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Deep digital maintenance

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Abstract With the emergence of Industry 4.0, maintenance is considered to be a specific area of action that is needed to successfully sustain a competitive advantage. For instance, predictive maintenance will be central for asset utilization, service, and after-sales in realizing Industry 4.0. Moreover, artificial intelligence (AI) is also central for Industry 4.0, and offers data-driven methods. The aim of this article is to develop a new maintenance model called deep digital maintenance (DDM). With the support of theoretical foundations in cyber-physical systems (CPS) and maintenance, a concept for DDM is proposed. In this paper, the planning module of DDM is investigated in more detail with realistic industrial data from earlier case studies. It is expected that this planning module will enable integrated planning (IPL) where maintenance and production planning can be more integrated. The result of the testing shows that both the remaining useful life (RUL) and the expected profit loss indicator (PLI) of ignoring the failure can be calculated for the planning module. The article concludes that further research is needed in testing the accuracy of RUL, classifying PLI for different failure modes, and testing of other DDM modules with industrial case studies.

Keywords Maintenance planning · Integrated planning (IPL) · Digital maintenance · Predictive maintenance · Industry 4.0

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1 Introduction

With the onset of Industry 4.0, there will be a game change in manufacturing. To ensure future competitive advantage, manufacturing companies must employ cyber-physical systems (CPS) [1]. One priority area for action in Industry 4.0 is the management of complex systems. The models in this system offer huge potential in Industry 4.0. For instance, the models can offer transparency of information and improve interdisciplinary cooperation. The focus of this paper is the cooperation between production and maintenance planning, which is denoted as integrated planning (IPL) [2]. In particular, in this concept, a key performance indicator (KPI) denoted profit loss indicator (PLI) is promising in data-driven predictive maintenance [3].

The digital world in Industry 4.0 will include two types of models [1]:

(i) Planning models. These models make it possible to build complex systems. An example of a planning model could be a reliability model used by an engineer to evaluate the reliability of a system. Here, the model will contain the engineers' knowledge.
(ii) Explanatory models. These models are often used to validate the engineers' design choices, e.g., a simulation model that can calculate the energy consumption in a factory.

McKinsey [4] points out 8 main value drivers for Industry 4.0: time to market, service/aftersales, resource/process, asset utilization, labor, inventories, quality and supply/demand match. Among these value drivers, maintenance is included in the following:

(i) Asset utilization. Predictive maintenance can drive value by decreasing the planned machine downtime, unplanned machine downtime, or changeover times. The predictive maintenance typically decreases the total machine downtime from 30% to 50% and extends the operation life from 20% to 40%.
(ii) Services and aftersales. Predictive maintenance combined with remote maintenance will typically reduce the maintenance cost from 10% to 40%.

It is, therefore, no surprise that the largest expected change in future maintenance is the shift from corrective to predictive maintenance [5]. To ensure the highest performance of an asset, an intelligent maintenance system must bring together technology, data, analyses, prognosis, and resources. This will also improve the maintenance planning function where more real-time data support the planner.

Artificial intelligence (AI) should be central for data-driven methods in Industry 4.0. A pure data-driven method should be regarded as a mathematical method where no phenomenological knowledge is needed [6]. An example of phenomenological knowledge in maintenance is the knowledge about physical processes involved in the degradation or reliability theory with support from expert judgment. In future maintenance, it is believed from the authors point of view that there will be a combination of data-driven methods and model-driven methods. This is also supported in future EU projects where "…measurements of a range of parameters at the level of components, machines and production systems should be carried out to provide data for building trend reference models for prediction of equipment condition, to improve physically-based models and to synchronize maintenance with production planning and logistics options." [7]. An important tool for the program DeepMind from Google is one among several that offer the next generation of AI [8]. Currently, it seems that DeepMind is able to learn more like a human; the program can learn tasks sequentially using skills it acquires on the way [9]. For maintenance, AI is considered to be a data-driven method, where an artificial neural network (ANN) is applied to estimate the remaining useful life [10]. In the context of process industry, a literature study has been conducted on data-driven methods [6]. This study presents the most popular data-driven methods in this industry branch: multivariate principle component analysis, partial least squares, ANN, neuro-fuzzy systems, support vector machines.

For example, ANN has been applied to predict failure of wind energy conversion systems [11]. The challenge today in AI is "catastrophic forgetting" where knowledge of the previously learned task is abruptly lost as information relevant to the current task is incorporated [12]. It seems that deep neural networks are currently the most successful machine-learning technique to solve this challenge. Thus, what was previously considered to be pure fiction, seems to be soon the reality. This will also affect the maintenance science and improve the maintenance models.

Figure 1 is based on earlier evaluations [13] and portrays a matrix of trends in Industry 4.0 and digital maintenance. Likewise, there has been a shift from lean production towards smart manufacturing; it is also expected to be a shift from maturing maintenance towards digital maintenance.

Inspired by the emergence of Industry 4.0 in manufacturing and the ever-increasing opportunities in AI, a new concept should emerge in maintenance management. The aim in this paper is, therefore, to develop a new maintenance model called deep digital maintenance (DDM).

The rest of this article is structured as follows: Section 2 presents the relevance and trends of maintenance in Industry 4.0. Section 3 develops the DDM model with relevant modules. Section 4 describes along with a demonstration of the modules. This article is concluded in section 5 with a brief discussion of the result from the testing.

