formal maintenance strategy (Jonsson, 1997; Alsyouf, 2009). This is typically reflected in top-down initiatives for short-term reduction of direct maintenance costs (Waeyenbergh & Liliane Pintelon, 2009), where maintenance organizations are perceived as cost centers that are necessary to have but always desirable to decrease the budgets for (Salonen & Deleryd, 2011). Consequently, while maintenance spending constitutes a large part of a manufacturing firm's operating budget, maintenance organizations often have little influence on the circumstances that are truly decisive of a firm's expenditures and earnings (Sandberg, 2013). These are also underlying reason as to why maintenance has low status within companies (Jonsson, 1997; Alsyouf 2009; Chinese and Ghirardo, 2010). The general perspective on industrial maintenance has therefore been expressed as that most maintenance organizations do not realise their full potential (Cholasuke *et al.,* 2004) and that maintenance practices can be greatly improved in the average manufacturing firm, regardless of industry or size (Jonsson, 1999). Therefore, in light of the current trends of digitalisation, it is evident that industrial maintenance practices must be radically improved to meet the current and future demands of manufacturing firms.

2.2. Maintenance performance

Performance at the level of the firm is often defined and operationalised differently (Miller et al. 2013), but most operations management researcher use measures of operational performance at the level of the plant, typically consisting of e.g. cost, quality, flexibility and lead time (Turkalainen & Ketokivi, 2012). Maintenance performance is ideally measured in terms of both internal efficiency and external effectiveness, where external effectiveness can be equated with the measures of operational performance. Arguably the most common industrial measurement of internal efficiency of maintenance is Overall Equipment Effectiveness (OEE) (Nakajima, 1988). OEE is a simple measure of productivity intended to capture and highlight equipment problems relevant to maintenance, and it contributes to making maintenance a strategic issue within a manufacturing firm (Jonsson & Lesshammar, 1999). There has been a long range of studies that publish industrial OEE data and thus highlight current problems with maintenance performance.

Over the past 25 years, the average industrial OEE has been consistently reported in empirical studies to be around 50-60% (Ahlmann, 1993; Ericsson, 1997; Ljungberg, 1998; Ingemansson, 2004; Almström & Kinnander, 2008; Ylipää *et al.* 2017), clearly indicating that a very large part of the total production capacity is vanished due to equipment losses. It is therefore not surprising that low OEE is argued to be one of the largest problems in industry today (Kumar *et al.* 2013), and it is evident that the average manufacturing firm has the potential to significantly improve productivity and efficiency by measuring, analyzing, reducing, preventing and eliminating production disturbances (Bokrantz *et al.* 2016b). In detailed OEE empirical studies, unplanned downtime represents around 10 percent of the total losses and availability is shown to have a large impact on the overall OEE, thus signaling a significant improvement potential for maintenance performance (Ylipää *et al.* 2017).

However, despite common belief, maintenance contributes far beyond the confines of availability. For example, a holistic categorization of expected performance outcomes from modernized maintenance operations at the plant- and firm-level is provided by Bokrantz et al. (2019b). Although not all losses within the OEE are attributable to maintenance (e.g. set-ups), the conservative perception is that maintenance activities are only capable of directly influencing planned and unplanned downtime losses. In contrast, maintenance also indirectly influence e.g. speed and quality losses (Muchiri *et al.* 2011), but even more importantly play a central role with regards to system losses (Li et al. 2009). In manufacturing, system losses occur largely due to ripple effects caused by machine downtime, specifically in the form of blockage and starvation (i.e. idle time). This mean that the direct control of downtime with maintenance activities has an indirect effect on idle times in the entire production system. Maintenance can influence these system losses by e.g. prioritizing activities towards the current system constraint (i.e. bottleneck) (Gopalakrishnan & Skoogh, 2018; Gopalakrishnan et al. 2019). The bottom line is that addressing maintenance requirements of individual machines is necessary but not sufficient. Instead, a system perspective is also needed in which the simultaneous maintenance of multiple pieces of equipment in a production system is aimed at optimizing the performance of the entire system, not solely the individual machines (Bokrantz *et al.* 2017a). In fact, Jin (2016) observe that most currently available solutions for diagnostics and prognostics are only capable of analysing component- and machine-level data. In contrast, there is clear need in industry for system-level solutions that can analyse multiple machines and/or entire production systems.

Maintenance digitalisation could support solving several of the above problems. One action that might treat the above problems is the development and implementation of the proposed digitalised maintenance concept in this article. The following sections demonstrate this by mapping tasks and features and exemplifying initiatives pursuing this change.

3. The conceptualisation and characteristics of a digitalised maintenance system

In this paper, a digitalised maintenance system is defined as "a system that utilises digital technology as a way to conduct or assist in conducting maintenance". In order to develop such a system, it is important to first conceptualise it; that is, to understand its tasks, features and input/output.

Several studies have discussed these tasks and requirements (Labib 2006; Lee *et al.* 2011; Al-Najjar and Algabroun 2017; Algabroun *et al.* 2017). In previous studies, a group of researchers developed the tasks and features of a maintenance approach for Industry 4.0 (Al-Najjar and Algabroun, 2017); they extracted software components using top–down analysis, creating a framework for a digitalised maintenance approach (Algabroun *et al.*, 2017). In contrast, in this paper we will use design tools from the field of software engineering (stepwise refinement in association with MAPE-K software architecture) to systematically analyse the principal maintenance objective with the aim of extracting the required tasks and subtasks. Stepwise refinement is employed as it uses a software engineering perspective and, hence, is more suitable for this purpose.

3.1. Using the stepwise refinement process to determine tasks

In the stepwise refinement approach, an abstract objective of a system is refined into one or more components with tasks that are more concrete and less abstract. This is done in such a way that these tasks collectively preserve the system's original objective. If a refined task remains abstract, then the refinement process continues until a level at which the subtasks are implementable (Abbott, 1987; Wooldridge, 1997; Refsdal *et al.,* 2015). This approach has several advantages, including: 1) it provides a foundation for a separation of concerns (i.e., each refined component is more independent); 2) the components become easier to understand, as they are smaller and more independent; and (consequently) 3) the maintenance, modification and development of the system are thereby simplified.

To perform the stepwise refinement analysis, we started by identifying the main objectives and then analysing and refining them. In general, the main objective of maintenance is to elevate the production machines' availability and promote their good health in a cost-effective way (Al-Najjar, 1997; Takata *et al.*, 2004; Sandberg, 2013). In order to achieve this objective, it is essential to 1) collect relevant data related to the machine and other working areas (such as production, quality, economy, etc.). 2) The collected data has to be analysed, so that it can be converted into useful and actionable information. Following this, 3) a suitable action and its time should be decided based on the received information. Finally, 4) the decision is executed at the determined time.

This pattern has similarities to the IBM's MAPE-K (Monitor, Analyse, Plan, Execute-Knowledge) self-adaptive software architecture (Kephart and Chess, 2003), and therefore, it has been adopted in this paper; self-adaptive software architecture allows designing a software system that autonomously adapts itself at runtime to deal with uncertainties (e.g. faults or variation in resources), examples of this approach can be found in Kramer and Magee, 2007 and Iftikhar and Weyns, 2014. In this paper, the authors claim that MAPE-K could be used as a base for conceptualising DM, as it has all of the necessary elements to conduct a maintenance action. This architecture can be summarised as four tasks: *monitor, analyse, plan*, and *execute* which share knowledge stored in a repository. These tasks can be viewed as the main steps of a maintenance action (Algabroun *et al.*, 2017). However, in the context of this paper, another component is important; namely, *user interface*, the means by which the user can interact with the system and be presented with the relevant information (Algabroun *et al.*, 2017).

Several constituents might be involved to conduct these tasks, such as sensors, communication systems, processors, middleware, databases, applications, actuators, etc. However, the technical specifications of these constituents and specific technologies are beyond the scope of this study.

The main tasks mentioned above (i.e. monitor, analyse, plan, execute and user interface) could be further analysed, extracting the following subtasks:

Monitor: In order to perform the required tasks and collectively achieve the objectives, it is essential that the system possesses the required information. Therefore, the system should have the ability to collect and receive data from sensors as well as that pertaining to other relevant working areas, such as production, economy, quality, etc. (Al-Najjar, 1996; Takata *et al.*, 2004; Sandberg, 2013). The collected data should be updated and stored in a data repository (e.g. a database or cloud) for future utilisation. As such, the subtasks here are named 1) *data collection* and 2) *data updates*.

Analyse: To determine the required maintenance action and the most profitable time at which it should be conducted, it is essential to analyse the collected data. This is to detect abnormalities in the production process, identify the causes behind and predict any likelihood of damage development and (should this occur) ascertain the damage severity. Moreover, when planning the maintenance action, all possible scenarios and their consequences should be first being identified. Accordingly, the subtasks here are 1) *abnormality detection*, 2) *diagnosis*, 3) *prediction*, 4) *severity assessment* and 5) *generation of possible scenarios*.

Plan: The plan that is best aligned with the company's goals and which suits its specific situation can be selected from the scenarios generated during the previous task. Any adjustments required by the company's specific situation can be entered and/or modified as a part of the *user interface* task. The selected plan would then have to be constructed in detail, with all the required resources (spare parts, human resources, tools, etc.) prepared accordingly. Thus, the subtasks here are 1) *plan selection* and 2) *plan construction*.

Execute: At the planned time (which would be determined as part of the previous task), the predetermined maintenance action is conducted. Several tools (such as augmented reality (AR)) could be used to perform maintenance actions efficiently and correctly (Mourtzis *et al.*, 2017; Palmarini *et al.*, 2018). Alternatively, documents that detail how to conduct the required maintenance could be employed. In some cases, actuators could be used to perform specific maintenance actions (Al-Najjar and Algabroun, 2018). Therefore, the subtask here is considered to be *execution assistance*.

User interface: This provides a means by which to interact with the system. For example, it might present the relevant information (such as diagnoses, predictions, maintenance work progress, completed tasks, maintenance recommendation, etc.) to the end users and other systems/working areas, as well as modifying or entering new information. Therefore, the subtasks here are considered to be: 1) *information visualisation* and 2) *user-input updates*. Figure 1 visualises the stepwise refinement analysis.

