# Data-driven Predictive Maintenance for Green Manufacturing

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*Abstract*—**With the current situation of high demand of sustainable manufacturing, different stakeholders have clear expectations for more environmental manufacturing and at the same time minimizing the operational costs. The role of maintenance plays a key role in the path towards sustainable manufacturing. For achieving green manufacturing, more data-driven predictive maintenance strategies is needed and is expected to reduce energy consumption, maintenance resources in terms of spare parts, and reduction of consumables in terms of example lubrication. The overall bottom-line for the predictive maintenance strategy is increased availability, reduction of maintenance hours in terms of reactive maintenance activities, and increased profit for the manufacturing business. For a predictive maintenance strategy, it is crucial to develop Key Performance Indicators (KPIs) for the maintenance management. Today, common KPIs such as availability and different indicators for maintenance cost has been developed. When aiming for more green manufacturing, a more integrated application of maintenance KPIs are needed. Today, the KPI Profit Loss Indicator (PLI) has been developed and demonstrated in the saw mill industry and is regarded to support a more integrated approach in terms of Integrated Planning (IPL). The aim of this article is develop a structured approach for data-driven predictive maintenance aligned with the concept of PLI. Through a case study, the approach is partly demonstrated for the manufacturing industry. The results in this demonstration shows that the data-driven maintenance strategy will have a positive impact of the PLI value and provide a sustainable manufacturing in long-term.**

*Keywords—Green Manufacturing; Integrated Planning; Maintenance Management; Predictive Maintenance*

## I. INTRODUCTION

In today's manufacturing companies, there has been an increased pressure to think beyond traditional economic measure and also evaluate environmental effects of the business [1]. From the European Commission it has been set up a target of sustainability [2]:

1. 20 % of energy from renewables
2. 20 % increase in energy efficiency

Furthermore, it is through an overall objective in the research programme Factories of the Future to promote the targets within EU 2020 for a smart, green and inclusive economy [3]:

- Energy- and resource-efficient manufacturing processes.

- Socially sustainable, safe and attractive workplaces.

- High-tech companies involved in innovative manufacturing.

The role of maintenance should affect all these targets with implementation of predictive maintenance. A possible definition of sustainable manufacturing can be [4]: *"The creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound."*

The role of maintenance is crucial in green manufacturing. For example in the aerospace industry, it is through life cycle assessment (LCA) found that the environmental impact of the maintenance phase is of importance and can not be ignored [5]. It is further concluded that although this industry has the highest reliability and safety requirements, there is more challenges in order to have a sustainable approach at the design stage. Also, an value stream mapping approach for the maintenance process in this industry has been performed [6]. Based on this analysis, it was possible to calculate an indicator for sustainability. The value from the indicator and the graphical representation of mapping of the value stream makes it is possible to identify the potential problem area and apply a so-called 6R method for improving the sustainability. This method considers 6 different approaches for improving sustainability [7]. In addition to Reduce, Reuse and Recycle of products, this methodology also focuses on Recovering, Redesigning and Remanufacturing of the products during the lifecycle. If scrappage occurs of the end product, redesign of the machine center could be an option in the design stage. Furthermore, sustainable machining technologies is considered to be an important sustainability principle [7]. As an example for such technology is dry machining where analytical modelling of predicting tool-life is applied.

Another example of industrial application of sustainable maintenance is a joint maintenance decision-making and energy management method [8]. In this method the optimal maintenance interval from a reliability perspective is adjusted towards a time window when there is a peak-period for electricity cost. As a result, the electricity cost of

manufacturing system can then be reduced. This method was further successfully tested in an auto assembly line.

