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Application of sensor data based predictive maintenance and artificial neural networks to enable Industry 4.0

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Abstract Possessing an efficient production line relies heavily on the availability of the production equipment. Thus, to ensure that the required function for critical equipment is in compliance, and unplanned downtime is minimized, succeeding with the field of maintenance is essential for industrialists. With the emergence of advanced manufacturing processes, incorporating predictive maintenance capabilities is seen as a necessity. Another field of interest is how modern value chains can support the maintenance function in a company. Accessibility to data from processes, equipment and products have increased significantly with the introduction of sensors and Industry 4.0 technologies. However, how to gather and utilize these data for enabling improved decision making within maintenance and value chain is still a challenge. Thus, the aim of this paper is to investigate on how maintenance and value chain data can collectively be used to improve value chain performance through prediction. The research approach includes both theoretical testing and industrial testing. The paper presents a novel concept for a predictive maintenance platform, and an artificial neural network (ANN) model with sensor data input. Further, a case of a company that has chosen to apply the platform, with the implications and determinants of this decision, is also provided. Results show that the platform can be used as an entry-level solution to enable Industry 4.0 and sensor data based predictive maintenance.

Keywords Predictive maintenance (PdM) platform · Industry 4.0 · Value chain performance · Anomaly detection · Artificial neural networks (ANN)

1 Introduction

Industry 4.0, predictive maintenance (PdM), and advanced manufacturing are examples on terms which have been prominent on industrialist's agenda for the last years. Additionally, national and union initiatives, e.g., the European Union 7.5 billion EUR "Digital Europe Programme" [1], targeting the mentioned terms is witnessed worldwide, underpinning the importance of succeeding with the digital transformation. Industry 4.0, or Industrie 4.0, was first introduced at the Hannover Messe in 2011, a German industrial fair, as an illustration for the new trend towards the networking of traditional industries [2], and is now seen as the fourth industrial revolution. Further, Industry 4.0 was included in the German "High-Tech Strategy 2020 Action Plan". China initiated "Made in China 2025", also called "China Manufacturing 2025", which focused on accelerating development of intelligent manufacturing equipment and products, and advanced manufacturing process intelligence [2, 3]. Moreover, USA has "Advanced Manufacturing" as their strategic plan, aiming to develop and transit new manufacturing technologies, educate, train, and connect the manufacturing workforce, and, lastly, expand the capabilities of the domestic manufacturing supply chain [4].

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To successfully implement Industry 4.0, three key features are seen as essential. These are prerequisites expected to be the reality in future production networks and are defined as three types of value chain integration. Combined, they focus on how new technology can be utilized to improve the overall value chain, with expected benefits being higher sales thanks to a larger market, increased customization, improved resource efficiency and productivity, and reduction of internal operating costs. The three types of integration are as follows [5–7].

(i) Horizontal integration as a basis for developing intercompany value chains and networks;
(ii) Vertical integration of hierarchical subsystems to create flexible and reconfigurable manufacturing systems;
(iii) Digital end-to-end engineering across the entire value chain of both the product and the associated manufacturing system.

The accessibility to data has increased significantly with the introduction of Industry 4.0 technologies, e.g., Internet of Things and Big Data, and the importance of competence on utilizing this data for gaining competitive advantages is underpinned by practitioners and theorists [8]. Examples of data-demanding technologies are cloud computing, artificial intelligence (AI) and PdM. Together with new smart technology, cloud computing is contributing to radically changing the manufacturing industry and reshaping enterprises worldwide. Cloud computing aims to offer on-demand computing services and, for industrialists, access to business-critical data and analytics will be essential for moving the focus from hindsight to foresight. Further on, cloud computing can form intelligent factory networks who support and enhance the level of collaboration throughout the value chain [9]. AI is a technology under rapid development, and with a wide application area. For example, AI is seen as central for data-driven methods within Industry 4.0, and in the field of maintenance, a model for deep digital maintenance with an AI module providing predictions of remaining useful life (RUL) is proposed [10]. AI applications for failure diagnosis, failure prognosis and lifetime estimation of wind turbines are also showing promising results [11, 12]. Another field delivering valuable opportunities is artificial neural network (ANN), which is an encouraging method for fault detection, diagnosis, prognosis, prediction, and classification. ANN models emulate a biological neural network, i.e., the central nervous systems of animals, particularly the brain [13, 14]. These models can deal with complex problems without sophisticated and specialized knowledge, provide an effective classification technique, and deal with nonlinear systems and low operational response time after the learning phase [15]. ANN models have been applied to a wide range of fields [12–17], but it is still of interest to explore ANN models into PdM and especially with sensor data as the main input.

For PdM, which aims to predict when an equipment failure might occur [14], there has been conducted numerous studies and the promised cost savings with successful implementation of PdM have been significant [10]. More development of PdM is expected, but currently, PdM seems to fall short of its possibilities in order to deliver what it promises [18, 19]. In general, a common challenge for industrialists to realize the promised advantages with PdM, is connected to manage big data and the capability to extract and utilize relevant data from multiple data sources [18, 20]. The founding bricks in accessing data and connecting the physical and digital world are sensors, and, as a result, they are one of the most critical factors for succeeding with Industry 4.0 and PdM [14, 19, 21]. However, for sensors and data to provide value, analyses and competence within data contextualization are crucial for enabling data-driven decision making [7]. Contextual data focus on unlocking organizational and technological data silos, and aim to integrate and make data from a range of sources available such as real-time streams of sensor data from equipment and process, historic behavioral data from historians, and information from the third parties on external factors [22]. In Ref. [22], they conducted a survey with 160 decision makers in IT and operation roles in global industrial companies, which showed that over 80% of the firms recognized the importance of industrial data in driving their business decisions and innovation. On the other hand, 83% experienced challenges with utilizing the data for delivering insights across their organization. A key finding from the survey, was that data contextualization will be crucial for succeeding with this challenge [22]. This is also supported by Ref. [7], where deep convergence and comprehensive connections are presented as two out of six technical features for smart factory production systems.

