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Perspectives on Smart Maintenance Technologies - A Case Study in Large Manufacturing Companies

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Abstract. The manufacturing industry faces significant technical challenges due to the industry 4.0 technologies, which play an essential role in maintenance development. Maintenance in industry 4.0, also named smart maintenance, maintenance 4.0, predictive maintenance, etc., is boosted using industry 4.0 technologies, such as Industrial Internet of Things (IIoT), Big Data and Analytics, Cloud Computing, Augmented Reality (AR), Additive Manufacturing (AM), etc. Previous research presents several smart maintenance technologies, but the manufacturing industry still finds it challenging to implement the technologies cost-effectively. One problem is that there is insufficient research on how smart maintenance technologies can be implemented cost-effectively and add value to the manufacturing industry. Therefore, this paper aims to explore perspectives on smart maintenance technologies: 1) if there are any implemented smart maintenance technologies, 2) in what context, 3) added values, 4) challenges, 5) opportunities, 6) advantages, and 7) disadvantages with the technologies. This paper presents the results of a case study based on an online open questionnaire with respondents working in maintenance organizations in large manufacturing companies.

Keywords. Smart Maintenance, Maintenance 4.0, Predictive Maintenance, Industry 4.0

1. Introduction

Digital development has resulted in a significant change in the manufacturing industry [1, 2]. Production systems are changing, such as strategy, processes, machinery types, and maintenance [3]. With increased competition and development in the manufacturing industry, companies are forced to increase their production efficiency and effectiveness [4, 5]. One aspect of achieving this is well-optimized maintenance since maintenance is the main function of keeping production systems running [6], and the importance of maintenance is highlighted in many studies [7, 8]. The manufacturing industry pays more attention to maintenance when the maintenance activities are well performed and support the organization's main goal [9]. Different maintenance concepts have been developed over time, such as Total Productive Maintenance (TPM) [10] and Reliability-Centered Maintenance (RCM) [11], which are the two more common concepts.

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The first industrial generation was concerned with fixing the equipment when it breaks, and the second one deals with scheduled overhaul and systems for planning and control. Condition Monitoring (CM), Design for reliability, and total quality maintenance were developed during the third industrial generation. The fourth industrial generation, have up to this point, focused on self-maintenance with zero down time, self-maintaining and self-healing features [12]. The progress in industry 4.0, has resulted in smart and intelligent factories [13]. It deals with Information and Communication Technologies (ICT), development of the internet and embedded systems technologies, which have resulted in several new technologies [14-16]. Previous research [17, 18] presents nine technological pillars of industry 4.0: 1) Industrial Internet of Things (IIoT), 2) Big Data and Analytics, 3) Horizontal and Vertical System Integration, 4) Simulation, 5) Cloud Computing, 6) Augmented Reality (AR), 7) Autonomous Robots, 8) Additive Manufacturing (AM), and 9) Cyber Security. The progress in industry 4.0 places a new demand for maintenance, and some of the mentioned technological pillars play an essential role in maintenance development [19, 20]. In addition, Condition Based Maintenance (CBM) is expected to play a dominant role in the industry 4.0 [20]. This is because the new demand of the maintenance technology approaches a predictive way through CBM technologies boosted using ICT, IIoT, Cloud Computing, Big Data and Analytics, AR [9], and Cyber-Physical System (CPS) [20]. Furthermore, Machine Learning and Artificial Intelligence (AI) are becoming major technologies for maintenance development and analysis [21, 22]. In addition, many industry pioneers are looking ahead to the industry 5.0, which is about a human-centric solution [59].