2 Maintenance in Industry 4.0

Although there are several definitions of Industry 4.0, most of them agree that CPS is a design principle [14]. To succeed with Industry 4.0, an architecture for cyber physical production control has been constructed [15]. CPS for maintenance is also central in Industry 4.0-based manufacturing systems [16]. In particular, Deutsches Institut für Normung (DIN) (in English, the German Institute for Standardization) points out in a roadmap for Industry 4.0 that smart maintenance will contribute to successful implementation [17]. Smart maintenance would enable Industry 4.0 and implement CPS, which are notable for its high degree of networking, digitization, decentralization and autonomy, efficiency, and availability.

2.1 5C architecture for Industry 4.0

Figure 2 illustrates the 5C architecture of CPS with 5 levels [16]. CPS can be comprehended as the use of logical properties of computers to control and monitor the dynamic properties of a physical asset [18]. In Industry 4.0, the logical properties of computers will improve the maintenance functions in a company and will control the technical conditions of physical assets better.

Level 1 of CPS comprises of connection to all relevant data. This connection performs digital data capturing of several types of data:

Cost focus (Before 1980)	Quality focus (1980-2010)	Customization focus (After 2010)
Mass production	Lean production	Smart manufacturing
Push policy Gantt charts Motion & time study Assembly line Statistical sampling Inventory optimization PERT/CPM MRP	Just-in time Pull policy Electronic data interchange TQM Baldrige award Kanban	Economies of scope Global manufacturing Agile manufacturing Internet-based manufacturing IoT, data analytics Cyber physical system & Industry 4.0
Reactive maintenance	Maturing maintenance	Digital maintenance
Corrective maintenance Ad-hoc planning Ad-hoc analysis	Preventive maintenance Maintenance budgeting CMMS & KPIs Use of experience Outsourcing LCC & maintenance under design TPM & TPS Maintenance mgt.loop Material properties Process improvement Root cause analysis Condition monitoring	Industry 4.0 Cyber-physical system DeepMind technology Proactive maintenance Predictive maintenance LCP and hidden factory Asset management Remaining useful life (RUL) Standardization Innovative visualization Green maintenance Integrated operations Core maintenance Maintenance optimization Maintenance engineering Maintainability performance

Fig. 1 Trends within maintenance, inspired by Ref. [13]

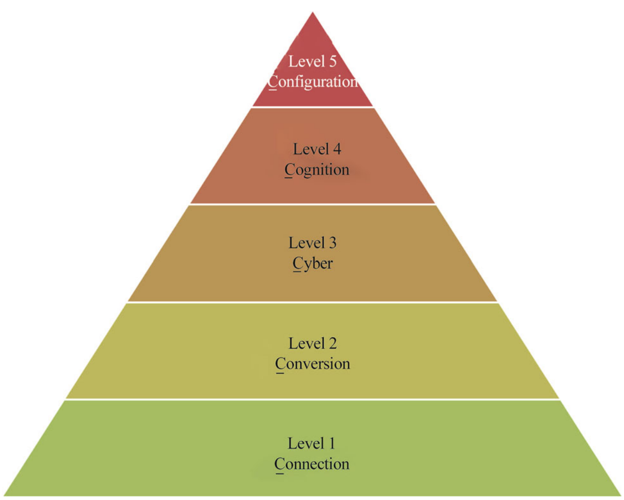

Fig. 2 5C architecture adapted from Ref. [16]

(i) Data from sensors. Real-time data capturing from sensors such as temperature and pressure;
(ii) Manual data. Data from manual registration and further processing in computerized maintenance management system (CMMS);
(iii) Cost data. Down time costs and maintenance costs such as man-hours and spare parts.

In Level 2, the data will be converted into meaningful information. For the machine, the information related to power consumption and levels of vibration are calculated. In maintenance logistics, the radio frequency identification (RFID) will keep track of the spare parts in the inventory and supply chain. In the CMMS system, the registered data will be structured in an asset register.

The big data excel in a cyber network in Level 3. Information is gathered from all the machines and the CMMS systems, thus enabling sophisticated maintenance analytics: machine prediction where remaining useful life is estimated, twin models for components and machines, synchronized maintenance and production planning, PLI evaluations, digital root cause analysis, modeling with expert judgment, physical models and data driven methods.

In Level 4, proper presentation of the analytics enables human interaction and evaluation by experts. The dashboard in Level 4 can be monitored in a control room or on a tablet. Hence, there are no requirements for the physical location of the dashboard; it only needs to have access to the internet.

Level 5 is the decision level where CPS either provides a digital advice or automatically controls the maintenance through self-maintenance. An example of digital advice would be the notification of remaining useful life based on which the maintenance planner should start scheduling future maintenance tasks. Self-maintenance could be the automatic maintenance of a machine that is non-intrusive and does not need the intervention of technicians.

Furthermore, the 5C architecture has also been proposed for predictive production systems using the approach of CPS [19]. It was further detailed that Level 5 in this model must comprise maintenance decision making, in which maintenance scheduling is an essential element. An important decision would then be when to schedule the maintenance. It has been demonstrated as a concept with CPS using ball screw prognostics. The improved maintenance scheduling approaches based on Industry 4.0 remain to be investigated in more detail.

2.2 Maturity model for Industry 4.0

A maturity model has been developed within Industry 4.0 [20, 21]. Figure 3 illustrates this model, which comprises of six development stages. Before starting the development path of Industry 4.0, activities for digitalization are necessary. In the Industry 4.0 maturity model, these activities are organized in two stages: computerization and connectivity. When the digitalization has been finalized, the development path for Industry 4.0 can start in the organization. For the energy sector, it is proposed that predictive maintenance should be positioned in stages 5 and 6 [20]. It is also important to emphasize that not all activities in the organization should be positioned in stage 6, but in a stage that represents the best trade-off between costs, capabilities, and benefits [21].