From the project Green Monitor, the authors endorse predictive maintenance as an important strategy for sustainable manufacturing [9]. In this project, it is for example investigated how consumption of hydraulic oil of a machine tool can be reduced. The plan in this activity is to change from traditional time based preventive maintenance towards predictive maintenance. By measuring relevant variables such as water content and degree of particles in the hydraulic oil, it is possible to calculate the remaining useful life (RUL) of the hydraulic oil and change it later than the conservative maintenance interval given from the supplier. When the hydraulic oil is changed only when necessary, it is assumed that it will be a substantial savings in waste of lubrication oil. Predictive maintenance strategy has also been demonstrated of its effectiveness in the semiconductor industry [10]. In this industry, RUL estimation for lenses was performed where the estimated and actual RUL values where compared. This predictive maintenance strategy would more optimally schedule the maintenance activities, resulting in reduced waste of energy and materials and hence increase the sustainability. Within predictive maintenance, application of Soft Sensors is also of interest where computer programs supports sensors to be more predictive in nature. An interesting class of Soft Sensors is data-driven [18].

A green and sustainable maintenance system model has been established in order to achieve the purposes of green maintenance [11]. The objective for green maintenance is among others to reduce energy and save resources. These objectives can be achieved by implementing several types of measures:

- Legislation law from authorities

- Technology measure

- Management measure

In a green maintenance system model several topics are of interest in order to achieve green maintenance [11]:

- Maintenance process

- Maintain equipment

- Consumption of energy

- Consumption of material

- Maintain material

In addition, a Venn diagram has been developed for visualizing the green maintenance concept model [12]. This model is shown in Figure 1 and covers the traditionally conceptual model of sustainability with environmental, societal and economic factors.
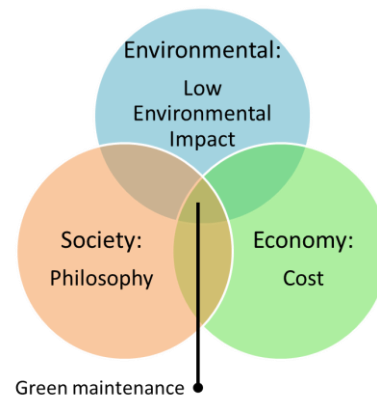


Fig. 1. Green maintenance conceptual model [12].

It has also been proposed a concept of sustainable maintenance management (SMM) and is defined as [13]: *"...all required processes for ensuring the acceptable assets condition by eliminating negative environmental impact, prudent in using resources, concern for the safety of employees and stakeholders, while at the same time economically sound."* One challenge with SMP is the lack of linkage between maintenance as a support function and corporate objectives. As a remedy, a proposed measuring system for sustainable maintenance performance has been established [13]. Although the levels corporate, tactical and functional levels were established, it is need for further development of suitable Key Performance Indicators (KPIs).

A promising KPI that measure the status of the green aspect in manufacturing is the Profit Loss Indicator (PLI) [14]. By measuring the unintended time losses and waste in manufacturing, this KPI should represent to what degree the manufacturing is sustainable. PLI calculation has been tested before in manufacturing industry [15]. In order to justify these savings, it is crucial that PLI can be documented and traced where the potential of the savings are.

The aim in this article is to develop a structured approach for data-driven predictive maintenance that is aligned with the concept of PLI.

This article is organized as follows: In Section 2 data-driven predictive maintenance is introduced. Further in Section 3, the PLI indicator is introduced. In Section 4 the case study is described with results from PLI calculations. Further in Section 5 an structured approach for data-driven predictive maintenance is developed and discussed. Finally in Section 6, future aspects are discussed with concluding remarks.

## II. DATA-DRIVEN PREDICTIVE MAINTENANCE

Condition-based maintenance (CBM) is a maintenance strategy that can improve the availability and avoid unnecessary maintenance actions [16]. This maintenance strategy can employ prognostics approach in the maintenance decision where RUL is estimated. A proposed taxonomy for predictive maintenance is shown in Figure 2 adapted from[16]. This taxonomy should be aligned with the maintenance terminology standard NS-EN 13306 [17]. In this standard

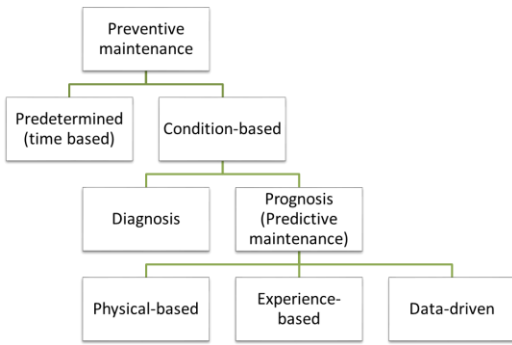predictive maintenance is a type of condition-based maintenance.