As shown in Refs. [23, 24], there exists numerous suppliers who provide sensors, data analytical services and other digital solutions. Additionally, in Ref. [25] they conducted a review on industrial wireless networks within Industry 4.0, showing the large number of applications. However, succeeding with contextualizing and utilizing data for enabling data-driven decision making within maintenance and value chain remains a challenge for many [7, 24], and design of successful applications is still lacking [25, 26]. To provide an Industry 4.0 vision for practitioners and academics to gather on, reference architectures such as the German reference architectural model Industrie 4.0 (RAMI 4.0) [27] and the China intelligent manufacturing system architecture (IMSA) [28] can be used. These reference architectures can become the backbone for full realization of Industry 4.0 if their maturity and sustainability are increased, but currently they are not completely suitable to support implementation of Industry 4.0 technologies, mainly due to their high level of abstraction and/or lack of detailed documentation [29, 30]. The need for more entry-level solutions for building up digital capabilities is required for successful implementation. Thus, a gap has been witnessed between the literature point of view, and the lack of empirical implementation experiences in practice. Based on this, the overall research question for this paper is: “How to develop an entry-level solution to enable Industry 4.0 and sensor data based predictive maintenance?”. This paper investigates on how maintenance and value chain data can collectively be used to improve value chain performance through prediction, and presents a novel concept for a PdM platform and an ANN model using sensor data as input. A case study on a company that has chosen to apply the PdM platform and the ANN model, with the implications and determinants of this decision, is also given. Research outcomes are expected to provide concrete suggestions regarding how such a PdM platform and ANN model can be constructed, implemented, and give examples of benefits. Solution for scaling and application to other companies and processes is also discussed.

The structure of this article is as follows. Section 2 discusses how Industry 4.0 is changing the view on maintenance and value chain, and presents the novel concept for a PdM platform. Section 3 provides the case study and ANN model, and Section 4 discusses the case study findings. Lastly, Section 5 concludes the paper.

2 Literature background

A definition of Industry 4.0 is presented in Ref. [6] as: “Industry 4.0 is a collective term for technologies and concepts of value chain organization. Within the modular structured smart factories of Industry 4.0, cyber-physical system (CPS) monitor physical processes, create a virtual copy of the physical world and make decentralized decisions. Over the internet of things (IoT), CPS communicates and cooperates with each other and humans in real-time. Via the internet of services (IoS), both internal and cross-organizational services are offered and utilized by participants of the value chain.” Industry 4.0 has been on everyone’s tongue during the last years, and industrialists have been expecting substantial gains in productivity, significantly higher levels of automation, and drastic improvements in resource efficiency by putting Industry 4.0 on their agenda [31]. However, reaping the promised Industry 4.0 benefits is challenging [31]. The following two sections present how developments within the field of maintenance and value chain can contribute in overcoming this challenge.

2.1 Predictive maintenance

The introduction of Industry 4.0, new technology and demands within the industry, also requires a significant increase in the level of maintenance [8], and, as a result, PdM has been highlighted. The work on PdM has contributed in changing the traditional view on maintenance, from being a costly unwanted necessity into seeing maintenance as a competitive advantage. The two main objectives for industrial maintenance are to deliver a high availability of production equipment and low maintenance costs [32], and PdM is expected to have a significant impact on these objectives with the introduction of Industry 4 technologies. PdM is also showing its importance to lean manufacturing and total productive maintenance (TPM). Lean manufacturing seeks to improve on productivity, quality, focus on the elimination of waste and to be customer oriented, and share similar goals as Industry 4.0 [33, 34]. TPM also includes the goal of elimination of waste, reduces costs and downtime through an improved maintenance function [35]. For both lean manufacturing and TPM, PdM can provide several ways of performance improvements, e.g., through better predictions reducing unnecessary maintenance, such as early replacement of components (identifying RUL) or increased production downtime due to equipment failures. PdM can also improve maintenance plans and procedures [36]. An overview of PdM system architectures, purposes and approaches is given in Ref. [37], and a definition of PdM is provided by EN 13306:2017 [38]: “Condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item.” The standard EN 13306:2017 [38] classifies PdM under the umbrella of preventive maintenance and condition-based maintenance (CBM), but PdM goes beyond CBM by adding a forecast to the maintenance being carried out.

PdM aims to maximize the life of equipment and reduce both planned and unplanned downtime, and, as a result, minimize maintenance costs. This is possible by analyzing data collected from components and equipment and using those analyzes to predict when a part will fail, enabling to perform maintenance actions at the right time. In terms of Industry 4.0, PdM is claimed to be central for asset utilization, services and after-sales [10]. For asset utilization, PdM is expected to decrease total machine downtime from 30% to 50%, and extend operation lifetime from 20% to 40% [10]. PdM combined with remote maintenance for services and aftersales, is assumed to reduce maintenance cost from 10%

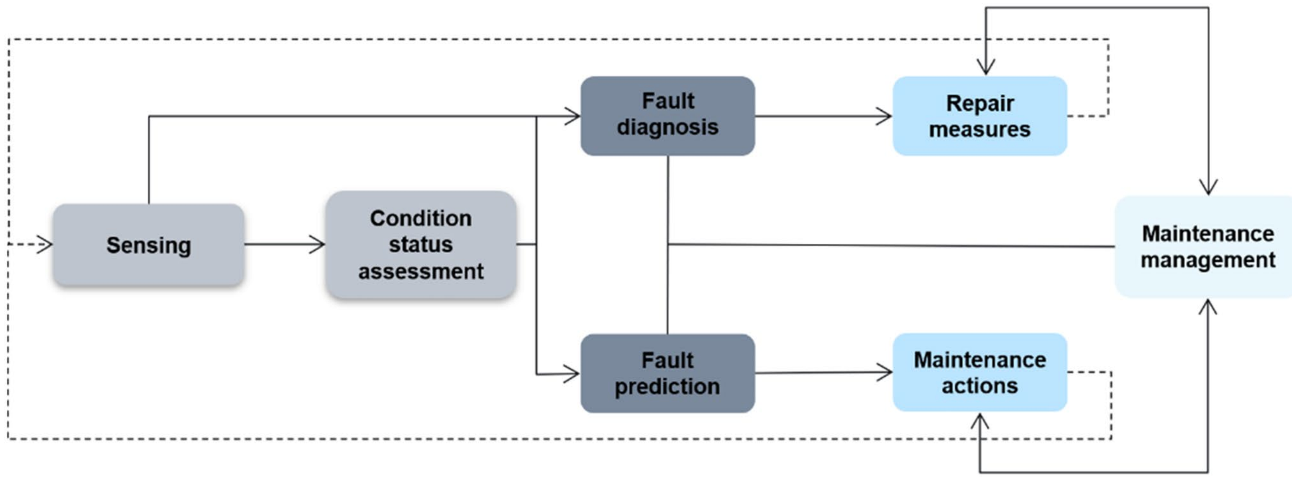


Fig. 1 PdM structure with its main elements, redrawn from Ref. [3]

to 40% [10]. Thus, the expected outcomes are significant, but several studies show that PdM seems to fall short of its possibilities in order to deliver what it promises [18, 39]. In fact, the added value of stand-alone PdM machine projects is often lower than asserted, as companies have extensive experience with wear and tear on their machines. Thus, there is a need for an overall concept for using digitization in an advantageous and holistic manner [18]. This is also supported by a Sino-German working group on PdM for Industry 4.0 [3, 40], where they conclude that the increasing flexibility and heterogeneity of future manufacturing systems, requires a systematic approach for PdM with a modular architecture. In more detail, the architecture shall enable easy adding or enhancing functional components for sensing, condition status assessment, diagnosis, and prediction [3, 40]. In addition to these functional components, it should be a flexible deployment of findings to different resources, e.g., data from a sensor can be visualized both in a dashboard at the equipment and used in a cloud center for conducting analyses with other contextual data [3, 40]. Figure 1 shows the overall structure for PdM, which is considered to be settled in Ref. [3], and further elaborated in Ref. [40].