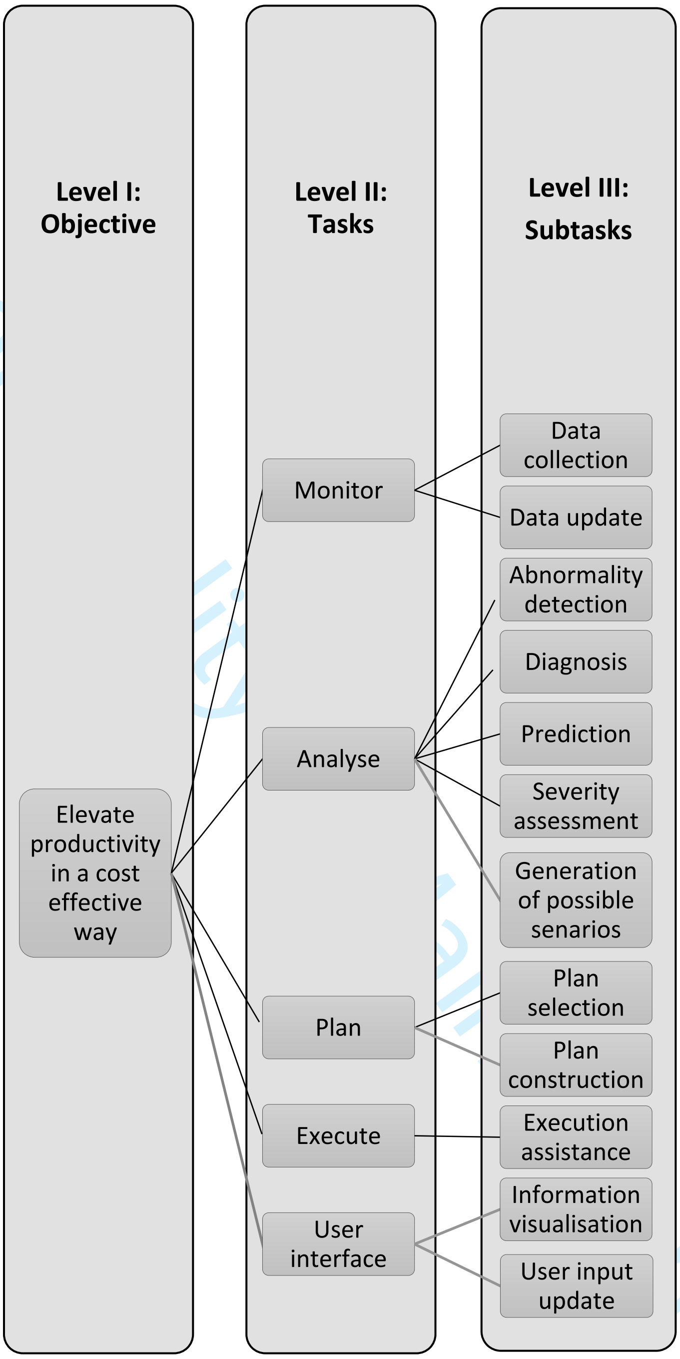

Figure 1: Stepwise refinement process used to find tasks and subtasks

3.2. Features of digitalised maintenance systems

Certain features can enhance the performance of digitalised maintenance systems; therefore, they should be taken into account during both the design and the development process. These features are discussed in several studies (Labib 2006; Lee *et al.* 2011; Al-Najjar *et al.* 2018) and can be summarised as follows:

- Modularity: a modular design enables system modifications through the adding, replacement or removal of modules using the plug-and-play principal (Hermann et al., 2016). This facilitates any adjustments to the maintenance system that are required in order to fulfil the dynamic demands of factories.

- Scalability: a digitalised maintenance system should possess the ability to include new machines in order to meet growing business needs.
- Decentralisation: evolving industrial concepts tend to be decentralised (Hermann *et al.*, 2016). For this reason, a digitalised maintenance system should be compatible with a decentralised production process.
- Interoperability: this allows communication among the elements within the maintenance system, as well as with other systems in the plant.
- Digitalisation: the proposed maintenance system relies heavily on digital technology; digitalisation facilitate integration and automation, as well as data collection, utilisation and storage.
- A consideration of production-based and economic key performance indicators (KPIs): one of the main objectives of maintenance is to improve production performance cost-effectively. For this reason, the maintenance system should be able to consider both production and economic KPIs in order to assess and improve maintenance impact.
- Automation: this promotes automated production processes and allows gaining quicker responses to events (e.g. faults).
- Real-time ability: In order for the maintenance system to respond rapidly to variation and to events that occur in production, it should possess the ability to collect and analyse data in real time.

3.3. Input–output

Based on the analysis provided in section 3.1, the input of this approach comes from three main sources: 1) condition monitoring sensors through the monitor task; 2) a data repository, such as a cloud or database which contains relevant information from other working areas; 3) directly from users (e.g. strategic goals), which is the input inserted using the task of user interface. These three input sources are used to provide the following three outputs: 1) maintenance recommendations (i.e. what maintenance action needs to be done and when this should happen). These recommendations are result from the analysis and plan tasks; 2) information to other working areas and/or maintenance personal (e.g. pending work, work progress, or closed work orders), and 3) automatic actions (see also Algabroun *et al.*, 2017). Figure 2 illustrates the input–output of the system.

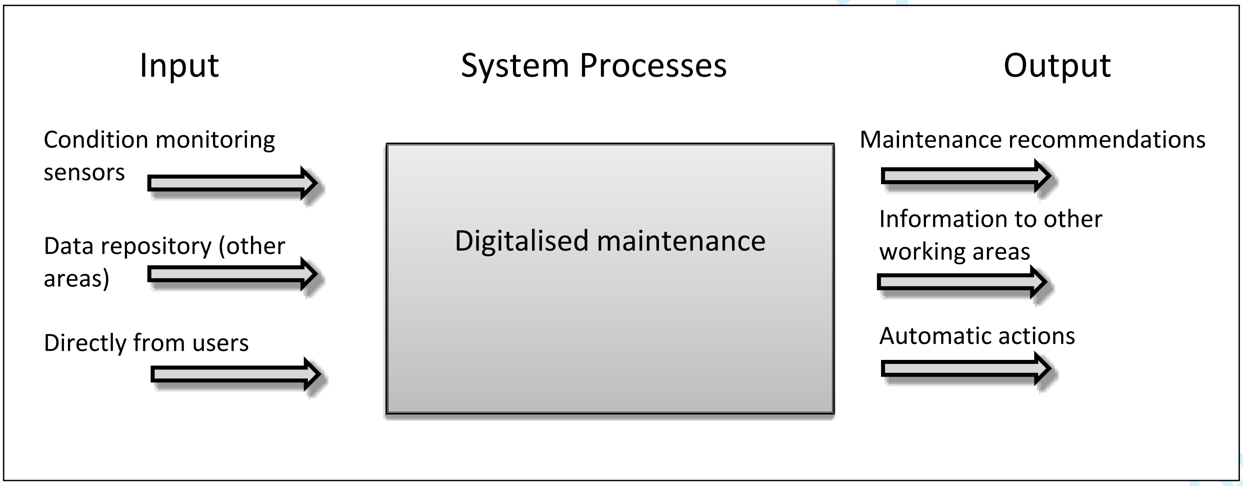

Figure 2: Input–output of the digitalised maintenance approach

Next section employs a typical scenario to exemplify the conceptualised system and to show how the software components can work together. To explore how the conceptualised DM system might solve the industrial problems identified in section 2, section 5 maps between the identified tasks and the problems.

4. Operational scenario

This section provides an exemplification using a scenario derived from the planned implementation of PreCoM project (Algabroun et al. 2020, see also section 6.1). Figure 3 illustrates the dynamic aspects of the scenario using unified modeling language (UML)-sequential diagram.

4.1. Presetting:

PreCoM is designed to be a distributed cloud based system, therefore, it contains several independent modules, in which each located in a different server and in a different location. The involved modules are: PreCoM Brain (a central control unit that orchestrates the interaction among modules using HTTP methods and controls the recommendations from the different modules to avoid contradictions), PreCoM Cloud, sensors, user interface (UI), augmented reality program (AR), abnormality detector (a software module named PreVib-ProLife, developed by Linnaeus University and E-maintenance Sweden AB), production scheduler, stress-condition evaluator (a module that assesses the available time for the machine through surveying the required maintenance actions and the time to conduct these actions) and maintenance schedule optimizer (a software module named MaintOpt, together with stress-condition evaluator developed by Linnaeus University and E-maintenance Sweden AB).

The machine considered in this scenario is a paper mill machine, named PM6, located in Spain that produces tissue papers.

4.2. Scenario

- In the PM6 machine, a damage is occurred in the bearing (i.e. deep groove ball bearings 618/500 M.C3) that is located in the yankee dryer cylinder (a machine component that is used to remove moisture from pulp in order to be further processed into paper) in the motor front. The bearing is monitored by a wireless triaxle vibration sensor (named Ronds RH605).
- The collected data is then sent by the sensor to a wireless data acquisition station (named Ronds RH560). Next, the data is preprocessed (in term of digital filtration, Fast Fourier Transform and Enveloping) and a POST request (HTTP method) is sent informing PreCoM Brain in PreCoM Cloud about the data availability. PreCoM Brain then initiates a GET request (HTTP method) to import the data.
- After the vibration measurements are obtained and stored in the Cloud, PreVib-ProLife module is invoked by PreCoM Brain using POST request to collect the data using GET request and start the analysis in order to detect abnormality, and if so, to provide the diagnosis and prediction of the deterioration in the near future, assessment of probability of failure and residual live, and recommend a maintenance action.
- PreVib started the analysis and detected an abnormality. Assume that the damage is mainly caused due a damage in the inner ring of the bearing, the rms value is obtained.
- Based on the analysis a warning level of 4 (where level of: 4 represents ‘maintenance should be planned’, 3 represents ‘Examine whenever it is possible’, 2 represents ‘Probable damage development, await’, 1 represents ‘No serious damage, await’ and 0

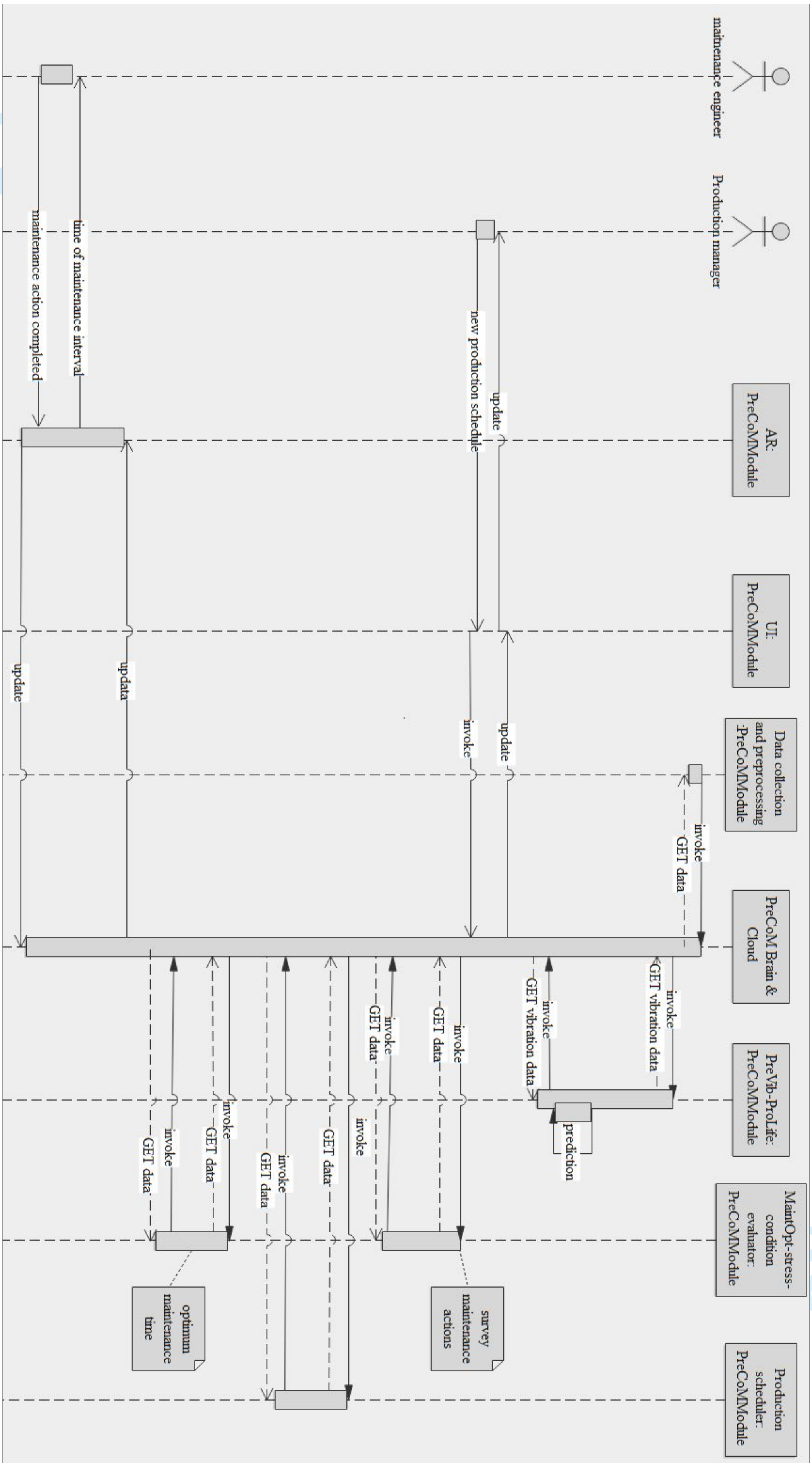

Figure 3: the scenario dynamics using sequential

represents 'No damage') is provided which indicated that damage in the bearing is developed and there is a need for maintenance. Based on ProLife analysis (i.e. probability of failure and residual live) the maintenance interval is decided automatically. The information is then stored in PreCoM Cloud.