The elaborated description of each development stage is as follows:

(i) Computerization. This stage concerns the different isolated information technologies that are used in the company.

(ii) Connectivity. In this stage the isolated information technologies are connected. An example is remote maintenance that connects the machine builder with the industrial end-user.

(iii) Visibility. This stage provides companies the opportunity to "see" what is happening. When the connectivity has been successfully implemented, it would be possible for the organization to create a digital shadow of the company. With real-time recording of events and states in the organization, it is possible to ensure an up-to-date digital model for the production plant at all times. In this stage, there is a new approach for data gathering and processing. In the new approach, data are not tied up to individual data analyses. Instead, data from several systems such as enterprise resource planning (ERP) and manufacturing execution system (MES) are combined, and data can be applied for several analysis methods.

(iv) Transparency. Based on the digital shadow created in stage 3, the next stage for the company is to understand why something is happening in the organization. The processed data in the organization must be analyzed with engineering knowledge and the support of new technologies that enable, for example, big data. With support from big data, extensive stochastic data analysis and machine learning methods can reveal interactions in the company's digital shadow.

(v) Prediction. Once transparency is established, it is possible to simulate the different future scenarios

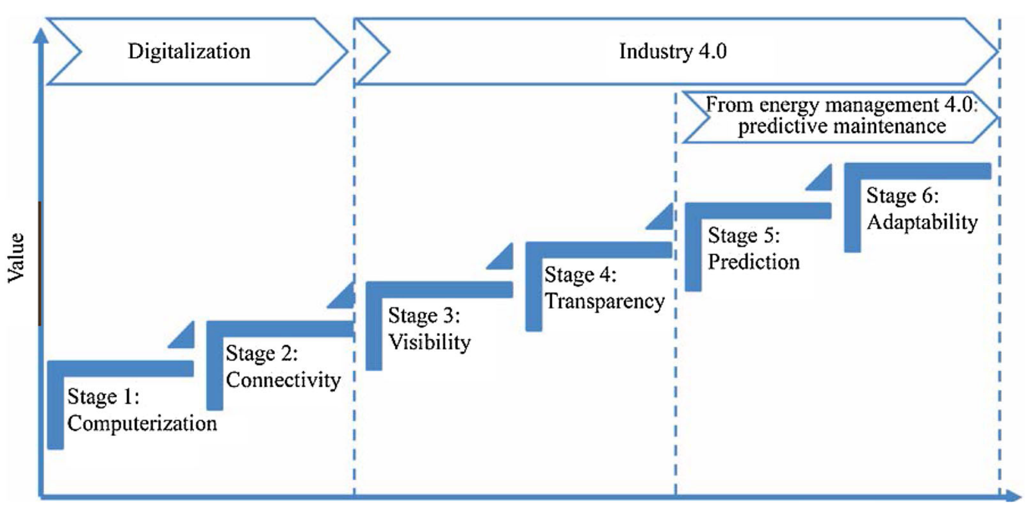

Fig. 3 Industry 4.0 maturity model

and evaluate the most likely ones. In this stage, the organization can predict future developments and take decisions before it is too late. For predictive maintenance, this involves the estimation of remaining useful life, thus providing sufficient time to schedule the maintenance activities for the relevant machine.

(vi) Adaptability. When the organization is able to predict future situations, this stage concerns the ability of the organization to become adaptive, whereby more actions are automated. This depends on the complexity of the decisions, the risk related to the decision, and the cost-benefit ratio in automating the decision. An example would be the rescheduling of planned orders due to machine breakdown. In predictive maintenance, this could concern rescheduling the maintenance plan due to change in the production schedule.

As in the case of 5C architecture, the maintenance scheduling and planning approaches based on Industry 4.0 still remains to be investigated in more detail.

3 DDM management model

Figure 4 illustrates the behavior of the DDM in terms of work processes. To ensure continuous improvement of DDM, the work processes follow the logic of the Deming cycle; PLAN-DO-CHECK-ACT [22]. The objectives and requirements for DDM comprise several maintenance functions:

(i) Technical: reduction of downtime,
(ii) Organizational: increase man-hours for predictive maintenance,
(iii) Economic: reduction of maintenance costs.

When the objectives and requirements for DDM have been established, the DDM modules can be applied. Table 1 elaborates the modules in DDM.

To focus on future maintenance work, IPL enables synchronization between maintenance and production planning. With a well-established maintenance dashboard and interaction with the production planner, the maintenance planner will be able to provide better and faster maintenance decisions. In parallel with IPL, the physical system conducts self-maintenance without requiring human interaction. Based on pre-defined rules, the system will adjust the production or automatically perform standard maintenance of the physical system.

After the self-maintenance and maintenance execution, the physical system achieves a certain level of technical condition. Based on the maintenance execution and self-maintenance, the DDM reports the results of the maintenance. Based on the findings in the report, a root cause analysis (RCA) will be conducted. In addition to traditional RCA methods such as Isikawa diagram and 5-why analysis, the analytics from data driven methods will be able to cluster the information into different cause categories. The maintenance dashboard enables the decision maker to evaluate the root cause. Once RCA has been conducted, the following improvements will be performed.

To ensure that each work process in DDM is followed up, deep digital maintenance management is positioned at the center of the loop. When necessary, this function will also include the audit of DDM. Further, in this section, the DDM modules AI, PLI, and planning are elaborated in more detail.