The PdM structure presented in Ref. [3], consists of seven interconnected elements. First, "Sensing" focuses on sensor modality and strategy for sensor placement. The selection of sensor technology and sensor placement are essential tasks for creating the most representative picture of asset condition, i.e., asset health. Further, sensing techniques can be categorized into direct sensing (measuring actual quantities directly indicating asset condition, e.g., toolmaker's microscope) and indirect sensing (measuring symptoms caused by degradation or a defect, e.g., change in vibration or temperature). Indirect sensing methods are often cheaper, less complex, and enable continuous measurement without interrupting operation [40]. Second, "Condition status assessment" is about assessing the collected data to determine asset health state, which creates a foundation for determining the current status on asset condition, i.e., an asset health indicator. The indicator can be visualized in the form of a traffic light, providing a fast and simple overview. Asset condition status on a whole system, or comprehensive equipment, can be given by aggregating the condition status of its functional components [40]. Third, "Fault diagnosis" (which can be divided into fault detection, fault location, fault isolation, and fault recovery) and "Fault prediction" (predicting the fault and RUL of an asset or a system) are both challenging tasks and consist of several possible methods based on analytical models, qualitative empirical knowledge, and data-driven methods. The premise of RUL prediction is the definition and identification of failure modes, and RUL of a manufacturing system can be defined as [41]: "The duration of the stable production of high-quality products." Here, ANN can be seen as an artificial intelligence technique for RUL prediction [42]. Together, "Fault diagnosis" and "Fault prediction" are coherent elements which provide a basis for the optimum "Repair measures", element four, and time for executing the "Maintenance actions", element five [40]. The last element, "Maintenance management" is where the information from the other elements are used for decision making in terms of developing an economical maintenance schedule, cost-effective maintenance strategy, and resource allocation (people, spare parts, tools, and time). Further, a linkage between maintenance management and operation management should also be present, as data from operations can improve PdM capabilities, but PdM can also support rapid and data-driven decision making across operations [40].

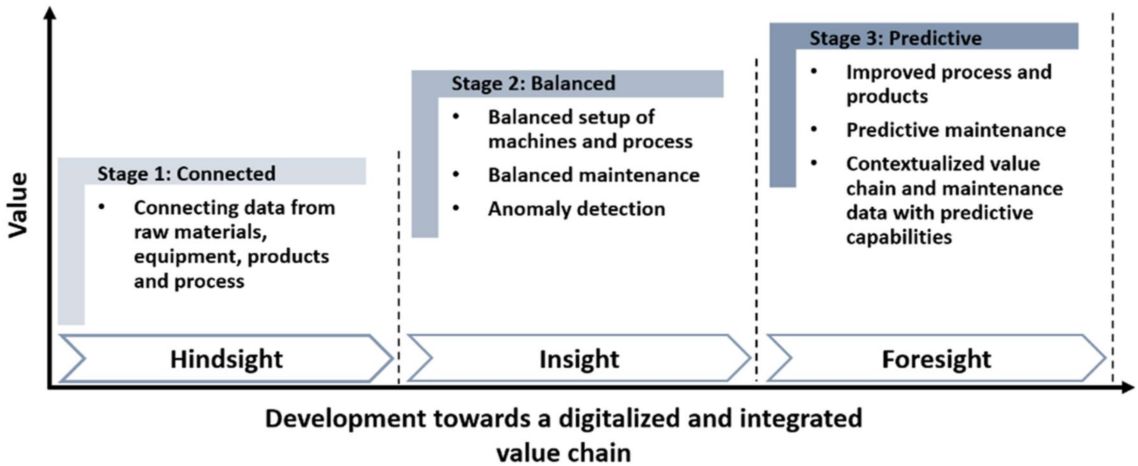


Fig. 2 Three conceptual stages towards a digitalized and integrated value chain

2.2 Digitalized and integrated value chain

The value chain concept was first introduced by Michael E. Porter in 1985, and the term was defined as [43]: "A value chain is a set of activities that a firm operating in a specific industry performs in order to deliver a valuable product or service for the market." The value chain concept was originally aiming at identifying value activities, as these are the building blocks of competitive advantage, and focusing on these activities can be used to define improvement needs or opportunities for companies [43]. Each value activity consists of two components, namely, a physical and an information processing component. The former includes the physical tasks required to fulfill the activity, and the latter are steps required to capture, manipulate, and channel data necessary to perform the activity [43, 44]. Porter identified two types of activities, namely, primary and support activities. First, the primary activities are inbound logistics, operations, outbound logistics, marketing and sales, and, lastly, service. These are defined as activities within the main value creation process for a traditional and general manufacturer. Second, the support activities are procurement, technology development, human resource management, and firm infrastructure. The role for these activities is to create a foundation for enabling and improving the function of primary activities [43], meaning that support activities also need to pursue technological advancements.

With the introduction of Industry 4.0 and new technology, many industries have reshaped their value chain, and focused on higher information content in both products and processes [43, 45]. For vertical integration, the importance of integrating the various information subsystems at different levels in the company is underpinned [6]. This is also discussed in Ref. [7], where it is claimed to be essential with: "vertical integration of actuator and sensor signals across different levels right up to the enterprise resource planning (ERP) level to enable a flexible and reconfigurable manufacturing system." Further, horizontal integration should focus on inter-corporation collaboration where information and material can flow fluently, enabling new value networks and business models [6, 7]. The end-to-end integration across the entire value chain will include cross-linking of stakeholders, products and equipment, from raw material acquisition to end of life [6].

Summarized, with the advancements in technology, increased level of competition, more demanding customers focus on sustainable production, the need for development goes for both the field of maintenance and value chain, and, additionally, the integration between the two fields. In Fig. 2, three conceptual stages with coherent elements seen as important in succeeding when moving to a digitalized and integrated value chain are proposed.

