Smart Maintenance in Asset Management – application with Deep Learning

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Abstract. With the onset the digitalization and Industry 4.0, the maintenance function and asset management in a company is forming towards Smart Maintenance. An essential application in smart maintenance is to improve the maintenance planning function with better criticality assessment. With the aid from artificial intelligence it is considered that maintenance planning will provide better and faster decision making in maintenance management. The aim of this article is to develop smart maintenance planning based on principles both from asset management and machine learning. The result demonstrates a use case of criticality assessment for maintenance planning and comprise computation of anomaly degree (AD) as well as calculation of profit loss indicator (PLI). The risk matrix in the criticality assessment is then constructed by both AD and PLI and will then aid the maintenance planner in better and faster decision making. It is concluded that more industrial use cases should be conducted representing different industry branches.

Keywords: Smart Maintenance, Anomaly detection, Asset Management.

1 Introduction

The mission of asset management can be comprehended as the ability to operate the physical asset in the company through the whole life cycle ensuring suitable return of investment and meeting the defined service and security standards [1]. Further, it is also stated in ISO 55000 that asset management will realize value from the asset in the organization where asset is a thing or item that has potential or actual value for the

company [2]. The role of the maintenance function in asset management has been further detailed in EN 16646 standard for physical asset management and considers the relationship between operating and maintaining the asset is [3]. In particular it is recommended in this standard that dedicated key performance indicator (KPI) can be applied in physical asset management. A proposed KPI that improves the integrated planning process between the maintenance and the production function in asset management is denoted as profit loss indicator (PLI). This indicator evaluates the different types of losses in production from an economic point of view. Also, PLI has been tested in different industry branches such as the petroleum industry [4] and manufacturing industry [5].

With the onset of digitalization in industry enabled by breakthrough innovations from Industry 4.0 changes the maintenance capability in the company. The shift is from a "off-line" maintenance function where data is collected and analyzed manually, towards a digital maintenance [6] and is often denoted as smart maintenance [7, 8].

Artificial intelligent (AI) and machine learning which is a central part of smart maintenance is considered as a fundamental way to process intelligent data. Yet, there is a difference between traditional machine learning and data driven artificial intelligence [9]. The difference lies in the performance of feature extractions, in manufacturing often mentioned as machine learning or Advanced Manufacturing. In this article anomaly detection for smart maintenance will be investigated more in details.

Application of AI is also relevant in order to improve the plant uptime. Anomaly in mechanical systems usually cause equipment to breakdown with serious safety and economic impact. For this reason, computer-based anomaly detection systems with high efficiency are imperative to improve the accuracy and reliability of anomaly detection, and prevent unanticipated accidents [10].

From a smart maintenance perspective, the result of a more digitalized asset management should also include that maintenance is planned with insight from the individual equipment in combination of the system perspective of the asset [6]. This need is further supported with empirical studies that points out the necessity for criticality assessment when increasing the productivity through smart maintenance planning [8]. In fact, maintenance planning is regarded to be unlikely to achieve optimum maintenance planning without a sound criticality assessment of the physical asset such as the machines [8].

Smart maintenance has also been denoted with other terms such as deep digital maintenance (DDM) [11] where application of PLI is of relevance. In DDM it still remains to investigate in appropriate scenarios for the planning capabilities in smart maintenance that includes anomaly detection and criticality assessment.

The aim of this article is to develop an approach for decision support in smart maintenance planning based on principles both from asset management and machine learning-based anomaly detection and criticality assessment.

The future structure of this article is as follows: Section 2 presents relevant literature in smart maintenance whereas Section 3 demonstrates an essential application in smart maintenance planning where criticality assessment is conducted based on anomaly detection and PLI calculation. Finally, Section 4 discuss the results with concluding remarks.

2 Smart Maintenance in Asset Management

2.1 The trend towards Smart Maintenance

To succeed with a successful asset management strategy it has been considered that it is vital to include PLI as an output for the strategy [12]. This has also been included in maintenance planning in the concept deep digital maintenance (DDM) [11]. In DDM it has also been demonstrated maintenance planning for one component. It remains to evaluate several work orders in maintenance planning in DDM. In asset management the machine learning method such as deep learning has gained popularity [13] where e.g. diagnostics of health states of power transformers has been applied [14]. In smart asset management a three-steps approach is proposed [13]:

1. Data gathering from observational data to evaluate the component condition and defining threshold rules.
2. Analysis of historical data to identify patterns that support in predictions of future failures.
3. Leverage the component condition with the defect of the failure. This step will also evaluate the economic perspective in the analysis.