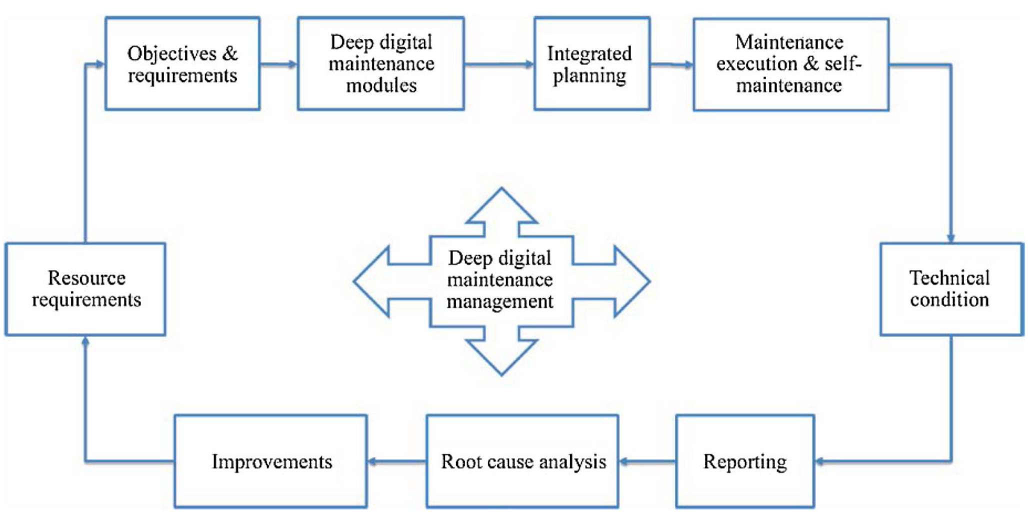

Fig. 4 Work processes for DDM, inspired by Ref. [22]

Table 1 Deep digital maintenance modules

Modules	Description
AI	This module offers the most successful machine-learning techniques such as deep neural networks, clustering, etc.
PLI	PLI will provide scenarios of unwanted events (e.g., breakdown) and provide analysis for RCA (taxonomy of the hidden factory).
Planning	The planning module will analysis the maintenance window and offer alternative maintenance plans. Furthermore, it will enable IPL where maintenance and production planning is integrated.

3.1 AI module

The purpose of the AI module is to provide accurate predictions of RUL for all known failure modes. Accurate predictions of RUL can contribute to lesser critical failures and lesser unnecessary maintenance, in addition to improved resource- and spare part planning [11]. Figure 5 shows the structure of the AI module.

Data are collected through an IoT hub, which communicates with IoT units using standard protocols. The IoT units can be IP-connected metering devices or non-IP-connected units through a connected gateway. Real-time data are fed to the data stream analytics and then stored in a database.

Machine learning (ML) is used to train the prediction models to recognize healthy patterns, un-healthy patterns, and anomalies. The prediction models are generated as code and applied to the datastream of the sensor readings to obtain real-time prediction of RUL [10]. The prediction results are communicated with the CMMS via e-mail or customized dashboards.

ML uses statistical techniques to learn and recognize patterns in big data. A code is generated from the prediction model and used for recognizing the patterns in a stream of data [23]. The output is the probability for the machine being in a particular state. For example, a binary parameter that indicates whether the machine will fail within x cycles is engineered, and the model is trained to predict the value of this parameter. In this case, the code will output a probability for this parameter being true or false, i.e., the probability that the machine will fail in less than x cycles. Deciding what to do with this probability is a business decision [24]. Figure 6 shows the typical ML process.

3.2 PLI module

When estimating the $\mathrm{PLI}_{\mathrm{Scenario}}$, the PLI cube shown in Fig.7 is needed [2]. This cube classifies the hidden factory in terms of time loss and waste. The time loss is based on the categories of overall equipment effectiveness (OEE), utilization degree of the equipment, amount of raw material consumed, and resource consumption. In resource consumption, the energy consumption is identified. For each category of time loss and waste, PLI will be the sum of the turnover loss and extra costs. For example, if an unplanned downtime occurs, PLI will calculate both the turnover loss in terms of reduced number of goods to sell as well as the extra costs in terms of corrective maintenance. Moreover, PLI can be calculated at the process level, plant level,