Fig. 2. Taxonomy for predictive maintenance adapted from [16].

From the process industry, it has been performed a literature review of how sensors should comprise capabilities for computational learning and accurate process data and insight in process knowledge [18]. Figure 3, which is based on the investigation from Kadlec [18], shows examples of which topics that would be dealt with both from the process industry perspective and the computational learning perspective.
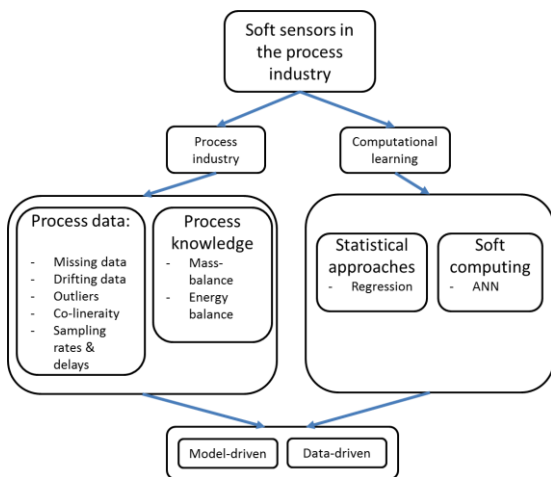


Fig. 3. Topics covered for developing both a model-driven and data-driven structure modified from [18].

From process industry, both process data and process knowledge must be further investigated. Process knowledge is also specified into several expertise of science such as mass balance and energy balance. The insight in these physical processes will be important to predict the technical condition of the equipment.

For process data, several phenomena must be identified and minimized. The missing data can be represented with a variable with constant value 0. The cause of missing data could be failure of a hardware sensor. Data outliers are sensor values that deviates from a meaningful value. The taxonomy for data outliers is obvious outliers and non-obvious outliers. The obvious outliners are those values violates physical constrains. An example could be a negative measurement from a pressure

sensor. A non-obvious outlier is not so easy to detect. These values do not violate any limitation but still do not reflect the correct variable state. Drifting data is another problem that occurs for process data. The causes for drifting process data can be categorized into two types:

- *Changes of the process*. The process undergoes a deterioration process and will have drifting data. An example could be decrease of flow from a pump due to abrasion during operation of the plant.

- *Changes from external conditions*. The external environment can change where for example the purity of raw material has decreased. This can also change the process state.

A common remedy for drifting process data is to apply a moving window technique. This technique will then update the model on periodical basis where only the most recent data is used. The data co-linearity is another problem in process data due to for example redundancy. In this case, two neighbouring temperature sensors will deliver strongly correlated measurements. This situation can cause an unnecessarily increase of complexity in the model where more data than the necessary required data is provided. The last problem of process data is sampling rates and measurement delays. Based on a procedure, measurement of some variables can be measured in a different point in time than others. This can cause a problem of synchronization when state of the process is evaluated. The measurement delays occurs when there is a process-related delay. An example could be the dwell period within a reactor. An approach to compensate this situation is to synchronize the variables. However, this synchronisation would require extensive process knowledge.

The data driven methods in Figure 3 can be both soft computing with artificial intelligence and use of statistical methods such as regression analysis. As an example of artificial intelligence could be application of Artificial Neural Network (ANN) that has been successfully applied for aerospace structures [19] and Wind Energy Conversion System [20].