- The recommendation is visualized by a user interface (UI) to the production and maintenance managers. Production manager requested a new production plan based on the occurred event.
- PreCoM Brain invoked the stress-condition evaluator module using POST request to survey the coming maintenance actions (e.g. if in the meantime breakdowns, malfunctions, Preventive Maintenance (time planned) as well as the actions recommended by PreCoM based on the diagnosis report). The stress-condition evaluator collected this data using GET request, perform the survey and the resulted information is then stored in PreCoM Cloud.
- PreCoM Brain invoked the production scheduler program using POST request in order to provide a new production schedule with respect to the new events. Production scheduler program collected the required data from PreCoM Cloud using GET request and started the analysis. The results are then sent to PreCoM Cloud.
- Next, as soon as the new production schedule has arrived at PreCoM Cloud, MaintOpt is invoked (using POST request) by the PreCoM Brain to provide the optimum maintenance interval time for conducting all the maintenance actions needed at that moment, see the bullet above. MaintOpt collected the data from PreCoM Cloud using GET request, analysed the data and results are stored in PreCoM Cloud.
- When the determined time for the maintenance action arrives, the maintenance technician uses AR tool to visualize the required information, e.g. to allocate the machine, the component and to visualize the required steps according to the best practices. When there is a difficulty in preforming the required action, a video call is performed with a more senior engineers to support the technician.
- When the work is executed, the work order is closed and other information is registered (e.g. time length needed to conduct the maintenance action recommended) for statistical analysis, and for continuous improvement purposes (e.g. assessing PreCoM impact of machine availability and maintainability).

4. Mapping the maintenance tasks to the problems of industry

In the previous sections, the conceptualisation of a digitalised maintenance system was conducted using stepwise refinement and then the concept is exemplified using a scenario. This conceptualised maintenance approach should aim to solve the problems faced by industry today. In order to highlight the relevance of this approach to the problems faced by industry, we map the tasks (outlined in section 3) to the problems in industry (outlined in section 2).

Table I lists the current problems (identified in section 2) and describes how the proposed approach might solve them. Following this, some initiatives in this field will be highlighted and the potential challenges involved in developing such an approach will be discussed.

Table I. lists the current problems (derived from section 2) and describes how the proposed approach might solve them

5. Initiatives in this field

There are several studies related to digitalised maintenance (Yuniarto and Labib, 2006; Camci, 2009; Lee *et al.*, 2011; Langeron *et al.*, 2015; Guillén *et al.*, 2016). The focus of these studies is only on some aspects or functions of the digitalised maintenance system considered in this study, such as prediction, condition-based maintenance and scheduling optimisation. However, as described in section 1 and 2, the focus of this paper is on a digitalised maintenance approach that covers the entire maintenance action process.

To strengthen the credibility of practically developing and implementing the maintenance approach proposed in section 3, as well as, to raise the awareness of interested developers and maintenance professionals about such initiatives, so they can follow their implementations. This section will therefore present some initiatives in this domain that fulfil the following two criteria: 1) practical initiatives; 2) similar initiatives to the approach presented in this paper. These initiatives are presented as follows:

6.1. Predictive Cognitive Maintenance Decision Support System (PreCoM)

PreCoM is a three-year (2017–2020) cross-functional project funded by the European Union's Horizon 2020 research and innovation programme (see https://www.precom-project.eu). The objective of this project is to develop, implement and evaluate a digitalised maintenance system that is able to detect and localise damages, assess severity, predict the remaining useful life, optimise production and maintenance scheduling, and assist in the repair work.

PreCoM consists of four modules:

- data gathering module that collects data from external sensors as well as embedded sensors in the machine tool,
- artificial intelligence module that analyses the gathered data using several models and algorithms including physical models, statistical models and machine-learning algorithms,
- secure integration module; this module is responsible for the integration of PreCoM modules with other systems in the company such as production planning and maintenance systems,
- user interface module which includes production dashboards as well as AR for maintenance staff.

This project is an innovative action that is designed in connection with real-world industrial companies and will be demonstrated and validated on three industrial facilities in three different sectors. These sectors are: 1) the low-volume sector, where large metal parts are manufactured; 2) the high-volume sector, which focuses on the production of reduction gears; and 3) continuous manufacturing processes in the field of paper manufacturing.

The expectations of the project are determined in measurable values, as follows:

1) Increase availability and maintainability by 15%
2) Reach 30% of time spent on predictive maintenance
3) Reduce failure-related accidents by 30%
4) Reduce energy consumption by 6–10%
5) Reduce raw material consumption by 7–15%.

6.2. VerSatilE plug-and-play platform-enabling remote pREdictive maintenance (SERENA)

SERENA is a three-year project (2017 - 2020) funded by the European Union that consists of 13 participants (see https://cordis.europa.eu/project/rcn/211752/factsheet/en) aims to develop a digitalised maintenance solution that fulfils the following demands: versatility; transferability; remote monitoring; and control. This will be achieved through: 1) a plug-and-play cloud-based solution for data management and processing; 2) systems for data collection and monitoring of machines' conditions; 3) artificial intelligence techniques for predictive maintenance and maintenance and production activity planning, 4) AR-based technologies to support the performance of maintenance actions and present information concerning machine conditions.

The solution will be demonstrated in different industrial domains (white goods, steel parts, metrological engineering, and elevator production). Its applicability in steel parts production will also be investigated.

The impact expectations of SERENA are:

1) 10% increase in-service efficiency
2) Greater utilisation of predictive maintenance
3) Improvements to accident mitigation.

6.3. 5C architecture

This approach is based on a five-layer architecture named 5C (Lee *et al.*, 2015). This architecture consists of five steps, from data collection to execution. The five layers are summarised as follows:

1) Smart connection: in this layer, relevant data are collected from machines through sensors and other relevant working areas through Enterprise Resource Planning (ERP), Computerised Maintenance Management System (CMMS), etc.
2) Data related to information conversion: the collected data from different working areas is analysed and converted into meaningful information.
3) Cyber layer: the information related to the other machines in the facility is collected in this layer. It will then be possible to implement more advanced analytics (e.g. a clustering techniques). This allows the condition of a particular machine to be compared to that of other machines.
4) Cognition: at this layer, a decision relating to the required maintenance action and the time at which it occurs can be made. This decision will be based on the knowledge acquired through the previous processes.
5) Configuration: the decision will be executed at this layer. The execution could take, for example, the form of maintenance recommendations or automatic actions through actuators.

An empirical study analysing this approach, using three band-saw machines in different locations as use studies, is presented in Bagheri *et al.* (2015). The goal was to achieve a balance between two parameters: production quality and production speed.

At the first level ("smart connection") the data was collected from add-on sensors as well as from the machines' controllers. The collected data was then initially analysed at a local industrial computer at the level of "data to information conversion". Following this, it was sent to the "cyber" layer, in the cloud. An adaptive prognostic algorithm was then used to determine a suitable working regime. Finally, at the "configuration" layer, the machines were set to adhere to the determined working regime.

6. Challenges

There are numerous enablers for the development and implementation of this approach. These include the continuous development of software and hardware with price reduction, as well as the evolution of new methods and concepts such as the Internet of Things (IoT), Internet of Service (IoS), and Cyber-Physical Systems (CPS). However, despite these enablers, the development and implementation of such a maintenance approach is a complex initiative that might involve a number of overlapping challenges in different areas.

The aim of this section is to discuss these challenges in order to help the developers to identify and consider them properly. To identify these challenges, a literature survey was conducted. Four main stages to execute this survey have been used. First, keywords that represent the entire project aspects were formed. Next, database search was conducted using the keywords. Then, the related papers were selected, and latterly, relevant information was extracted.

The keywords that represent the study problem were: maintenance, intelligent, digitalisation, digitisation, automation, smart, problems, challenges, industrial internet of things, industry 4.0, connected industry and maintenance 4.0. Then, the keywords were used to search in databases using different ways of combination and thesauruses. The search was Boolean based using the One-Search engine (provided by Linnaeus University), which is linked to different databases such as IEEE, Springer Link, Emerald and Science Direct as well as Google. Then, in the One-Search engine the unrelated subjects were removed (e.g. health science, social comparison, etc.) and the following inclusion criteria were employed: full text available, English language, peer reviewed, academic journals, conference materials and book chapters. After reading the abstracts, 26 articles were selected, and eventually, 12 articles found to be relevant after going through the articles and their references list.

The challenges were found fragmented in twelve articles (Kagermann *et al.*, 2013; Deloitte, 2015; Ma *et al.,* 2016; Halenár *et al.*, 2016 ; Zhu *et al.*, 2017; Bokrantz et al. 2017; Khan *et al.,* 2018; Wabner, 2018; Simon *et al.*, 2018; Algabroun, 2019; Bokrantz et al; 2019a; Bokrantz et al. 2019b). These challenges could be categorised under the following five major categories: technological advancements; data utilisation; human resources competence; regulations and standards; and capital investments. A description of these challenges is provided below.

6.1. Technological advancements

The proposed maintenance approach could be realised and developed using recent technological advancements; however, various technological challenges might still be faced. These challenges will vary as a result of different factors, such as type of industry, environment and size of factory.

For instance, in some industrial cases where remote data measurements are required, some factors such as harsh environments or the existence of large-body obstacles could cause difficulties when attempting to implement a reliable data acquisition system (Ma *et al.,* 2016; Zhu *et al.*, 2017; Khan *et al.,* 2018). Additionally, the limited battery life of the wireless sensors will pose a challenge when used in some applications, particularly in inaccessible areas (Algabroun, 2019).

Another example of a technological challenge is the utilisation of AR tools when a manual job is required. In this case, the development of an industry-applicable AR tools that support hands-free interaction could be difficult (Wabner, 2018).