Also smart maintenance is outlined as a key element in the Industry 4.0 roadmap for Germany [15]. In this strategic roadmap, smart maintenance is considered to improve the competitive advantage for the maintenance function in the company and is an "enabler" itself for successful Industry 4.0 implementation where maintenance data is shared between manufacturer, operator, and industry service. Furthermore, smart maintenance has also other important characteristics:

- A common "language" of maintenance processes defined in EN 17007 [16].
- Maintenance technology support with e.g., artificial intelligence (AI) [7].

In smart maintenance this has been addressed with the need for artificial intelligence (AI) [7]. Despite that maintenance work supported by AI still has barriers to overcome, it is considered to be an effort worth taking. With support from deep learning, we can create knowledge of extracted features in an end-to-end process [9]. For instance, neural networks make the smart data to predict what will happen and take proactive actions based on improved pattern.

To succeed with smart maintenance in asset management, the emphasizes of specific plans for maintenance over a long span of time is expected to ensure the greatest value of equipment over its life cycle [7].

In smart maintenance it is also stressed that it is vital to have established criticality assessment in maintenance planning [6, 8]. In particular it is concluded that data-driven machine criticality assessment is essential for achieving smart maintenance planning.

2.2 Smart Maintenance Framework

To ensure value creation in smart maintenance it is necessary to devise a sound framework in smart maintenance. Figure 1 illustrates our proposed framework and is inspired from [17] and [18]. The starting point in this framework is the data source and includes external data such as inventory data of spare parts from suppliers. In addition, product

data is from the equipment such as condition monitoring data, as well as enterprise data from computerized maintenance management system (CMMS). All the raw data sources are then aggregated in multiple formats in a data cloud.

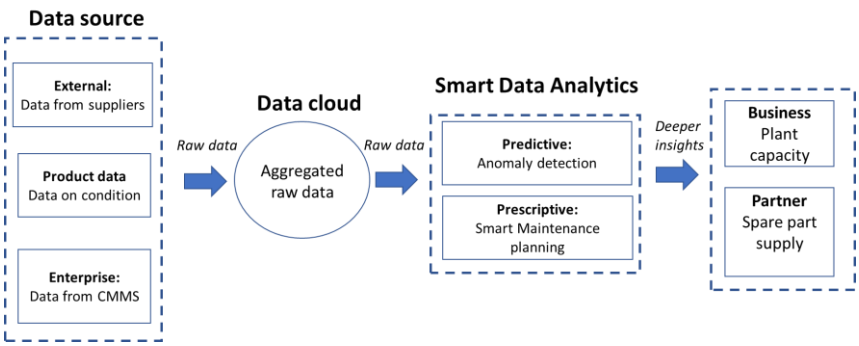

Fig. 1. Value creation with data in smart maintenance framework inspired from [17] and [18].

The raw data is further applied as for smart data analytics including both predictive and prescriptive analytics. In the maintenance field, the predictive analytics will comprise e.g. forecasts of the technical condition of the machine. To ensure value creation of the physical asset it is also important to include prescriptive analytics that supports in recommended actions in maintenance planning. This will include anomaly detection to evaluate the probability of future machine breakdowns. In addition, it is also necessary to evaluate the consequences of the machine failure. In DDM, the PLI seems promising for this purpose [11]. To assess the criticality of the machine in maintenance planning, both the probability and the consequence can be combined in a risk matrix.

The result of smart data is deeper insight in the business, where e.g., the plant capacity has increased as well as deeper insights of the partners where e.g., spare part supply is improved.

3 Smart Maintenance Planning with Criticality Assessment

As shown in Figure 1 and explained above, criticality assessment [8] could be an essential element of prescriptive analysis in our smart maintenance framework. In overall a criticality assessment should evaluate both the probability and consequences for each failure of the equipment. We hereby use a demonstration use case to explain our proposal of criticality assessment with three steps: structured approach (1) PLI estimation; (2) the anomaly degree calculation; (3) the criticality assessment. So far, few companies have collected data that can be used for PLI estimation and anomaly detection, we could not get both data from the same machine. The data we present in the case study come from two different machines. However, for the demonstration purpose and for explaining our ideas, we believe it is applicable to merge the data to explain our idea by assuming that the data come from the same machine.