The proposed three conceptual stages are also defined into hindsight, insight, and foresight, describing the way of working. Stage 1 "Connected", targets to create a data foundation from raw materials, equipment, products and process, as conceptualized in Ref. [46]. At this stage, the way of working is focused on hindsight. Hence, a reactive approach is presented and the ability of understanding the whys, hows and potential improvements are only obvious after an event has occurred. Stage 1 creates the foundation for data-driven decision making in stage 2, "Balanced". Here, data are utilized to provide insight, and an accurate and deep understanding of the current situation. Thus, setup of machines and process can be balanced based on need and variance is managed to keep processes lean and stable. For example, in Ref. [47], the concept of a balanced maintenance program is presented, with anomaly detection and machine load as critical factors for deciding maintenance actions. Lastly, stage

3 "Predictive", aims at predicting future maintenance need, setup and design of both value chain process and final products. Possessing contextualized value chain and maintenance data with predictive capabilities, enables decision making and working in a foresight manner. For example, Ref. [48] presents a method for combining knowledge-driven and data-driven anomaly detection, fault recognition and root cause analysis (RCA) for PdM.

The proposed three conceptual stages can also be seen up against the six stages in the development towards smart maintenance presented in Ref. [10], which evaluate the degree of succession of maturity stages within Industry 4.0.

2.3 Predictive maintenance platform

In terms of platforms within digitalization and Industry 4.0, there is a lack of unified use of terminology and definitions. Some examples on use of terminology are sensor platform [49, 50], industrial internet of things (IIoT) platform [51], Industry 4.0 system/platform [52], PdM platform [53–55], smart manufacturing system [56], and digital platform [57]. The research institute Mercator Institute for China Studies published a report on the development within digital platforms in China. Here, they claim that for China, digital platforms are a crucial tool to realize its goal of becoming an industrial superpower by 2025, and present that [57]: "digital platforms in the manufacturing sector are considered crucial to upgrade industry, improve productivity, optimize resource allocation and increase employment". Further, the same report also presents a working definition of a digital industrial platform [57]: "a digital industrial platform, often also referred to as an industrial internet of things (IIoT) platform, is essential for linking machines and devices in a smart, connected factory with applications (typically on a cloud). The platform collects, stores, processes and delivers data and is the basis for monitoring manufacturing processes, for predictive and automated maintenance, digital integration of value chains or customization of design and production." This working definition underpins the importance of PdM and digital integration of value chains for succeeding with Industry 4.0, which also is highlighted in German reports [5, 39, 40, 58]. However, and another similarity for China and Germany, it is challenging for industrialists to reap the promised benefits connected to PdM. This is also seen in small and medium-sized enterprises (SMEs) in China, where the phrase "not daring to use it, not being able to use it, can't be bothered to use it" has been used to describe SMEs general view on implementing data-based solutions like PdM [57]. For SMEs in Europe and USA, a similar situation is claimed to be present and the importance of developing special approaches to introduce and apply Industry 4.0 technologies is highlighted [59, 60]. As a contribution in this regard, the authors have developed and proposed a novel concept for a PdM platform, presented in Fig. 3.

There is no unified way for how a digital platform or PdM platform should be designed. Although, as an inspiration, according to Refs. [59, 61], an IoT architecture includes four main layers.

(i) Sensing layer—is integrated with available hardware objects to sense the statuses of things, e.g., a sensor connected to a machine;
(ii) Network layer—is the infrastructure for sharing and exchanging data and enables wireless or wired connection between the things;
(iii) Service layer—is to create and manage services required by users or applications;
(iv) Interface layer—is the interaction methods with users or applications.

2.4 Novel concept for a predictive maintenance platform

Advances in platforms for Industry 4.0 have made good progress for generic models. For example, the German RAMI 4.0 has presented the main layers for a holistic approach to Industry 4.0, and serves as an orientation framework for the stakeholders and classification of applications in the industrial sector [27]. On the other hand, more in-depth detailed concepts, and industrial implementation experiences are needed to provide successful and scalable solutions for Industry 4.0 and PdM. One of the research objectives for this paper is to provide concrete suggestions regarding how a PdM platform can be constructed, implemented, and give examples of benefits. This includes discussing solutions for scaling and usability. The purpose of the PdM platform is to serve as an entry-level solution to enable Industry 4.0 and sensor data based PdM. Figure 3 presents a novel concept for a PdM platform, which includes elements from the PdM structure presented in Refs. [3, 40], and a value chain perspective.

The first step in the PdM platform is determining the raw data collection. Selection of sensor type and placement is based on a thorough analysis, e.g., failure mode effects (and criticality) analysis (FME(C)A) or failure mode and symptoms analysis (FMSA), as presented in the standard ISO 17359:2018 [62]. Additionally, to support this selection process, sensor management guidelines, as proposed in Ref. [46], can be used. Performing consequence classification, as described in the standard NORSOK Z-008 [63], as an initial step for determining what assets to be prioritized to the PdM platform is also suggested. For ensuring ease of implementation and bringing costs down, the sensors are battery powered, wireless, and measure physical data, e.g., vibration, temperature, pressure, flow or level, which is digitized at sensor level and locally transported to an IIoT gateway