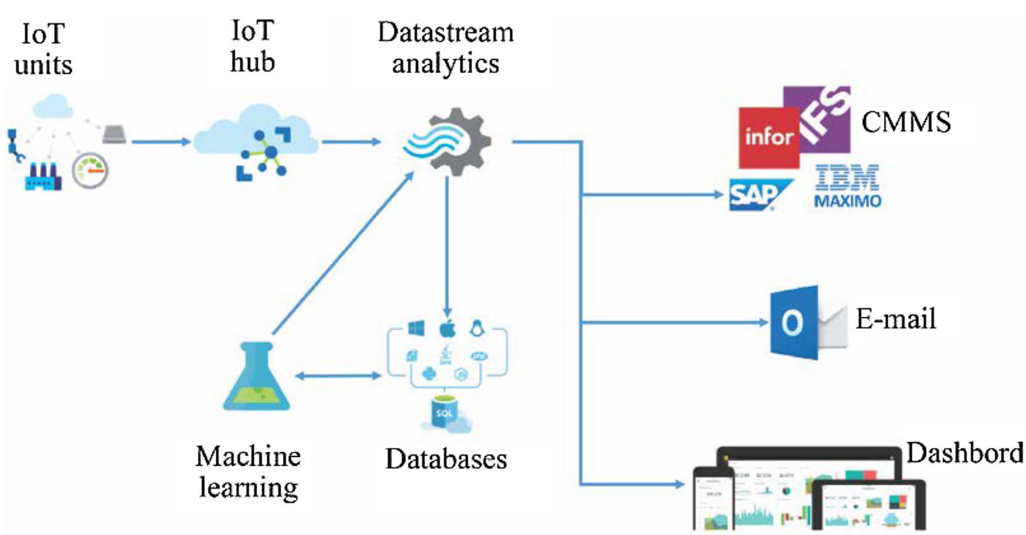

Fig. 5 Structure of the AI module

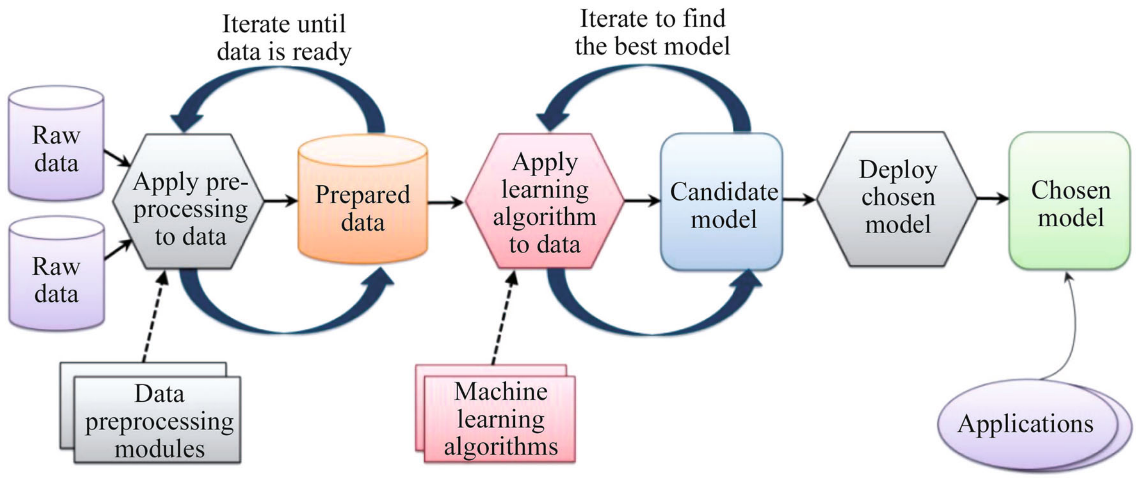

Fig. 6 Typical ML process adapted from Ref. [24]

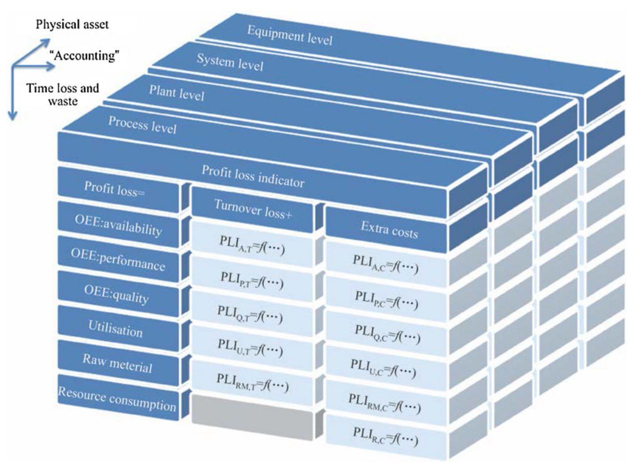

Fig. 7 PLI cube, adapted from Ref. [2]

system level, or equipment level. The estimation of the expected PLI value, $PLI_{Expected}$, in this paper is based on an earlier case study of one specific event [3]. With the capabilities of AI, the future expected PLI value could also be predicted without historical events for PLI.

3.3 Planning module

The purpose of maintenance planning is to achieve a reliable plant capacity [25]. A central principle in maintenance planning is the ability to concentrate on future work. In this paper, the future time horizon is denoted as $T_{horizon}$. To focus on future work, the CMMS will administer the maintenance data and release maintenance work orders for craft technicians. The CMMS improves the entire maintenance management function with analyses from asset data collection systems, supporting automated preventive work orders based on data-driven insight [26]. CMMS is also vital for the coordination of maintenance activities related to both availability and productivity [27]. The strength of CMMS in maintenance planning lies in its ability to schedule complex, fast-moving workloads. In addition, CMMS improves the cost management and controls the resources better.

A challenge with CMMS is that it tends to have a "black hole". This metaphor describes a system that is greedy for data input but seldom provides output in terms of decision support. In particular, predictive maintenance data analysis can be a "black hole" in the CMMS module and tends to lag behind [27]. Other "black holes" in systems that are available in the market, but are not applied are [28] condition monitoring analytics, diagnostics of equipment failure, decision support to resource allocation, and decision analysis support.

For CMMS, there exists different business processes for maintenance planning. For example, in SAP, there are two business processes for planning, preventive maintenance, and planned repair. In preventive maintenance, there are fixed time intervals for the maintenance activities, whereas planned repair maintenance is scheduled after a notification is registered due to a failure [29]. Inspired by the business process of planned repair, we propose a business process for planned predictive maintenance with the following steps:

(i) Notification. The predictive analysis system automatically sends a notification to the CMMS when RUL is approximately the same size as the planning horizon. In the notification, an expected PLI value is calculated, expressing the expected PLI during the planning horizon.

(ii) Planning and controlling. The schedule in the planning horizon is shown in a dashboard where the planner can control the capacity of the maintenance resources. It is further decided if the planner will ignore this notification and wait for a new one, or if he will then schedule the maintenance activities into the planning horizon.