III. PLI IN MANUFACTURING

PLI has been developed as a tool for Integrated Planning (IPL) between the maintenance manager and the production manager. The first step for developing this KPI was to evaluate Overall Equipment Effectiveness (OEE) with following question [21]: How much money is lost since we still have a hidden factory in terms of six big losses? Data from the smelting industry supported that the monetary form of OEE would be substantial. The next step in the smelting industry was to calculate the PLI value based on OEE. For example, minor stoppages, which reduces the OEE value, resulted in a loss of delivered volume to the customer measured in ton. By calculating this loss with the sale price in $/ton results in a PLI value for the minor stoppages in the smelting industry. Further research with case study from the saw mill industry lead to a model with representation of a PLI cube as shown in Figure 4 [14].
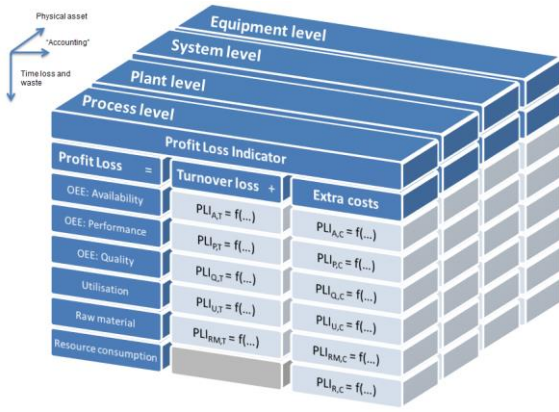
Fig. 4. PLI cube [14].

This cube represents all the variables that must be accounted for when calculating PLI. It has also been performed PLI calculation for the O&G industry [22] and also for qualitatively evaluation in the smelting industry and manufacturing industry [15].

The PLI indicator can measure several aspects of sustainability. The comparison between OEE and the waste categories from Toyota has also been performed [14]. In this comparison, following OEE elements is related to waste:

- Performance loss: Minor stoppage losses related to waiting.

- Quality loss: Defects and rework related to incorrect processing.

In addition, the environmental aspect is also covered through raw material and resource consumption in the PLI cube.

## IV. CASE STUDY DESCRIPTION AND RESULTS

The purpose of the case study is to demonstrate the PLI model which is an essential step in developing a predictive maintenance concept. The specific case is a malfunction of an oil cooler in a machine center. This malfunction was first observed through a scrappage of the product in production and which also led to an unplanned downtime. The malfunction of the oil cooler led to instability of the production process and damaged part (scrappage). Before the malfunction of the oil cooler the temperature value increased significantly. After the scrappage of product, a quality audit meeting was performed to evaluate the cause and consequence of the scrappage. When the unplanned downtime occurred, maintenance personnel first inspected the machine and found out the cause of the downtime which was malfunction of the oil cooler. Then they took out the oil cooler from the machine and changed it with a new oil cooler. Due to anonymity, the specific time window for the unplanned downtime is not accurate. However, a realistic time window for such a downtime with 6 days is used instead.

The PLI results is shown in Table 1. The related PLI elements can be traced to both availability loss due to the unplanned downtime and the scrappage of damage part as a quality loss. Most PLI elements applied in for calculation is

extra expenditures in terms of quality audit meeting and maintenance costs. The turnover loss in PLI is found from the loss of internal machine revenue which is an expected revenue for operating the machine.