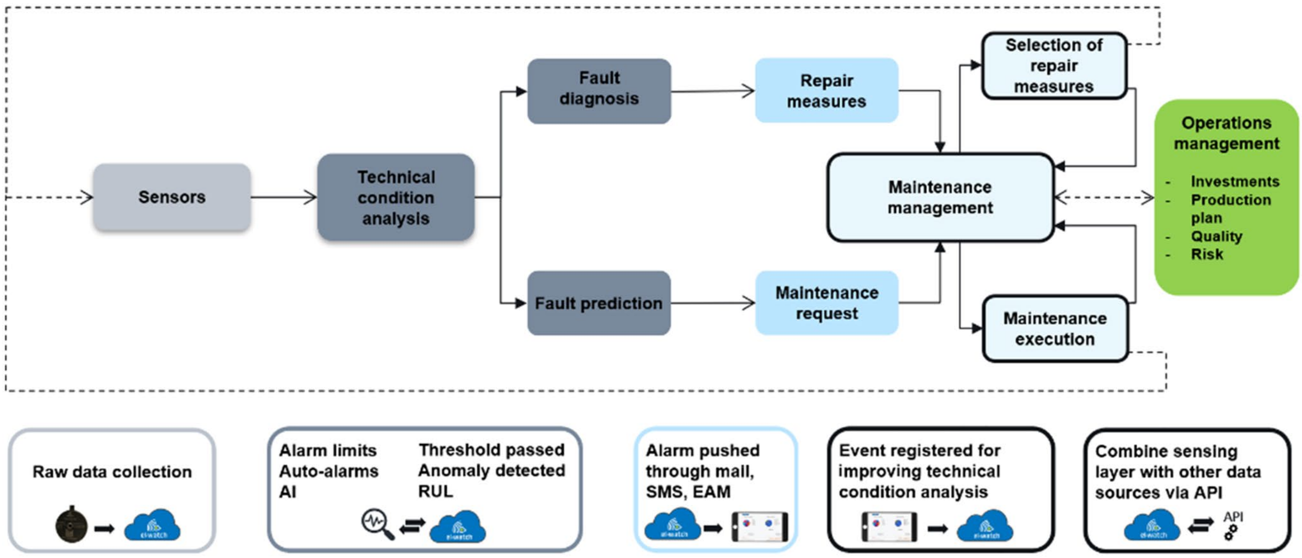


Fig. 3 Novel concept for a PdM platform

by short range radio connection (ISM 868/915 MHz or 2.4 GHz). The IIoT gateway utilizes 4G/5G cellular connection, ethernet connection or a combination to deliver the sensor data (using MQTT) to the IIoT cloud for further processing. The IIoT gateway can also act as an edge device and relay messages directly back to other local devices, reducing use of bandwidth.

In the second step, the raw data have arrived to the IIoT cloud and are processed, labeled, stored, and, if desirable, pushed to other clouds through API. Here, technical condition analysis combines the sensor data, historical data, and previous experience to qualitatively and manually set alarm limits. The sensor data and alarm limit thresholds are monitored by computer algorithms, which immediately act if limits are breached or anomalies detected. Thus, anomaly detection, which is further described in the standard ISO 13379-1:2012 [64], is the initial form of prediction and provides the maintenance request. More advanced algorithms and modules based on AI, such as ANN models, and generating suggestions for auto-alarms and calculations of RUL, can be added when more experience is gained, and contextualized data are available. Further, for fault diagnosis, the FME(C)A and/or FMSA can together with an RCA form a qualitative approach to pinpoint possible repair measures. A quantitative approach to fault diagnosis with ANN models and other data-driven methods can also be added on a later stage.

Step three is where the triggered alarms, maintenance request and repair measures are presented to the user. This can be in the form of an alarm pushed by, depending on degree of importance, electronic mail, text message, or dashboard with further integration, through an application programming interface (API), to e.g., an enterprise asset management (EAM) system.

Lastly, step four concerns a cost-benefit selection of repair measures, planning and scheduling maintenance execution. Maintenance management and operation management must be integrated to balance decisions involving strategic investments, production plan, quality control and risk management, with the overall goal of improving value chain performance. For this matter, the functional connections between maintenance management and manufacturing operations management presented in the standard IEC 62264-1:2013 [65] can be used as guidelines. For decision-making, contextualized data are prerequisites, as data from operations can improve PdM capabilities, but maintenance data can also support decisions across operations, e.g., by indicating utilization of machine capacity and if the required function is available when desired. Here, sensor data can be integrated through API between, e.g., the EAM system and manufacturing execution system (MES). Registration of the executed maintenance action finalizes this step and serves as input for improving the technical condition analysis, raw data collection, and enhancing anomaly detection and ANN models understanding of asset behavior.

3 Case study

To discuss the technological development within maintenance and value chain, and contribute with empirical implementation experiences within these fields, a case from Talgø MøreTre AS is studied. This company has chosen to apply

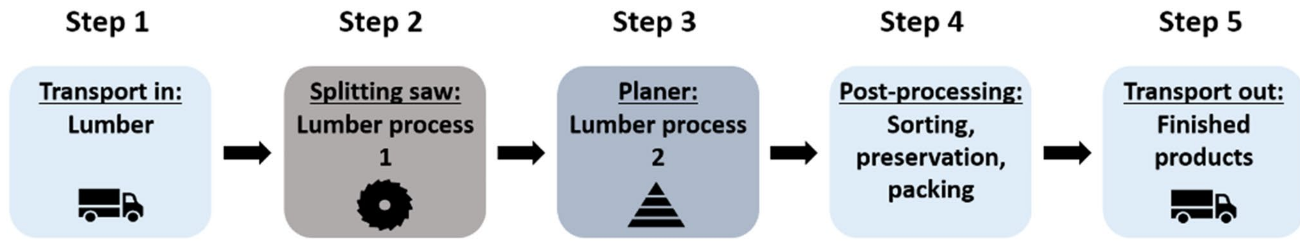


Fig. 4 Simplified overview of the main steps in the value chain at Talgø MøreTre AS

a PdM platform to their production process. The case study is designed to investigate potential verification of the theoretical concept for the PdM platform, by generating an in-depth, multi-faceted understanding of the PdM platform in an industrial setting. It is also investigated how an ANN model can utilize the obtained sensor data, including confusion matrix, loss function, and accuracy rate developed with the software TensorFlow. The case study was proceeded with the following steps.

(i) Provide an overview of the main steps in the value chain for the case company and select the most critical asset to be evaluated;
(ii) Determine raw data collection and define sensor technology and placement through an FMSA for the critical asset;
(iii) Implementation of the PdM platform and development of an ANN model using sensor data as main input;
(iv) Evaluation of case study findings and usability of the results for decision support.

The next three sections describe the case study and company, present the development of the ANN model and case study findings.

3.1 Case study description

Talgø MøreTre AS is an SME located in Surnadal municipality in Norway and is a lumber producer which has established itself as a significant player in the Norwegian lumber market. Their products are mainly within terraces and cladding, as well as finished elements, and lumber is delivered for approximately 58.9 million USD annually (2019) to Norwegian building material stores and other construction industries.

Since 2014 Talgø MøreTre AS, with its 70 employees, has increased their production capacity from 20 000 m^3 to 80 000 m^3 of lumber running through their value chain. Simultaneously with this increasement, a continuous challenge of ensuring stable technical condition of the production equipment occurred. The technical condition of a splitting saw was highlighted as a major concern by the operators, as it was the bottle neck in their value chain. Figure 4 presents a simplified overview of the main steps in the value chain at Talgø MøreTre AS.

The first step in the value chain is transportation of lumber into the production facility at Talgø MøreTre AS. Second, the lumber is fed through the splitting saw for dimensioning, which is the initial lumber process, i.e., lumber process 1. Third, the lumber is run through a planer, for surface and thickness adjustments, i.e., lumber process 2. Fourth, post-processing includes sorting, preservation of the lumber with a variety of treatment solutions, and packing. Lastly, the finished products are transported out to the customers. With the mentioned overall increase in production capacity, the splitting saw needs to be operated over its design capacity. Additionally, the splitting saw is without external cooling, and, as a result, managing overheating of the saw blade and saw wheels has been a major challenge. High temperature increase on the saw blade results in loss of saw blade tension, which leads to lack of quality and rejected products. In addition to loss of saw blade tension, the 450 kg saw wheels can also be overheated when the splitting saw is under heavy load and the saw blades are worn. Other damages of the system are also a risk with continued temperature increasement. Replacing the saw blade and letting the saw wheels cool down result in approximately two hours of unplanned downtime. Figure 5 provides a picture of the splitting saw.