As mentioned, digital development has resulted in a significant change in the manufacturing industry. Regarding the maintenance departments, they are trying to implement smart maintenance technologies in order to improve productivity and reduce maintenance costs [51]. Previous research presents many technologies for smart maintenance, (e.g. “Self-Maintenance” [12, 23-27], “Engineering Immune System” [23], “Smart maintenance model using the cyber-physical system” [20], “Maintenance 4.0” [9], “Smart Maintenance” [28, 29], “Predictive Maintenance of Machine Tool Systems Using Artificial Intelligence Techniques Applied to Machine Condition Data” [21] , “Machine learning for predictive maintenance of industrial machines using IoT sensor data” [22] etc.), and how these technologies can be implemented. However, the manufacturing industry still finds it challenging to implement smart maintenance technologies cost-effectively [19]. One problem is that there is insufficient research on how smart maintenance technologies can be implemented cost-effectively and add value to the manufacturing industry [30]. Lundgren et al. [31] have explained that further research is needed to support the manufacturing industry in smart maintenance. Therefore, this paper aims to explore perspectives on smart maintenance technologies. First, we investigate whether there have been any implemented smart maintenance technologies, and if so, in what context. Second, we explore perspectives from the manufacturing industry on added values, challenges, opportunities, advantages, and disadvantages with the technologies.

2. Methodology

2.1. Data Collection

Karlsson et al. [32] have explained that case studies can be used for different types of research purposes, such as exploration, theory building, testing, and elaboration/refinement. One or several data collection techniques can be used in case studies, such as interviews, questionnaires, and observations [33]. Triangulation, which means a combination of different data collection techniques, can offset weaknesses in one technique by strength in another [34].

A case study based on online open questionnaire questions [33, 35] with respondents who are working in maintenance organizations in large manufacturing companies is used in this paper, to explore perspectives on smart maintenance technologies. The questionnaire was created with Google Forms and consists of seven questions (shortened): 1) what type of smart maintenance technologies have been implemented, 2) in what context are the smart maintenance technologies implemented, 3) if the implemented smart maintenance technologies have added any values to the maintenance organization, 4) challenges with the implemented smart maintenance technologies, 5) opportunities with the implemented smart maintenance technologies, 6) advantages of the implemented smart maintenance technologies, and 7) disadvantages of the implemented smart maintenance technologies. The questionnaire was sent to eleven large manufacturing companies, see Table 1. One of the weaknesses of a questionnaire is that respondents cannot get support if some of the questions are unclear [33]. To offset this weakness, unstructured interviews [33] and e-mail conversations were used with respondents who were in need of support.

Table 1. Case companies

Case company	Approx. employees (World-wide)	Type
A	957 (27500)	Automotive industry.
B	1500 (30 000)	Transportation industry.
C	1100 (11000)	Robotics industry.
D	63 (440)	Components industry.
E	53 (1200)	Automotive industry
F	775 (9000)	Nuclear industry.
G	125 (44500)	Air and gas sensing industry.
H	1426 (4100)	Metal cutting solutions industry.
I	825 (14600)	Transportation industry.
J	13525 (50000)	Transportation industry.
K	23000 (40000)	Automotive industry.

2.2. Data Analysis

Säfsten and Gustavsson [33] have explained that qualitative data analysis can be used when the data is collected through interviews, open questionnaire questions, observations, and text documents. According to Miles et al. [36], qualitative data analysis consists of three steps: 1) data reduction, 2) data display, and 3) making conclusions. The first step is about making the data manageable using transcribing, coding, and initial analysis. The second step is about visualizing the data using, for example, matrices and charts. In the last step, the decision is made by looking for patterns and explanations, creating clusters, making comparisons, and analyzing changes over time [33].

In this paper, the data from the open questionnaire was converted to a table using Microsoft Excel, initially analyzed, and the empirical data was coded as implemented technologies, added values, challenges, opportunities, advantages, and disadvantages. The data was visualized in the form of a matrix in Microsoft Excel, sorted based on what smart maintenance technologies were implemented and in what context, added values, challenges, opportunities, advantages, and disadvantages with the implemented technologies. Based on that, a deeper understanding of the perspectives on smart maintenance technologies were provided through looking for explanations and making comparisons between different technologies and case companies.