(iii) Implementation. This phase comprises both withdrawal of spare parts and processing of the actual maintenance work order.

(iv) Completion. After the maintenance task has been completed, the feedback is reported back to the maintenance planner.

3.3.1 Notification

The notification is a trigger mechanism for maintenance planning, when the request is registered. In DDM, the following information is automatically registered in the CMMS: $PLI_{Expected}$, which will occur at the end of time horizon $T_{horizon}$.

There can be several occasions for this notification in CMMS. To ease the administrative planning function, three opportunities are offered to the planner with a notification (see Table 2).

3.3.2 Planning and controlling

Once the notification has been registered in the CMMS, the maintenance planner can plan the future maintenance work and control if necessary maintenance resources are available. Figure 8 illustrates an example of an IPL dashboard, where the planner can evaluate the available maintenance windows within the planning horizon $T_{horizon}$.

At the end of the planning horizon, it is expressed what the expected PLI value would be. Based on this number and the available maintenance windows and capacity, the planner must decide whether to ignore this opportunity or to schedule the future maintenance activity within this planning horizon. This dashboard is also shared with the production planner, enabling IPL.

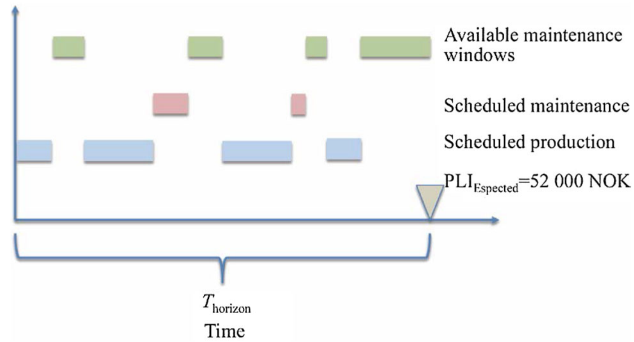

Fig. 8 IPL dashboard

4 Testing the DDM model

The starting point is to define the different scenarios for unplanned events. To classify a future scenario, the following information is necessary:

(i) Description of the initiating situation, which can be a failure mode;

(ii) The parts of the physical asset that are involved in the scenario;

(iii) The further consequences of PLI: the duration of the situation, the scrappage in production, the total cost of PLI, skills of the craft technicians, the quality of the maintenance tools used for conducting maintenance, type of spare parts required, the supplier needed in conducting the maintenance.

In this paper, the following scenario is defined: “malfunction of oil cooler in a machine center”.

4.1 PLI module

The case study in Ref. [3] investigates the malfunction of an oil cooler in a machine center. The malfunction was first

Table 2 Notification logic

No. of notification	Criteria for notification
1	A conservative value of $PLI_{Expected}$ triggers the notification. This notification can be ignored if there are no capacity for conducting maintenance
2	A higher value of $PLI_{Expected}$ is chosen for this notification. This notification is the most likely one to be chosen by the planner. If there are still challenges with capacity, the planner should consider to ask the production planner to change the production plan so that the maintenance activity can be performed
3	This is the highest value of $PLI_{Expected}$ and is considered as a worst case where maintenance must be conducted within this time horizon to prevent a failure. The maintenance should be performed as soon as possible with first available maintenance window. If maintenance resources are not available, they should be reallocated for this maintenance task. It is also expected that the production planner should re-plan in order to help the maintenance planner to conduct the maintenance as soon as possible

observed in terms of scrappage of product with unplanned downtime. Before the failure occurred, the temperature of the oil cooler increased significantly, causing instability in the production process. After the observed scrappage, a quality audit meeting was conducted to evaluate the cause and consequence of the scrappage. In addition, maintenance personnel performed inspection on the machine center when the unplanned downtime occurred. They found out that the cause of downtime was the malfunction of the oil cooler. The oil cooler was then replaced with a new one. Due to anonymity, the time window for the downtime is not accurate. Instead, it is assumed that a realistic duration of the downtime is 6 days.

Table 3 shows the results of calculating the PLI value for this event [3]. Both the availability and quality losses can be traced to PLI. The main contribution of the PLI value is the damaged part (scrappage) and loss of internal machine revenue. The internal machine revenue is the expected revenue for operating the machine. The loss of internal machine revenue is the expected revenue loss due to the downtime of the machine. The revenue rate should be based on the norm decided by the company.

Figure 9 illustrates the PLI event "malfunction of oil cooler" [3]. The loss of internal revenue from the machine center will start immediately after scrappage of the part and failure of the machine. Moreover, the quality audit meeting and maintenance activities are performed sequentially. During the maintenance activities, there is a significant increase in the maintenance costs when the oil cooler is replaced.