As the splitting saw was operated over its design capacity and no data measurements, e.g., temperature, was available directly from the machine, calculating the optimal operation speed could be categorized as guesswork performed, individually, by the 14 operators. Thus, to avoid high costs connected to unplanned downtime and maintenance repairs, the operating speed for the splitting saw was kept well down on the safe side. On the other hand, this strategy resulted in splitting saw becoming a major bottleneck, leading to challenges in meeting the increasing customer demand.

To overcome the challenges with the splitting saw, the management team at Talgø MøreTre AS discussed investing in a new splitting saw, a cost of approximately 400 000 USD. However, they decided to first investigate on using wireless sensors for condition monitoring (CM), as this potentially

Fig. 5 Splitting saw at Talgø MøreTre AS

could lead to insight into optimal operation speed. The selected solution was to implement a PdM platform, as presented in Fig. 3, with a wireless infrared (IR) temperature sensor, vibration sensor, and power usage sensor as a basis for the raw data collection. The IR sensor was placed on the chassis of the splitting saw for measurement of the saw blade surface temperature. The vibration sensor and power usage sensor were placed on the 55 kW electrical engine running the splitting saw. Table 1 shows the simplified FMSA for the critical subparts of the splitting saw.

Measurements from the sensors, every two minutes, are sent via radiofrequency 868 MHz to a gateway, and stored in the IIoT cloud. Further, the measurements are presented as a live temperature graph in a web-based dashboard available for the operators through tablets and mobile phones. After gaining operational experience, sensor data, and insight on

Table 2 Input and outputs of ANN model

Model output	Input
Blade temperature (Sensor A)	Blade temperature (*t*–1, Sensor A) Current (*t*, Sensor B) Vibration acceleration RMS g (*t*, Sensor C) Sensor C temperature (*t*)

the saw blade surface temperature from the IR sensor, an alarm limit was set when the surface temperature reached 48 °C. For the operators, this alarm limit provided an early warning, i.e., anomaly detection, to reduce operation speed, well in time to avoid overheating the splitting saw, and to start planning a maintenance action of changing the saw blade before failure and in line with the production plan.

3.2 ANN model with sensor data input

To establish the normal behavior ANN model and make predictions on saw blade temperature and splitting saw operation, the variables that can affect this must be taken into consideration to build an accurate model. Accordingly, the sensor data providing input for the model are the IR sensor (Sensor A) measuring saw blade temperature, power usage (current measurement form Sensor B), vibration sensor with temperature measurement (Sensor C). Table 2 shows the parameters selected to establish the ANN model with its input and outputs.

The data collection and preprocess for the ANN model emphasize the connection between the operation of the saw blade and the saw blade surface temperature, which is the most critical part. The upper limit of temperature alarm 48 °C is further used in defining the data in use. The artificially constructed forward neural network is used to classify and recognize the state of the saw blade. Table 3 shows the raw datasets used for the ANN model [66].

Next, the temperature data, with total dataset being 8 360, were recorded in the csv file for the column with Â°C IR avg and the temperature was set to less than 48 °C to 0, and vice versa. Further, the program TensorFlow was used and LabelEncoder selected to code the data labeled,

Table 1 Simplified FMSA for the critical subparts of the splitting saw machine

Subpart	Function	Failure mode	Effect	Failure symptom	Recommended sensor for CM
Saw blade	Saw through wood	Loss of saw blade tension	Lack of quality and rejected products	Overheated and/or worn saw blade	IR sensor for measuring surface blade temperature
Saw wheel	Run saw blade	Overheating	Saw wheel malfunction and further damage	Overheating due to heavy load and/or worn saw blade	Vibration sensor and power usage sensor on the electrical engine

Table 3 Raw datasets [66]

Avg	High	Low	Â°C IR avg	Â°C IR high	Â°C IR low	Sample qty	rssi avg	rssi high	rssi low
0.274	0.891	0	24.2	28.6	22.7	30	69	−65.5	−106.0
0	0	−1	23.0	72.0	−1.0	38	−86	−79.5	−102.5
231	273	206	25.8	30.7	21.5	14	−78	−75.5	−82.5
0.002	0.007	0	24.2	25.5	22.8	31	−67	−65.5	−67.5
–1	−1	−1	−1.0	−1.0	−1.0	28	−84	−82.0	−94.0
206	207	205	21.3	21.5	21.1	15	−76	−76.0	−76.5
0.003	0.007	0	25.6	25.9	25.5	30	−66	−65.5	−67.5

and MinMaxScaler normalized the data. Figure 6 shows an example of normalized data, randomly selected 75% data as training set and 25% data (2 090 data) as testing set.

The model =Sequential() is used to build a forward ANN model and the structure of ANN model is shown in Fig. 7.

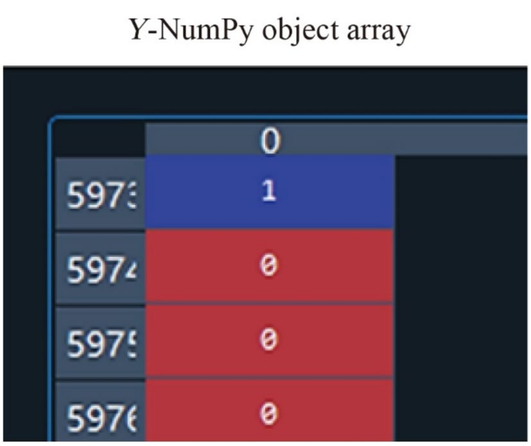


Fig. 6 Data normalization conducted through the software TensorFlow

Dropout technology is added to the network to prevent network over-fitting problems, and the activation function is set to sigmoid. Moreover, the cross entropy of the two classifications is used as the loss function, the Adam optimizer, with accuracy and confusion matrix are used in the model to evaluate the network classification. The 25% dataset is used as the validation set to get the loss function. The accuracy and confusion matrix results are shown in Figs. 8 and 9.

Through the results of the loss function and accuracy rate, it can be concluded that the classification accuracy rate of the ANN model is greater than 0.98, and the accuracy of the model recognition can also be seen intuitively in the confusion matrix, i.e., the accuracy of the saw blade state can be achieved through the presented ANN model.