3. Smart Maintenance Technologies

In this paper, smart maintenance technologies are related to the nine technological pillars of industry 4.0, CPS, and AI.

As mentioned before, some of the nine technological pillars of industry 4.0 play an essential role in maintenance development [19]. The IIoT is an adapted concept of the Internet of Things (IoT), used in the industrial field [37], to a machine-to-machine interaction without human intervention [38]. Thanks to IIoT, it is possible to interconnect physical objects through sensors using standard internet protocols [19]. The machines and its components can be connected through IIoT and thereby collect data, such as vibration, pressure, temperature, acoustics, and viscosity [39]. Lee et al. [40] have identified that IIoT is the basic technology for the CPS concept. CPS is characterized by integrating the physical and digital world, consisting of computing facilities, communication, and data collecting and storage used to monitor and control the physical world in real-time [41]. CPS allows data collection regarding the current component state in real-time, which is the base for Big Data and Analytics [42]. This data can be used to support maintenance planning and predict component deterioration [19]. As mentioned above, Al-Najjar et al. [20] have developed “Smart maintenance model using the cyber-physical system”, which presents CBM boosted through using CPS. When applying this concept: first, the machine collects data, such as vibration data, used to monitor the health of a component. In the second step, actions are recommended, or work orders are sent. Specific maintenance actions are automatically conducted in the third step, and what maintenance actions, when and where to have to be done manually, are reported to the maintenance department in the last step [20]. Witkowski [43] has defined Big Data and Analytics through 4 parts, i.e., 4V: 1) Volume, the amount of data, 2) Variety, the variety of data, 3) Velocity, the speed of generation of new data and analysis, 4) Value, the value of the data. Compared to existing (elderly) tools, Big Data and Analytics support advanced data analysis [43] and real-time decision-making [44]. Yan et al. [45] have studied predictive maintenance solutions using Big Data and Analytics to improve system reliability. This big data is generated from 1) machine operation, such as data from the control system and equipment operation, 2) environmental conditions, such as indoor temperature and noises, 3) fault detection and system status monitoring data and 4) machine usage data, such as availability and repair rate [45]. In addition, Maintenance 4.0, developed by Cachada et al. [9], consists of data collection, analysis, and decision making using Big Data and Analytics. Cloud Computing is used in the industrial field for effective data sharing between systems at an entire company and data storage [14].

Jantunen et al. [46] have discussed CBM of machines using Big Data and Analytics that use Cloud Computing to store the collected data. According to Markus et al. [47], Big Data and Analytics and Cloud Computing are two significant technologies for CPS for storing and analyzing data.

Simulation is based on mathematical modelling and algorithms used for optimization of processes [60]. It can be used to support a production system's design and enable effective maintenance and optimization based on real-time data from intelligent systems [48]. Simulation can also be used to predict the production system's behavior and thereby support maintenance scheduling and decisions [49].

AR is a human-machine interaction technology based on combining 3D virtual objects with a 3D real environment in real-time [50]. Roy et al. [51] have explained how AR can be used for maintenance support and training, and it is becoming a major tool for maintenance development. AR enables effective maintenance, offering step-by-step guidance for diagnostics, inspection, and training operations [51].

Autonomous Robots are cooperative and can interact with each other or safely directly with a human [52]. According to Silvestri et al. [19], Autonomous Robots can be used to collect inspection data or perform maintenance tasks.

AM is characterized by converting a digital design (i.e., 3D-CAD) to a physical object [48]. 3D-CAD can be used to create knowledge about the equipment, manufacturing, operation, and thereby maintenance [48].

In Horizontal and Vertical Integration, the whole supply chain, suppliers, materials, logistics, etc., is integrated [42].

Shared information is protected from cyber-attacks through Cyber Security [53].

Kour et al. [54] have defined AI as a technique that can perform activities that mimic human behavior. Machine Learning is a technique within AI that makes a system learn by itself. Supervised learning, Unsupervised learning, Semi-Supervised learning, and Reinforcement learning are four Machine Learning techniques [54].