The challenges will also vary based on the size of the enterprise. For example, some of the technology required by the proposed approach(e.g. Information and Communication Technologies ICT) could be too complex for small and medium enterprises, restricting its adoption (Wabner, 2018).

Issues related to safety and security aspects could present challenges when designing and developing the proposed maintenance approach. The developed technology must expose neither the environment nor people to harm. It must also protect data and information against abuse and/or unauthorised use. This will require the development of security reference architectures and unique identifiers (Kagermann *et al.*, 2013; Deloitte, 2015).

6.2. Data utilisation

Data coming from different systems and working areas provides tremendous value to maintenance and production activities, providing it is properly exploited.

Continuous data expansion presents major challenges; these include how to manage a large quantity of data as well as how to develop more accurate prognostic algorithms that incorporate deterministic approaches. Additionally, methods that utilise the data to accurately estimate the economic impact of maintenance are not yet well developed (Wabner, 2018). Most importantly, data utilisation must span all the way from collection and analysis to decision-making. Data has no value unless it is used to drive decision-making within maintenance (Bokrantz et al. 2019a).

6.3. Human resources

Implementing such a digitalised maintenance approach will present many employees with new challenges. There will be greater need for more sophisticated digital competence. Additionally, organisations will have to pay greater attention to proper recruitment, training and education if they are to leverage competence within the organisation (Kagermann *et al.*, 2013; Bokrantz et al. 2017). More specifically, maintenance employees must develop new and higher levels of analytical-, ICT- , social-, business-, adaptability- and technical skills (Bokrantz et al. 2019a).

6.4. Regulation and standards

This maintenance approach relies on data and information exchange among different elements to achieve its tasks. These elements include machines, sensors, humans, artificial intelligence and relevant working areas. Collaboration would be impossible without developing appropriate standards that specify the nature of the interactions that occur among these elements.

Several attempts at developing such standards are currently still in progress (Simon *et al.*, 2018). Due to the delay in forming proper standards, the integration of and communication among these elements will be a challenge (Deloitte, 2015; Halenár *et al.*, 2016). Legal issues will also have to be taken in consideration regarding, for example, liability issues, data ownership, intellectual property, and safety and security (Deloitte, 2015; Bokrantz et al. 2017).

6.5. Capital investment

Implementing this concept is technologically intensive; therefore, purchasing or modifying the currently available systems (e.g. sensors, data acquisition systems and software) will be necessary in many cases and will probably require an investment in maintenance with a considerable cost (Wabner, 2018). However, it has been reported by many studies that maintenance has often been regarded by top management as a cost centre, rather than as a profitable opportunity (Alsyouf, 2004; Takata *et al.*, 2004; Al-Najjar, 2007; Pintelon and Parodi-Herz, 2008; Salonen and Deleryd, 2011). This is due to a lack of realisation and understanding of the impact of maintenance on a company. In addition to capital investments, companies must also invest in a variety of intangible complementarities such as training, education and organizational re-design (Bokrantz et al. 2019b).

Although, over the last decade, companies have started to recognise maintenance as a profit generator and an essential element to achieving companies' objectives (Alsyouf, 2004; Pintelon and Parodi-Herz, 2008), the cost factor is still a determinant aspect when making a decision (Wabner, 2018). As such, financial justification still has to be demonstrated (Bokrantz et al. 2019b). In general, the impact of maintenance cannot easily be accurately estimated (Alsyouf, 2004; Al-Najjar, 2007) and therefore this justification could be also a challenge.

7. Conclusion

Innovative maintenance approaches have had to be developed in order to cope with the new digitalised technology employed in industry and ensure its sustainability. This study aims to conceptualise a digitalised maintenance system in order to give new insights, organise thoughts and understand its boundaries and challenges. It discusses a digitalised maintenance approach with consideration of maintenance problems. Maintenance problems that are faced by industry was discussed and categorised into two categories; practices and performance. The gap between maintenance in theory and practice emphasises the importance of considering an empirical approach of this concept for a future study.

A conceptualisation of a digitalised maintenance approach was presented, using stepwise refinement in association with MAPE-K. Using MAPE-K in the conceptualisation will ease utilising it as a software system architecture during the implementation. This maintenance approach was then exemplified in an operational scenario derived from the implementation of the PreCoM project. Then the characteristics of the conceptualised approach were mapped to the identified problems in maintenance. The mapping showed how this maintenance approach might support solutions to these problems.

The authors of this paper argue that this approach could be realised using existing technology. Despite the many enablers to realising this approach; however, there might also be challenges. These challenges can be categorised as technological advancements, data utilisation, human resources competence, regulations and standards, and capital investments. Three initiatives in this domain were presented that can strengthen the credibility of developing and implementing such an approach.

In conclusion, this study showed that maintenance suffers from many problems. It will be necessary to develop new maintenance approaches in order to solve current industrial problems, exploit emerging digital technologies and elevate future industries. The mapping between the tasks of DM and maintenance problems shows a potential of this concept to solve maintenance problems, which could be examined empirically in a future work.

This paper showed the implementation of stepwise refinement with the association to IBM'S self-adaptive software architecture to guide the analysis process. The combination of these tools could be useful for the developers of digital community in order to facilitate the conceptualisation of self-adaptive complex systems. The development of new maintenance approaches has to be in line with real-world needs if these approaches are to achieve practical and applicable solutions. This paper aims to help maintenance practitioners from both academia and industry to understand and reflect on the problems related to maintenance, as well as to comprehend the requirements of a digitalised maintenance and the challenges that may arise.

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Development of digitalised maintenance - A concept

Abstract:

Purpose – This paper presents a concept for digitalised maintenance (DM), maps the conceptualised DM to maintenance problems in industries and highlights challenges that might be faced when realizing this concept.

Design/methodology/approach – First, maintenance problems that are faced by the industry were presented, followed by a conceptualisation of DM. Next, a typical operational scenario was used as an exemplification to show system dynamics. The characteristics of this conceptualised DM were then mapped to the identified maintenance problems of industry. Then, interesting initiatives in this domain were highlighted, and finally, t~~T~~he challenges to realize this approach were discussed~~., and finally, interesting initiatives in this domain were highlighted.~~

Findings –This paper identified a set of problems related to maintenance in industry. In order to solve current industrial problems, exploit emerging digital technologies and elevate future industries, it will be necessary to develop new maintenance approaches. The mapping between the criteria of DM and maintenance problems shows the potential of this concept and gives a reason to examine it empirically in ~~a~~ future work.

Originality/value – This paper aims to help maintenance professionals from both academia and industry to understand and reflect on the problems related to maintenance, as well as to comprehend the requirements of a digitalised maintenance and challenges that may arise.

1. Introduction

In today's competitive market, manufacturers strive to adapt new technologies in order to improve their performance and secure their market share. Many studies have highlighted the importance of maintenance in enhancing the performance and the profitability of the production process (Al-Najjar, 2000; Waeyenbergh and Pintelon, 2002; Alsyouf, 2004). According to Djurdjanovica *et al.* (2003), implementing a proper maintenance activity can save a company up to 20% due to the resulting smaller production losses, improved product quality, etc.

There have been three industrial revolutions in the past 200 years, driven by mechanisation, electrical power, and information technology (Deloitte, 2015; Drath & Horch, 2014; Kagermann et al., 2013). Now a fourth industrial revolution is expected as a result of the recent technological advancements in the Internet of Things (IoT), the Internet of Services (IoS) and Cyber Physical Systems (CPS). The fourth industrial revolution is characterised by the vertical integration of systems at different hierarchical levels of the value creation chain and the business process as well as by the horizontal integration of several value networks within and across the factory and end-to-end engineering integration (S. Park, 2016; Thoben et al., 2017).

~~Recently, there have been technological advancements and moves towards digitalisation in factories, as well as the development of increasingly complex machines.~~ As such, innovative maintenance paradigms, techniques, tools and systems are necessary in order to fulfil the demands of future industries~~, such as Industry 4.0, Smart Factories, Industrial Internet, etc.~~, as well as, to benefit from the technological advances, which serve as enablers to solve the problems faced by industry (Bokrantz *et al.*, 2017).

With the digital trend in ~~industry~~the recent industrial concepts, such as Industry 4.0, Smart Factories, Industrial Internet, etc., several maintenance terminologies are ~~raised~~ proposed to explain maintenance in digitalised industry, such as Prognostic and health management (PHM), Maintenance 4.0 and Smart Maintenance (Bokrantz *et al.*, 2019). For example, PHM is described as a group of technologies and strategies to promote diagnostic, prognostic and maintenance of a product, machine or process (Qiao and Weiss, 2016; Ayad, Terrissa and Zerhouni, 2018). Maintenance 4.0 is developed to fulfil the demands of Industry 4.0 (Cachada et al., 2018), with an emphasis on maintenance aspects involving data collection, analysis, decision making and visualisation of assets (Kans, Galar and Thaduri, 2016). Smart M~~m~~aintenance is defined by Bokrantz et al., (2019) as ~~an~~ “an organisational design ~~that allows managing the maintenance of manufacturing plants with pervasive digital technologies~~for managing maintenance of manufacturing plants in environments with pervasive digital technologies” (p 11)~~.~~. It is characterised by data-driven decision-making, human capital resource~~s, and~~ internal integration and external integration. To engineer such maintenance solutions, it is essential to determine their tasks and features. Several researchers discussed maintenance tasks for digitalised maintenance (DM) (Labib 2006; Lee *et al.* 2011; Al-Najjar and Algabroun 2017; Algabroun *et al.* 2017). However, these tasks should be extracted with a connection to the principal maintenance objectives. Therefore in this paper, we extract these tasks from the principal maintenance objective using established tools in the domain of software engineering, i.e., stepwise refinement in association with the IBM’s MAPE-K self-adaptive software architecture (Kephart and Chess, 2003). These software tools are employed as it is expected that software will play a significant role in DM, and hence, a proper software engineering perspective is important.

~~Showing~~ Demonstrating the potential of such a concept in a case study requires the full development of the maintenance system, as well as, digitalised industry, which is not the case in this study. As such, in this conceptual work, we employ a typical operational scenario as an illustration of this concept. This scenario is derived from an initiative to develop such a concept. Furthermore, we outline maintenance problems faced by industry ~~and then we~~followed by employing~~ed~~ a logical mapping to indicate the potential of DM and reason how the extracted tasks might solve maintenance problems faced by industry. Moreover, we highlight the challenges that ~~might be faced~~are likely to be faced during the development of DM, in order to help developers to consider them properly, as well as, present interesting initiatives to realise such a concept.

Hence, the aims of this study are as follows: 1) to discuss maintenance problems faced by industry; 2) to conceptualise digitalised maintenance, that is determine its tasks, features and input-output, ~~and~~implement them in a realistic scenario, and then, map them to the maintenance problems identified in aim 1; 3) to strengthen the credibility of developing and implementing such a concept by presenting initiatives in this area ~~to discuss the challenges that might be faced when realizing such a concept~~; and 4) to discuss the challenges that might be faced when realizing such a concept. ~~to strengthen the credibility of developing and implementing such a concept by presenting initiatives in this area.~~

2. The problems and needs of industry today

Maintenance research is a subset of Operations Management (OM) (Holweg et al. 2018). The general empirical inquiry within OM is to explain variation in firm activities (i.e. *practices*) and the influence of such activities on business success (i.e. *performance*). That is, understanding what companies do and how that leads to results; an understanding which constitutes the basis for prescribing actions to practitioners by answering the question: if a company does practice X, will performance improve? (Bromiley & Rau, 2014; Ketokivi, 2016). Within maintenance, this can e.g. be to show that continuous improvements and spare part management improve maintenance performance (Gandhare et al. 2018). Therefore, this section presents current industrial problems with respect to maintenance practices and performance, as highlighted in empirical literature. The problems are not intended to be exhaustive, but rather to provide an overview that supports a mapping of the proposed digitalised maintenance concept with the real needs of industrial practice (Section 4).