4.2 AI module

Since we did not obtain condition-monitoring data for the oil cooler, we used data from another type of equipment to test the AI module. For demonstrating how to perform predictive maintenance, a case based on the data for an aircraft turbofan engine is used instead. In the demonstration, a predictive maintenance model is developed using

Table 3 Expected PLI of ignoring the notification [3]

Situation	Type of PLI	PLI value/ NOK
Damaged part (scrappage)	Quality: extra cost	120 000
Quality audit meeting	Quality: extra cost	3 500
Maintenance labor costs	Availability: extra costs	21 570
New oil cooler	Availability: extra costs	47 480
Loss of internal machine revenue	Availability: turnover loss	129 600
Sum		322 150

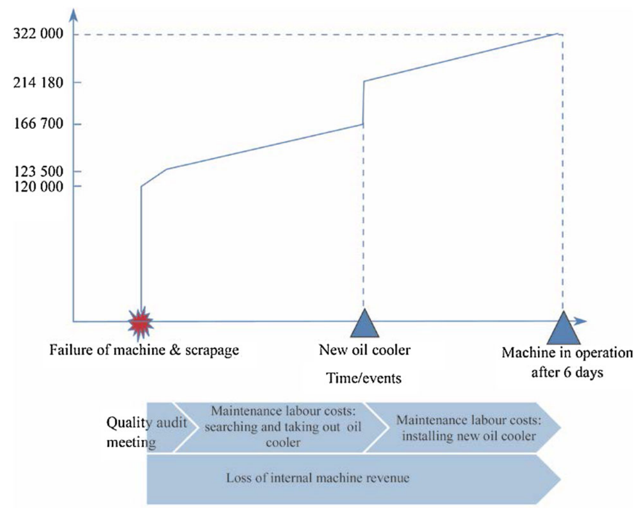

Fig. 9 Scenario "malfunction of oil cooler" [3]

Microsoft Azure Machine Learning and applied to a simulated dataset [30].

The predictive maintenance demonstration is based on a dataset from the NASA Prognostics Center of Excellence [31]. The dataset comprises of degradation simulation run-to-failure data that contains settings and sensor readings for run-to-failure of 100 turbofan jet engines. For each of the engines, the dataset includes: operation cycle, which is a time unit; 3 different settings, i.e., throttle, blade pitch, etc.; 21 sensor readings, i.e., pressure in the high-pressure compressor, temperature at the nozzle, etc.

Table 4 lists the data for the first 10 cycles of engine id 1 and it illustrates how the data is structured.

The first iterative process in machine learning is the pre-processing of the data and feature engineering. A binary parameter that indicates whether the RUL is more or less than 10 cycles is engineered. Of the data, 80% is used for training the model, and 20% is used for evaluating the model.

The next iterative process is to apply machine-learning algorithms. These algorithms generate candidate models and will iterate to find the most fitted prediction model. The model is trained to predict the value of the engineered binary parameter, thus the problem is a two-class classification problem. The output of the model is the probability that RUL>10 cycles, hereinafter denoted as P_r (RUL>10). After iterations with logistic regression, neural network, decision forest, and decision jungle, it is found that the two-class neural network gives the best prediction model for the turbofan jet engine run-to-failure dataset.

To demonstrate the results, P_r (RUL>10) for the entire lifetime of one engine is plotted in Fig.10. In addition, Fig. 11 shows the same plot, zoomed in on the end of the lifetime, in which the point-of-failure and cycles with P_r = 10 are also indicated.

Table 4 Data example for the 10 first cycles of engine id 1 [31]

Cycle	Setting			Sensor				
	1	2	3	1	2	…	20	21
1	− 0.0007	− 0.0004	100	518.67	641.82	…	39.06	23.4190
2	0.0019	− 0.0003	100	518.67	642.15	…	39.00	23.4236
3	− 0.0043	0.0003	100	518.67	642.35	…	38.95	23.3442
4	0.0007	0	100	518.67	642.35	…	38.88	23.3739
5	− 0.0019	− 0.0002	100	518.67	642.37	…	38.90	23.4044
6	− 0.0043	− 0.0001	100	518.67	642.10	…	38.98	23.3669
7	0.0010	0.0001	100	518.67	642.48	…	39.10	23.3774
8	− 0.0034	0.0003	100	518.67	642.56	…	38.97	23.3106
9	0.0008	0.0001	100	518.67	642.12	…	39.05	23.4066
10	0.0033	0.0001	100	518.67	641.71	…	38.95	23.4694

The results of the case study show that the prediction model for the turbofan jet engine has close to zero false predictions during the lifetime of the engine and that it accurately predicts the RUL close to the selected alarm level.

4.3 Planning module

The result of the AI module will also result in an expected PLI value, $PLI_{Predictive\ maintenance}$. As an example we assume that the planned downtime of oil cooler is in average 3 days and that the maintenance activity is completed within the maintenance window. Table 5 therefore shows the PLI elements that will occur during the period. Figure 12 further illustrates the event of performing predictive maintenance. The PLI in the predictive maintenance is based on the PLI value from the case study of malfunction of oil cooler.

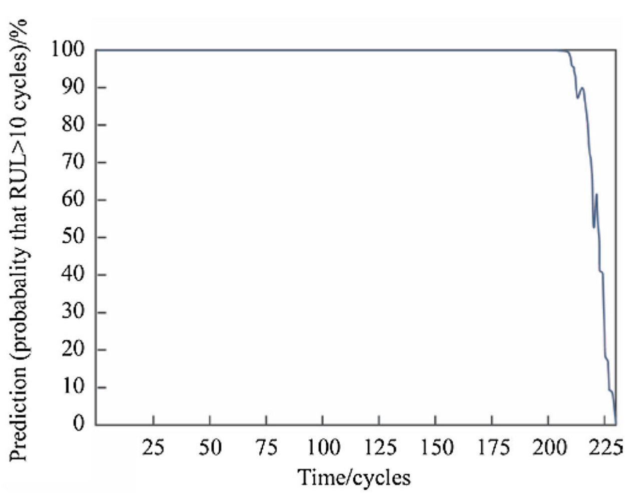

Fig. 10 Predicted probability that RUL>10 cycles for entire lifetime of the engine

5 Discussions and concluding remarks of DDM

The aim of this article was to develop a new maintenance model called DDM. The DDM is based on both the architecture for CPS and the work processes from the deming cycle. The DDM model was also tested to evaluate the applicability.