Supervised learning is used to forecast events based on the previously labeled data [54]. Linear regression is one of several algorithms within Supervised learning. It can do prediction based on continuous variables [58]. According to Yuan and Liu [55], Supervised learning is based on labeled condition monitoring data that can be used for diagnosis and prognosis. Diagnosis deal with finding the source of a problem and prognosis predicting the occurrence of a problem [56].

Unsupervised learning is the opposite of Supervised learning and uses unlabeled data. K Means Clustering, which is used for solving clustering problems, is one of several algorithms within Unsupervised learning [58]. Amruthnath el al. [39] have written that Unsupervised learning is a better option when minimal or no historical data is available. In their article about Unsupervised learning for early fault detection in predictive maintenance, they have written that Unsupervised learning is a better option to minimize maintenance cost when minimal or no historical maintenance data is available. Based on simple vibration data, they have tested this technique to detect faults early.

Supervised learning requires labeled data which is expensive and time consuming [55, 57]. Unsupervised learning does not require any labeled data, which means it cannot cluster an unknown data accurately [57]. Semi-Supervised learning uses both the labeled and unlabeled data [54]. According to Reddy et al. [57], the Semi-Supervised learning can be used to overcome the drawbacks of Supervised and Unsupervised learning.

The last one, Reinforcement learning, helps machines determine the ideal behavior to maximize their performance [54].

4. Empirical Findings

In this section, the result from the questionnaire will be introduced. The result consists of the type of smart maintenance technologies implemented in each case company, the context, added values, challenges, opportunities, advantages, and disadvantages with the implemented technologies.

At the case company A, IIoT and sensors for machine connection and CBM have been implemented. Regarding the added values, the respondents at the case company mentioned that they had not had any added values yet. The company's challenges are "*Getting money for relatively untested techniques.*" and convincing the IT department to implement these types of technologies due to the Cyber Security. The collection of vibration and temperature data used to predict failures, data-based maintenance decision-making, and performing maintenance actions before functional failures, are the opportunities/advantages, and *"Start-up costs"* is disadvantage, mentioned by the respondents at the case company.

At case company B, sensors for maintenance data collection have been implemented. The added value is *"Reduction of unplanned stops"*, as mentioned by the respondent at the case company, which results in less production disturbances. "*Knowledge and the will to change"* and *"Accept change."*, are the challenges, *"Get control over machine health and take decisions based on facts."*, and *"We can see abnormalities before the breakdown and do the correct action in time."*, are the opportunities and advantages, and "*None!*" disadvantages, were mentioned by the respondent at the case company.

At case company C, Big Data and Analytics for production data collection including maintenance data, have been implemented. The added value, mentioned by the respondent at the case company, is "*It is easier to recruit young people if we have more technology in our department".* Convincing the IT department to implement these types of technologies is, by the respondent mentioned, as the case company's challenge, due to the Cyber Security. "*Be more cost efficient.*" was mentioned by the respondent at the case company as an opportunity, *"Be more predictable and conditioned based, based on fact rather than feelings.*", are the advantages, and *"In the future, you don't have the mechanical knowledge, if you only rely on the computer and not your sense (ear, eyes, nose)",* was the disadvantage, mentioned by the respondent at the case company.

At case company D, sensors to make condition data accessible in real-time have been implemented. The added values, mentioned by the respondent at the case company, are "*Automated monitoring of condition and data accessible for maintenance supervisors and technicians from the office*", and the challenge is "*The technology may not be available for our older machines and how to monitor data efficiently may be a problem.".* "*Planned repairs instead of unplanned",* which results in *"Less production disturbances*", is the opportunity, "*Less unplanned stops in production*" is the advantage, and "*Start-up costs*" is the disadvantage, mentioned by the respondent at the case company.