3.3 Case study findings

After implementing the PdM platform, improvements in performance, safety, and maintenance costs occurred. In terms of performance, case results showed a 40% increase in capacity for the splitting saw. Along with this increasement, the production equipment next in the value chain, the planer, was now sufficiently fed. Thus, the splitting saw was no longer a bottleneck, and satisfactory performance in these

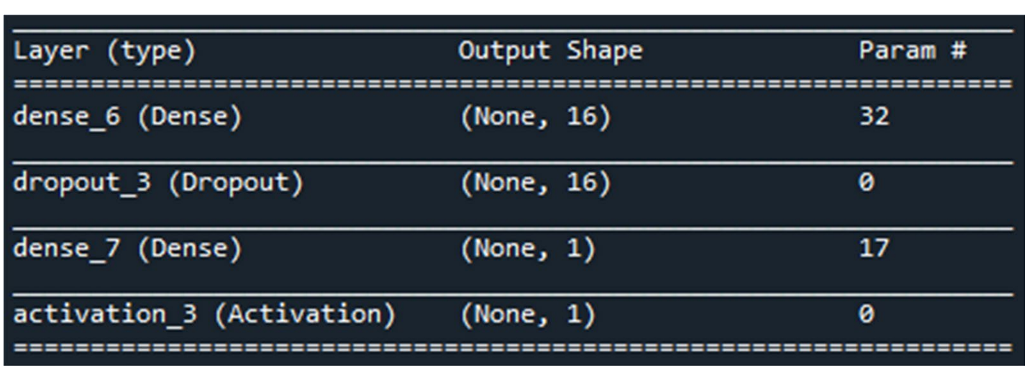
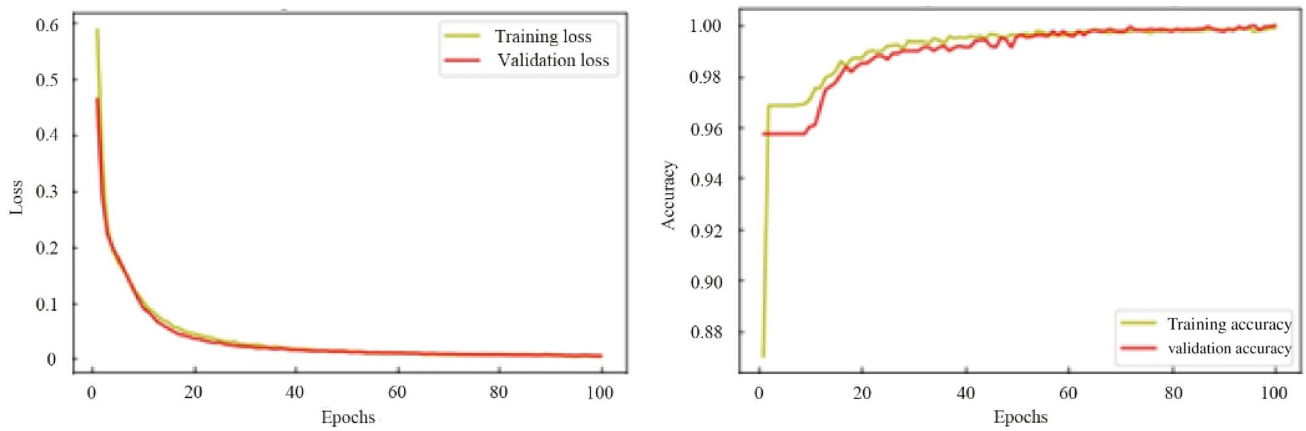


Fig. 7 Structure of ANN model developed with the software TensorFlow



(a) Training and validation loss

(b) Training and validation accuracy

Fig. 8 Loss function and accuracy created through the software TensorFlow

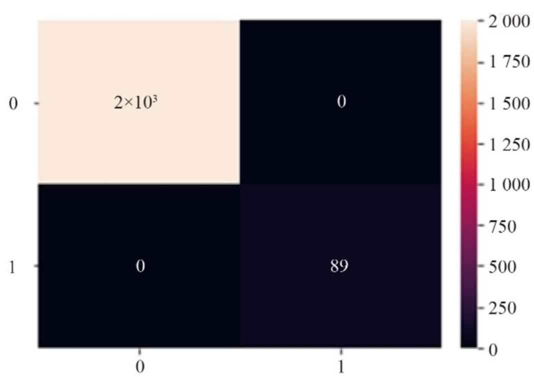


Fig. 9 Confusion matrix built in the software TensorFlow

two value chain steps could be achieved. Within safety, the reduction of saw blades failures improved the level of safety for the operators, as these failures could lead to metal fragments being ejected. For maintenance costs, moving from the strategy of run-to-failure on the saw blades, with a high degree of unplanned downtime, over to a more predictive strategy and enabling scheduling maintenance actions to planned stops, resulted in large maintenance cost savings and a high return on investment. The ANN model shows promising results for classification and recognizing the state of the saw blade, but more work is needed to develop predictive capabilities.

In addition to the mentioned improvements, a change in the way of working also developed. For the operators, the sensor data provided better understanding of technical condition of the splitting saw, and how maintenance actions and changes in machine load could affect this. Moreover, the degree of ownership also increased for the operators, as their actions could be seen as changes in the data and further connected to the mentioned improvements. For the maintenance management team, the successful application on the splitting saw provided motivation for scaling the solution to other production equipment. Thus, as a test, wireless sensors with combined vibration and temperature measurement was mounted inside the planer to gather data from the bearings connected to the spindle, as spindle failures were connected to high costs with unplanned downtime and maintenance repairs. The sensor data were intended to provide anomaly detection for the bearings, as RCA from previous spindle failures had shown that worn bearings often was the initiating event. After a test period, the data foundation was sufficient to enable anomaly detection and give an early warning for a maintenance action of changing the bearings.

4 Discussion of case study findings

The case study findings show that, prior to the implementation of the PdM platform, the view on Industry 4.0 technologies and PdM in Talgø MøreTre AS was quite similar as in most of the other SMEs in China, Europe, and USA. Hence, a general skepticism, which can be connected to lack of competence on new technology and its implementation, economic resources, and willingness to invest in new technology, and insufficient understanding for how such technologies can be utilized to improve value chain performance. As discussed in Ref. [6], this view is also present in other Norwegian SMEs, especially for companies with low level of production repetitiveness.