2.1. Maintenance practices

A practice is defined as an activity or a set of activities that a variety of firms may execute (Bromiley & Rau, 2014). An overview of problems with current industrial maintenance practices that could be positively influenced by the proposed maintenance approach is presented below.

Most simply, the role of the maintenance organization is to maintain plant equipment according to the company policy. That is, to ensure that all equipment is up and running and in healthy condition, not to repair them after failure. However, a long range of studies have consistently shown that reactive maintenance dominates industrial practice and that too little time and effort are spent on preventive actions (Lee Cooke, 2003; Chinese and Ghirardo, 2010; Jin *et al.* 2016; Ylipää *et al.* 2017). These findings are alarming in light of the empirical evidence which shows that reactive maintenance is negatively associated with performance (Swanson, 2001).

To move from reactive to preventive practices and thus meet their objectives, maintenance organizations need to utilise supportive digital technologies and adopt more sophisticated engineering approaches. However, studies point towards that the awareness and adoption of such approaches are limited in industry. For example, very few predictive maintenance practices are utilised in industry (Jin *et al*. 2016), maintenance is rarely involved in the engineering work in early phases of plant design and development (Sandberg, 2013; Bokrantz *et al.* 2016a), and even the most common maintenance concepts Total Productive Maintenance (TPM), Reliability-centered Maintenance (RCM) and Condition-based Maintenance (CBM) are not extensively used (Alsyouf 2008; Bokrantz *et al.* 2016a). Moreover, many theoretical assumptions about how practitioners actually use CBM do not hold against empirical evidence (Veldman et al. 2011), and using CBM in practice is much more complex and time-consuming compared to what is being described in literature (Akkermans et al, 2018). Although, CBM was introduced in the middle of the last century (Prajapati, Bechtel and Ganesan, 2012; Ruiz-Sarmiento et al., 2020), and since then, numerous techniques for condition monitoring were developed, including shock pulses, temperature monitoring, vibration, and acoustic emission (Prajapati, Bechtel and Ganesan, 2012; De Azevedo, Araújo and Bouchonneau, 2016), in industry however, CBM implementation is yet limited to significant components. The costs of its life cycle and its complex technology could be some of the reasons behind its limited applications (Guillén et al., 2016). Furthermore, companies also face a variety of organizational and human implementation challenges that prevents them from extensively using CBM and other data-driven maintenance practices (van de Kerkhof et al., 2016; Gopalakrishnan et al. 2019).

Since the introduction of Information Technology (IT) within the maintenance realm, e.g. Computerised Maintenance Management Systems (CMMS), the use of IT to improve maintenance practices has been a major interest among researchers (Muller *et al.* 2008). The expanding data amount in maintenance departments has motivated the needs for CMMS to manage and access data in real time. However, utilising the stored data to provide instructions and guidelines to engineers, as well as, to mangers to provide appropriate decision remains a challenge (Rastegari and Mobin, 2016). Furthermore, CMMS lacks the decision analysis capabilities and it is mainly used as an administrative tool (Kans, 2008; Rastegari and Mobin, 2016). Today, data-driven decision-making is a core dimension of modernised maintenance management (Bokrantz, 2019a; 2019b). However, CMMS and company-wide IT solutions are still not completely diffused in industry (Kans, 2013), and maintenance information systems are often decoupled from the rest of the plant (Sandberg, 2013), which can be a barrier in collecting data from working areas which are relevant to maintenance such as economy, quality and production. Therefore, management of information systems within maintenance often represents a weak link for improving performance (Naji et al. 2019). To increase the use of data-driven maintenance practices, a clearly expressed industrial need is simple and user-friendly decision support systems (Bokrantz *et al.* 2017a). However, user-friendly industrial applications of predictive maintenance are still scarce (Vogl *et al.* 2016) and maintenance organizations often lack the relevant data to drive decision making (Jin *et al.* 2016). In addition, lack of quality data is a common and critical concern for maintenance decision making (Lin *et al.*, 2007; Bokrantz *et al.* 2017b; Kumar et al. 2014), and it is one of the reasons for the low use of advanced analytics in maintenance practice (Zio, 2009). Extensive data management challenges are further corroborated by the case study in Razmi-Farooji et al. (2019). Hence, neither data with sufficient quality nor user-friendly systems for advanced maintenance analytics is readily accessible to the manufacturing industry.

On a strategic level, there is often limited connection between the maintenance strategy and the corporate strategy (Lee Cooke, 2003), and many companies do not even have a formal maintenance strategy (Jonsson, 1997; Alsyouf, 2009). This is typically reflected in top-down initiatives for short-term reduction of direct maintenance costs (Waeyenbergh & Liliane Pintelon, 2009), where maintenance organizations are perceived as cost centers that are necessary to have but always desirable to decrease the budgets for (Salonen & Deleryd, 2011). Consequently, while maintenance spending constitutes a large part of a manufacturing firm's operating budget, maintenance organizations often have little influence on the circumstances that are truly decisive of a firm's expenditures and earnings (Sandberg, 2013). These are also underlying reason as to why maintenance has low status within companies (Jonsson, 1997; Alsyouf 2009; Chinese and Ghirardo, 2010). The general perspective on industrial maintenance has therefore been expressed as that most maintenance organizations do not realise their full potential (Cholasuke *et al.*, 2004) and that maintenance practices can be greatly improved in the average manufacturing firm, regardless of industry or size (Jonsson, 1999). Therefore, in light of the current trends of digitalisation, it is evident that industrial maintenance practices must be radically improved to meet the current and future demands of manufacturing firms.

2.2. Maintenance performance

Performance at the level of the firm is often defined and operationalised differently (Miller et al. 2013), but most operations management researcher use measures of operational performance at the level of the plant, typically consisting of e.g. cost, quality, flexibility and lead time (Turkalainen & Ketokivi, 2012). Maintenance performance is ideally measured in terms of both internal efficiency and external effectiveness, where external effectiveness can be equated with the measures of operational performance. Arguably the most common industrial measurement of internal efficiency of maintenance is Overall Equipment Effectiveness (OEE) (Nakajima, 1988). OEE is a simple measure of productivity intended to capture and highlight equipment problems relevant to maintenance, and it contributes to making maintenance a strategic issue within a manufacturing firm (Jonsson & Lesshammar, 1999). There has been a long range of studies that publish industrial OEE data and thus highlight current problems with maintenance performance.

Over the past 25 years, the average industrial OEE has been consistently reported in empirical studies to be around 50-60% (Ahlmann, 1993; Ericsson, 1997; Ljungberg, 1998; Ingemansson, 2004; Almström & Kinnander, 2008; Ylipää *et al.* 2017), clearly indicating that a very large part of the total production capacity is vanished due to equipment losses. It is therefore not surprising that low OEE is argued to be one of the largest problems in industry today (Kumar *et al.* 2013), and it is evident that the average manufacturing firm has the potential to significantly improve productivity and efficiency by measuring, analyzing, reducing, preventing and eliminating production disturbances (Bokrantz *et al.* 2016b). In detailed OEE empirical studies, unplanned downtime represents around 10 percent of the total losses and availability is shown to have a large impact on the overall OEE, thus signaling a significant improvement potential for maintenance performance (Ylipää *et al.* 2017).

However, despite common belief, maintenance contributes far beyond the confines of availability. For example, a holistic categorization of expected performance outcomes from modernized maintenance operations at the plant- and firm-level is provided by Bokrantz et al. (2019b). Although not all losses within the OEE are attributable to maintenance (e.g. set-ups), the conservative perception is that maintenance activities are only capable of directly influencing planned and unplanned downtime losses. In contrast, maintenance also indirectly influence e.g. speed and quality losses (Muchiri *et al.* 2011), but even more importantly play a central role with regards to system losses (Li et al. 2009). In manufacturing, system losses occur largely due to ripple effects caused by machine downtime, specifically in the form of blockage and starvation (i.e. idle time). This mean that the direct control of downtime with maintenance activities has an indirect effect on idle times in the entire production system. Maintenance can influence these system losses by e.g. prioritizing activities towards the current system constraint (i.e. bottleneck) (Gopalakrishnan & Skoogh, 2018; Gopalakrishnan et al. 2019). The bottom line is that addressing maintenance requirements of individual machines is necessary but not sufficient. Instead, a system perspective is also needed in which the simultaneous maintenance of multiple pieces of equipment in a production system is aimed at optimizing the performance of the entire system, not solely the individual machines (Bokrantz *et al.* 2017a). In fact, Jin (2016) observe that most currently available solutions for diagnostics and prognostics are only capable of analysing component- and machine-level data. In contrast, there is clear need in industry for system-level solutions that can analyse multiple machines and/or entire production systems.

Maintenance digitalisation could support solving several of the above problems. One action that might treat the above problems is the development and implementation of the proposed digitalised maintenance concept in this article. The following sections demonstrate this by mapping tasks and features and exemplifying initiatives pursuing this change.

3. The conceptualisation and characteristics of a digitalised maintenance system

In this paper, a digitalised maintenance system is defined as "a system that utilises digital technology as a way to conduct or assist in conducting maintenance". In order to develop such a system~~a digitalised maintenance~~, it is important to first conceptualise it; that is, to understand its tasks, features and input/output.

Several studies have discussed these tasks and requirements (Labib 2006; Lee *et al.* 2011; Al-Najjar and Algabroun 2017; Algabroun *et al.* 2017). In previous studies, a group of researchers developed the tasks and features of a maintenance approach for Industry 4.0 (Al-Najjar and Algabroun, 2017); they extracted software components using top–down analysis, creating a framework for a digitalised maintenance approach (Algabroun *et al.*, 2017). In contrast, in this paper we will use design tools from the field of software engineering (stepwise refinement in association with MAPE-K software architecture) to systematically analyse the principal maintenance objective with the aim of extracting the required tasks and subtasks. Stepwise refinement is employed as it uses a software engineering perspective and, hence, is more suitable for this purpose.

3.1. Using the stepwise refinement process to determine tasks

In the stepwise refinement approach, an abstract objective of a system is refined into one or more components with tasks that are more concrete and less abstract. This is done in such a way that these tasks collectively preserve the system's original objective. If a refined task remains abstract, then the refinement process continues until a level at which the subtasks are implementable (Abbott, 1987; Wooldridge, 1997; Refsdal *et al.,* 2015). This approach has several advantages, including: 1) it provides a foundation for a separation of concerns (i.e., each refined component is more independent); 2) the components become easier to understand, as they are smaller and more independent; and (consequently) 3) the maintenance, modification and development of the system are thereby simplified.