At case company E, Big Data and Analytics and sensors in "*Small areas mainly as pilots*" have been tested, therefore no added values were mentioned by the respondent at the case company. The challenge is convincing the finance department to implement new and relatively untested new technologies. "*… we will only implement if it has a good return on investment and when the technology is mature.*", as mentioned by the respondent at the case company. The opportunities are "*Gradually moving from reactive to predictive maintenance and building knowhow*", and no advantages/disadvantages were mentioned, because they have not implemented any technologies yet, except the pilot project in small areas, mentioned by the respondent at the case company.

At case company F, no smart maintenance technologies have been implemented or tested in the maintenance organization. The respondent mentioned that they use Systems Applications Products (SAP) as Computerized Maintenance Management System (CMMS). The respondent mentioned the challenge is accepting changes to start testing new technologies in small areas as pilot projects.

At case company G, no smart maintenance technologies have been implemented or tested in the maintenance organization. "*Unfortunately, we still have a way to go to be there ...*", "*… we have taken a step from corrective maintenance to preventive maintenance.*", mentioned by the respondent at the case company. "*We have tried to get a budget for a maintenance system but have not gotten through it yet. At the same time, there are intentions that we will move forward with maintenance development, that it will be profitable preventive maintenance.*", mentioned by the respondent at the case company.

At case company H, no smart maintenance technologies have been implemented yet. "*We are just at the start of many interesting projects linked to the smart maintenance development.*", as mentioned by the respondents at the case company.

At case company I, IIoT, Big Data and Analytics, Machine Learning, Sensors, VR, Cyber Security and AM have been implemented in manufacturing engineering, and some of them for maintenance development. Big data and analytics are used for "*Production monitoring",* for short-stops, breakdowns, and availability, and "*Energy measurement system"* for electricity consumption, compressed air, and district heating, mentioned by the respondent at the case company. Machine learning in robots which results in predictive maintenance instead of corrective/preventive maintenance, mentioned by the respondent at the case company. IIoT is used for "*...track process data for welding equipment*", for power sources, wire feed, etc., and "*Implementation of Machine Learning for this is started*", mentioned by the respondent at the case company. The respondent at the case company mentioned, "*Tooling department makes tools and spare parts in steel and plastic*", as the AM is used for. "*VR is used frequently in the manufacturing engineering when preparing for new models, new or modified workplaces*", "*AR is planned for a pilot project within maintenance,*" and Cyber security is "*Controlled/supported by the IT department*", mentioned by the respondent at the case company. The added value is "*tracking of process data*" which help the case company "*...become more predictive*", the challenges are "*Competence to use new technology*", the opportunities are "*Increased knowledge on how equipment works and degradation progress*", the advantages are "*... information about disturbances, which is essential for tracking availability*", "*Machine learning in robots gives maintenance information on a much deeper level than before. We get support in predictive thinking instead of corrective/preventive*", "*Tracking process data for wire feed gives us much more information about what is happening and input to maintenance as well as operators.*", and "*AM for making of old spare parts",* and the disadvantages are "*we do not always have enough resources and competencies",* mentioned by the respondent at the case company.

At case company J, sensors and IIoT have been implemented for maintenance. "S*ensor that monitor the vibration, sensors are connected to IIoT-platform to analyze and visualize the data.",* mentioned by the respondent at the case company. The added values are "*Defects detection at an earlier stage, monitor equipment in real time, correct maintenance at the right time, saving on spare parts, and reducing downtime and* *breakdowns.”*, the challenges are “*know what you want to monitor, which data you should send to the IIoT-Platform and how often you will retrieve the data from the sensors.*”, the opportunities are performing maintenance actions before functional failures, the advantages are *“... such as smart factory and smart maintenance, ...*”, and the disadvantages are “*Extra cost, required resources and skills in automation.*”, mentioned by the respondent at the case company.