TABLE I. PLI RESULT FROM CASE STUDY

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

The events occurring during the PLI events is further shown in Figure 5. As shown in the figure, the loss of internal revenue from machine will start immediately after failure of the machine is detected through damaged part (scrappage). In addition, it is a sequential activities of quality audit meeting and maintenance activities. During the maintenance activity, there is also a replacement of the oil cooler which contribute significantly to the maintenance costs and increased PLI.
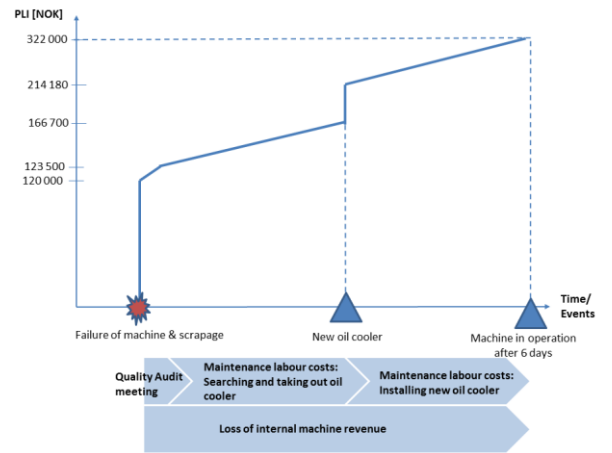


Fig. 5. PLI event of unplanned downtime.

## V. AN STRUCTURED APPROACH FOR DATA-DRIVEN PREDICTIVE MAINTENANCE

Based on the insight of predictive maintenance and the PLI model, a structured approach for data driven predictive maintenance is proposed in Figure 6. In step 1 a hybrid model is applied for estimating RUL of the relevant component. In the case study, a first approach for building the hybrid model would be to use expert judgement. In this model, expert judgement would establish the threshold values from temperature curves of the oil cooler. Furthermore, this model could be built with physical models from thermodynamics and also data driven approach with use of e.g. ANN. In addition, the RUL estimate will not be a deterministic value but will

instead be a stochastic variable due to uncertainty. A suitable approach for tackling this uncertainty would be to use three types of estimated values; worst case of RUL, most likely case of RUL and best case of RUL.

Further, in step 2 the estimated value of PLI is calculated for the unplanned event. Based on history data, PLI calculations such as shown in Table 1 would support an estimated PLI value. It is also possible to adjust this value when new information is available. For example, if it is expected that improved repair routines have been successfully implemented in the organisation, the expected maintenance labour costs could be reduced.
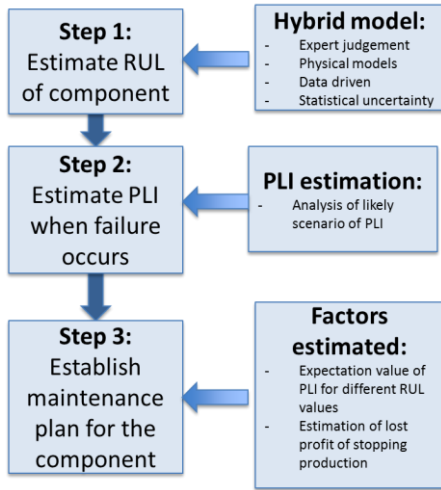


Fig. 6. Structured approach for data driven predictive maintenance

Further in step 3, the maintenance plan is established. Based on the different scenarios for RUL estimates (worst case, most likely and best case) and the estimated PLI, it is possible to propose different maintenance intervals and the expected PLI for each interval. These PLI values can then be further evaluated against production plans. From production plans it should be specified what would be the lost profit when the machine has planned downtime for maintenance. If this value is less than the PLI for unplanned downtime, the planned maintenance schedule should be performed. This would then also be an approach for IPL between production plans and maintenance plans.

## VI. Future aspects of PLI and concluding remarks

This paper has demonstrated how PLI is calculated which will be a step in data-driven predictive maintenance. If RUL is estimated and taken into account for maintenance plan, this can in future reduce the PLI values for unplanned downtime. Reduction of this type of PLI value will also increase the sustainability aspect in green maintenance. For example, the environmental aspect will improve through e.g. reduction of scrappage which is considered as waste and associated disposal.

An important aspect which must be tackled in future is to enable accounting of the PLI in real-time. A challenge today is

that due to both lack of technology and organizational factors, there can be delays for accounting the PLI value.

It is concluded that the structured approach for predictive maintenance should be investigated and developed further in detail. In particular it is of interest to demonstrate it for IPL.

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