The novel concept for a PdM platform can be seen as a contribution to theory by bridging the gap between generic overall PdM structures, e.g., as described in Refs. [3, 40], and implementation of a PdM solution in an industrial setting. The PdM platform presents examples on technologies to be used, and relevant integrations to other systems. Suggestions on standards concerning methods, e.g., FME(C)A, FMSA, and anomaly detection, relevant for implementation and use of the PdM platform is given to aid the users. For Talgø MøreTre AS, a simplified FMSA was conducted to support sensor placement and selection of sensor technology, utilizing the extensive experience on the value chain and its bottleneck, the splitting saw. In terms of choosing method for fault prediction, anomaly detection was the natural choice for Talgø MøreTre AS, as an early warning on a well-known symptom for failure provided sufficient time for making adjustments and planning a maintenance action. In addition, the ANN model shows the opportunities of utilizing sensor data to a greater extent, and its position within PdM. The alternative of other quantitative approaches, e.g., RUL can be seen as a balance between cost and value. This trade-off can be linked to findings in Ref. [18], where it is claimed that the added value of stand-alone PdM machine projects is often lower than expected, as companies have extensive experience with wear and tear on their machines.

In the PdM platform, a value chain perspective is included to underpin the importance of focusing on the linkage and integration between maintenance and operation. Further, by bringing in this perspective and seeing the bigger picture, utilizing contextualized data and making decisions with the overall goal of improving value chain performance is highlighted. This is in line with Ref. [18], where the need for using digitization in an advantageous and holistic manner is presented, and the results in Ref. [22], showing that succeeding with data contextualization is crucial for delivering insights across the organization and for enabling data-driven decision making. For Talgø MøreTre AS, the three stages in Fig. 2 can be used to present their transition into possessing a more integrated and digitalized value chain. From initially being at "Stage 0", to connecting sensors on the splitting saw and planer in Stage 1, into enabling anomaly detection in Stage 2, and predicting future maintenance need and planning this along with the production plan in Stage 3. For bigger companies with a more complex value chain, data from raw materials, environment, products, and process can be included in Stage 1 to provide a more comprehensive context for supporting data-driven decision making.

For operators at Talgø MøreTre AS, the implementation of the PdM platform resulted in increased ownership and understanding of how their actions affect the value chain. Moving from decisions based on guesswork over to data, enabled the operators to perform their job more efficiently. This can be seen up against Ref. [27], where the importance of considering how actions of human actors are taken into account in a PdM system is highlighted, and research on Operator 4.0, e.g., in Ref. [67], where it was investigated on how Industry 4.0 technologies would affect and set new requirements for operators working in an Industry 4.0 environment. The case study findings underpin the potential benefit of providing improved decision support for operators, as presented in Ref. [67], and can be seen as proof of concept on a sensor-based feedback system.

After implementation of the PdM platform, the maintenance management team at Talgø MøreTre AS quickly realized its potential and started looking for scaling opportunities. This is in line with Ref. [40], where the importance of a PdM structure being modular and scalable, and providing minimal configuration effort, is highlighted. Additionally, in terms of possibilities with Industry 4.0 technologies, the PdM platform provided an eye opener for Talgø MøreTre AS. As discussed in Ref. [6], this can be seen as an approach needed to initiate an Industry 4.0 journey. Further, the importance of a company or industry specific approach to reap the opportunities and benefits from Industry 4.0 is underpinned by Ref. [6]. As a contribution for this matter, a generalized approach for initiating a PdM platform is given in Fig. 10. Here, consequence classification creates a foundation and overview of critical assets to pursue a PdM strategy, performing FME(C)A and/or FMSA, along with PdM platform implementation, results in a defined selection of sensor technology and placement, and a scalable solution for enabling expansion and gaining improvements throughout the value chain.

5 Conclusions, limitations and further research

This paper has discussed the development, and need for integration, within the fields of maintenance and value chain along with the introduction of Industry 4.0. As a contribution for this matter, the paper presents a novel concept for a PdM platform and an ANN model, and a case study at Talgø MøreTre AS, a Norwegian SME, providing empirical implementation experience in an industrial setting. Case study shows that, with the implementation of the PdM platform, Talgø MøreTre AS moved from a firefighting maintenance strategy, into using contextualized data with predictive capabilities for enabling maintenance actions to be planned before failure and in line with the production plan. Sensor data available to the operators provided better understanding and competence on parameters affecting technical condition of the production equipment, and, as a result, increased the production capacity to a level that investments in new equipment could be postponed. This shows that the PdM platform can be used as an entry-level solution to enable Industry 4.0 and sensor data based PdM. The ANN model also shows promising results with high accuracy of determining the saw blade state. In terms of scaling and for companies with a more complex value chain, a generalized approach for initiating a PdM platform is given. This provides

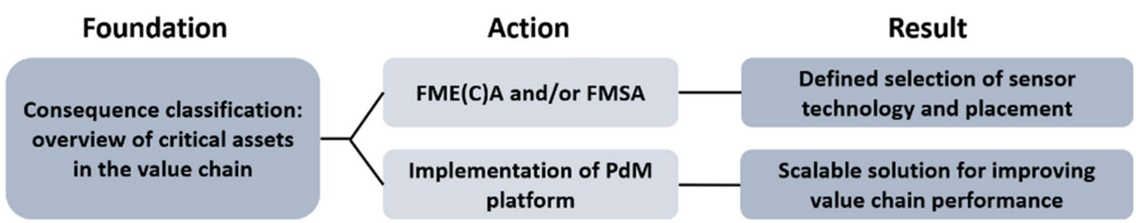


Fig. 10 Generalized approach for initiating a PdM platform

the necessary prerequisites for companies aiming to implement the PdM platform, by establishing an overview of critical assets in the value chain and conducting a FMSA to define selection of sensor technology and placement to be used in the PdM platform.

A limitation to the study and for evaluation of the PdM platform is the number of case companies included. Conducting a study in only one company limits the level of generalization of results, and if the approach is applicable to other companies or industries. Another limitation of the structure of the PdM platform is the lack of detail in terms of connectivity to other systems such as MES and EAM, which can be essential for companies requiring a high degree of contextual information for decision making. There is also a limitation that the ANN model and analysis methods used require a noteworthy amount of failure data before the results can provide decision support for end-users. Results are also highly dependent on correct selection and placement of sensors.

Further research should include case studies on the PdM platform and the ANN model in other companies and different industries to strengthen its maturity and sustainability. Further development of the PdM platform is proposed to include more ways to integrate historical data and systems such as MES and EAM. A more seamless integration with the ANN model should also be developed. Research is also needed on how other Industry 4.0 technologies can be added in a cost-beneficial way. Evaluating the generalized approach for initiating a PdM platform, and its role in a roadmap towards Industry 4.0, is also proposed for further work. More detailed investigation should be conducted on how the PdM platform further can integrate maintenance and operation for enabling contextualized data-driven decision making throughout the value chain in an Industry 4.0 environment.

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