To perform the stepwise refinement analysis, we started by identifying the main objectives and then analysing and refining them. In general, the main objective of maintenance is to elevate the production machines' availability and promote their good health in a cost-effective way (Al-Najjar, 1997; Takata *et al.*, 2004; Sandberg, 2013). In order to achieve this objective, it is essential to 1) collect relevant data related to the machine and other working areas (such as production, quality, economy, etc.). 2) The collected data has to be analysed, so that it can be converted into useful and actionable information. Following this, 3) a suitable action and its time should be ~~determined~~ decided based on the received information. Finally, 4) the decision is executed at the determined time.

This pattern has similarities to the ~~famous~~ IBM's MAPE-K (Monitor, Analyse, Plan, Execute-Knowledge) self-adaptive software architecture (Kephart and Chess, 2003), and therefore, it has been adopted in this paper; self-adaptive software architecture allows designing a software system that autonomously adapts itself at runtime to deal with uncertainties (e.g. faults or variation in resources), examples of this approach can be found in Kramer and Magee, 2007 and Iftikhar and Weyns, 2014. In this paper, the authors claim that MAPE-K could be used as a base for conceptualising DM, as it has all of the necessary elements to conduct a maintenance action. This architecture can be summarised as four tasks: *monitor, analyse, plan*, and *execute* which share knowledge stored in a repository. These tasks can be viewed as the main steps of a maintenance action (Algabroun *et al.*, 2017). However, in the context of this paper, another component is important; namely, *user interface*, the means by which the user can interact with the system and be presented with the relevant information (Algabroun *et al.*, 2017).

Several constituents might be involved to conduct these tasks, such as sensors, communication systems, processors, middleware, databases, applications, actuators, etc. However, the technical specifications of these constituents and specific technologies are beyond the scope of this study.

The main tasks mentioned above (i.e. monitor, analyse, plan, execute and user interface) could be further analysed, extracting the following subtasks:

Monitor: In order to perform the required tasks and collectively achieve the objectives, it is essential that the system possesses the required information. Therefore, the system should have the ability to collect and receive data from sensors as well as that pertaining to other relevant working areas, such as production, economy, quality, etc. (Al-Najjar, 1996; Takata *et al.*, 2004; Sandberg, 2013). The collected data should be updated and stored in a data repository (e.g. a database or cloud) for future utilisation. As such, the subtasks here are named 1) *data collection* and 2) *data updates*.

Analyse: To determine the required maintenance action and the most profitable time at which it should be conducted, it is essential to analyse the collected data. This is to detect abnormalities in the production process, identify the causes behind and predict any likelihood of damage development and (should this occur) ascertain the damage severity. Moreover, when planning the maintenance action, all possible scenarios and their consequences should be first being identified. Accordingly, the subtasks here are 1) *abnormality detection*, 2) *diagnosis*, 3) *prediction*, 4) *severity assessment* and 5) *generation of possible scenarios*.

Plan: The plan that is best aligned with the company's goals and which suits its specific situation can be selected from the scenarios generated during the previous task. Any adjustments required by the company's specific situation can be entered and/or modified as a part of the *user interface* task. The selected plan would then have to be constructed in detail, with all the required resources (spare parts, human resources, tools, etc.) prepared accordingly. Thus, the subtasks here are 1) *plan selection* and 2) *plan construction*.

Execute: At the planned time (which would be determined as part of the previous task), the predetermined maintenance action is conducted. Several tools (such as augmented reality (AR)) could be used to perform maintenance actions efficiently and correctly (Mourtzis *et al.*, 2017; Palmarini *et al.*, 2018). Alternatively, documents that detail how to conduct the required maintenance could be employed. In some cases, actuators could be used to perform specific maintenance actions (Al-Najjar and Algabroun, 2018). Therefore, the subtask here is considered to be *execution assistance*.

User interface: This provides a means by which to interact with the system. For example, it might present the relevant information (such as diagnoses, predictions, maintenance work progress, completed tasks, maintenance recommendation, etc.) to the end users and other systems/working areas, as well as modifying or entering new information. Therefore, the subtasks here are considered to be: 1) *information visualisation* and 2) *user-input updates*. Figure 1 visualises the stepwise refinement analysis.

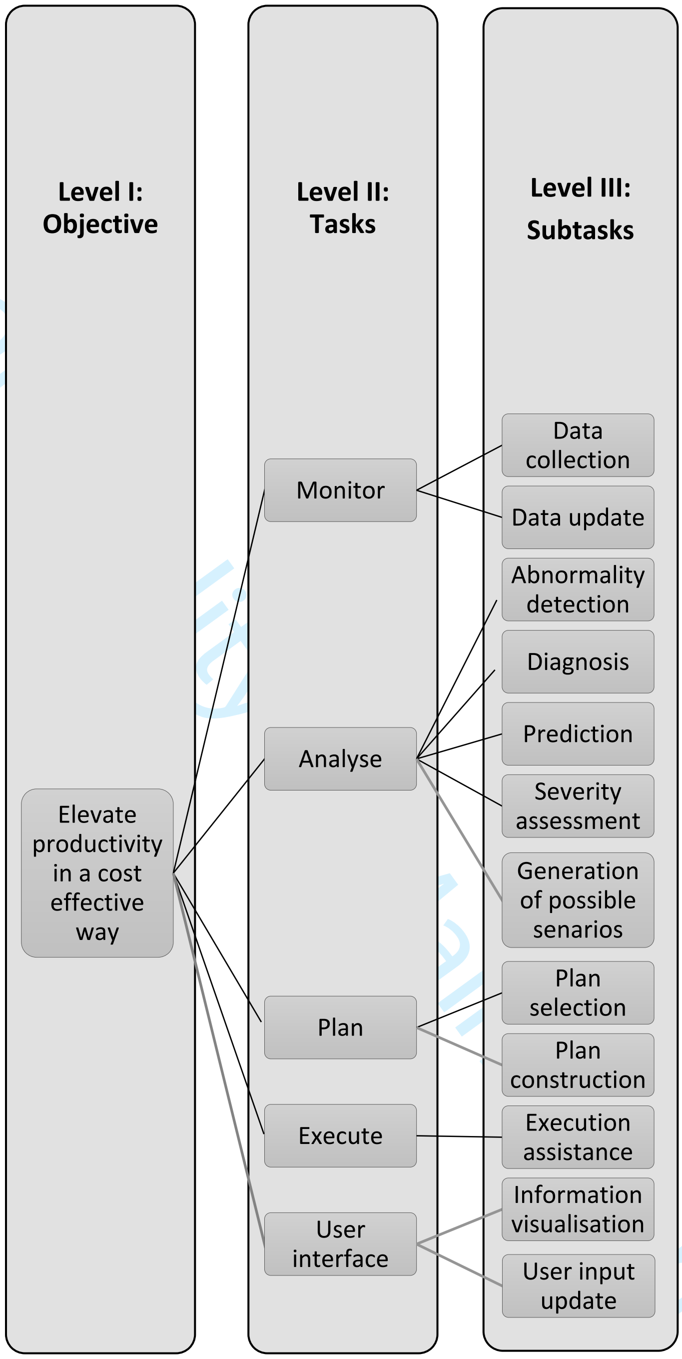

Figure 1: Stepwise refinement process used to find tasks and subtasks

3.2. Features of digitalised maintenance systems

Certain features can enhance the performance of digitalised maintenance systems; therefore, they should be taken into account during both the design and the development process. These features are discussed in several studies (Labib 2006; Lee *et al.* 2011; Al-Najjar *et al.* 2018) and can be summarised as follows:

- Modularity: a modular design enables system modifications through the adding, replacement or removal of modules using the plug-and-play principal (Hermann et al., 2016). This facilitates any adjustments to the maintenance system that are required in order to fulfil the dynamic demands of factories.

- Scalability: a digitalised maintenance system should possess the ability to include new machines in order to meet growing business needs.
- Decentralisation: evolving industrial concepts tend to be decentralised (Hermann *et al.*, 2016). For this reason, a digitalised maintenance system should be compatible with a decentralised production process.
- Interoperability: this allows communication among the elements within the maintenance system, as well as with other systems in the plant.
- Digitalisation: the proposed maintenance ~~approach~~ system relies heavily on digital technology; digitalisation facilitate integration and automation, as well as data collection, utilisation and storage.
- A consideration of production-based and economic key performance indicators (KPIs): one of the main objectives of maintenance is to improve production performance cost-effectively. For this reason, the maintenance system should be able to consider both production and economic KPIs in order to assess and improve maintenance impact.
- Automation: this promotes automated production processes and allows gaining quicker responses to events (e.g. faults).
- Real-time ability: In order for the maintenance system to respond rapidly to variation and to events that occur in production, it should possess the ability to collect and analyse data in real time.

3.3. Input–output

Based on the analysis provided in section 3.1, the input of this approach comes from three main sources: 1) condition monitoring sensors through the monitor task; 2) a data repository, such as a cloud or database which contains relevant information from other working areas; 3) directly from users (e.g. strategic goals), which is the input inserted using the task of user interface. These three input sources are used to provide the following three outputs: 1) maintenance recommendations (i.e. what maintenance action needs to be done and when this should happen). These recommendations are result from the analysis and plan tasks; 2) information to other working areas and/or maintenance personal (e.g. pending work, work progress, or closed work orders), and 3) automatic actions (see also Algabroun *et al.*, 2017). Figure 2 illustrates the input–output of the system.

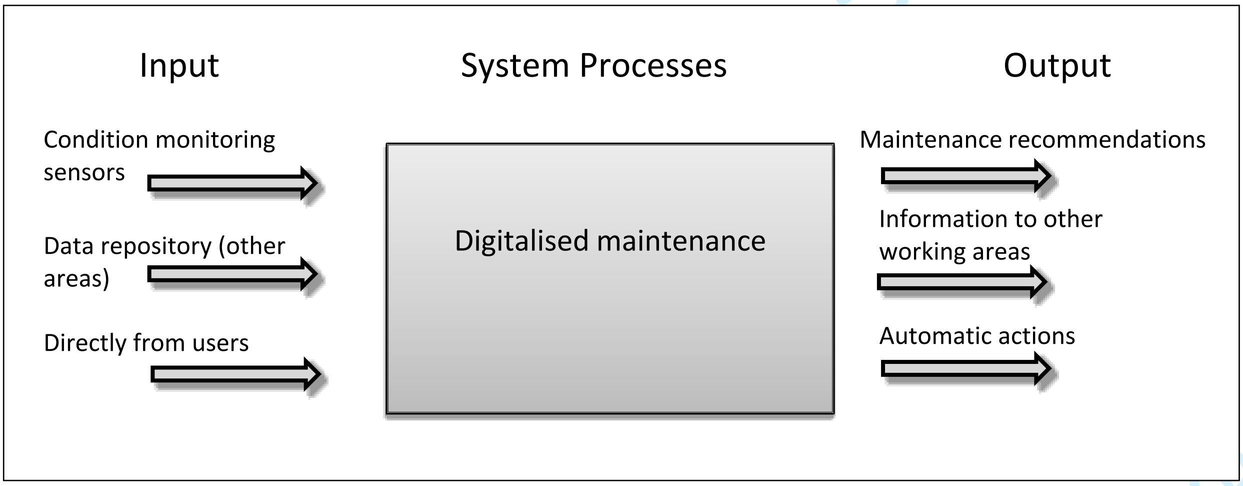

Figure 2: Input–output of the digitalised maintenance approach

Next section employs a typical scenario to exemplify the conceptualised ~~approach~~system and to show how the software components can work together. To explore ~~the ability~~how ~~of~~ the conceptualised DM system might ~~to~~ solve the industrial problems identified in section 2, ~~the next~~ section 5 maps between the identified tasks and the problems.