As the first attempt for testing this model, the planning module for predictive maintenance was investigated. The quality of this test relied on having realistic data. With PLI calculation from a case study in manufacturing, and estimation of RUL based on simulated data from a gas turbine, this article should be considered to increase the quality of testing the planning module.

Several challenges for DDM must be identified and discussed. A challenge with this testing is that the condition monitoring data for prediction are based on an industrial context other than the manufacturing industry. For predictions related to the manufacturing industry, there could be other results in terms of the precision of RUL and

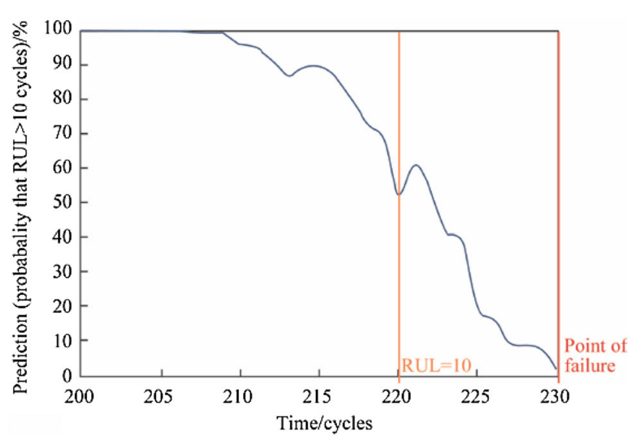

Fig. 11 Predicted probability that RUL>10 cycles for end-of-life of the engine

Table 5 Expected PLI of predictive maintenance

Situation	Type of PLI	PLI value/ NOK
Maintenance labour costs	Availability: extra costs	10 785
New oil cooler	Availability: extra costs	47 480
Loss of internal machine revenue	Availability: turnover loss	64 800
Sum		123 065

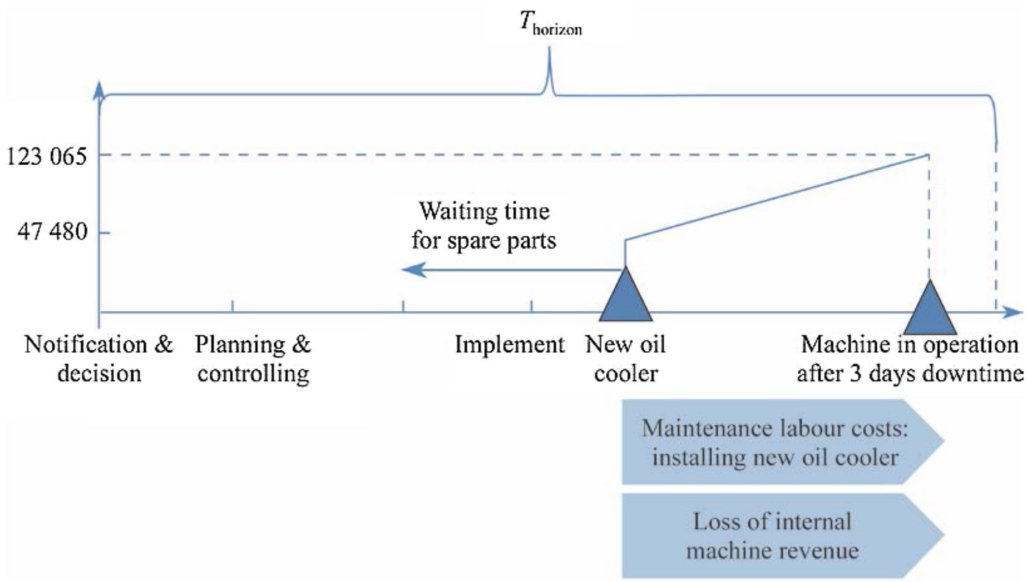

Fig. 12 PLI calculation when performing predictive maintenance

the size of the maintenance window. Nevertheless, using real data to conduct the prediction will strengthen the confidence of conducting predictive maintenance. It should also be investigated whether the different industry branches are actually quite different with respect to estimating the RUL.

A second challenge is the calculation of PLI. This can be context driven, where the failure modes affect the types of consequences that will occur, the magnitude of PLI, and the PLI elements that are of relevance. For instance, if the failure of an oil cooler occurs in the oil and gas industry, scrappage would not be of relevance; however, the magnitude of availability losses could be bigger. Therefore, it is important to have similar contexts when comparing PLI with other case studies. Benchmarking is an example where comparing different PLI values supports continuous improvement. However, PLI is also of interest in IPL as a tool for measuring the consequences of ignoring maintenance planning. In addition, more work is necessary in terms of automating the PLI calculation, which is performed manually at present. This would require more precision in measuring the financial perspectives in real-time. For instance, when maintenance costs are measured, there must be a pre-defined cost rate.

A third challenge is the implementation of the existing CMMS. During the implementation, it is important to have tight cooperation with both the end-user and the software provider for CMMS. The end-user will ensure that the correct functionality is established for DDM, while the software provider will ensure that the necessary interfaces with CMMS are established.

Thus, a framework has been developed for DDM, and the planning module has been tested. Further research on DDM would include testing the accuracy of RUL with different maintenance windows, classification of PLI values for different failure modes, and testing the other DDM modules with industrial case studies.

To improve the theory of DDM and to ensure scholarly relevance in the research quality, the results must have high degree of generality. Thus, in future researches, this concept should be demonstrated with other case studies from different application areas and industry branches. This will also improve the utility value with more contribution to practical applications.

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