At case company K, IIoT, Big Data and Analytics, AM and AR have been implemented for maintenance. IIoT is used for machine connection, Big Data and Analytics for maintenance planning, AM for making spare parts and AR for remote support tool. The added values are “*spare parts and availability*” and “*Competence and deeper process knowledge*”, the challenges are “*To align organizational structures into the transformation”* and *“Management awareness.*”, the opportunities are “*To have a more strategic way of planning the maintenance resources. Less storage and a better collaboration with production, quality and logistic on shared data”,* the advantages are *“More transparent organization and more value oriented.”,* and the disadvantages are *“More vulnerable when you are dependent on complex IT systems.”,* mentioned by the respondent at the case company.

Table 2 presents a summary of the empirical findings.

Table 2. A summary of the implemented smart maintenance technologies, added values, opportunities/advantages, and the challenges/disadvantages, mentioned by the respondents at the case companies. The table columns/rows are to be read independently.

Impl. Smart Maint. Tech.	Added values	Opportunities/ Advantages	Challenges/ Disadvantages
IIoT for machine connection.	Reduction of unplanned stops.	Do the correct maintenance actions in time.	Start-up cost.
Sensors for maintenance data collection including real-time maintenance data accessible.	Automated condition monitoring.	Cost efficient.	Cyber Security.
Big Data and Analytics for production data collection including maintenance data, and maintenance planning.	Tracking of process data.	Less production disturbances.	Change Management.
Machine learning for predictive maintenance.	Failure prediction.	From reactive to predictive maintenance.	The technology may not be available for the older machines.
AM for spare parts making for old machines.	Spare parts availability.	Increased knowledge on how equipment works and degradation progress.	Resources and competence.
AR for remote support tool.	Competence and deeper process knowledge.	Supporting Maintenance planning	Know what to monitor.
		Decision making based on data and fact.	Know what type of data to collect.
		Less unplanned stops in production.	

5. Discussion and Conclusions

This paper aims to explore perspectives on smart maintenance technologies: 1) if there are any implemented smart maintenance technologies, 2) in what context, 3) added values, 4) challenges, 5) opportunities, 6) advantages, and 7) disadvantages.

The empirical findings present that companies within the manufacturing industry still find it challenging to implement smart maintenance technologies cost-effectively. Three (out of eleven) manufacturing companies in this study had not yet implemented any smart maintenance technologies and one other company had only implemented a smaller pilot. Even though many added values and opportunities and advantages (see below) with smart maintenance technologies are mentioned by the respondents, still several respondents also mention that they find it difficult to know what to monitor and to know what type of data to collect.

The related theories present several smart maintenance technologies [19]. Some of the smart maintenance technologies that have been implemented, or tested in pilot projects, mentioned in this study, are IIoT for machine connection, sensors for maintenance data collection and real-time maintenance data accessible, Big Data and Analytics for production data collection including maintenance data, Machine Learning which results in predictive maintenance instead of corrective/preventive maintenance, AM for making tools and spare parts in steel and plastic for old machines, AR for remote support tool, etc.

The empirical findings present several added values, such as reduction of unplanned stops which result in less production disturbances, real-time condition monitoring, failure prediction at an earlier stage, corrective maintenance at the right time, etc. Some of the identified challenges are to convince the IT department to implement these types of technologies due to the Cyber Security, to finance the relatively untested technologies, knowledge, the will to change, the technologies may not be available for older machines, competence to use technologies, know what to monitor and what kind of data to collect, etc. The respondents mentioned several opportunities/advantages at the case companies, such as the collection of vibration and temperature data used to predict failures, data-based maintenance decision making, performing maintenance actions before functional failures, be more cost-efficient, gradually move from reactive to predictive maintenance, increased knowledge on how the equipment works and degradation progress, etc. Some of the disadvantages mentioned by the respondents at the case company were start-up costs, resources, competence, etc.

As mentioned before, due to insufficient research, the manufacturing industry still finds it challenging to implement smart maintenance technologies cost-effectively [19, 30, 31], which is mentioned by several respondents from several case companies in this study also.

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