4. Operational scenario

This section provides an exemplification using a scenario derived from the planned implementation of PreCoM project (Algabroun et al. 2020, see also section 6.1). Figure 3 illustrates the dynamic aspects of the scenario using unified modeling language (UML)-sequential diagram.

4.1. Presetting:

PreCoM is designed to be a distributed cloud based system, therefore, it contains several independent modules, in which each located in a different server and in a different location. The involved modules are: PreCoM Brain (a central control unit that orchestrates the interaction among modules using HTTP methods and controls the recommendations from the different modules to avoid contradictions), PreCoM Cloud, sensors, user interface (UI), augmented reality program (AR), abnormality detector (a software module named PreVib-ProLife, developed by Linnaeus University and E-~~maintnenace~~maintenance Sweden AB), production scheduler, stress-condition evaluator (a module that assesses the available time for the machine through surveying the required maintenance actions and the time to conduct these actions) and maintenance schedule optimizer (a software module named MaintOpt, together with stress-condition evaluator developed by Linnaeus University and E-maintenance~~maintnenace~~ Sweden AB).

The machine considered in this scenario is a paper mill machine, named PM6, located in Spain that produces tissue papers.

4.2. Scenario

- In the PM6 machine, a damage is occurred in the bearing (i.e. deep groove ball bearings 618/500 M.C3) that is located in the yankee dryer cylinder (a machine component that is used to remove moisture from pulp in order to be further processed into paper) in the motor front. The bearing is monitored by a wireless triaxle vibration sensor (named Ronds RH605).
- The collected data is then sent by the sensor to a wireless data acquisition station (named Ronds RH560). Next, the data is preprocessed (in term of digital filtration, Fast Fourier Transform and Enveloping) and a POST request (HTTP method) is sent informing PreCoM Brain in PreCoM Cloud about the data availability. PreCoM Brain then initiates a GET request (HTTP method) to import the data.
- After the vibration measurements are obtained and stored in the Cloud, PreVib-ProLife module is invoked by PreCoM Brain using POST request to collect the data using GET request and start the analysis in order to detect abnormality, and if so, to provide the diagnosis and prediction of the deterioration in the near future, assessment of probability of failure and residual live, and recommend a maintenance action.
- PreVib started the analysis and detected an abnormality. Assume that the damage is mainly caused due a damage in the inner ring of the bearing, the rms value is obtained.
- Based on the analysis a warning level of 4 (where level of: 4 represents 'maintenance should be planned', 3 represents 'Examine whenever it is possible', 2 represents 'Probable damage development, await', 1 represents 'No serious damage, await' and 0

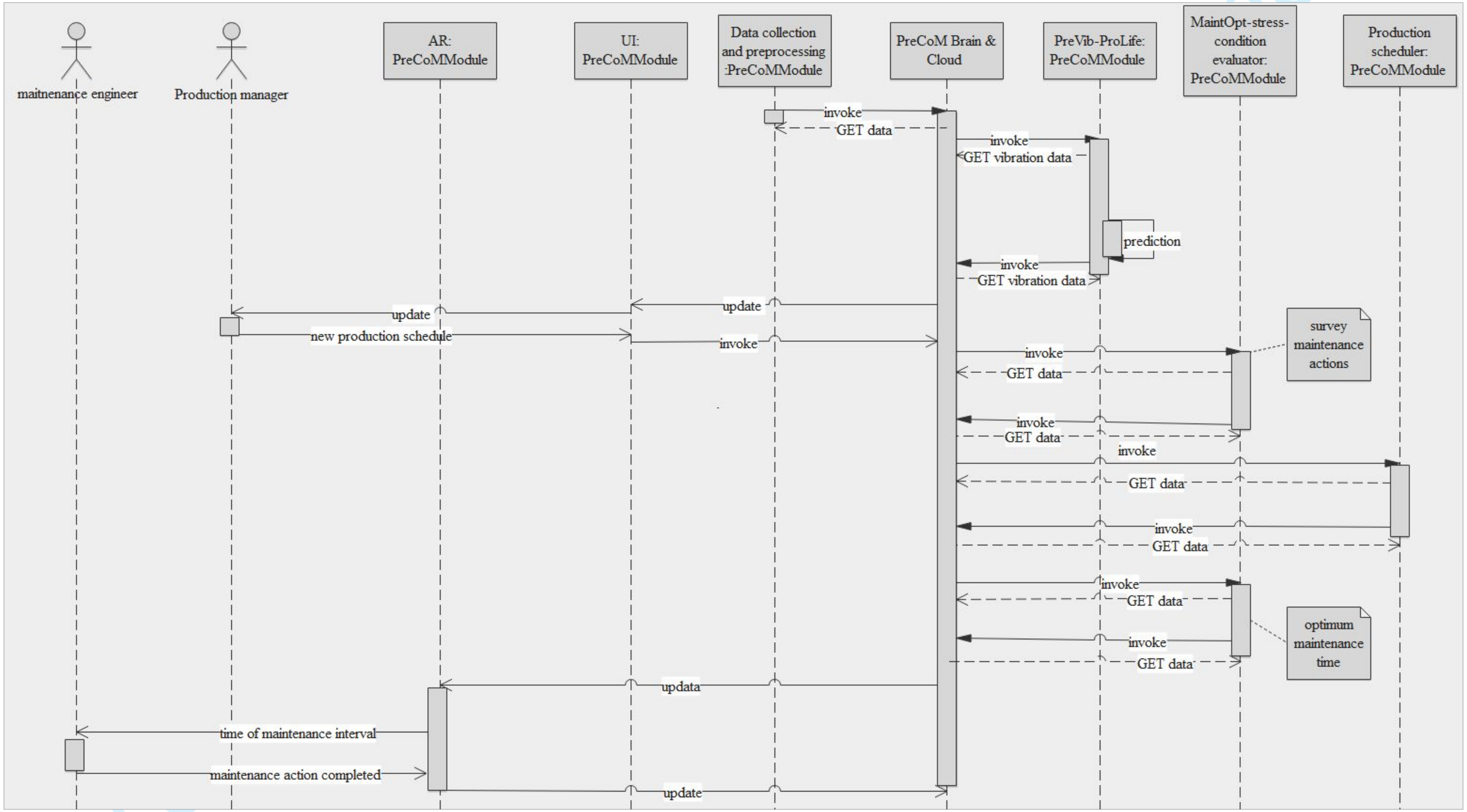

Figure 3:~~1~~ the scenario dynamics using sequential

represents 'No damage') is provided which indicated that damage in the bearing is developed and there is a need for maintenance. Based on ProLife analysis (i.e. probability of failure and residual live) the maintenance interval is decided automatically. The information is then stored in PreCoM Cloud.

- The recommendation is visualized by a user interface (UI) to the production and maintenance managers. Production manager requested a new production plan based on the occurred event.
- PreCoM Brain invoked the stress-condition evaluator module using POST request to survey the coming maintenance actions (e.g. if in the meantime breakdowns, malfunctions, Preventive Maintenance (time planned) as well as the actions recommended by PreCoM based on the diagnosis report). The stress-condition evaluator collected this data using GET request, perform the survey and the resulted information is then stored in PreCoM Cloud.
- PreCoM Brain invoked the production scheduler program using POST request in order to provide a new production schedule with respect to the new events. Production scheduler program collected the required data from PreCoM Cloud using GET request and started the analysis. The results are then sent to PreCoM Cloud.
- Next, as soon as the new production schedule has arrived at PreCoM Cloud, MaintOpt is invoked (using POST request) by the PreCoM Brain to provide the optimum maintenance interval time for conducting all the maintenance actions needed at that moment, see the bullet above. MaintOpt collected the data from PreCoM Cloud using GET request, analysed the data and results are stored in PreCoM Cloud.
- When the determined time for the maintenance action arrives, the maintenance technician uses AR tool to visualize the required information, e.g. to allocate the machine, the component and to visualize the required steps according to the best practices. When there is a difficulty in preforming the required action, a video call is performed with a more senior engineers to support the technician.
- When the work is executed, the work order is closed and other information is registered (e.g. time length needed to conduct the maintenance action recommended) for statistical analysis, and for continuous improvement purposes (e.g. assessing PreCoM impact of machine availability and maintainability).

4. Mapping the maintenance tasks to the problems of industry

In the previous sections, the~~a~~ conceptualisation of a digitalised maintenance system was conducted using stepwise refinement and then the concept is exemplified using a scenario. This conceptualised maintenance approach should aim to solve the problems faced by industry today. In order to highlight the relevance of this approach to the problems faced by industry, we map the tasks (outlined in section 3) to the problems in industry (outlined in section 2).

Table I lists the current problems (identified in section 2) and describes how the proposed approach might solve them. Following this, some initiatives in this field will be highlighted and the potential challenges involved in developing such an approach will be discussed.

Table I. lists the current problems (derived from section 2) and describes how the proposed approach might solve them

~~5. Challenges~~

~~There are numerous enablers for the development and implementation of this approach. These include the continuous development of software and hardware with price reduction, as well as the evolution of new methods and concepts such as the Internet of Things (IoT), Internet of Service (IoS), and Cyber-Physical Systems (CPS). However, despite these enablers, the development and implementation of such a maintenance approach is a complex initiative that might involve a number of overlapping challenges in different areas.~~

~~The aim of this section is to discuss these challenges in order to help the developers to identify and consider them properly. To identify these challenges, a literature survey was conducted. Four main stages to execute this survey have been used. First, keywords that represent the entire project aspects were formed. Next, database search was conducted using the keywords. Then, the related papers were selected, and latterly, relevant information was extracted.~~

~~The keywords that represent the study problem were: maintenance, intelligent, digitalisation, digitisation, automation, smart, problems, challenges, industrial internet of things, industry 4.0, connected industry and maintenance 4.0. Then, the keywords were used to search in databases using different ways of combination and thesauruses. The search was Boolean based using the One-Search engine (provided by Linnaeus University), which is linked to different databases such as IEEE, Springer Link, Emerald and Science Direct as well as Google. Then, in the One-Search engine the unrelated subjects were removed (e.g. health science, social comparison, etc.) and the following inclusion criteria were employed: full text available, English language, peer reviewed, academic journals, conference materials and book chapters. After reading the abstracts, 26 articles were selected, and eventually, 12 articles found to be relevant after going through the articles and their references list.~~

~~The challenges were found fragmented in twelve articles (Kagermann *et al.*, 2013; Deloitte, 2015; Ma *et al.*, 2016; Halenár *et al.*, 2016 ; Zhu *et al.*, 2017; Bokrantz et al. 2017; Khan *et al.*, 2018; Wabner, 2018; Simon *et al.*, 2018; Algabroun, 2019; Bokrantz et al; 2019a; Bokrantz et al. 2019b). These challenges could be categorised under the following five major categories: technological advancements; data utilisation; human resources competence; regulations and standards; and capital investments. A description of these challenges is provided below.~~

~~*5.1. Technological advancements*~~

~~The proposed maintenance approach could be realised and developed using recent technological advancements; however, various technological challenges might still be faced. These challenges will vary as a result of different factors, such as type of industry, environment and size of factory.~~