Step 1: PLI estimation

The calculation of profit loss indicator is applied based on earlier case study from both [11] and [5]. The case study considers the malfunction of an oil cooler in a machine center. The malfunction was first observed when the machine cantered produced scrappage. A quality audit meeting evaluated economic loss of this scrappage. In addition, maintenance personnel conducted inspection on the machine center and found that the cause of this situation was due to malfunction of the oil cooler. This oil cooler was replaced, and the machine center had in total 6 days with downtime. In addition to scrappage it was also evaluated that the machine had lost revenue due to the downtime. Table 1 summarizes the different type of losses that occurred due to this situation of the malfunction of machine center.

Table 1. Expected PLI of malfunction of a machine center based on both [11] and [5].

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

When the consequences for the failure has been estimated, the next step is to calculate the anomaly degree (AI) for the physical asset and the industrial equipment's.

Step 2: Anomaly degree (AD) Calculation

Figure 2 shows the obtained anomaly degree (AD) of one machine. An increasing AD will indicate an increasing probability of equipment failure. When maintenance planning is conducted, updated information about the anomaly degree for each equipment should be collected and analyzed.

Likewise the calculation of PLI, the data used for calculating AD is also from an actual industry equipment. However, the data is not from a machine center and represents another industry branch. The primary datasets include failure records and measurement data from the monitoring system. The target is to obtain the anomaly degree of the equipment by using machine learning based analysis approaches. In the experiment, we labelled both failure and normal records. Thus, the obtained anomaly degree can describe the difference between the target observation and normal samples.

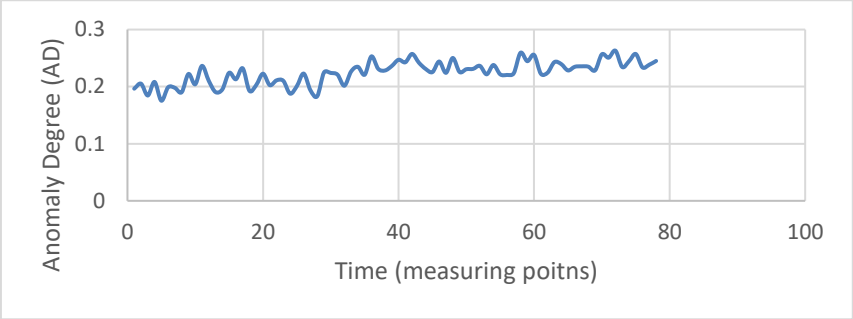

Fig. 2. Change of anomaly degree (AD)

During the experiment to calculate AD, we adjusted the measurement data collected in different scales to a common scale. Then, we applied standard normalization to preprocess the raw data. The applied machine learning model is constructed through a fully connected deep neural network with seven hidden layers. SoftMax is used as the activation function of the final output layer. Leaky Relu is applied as the activation functions of the hidden layers. The number of nodes in hidden layers of the constructed deep neural network is 64, 32, 32, 16, 16, 8, 2, respectively, to train the neural network smoothly. We selected Adam and categorical cross-entropy as the optimizer and loss function during the training process. Results in Figure 2 demonstrates the obtained anomaly degree of the machine from the analysis using deep neural network, which represents the degradation of the machine's health state along the time.

Step 3: Criticality assessment

When both the probability and the consequences have been evaluated for a future malfunction of a machine, the criticality assessment can be performed in a risk matrix.

Figure 3 illustrates a proposed risk matrix in smart maintenance that supports planning of preventive work orders. In the consequence category, the PLI is established for the physical asset and classified as "medium, high" in. The probability category is evaluated with AD. By trending AD in the risk matrix it is possible to evaluate when a preventive maintenance work order should be executed and the possible costs and consequences

The color code is following a traffic-light logic; if the equipment is located in green zone, no further actions are necessary. If the equipment is in a yellow zone, it is an early warning where maintenance actions should be executed. If the equipment is in the red zone, it is an alarm where immediate maintenance actions should be executed.

In addition to the color-code system each field in the matrix is marked with a number indicating a priority number. The criticality is of the machine has a yellow code in the start but will have a red color code if no maintenance actions are performed. When the maintenance planner has several machines that are being criticality assessed, it will be possible to prioritize which machine that should be maintained first.