~~For instance, in some industrial cases where remote data measurements are required, some factors such as harsh environments or the existence of large-body obstacles could cause difficulties when attempting to implement a reliable data acquisition system (Ma *et al.*, 2016; Zhu *et al.*, 2017; Khan *et al.*, 2018). Additionally, the limited battery life of the wireless sensors will pose a challenge when used in some applications, particularly in inaccessible areas (Algabroun, 2019).~~

~~Another example of a technological challenge is the utilisation of AR tools when a manual job is required. In this case, the development of an industry-applicable AR tools that support hands-free interaction could be difficult (Wabner, 2018).~~

~~The challenges will also vary based on the size of the enterprise. For example, some of the technology required by the proposed approach(e.g. Information and Communication Technologies ICT) could be too complex for small and medium enterprises, restricting its adoption (Wabner, 2018).~~

~~Issues related to safety and security aspects could present challenges when designing and developing the proposed maintenance approach. The developed technology must expose neither the environment nor people to harm. It must also protect data and information against abuse and/or unauthorised use. This will require the development of security reference architectures and unique identifiers (Kagermann *et al.*, 2013; Deloitte, 2015).~~

~~*5.2. Data utilisation*~~

~~Data coming from different systems and working areas provides tremendous value to maintenance and production activities, providing it is properly exploited.~~

~~Continuous data expansion presents major challenges; these include how to manage a large quantity of data as well as how to develop more accurate prognostic algorithms that incorporate deterministic approaches. Additionally, methods that utilise the data to accurately estimate the economic impact of maintenance are not yet well developed (Wabner, 2018). Most importantly, data utilisation must span all the way from collection and analysis to decision-making. Data has no value unless it is used to drive decision-making within maintenance (Bokrantz et al. 2019a).~~

~~*5.3. Human resources*~~

~~Implementing such a digitalised maintenance approach will present many employees with new challenges. There will be greater need for more sophisticated digital competence. Additionally, organisations will have to pay greater attention to proper recruitment, training and education if they are to leverage competence within the organisation (Kagermann *et al.*, 2013; Bokrantz et al. 2017). More specifically, maintenance employees must develop new and higher levels of analytical-, ICT- , social-, business-, adaptability- and technical skills (Bokrantz et al. 2019a).~~

~~*5.4. Regulation and standards*~~

~~This maintenance approach relies on data and information exchange among different elements to achieve its tasks. These elements include machines, sensors, humans, artificial intelligence and relevant working areas. Collaboration would be impossible without developing appropriate standards that specify the nature of the interactions that occur among these elements.~~

~~Several attempts at developing such standards are currently still in progress (Simon *et al.*, 2018). Due to the delay in forming proper standards, the integration of and communication among these elements will be a challenge (Deloitte, 2015; Halenár *et al.*, 2016). Legal issues will also have to be taken in consideration regarding, for example, liability issues, data ownership, intellectual property, and safety and security (Deloitte, 2015; Bokrantz et al. 2017).~~

~~*5.5. Capital investment*~~

~~Implementing this concept is technologically intensive; therefore, purchasing or modifying the currently available systems (e.g. sensors, data acquisition systems and software) will be necessary in many cases and will probably require an investment in maintenance with a considerable cost (Wabner, 2018). However, it has been reported by many studies that maintenance has often been regarded by top management as a cost centre, rather than as a profitable opportunity (Alsyouf, 2004; Takata *et al.*, 2004; Al-Najjar, 2007; Pintelon and Parodi-Herz, 2008; Salonen and Deleryd, 2011). This is due to a lack of realisation and understanding of the impact of maintenance on a company. In addition to capital investments, companies must also invest in a variety of intangible complementarities such as training, education and organizational re-design (Bokrantz et al. 2019b).~~

~~Although, over the last decade, companies have started to recognise maintenance as a profit generator and an essential element to achieving companies' objectives (Alsyouf, 2004; Pintelon and Parodi-Herz, 2008), the cost factor is still a determinant aspect when making a decision (Wabner, 2018). As such, financial justification still has to be demonstrated (Bokrantz et al. 2019b). In general, the impact of maintenance cannot easily be accurately estimated (Alsyouf, 2004; Al-Najjar, 2007) and therefore this justification could be also a challenge.~~

~~6.~~5. Initiatives in this field

There are several studies related to digitalised maintenance (Yuniarto and Labib, 2006; Camci, 2009; Lee *et al.*, 2011; Langeron *et al.*, 2015; Guillén *et al.*, 2016). The focus of these studies is only on some aspects or functions of the digitalised maintenance system considered in this study, such as prediction, condition-based maintenance and scheduling optimisation. However, as described in section 1 and 2, the focus of this paper is on a digitalised maintenance approach that covers the entire maintenance action process.

~~The aim of this section is T~~to strengthen the credibility of practically developing and implementing the maintenance approach proposed in section 3, as well as, to raise the awareness of interested developers and maintenance professionals about such initiatives, so they can follow their implementations. This section will therefore present some initiatives in this domain that fulfil the following two criteria: 1) practical initiatives; 2) similar initiatives to the approach presented in this paper.

~~To find relevant initiatives, a similar survey process employed in section 5 was used. The used keywords to conduct the survey were: maintenance, intelligent, digitisation, digitalisation, automation, smart, application, case study, industrial internet of things, industry 4.0, connected industry and maintenance 4.0. After going through the abstracts and webpages, 11 articles were selected, and eventually, three articles found to be relevant, which are: two European Union–funded projects and one case study.~~ These initiatives are presented as follows:

6.1. Predictive Cognitive Maintenance Decision Support System (PreCoM)

PreCoM is a three-year (2017–2020) cross-functional project funded by the European Union's Horizon 2020 research and innovation programme (see https://www.precom-project.eu). The objective of this project is to develop, implement and evaluate a digitalised maintenance system that is able to detect and localise damages, assess severity, predict the remaining useful life, optimise production and maintenance scheduling, and assist in the repair work.

PreCoM consists of four modules:

- data gathering module that collects data from external sensors as well as embedded sensors in the machine tool,
- artificial intelligence module that analyses the gathered data using several models and algorithms including physical models, statistical models and machine-learning algorithms,
- secure integration module; this module is responsible for the integration of PreCoM modules with other systems in the company such as production planning and maintenance systems,
- user interface module which includes production dashboards as well as AR for maintenance staff.

This project is an innovative action that is designed in connection with real-world industrial companies and will be demonstrated and validated on three industrial facilities in three different sectors. These sectors are: 1) the low-volume sector, where large metal parts are manufactured; 2) the high-volume sector, which focuses on the production of reduction gears; and 3) continuous manufacturing processes in the field of paper manufacturing.

The expectations of the project are determined in measurable values, as follows:

1) Increase availability and maintainability by 15%
2) Reach 30% of time spent on predictive maintenance
3) Reduce failure-related accidents by 30%
4) Reduce energy consumption by 6–10%
5) Reduce raw material consumption by 7–15%.

6.2. VerSatilE plug-and-play platform-enabling remote pREdictive maintenance (SERENA)

SERENA is a three-year project (2017 - 2020) funded by the European Union that consists of 13 participants (see https://cordis.europa.eu/project/rcn/211752/factsheet/en) aims to develop a digitalised maintenance solution that fulfils the following demands: versatility; transferability; remote monitoring; and control. This will be achieved through: 1) a plug-and-play cloud-based solution for data management and processing; 2) systems for data collection and monitoring of machines' conditions; 3) artificial intelligence techniques for predictive maintenance and maintenance and production activity planning, 4) AR-based technologies to support the performance of maintenance actions and present information concerning machine conditions.

The solution will be demonstrated in different industrial domains (white goods, steel parts, metrological engineering, and elevator production). Its applicability in steel parts production will also be investigated.

The impact expectations of SERENA are:

1) 10% increase in-service efficiency
2) Greater utilisation of predictive maintenance
3) Improvements to accident mitigation.

6.3. 5C architecture

This approach is based on a five-layer architecture named 5C (Lee *et al.*, 2015). This architecture consists of five steps, from data collection to execution. The five layers are summarised as follows:

1) Smart connection: in this layer, relevant data are collected from machines through sensors and other relevant working areas through Enterprise Resource Planning (ERP), Computerised Maintenance Management System (CMMS), etc.
2) Data related to information conversion: the collected data from different working areas is analysed and converted into meaningful information.
3) Cyber layer: the information related to the other machines in the facility is collected in this layer. It will then be possible to implement more advanced analytics (e.g. a clustering techniques). This allows the condition of a particular machine to be compared to that of other machines.
4) Cognition: at this layer, a decision relating to the required maintenance action and the time at which it occurs can be made. This decision will be based on the knowledge acquired through the previous processes.
5) Configuration: the decision will be executed at this layer. The execution could take, for example, the form of maintenance recommendations or automatic actions through actuators.

An empirical study analysing this approach, using three band-saw machines in different locations as use studies, is presented in Bagheri *et al.* (2015). The goal was to achieve a balance between two parameters: production quality and production speed.

At the first level ("smart connection") the data was collected from add-on sensors as well as from the machines' controllers. The collected data was then initially analysed at a local industrial computer at the level of "data to information conversion". Following this, it was sent to the "cyber" layer, in the cloud. An adaptive prognostic algorithm was then used to determine a suitable working regime. Finally, at the "configuration" layer, the machines were set to adhere to the determined working regime.

6. Challenges

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7. Conclusion

Innovative maintenance approaches have had to be developed in order to cope with the new digitalised technology employed in industry and ensure its sustainability. This study aims to conceptualise a digitalised maintenance system in order to give new insights, organise thoughts and understand its boundaries and challenges ~~of digitised maintenance~~. It discusses a digitalised maintenance approach with consideration of maintenance problems. Maintenance problems that are faced by industry was discussed and categorised into two categories; practices and performance. The gap between maintenance in theory and practice emphasises the importance of considering an empirical approach of this concept for a future study.

A conceptualisation of a digitalised maintenance approach was presented, using stepwise refinement in association with MAPE-K. Using MAPE-K in the conceptualisation will ease utilising it as a software system architecture during the implementation. This maintenance approach was then exemplified in an operational scenario derived from the implementation of the PreCoM project. Then the characteristics of the conceptualised approach were mapped to the identified problems in maintenance. The mapping showed how this maintenance approach might support solutions to these problems.

The authors of this paper argue that this approach could be realised using existing technology. Despite the many enablers to realising this approach; however, there might also be challenges. These challenges can be categorised as technological advancements, data utilisation, human resources competence, regulations and standards, and capital investments. Three initiatives in this domain were presented that can strengthen the credibility of developing and implementing such an approach.

In conclusion, this study showed that maintenance suffers from many problems. It will be necessary to develop new maintenance approaches in order to solve current industrial problems, exploit emerging digital technologies and elevate future industries. The mapping between the tasks of DM and maintenance problems shows a potential of this concept to solve maintenance problems, which could be examined empirically in a future work.

This paper showed the implementation of stepwise refinement with the association to IBM'S self-adaptive software architecture to guide the analysis process. The combination of these tools could be useful for the developers of digital community in order to facilitate the conceptualisation of self-adaptive complex systems. The development of new maintenance approaches has to be in line with real-world needs if these approaches are to achieve practical and applicable solutions. This paper aims to help maintenance practitioners from both academia and industry to understand and reflect on the problems related to maintenance, as well as to comprehend the requirements of a digitalised maintenance and the challenges that may arise.

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