Profit Loss / Anomality	PLI=«Low»	PLI= «Low, Medium»	PLI=«Medium»	PLI= «Medium, High»	PLI=«High»
I (**Near** failure event) AD = [40 – 100]	3	2	2	1	1
II (**High** degree of anomality) AD = [30 – 40 >	4	3	2	2	1
III (**Medium** degree of anomaly) AD = [20 – 30 >	5	4	3	2 **Alarm!**	2
IV (**Low** degree of anomaly) AD = [10 – 20 >	6	5	4	3 **Early Warning!**	3
V (**Beginning** anomaly) AD = [0 – 10 >	6	6	5	4	4

Fig. 3. Risk matrix as criticality assessment for equipment

4 Discussion and concluding remarks

This article has demonstrated application of criticality assessment, which can be an essential element of our proposed smart maintenance framework, with application of both PLI as well as anomaly degree calculation. The benefit of this system is that the maintenance planner will have a "digital advisor" for evaluating the anomaly that can enable a faster and better decision-making process in maintenance planning. It is expected that the deep learning method with deep neural network will be further investigated and developed due to it's promising results in AD.

Also, with the aid from PLI calculations, it is possible to improve the evaluation of the consequences of e.g., machine breakdown. In a risk matrix it is then possible to establish a work priority system where some equipment with anomaly should be prioritized before others. For example, if there are future work orders both categorized in yellow sector andred sector, it would recommend to prioritize the work in the red sector.

There are also some challenges with the criticality assessment that should be addressed in future research in contribution to theory of criticality assessment. First, it is of importance to improve the accuracy of both anomaly degree calculation as well as calculation of PLI. Second, it will be of importance to evaluate sound criteria for each category in the risk matrix. Yet, this seems to also be a challenge in existing risk matrices. A more practical aspect that needs to be investigated is to evaluate how the digital approach of the risk matrix will interfere with existing criticality assessment and still not reduce the performance of the physical asset.

Although a use cases have been applied with data from different industry branches to demonstrate the criticality assessment, further research will also require a coherent demonstration in several industry sectors, including both manufacturing industry as well as the process industry.

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Reference

1. Schneider, J., et al., *Asset management techniques.* International Journal of Electrical Power & Energy Systems, 2006. **28**(9): p. 643-654.
2. ISO, *ISO 55000 Asset management - Overview principles and terminology*. 2014: Switzerland.
3. CEN, *EN 16646: Maintenance - Maintenance within physical asset management*. 2014.
4. Rødseth, H., et al., *Increased Profit and Technical Condition Through New KPIs in Maintenance Management*, in *Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015)*, K.T. Koskinen, et al., Editors. 2016, Springer International Publishing: Cham. p. 505-511.
5. Rødseth, H. and P. Schjølberg, *Data-driven Predictive Maintenance for Green Manufacturing*, in *Advanced Manufacturing and Automation VI*. 2016, Atlantis Press. p. 36-41.
6. Bokrantz, J., et al., *Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030.* International Journal of Production Economics, 2017. **191**: p. 154-169.
7. Yokoyama, A. *Innovative Changes for Maintenance of Railway by Using ICT-To Achieve "smart Maintenance"*. in *Procedia CIRP*. 2015.
8. Gopalakrishnan, M., et al., *Machine criticality assessment for productivity improvement: Smart maintenance decision support.* International Journal of Productivity and Performance Management, 2019.
9. Wang, J., et al., *Deep learning for smart manufacturing: Methods and applications.* Journal of Manufacturing Systems, 2018. **48**: p. 144-156.
10. Li, Z., et al., *A deep learning approach for anomaly detection based on SAE and LSTM in mechanical equipment.* The International Journal of Advanced Manufacturing Technology, 2019. **103**(1): p. 499-510.
11. Rødseth, H., P. Schjølberg, and A. Marhaug, *Deep digital maintenance.* Advances in Manufacturing, 2017. **5**(4): p. 299-310.
12. Rødseth, H. and R. Eleftheradis, *Successful Asset Management Strategy Implementation of Cyber-Physical Systems*, in *WCEAM 2108*. 2019.
13. Khuntia, S.R., J. Rueda, and M. Meijden, *Smart Asset Management for Electric Utilities: Big Data and Future*. 2017.
14. Tamilselvan, P. and P. Wang, *Failure diagnosis using deep belief learning based health state classification.* Reliability Engineering & System Safety, 2013. **115**: p. 124-135.
15. DIN, *German Standardization Roadmap - Industry 4.0*, in *Version 3*. 2018: Berlin.
16. CEN, *EN 17007: Maintenance process and associated indicators*. 2017.
17. Porter, M.E. and J.E. Heppelmann, *How smart, connected products are transforming companies.* Harvard Business Review, 2015. **2015**(October).
18. Schlegel, P., K. Briele, and R. H. Schmitt, *Autonomous Data-Driven Quality Control in Self-learning Production Systems: Proceedings of the 8th Congress of the German Academic Association for Production Technology (WGP), Aachen, November 19-20, 2018*. 2019. p. 679-689.