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The adoption of prognostic technologies in maintenance decision making: a multiple case study

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Abstract

Progresses in prognostic maintenance technologies offer opportunities to aid the asset owner in optimal maintenance and life cycle decision making, e.g. replacement or life-time extension of physical assets. Using accurate lifetime predictions is critical for ensuring just-in-time maintenance. Although there is considerable literature on specific techniques, reports on the adoption and usage of these methods show that only a small amount of companies have applied these techniques. This study therefore investigates why and how asset owners adopted and selected specific prognostic techniques and compares this with the literature. Based on the literature, a framework on generalized routes to implement prognostic technologies for maintenance decision making will be presented. Therefore, the main assumptions and descriptions in literature on the use of prognostic technologies are expressed in several postulates. These postulates are confronted with industrial practice by a multiple-case study conducted in different industries in the Netherlands. Results show issues and challenges companies experience in applying the right prognostic techniques. Among these are the identification of the correct parameters to measure, the translation of the gathered data into useful maintenance decision support and the need for guidance in prognostic technology route determination.

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Keywords: life cycle management; maintenance decision making; prognostics; diagnostics.

1. Introduction

Progresses in the development of prognostic maintenance techniques to aid the asset owner in optimal maintenance decision making, e.g. replacement or life-time extension of assets, are extensively discussed in the literature. Prognostic techniques can be used to reduce business and safety risks caused by unexpected failures of critical systems and reduce life cycle costs [1]. However, many companies applying these techniques experience a gap between potential and realized benefits and therefore rate their current success as only 'satisfactory' [2]. More widespread adoption of these technologies needs an in-depth evaluation of its use within companies [3]. As an example, little detail is presented in the literature about the what, how and why of remote monitoring technologies [4].

In general, prognostic techniques enable asset owners to predict the future state of systems including health assessment, detecting incipient failure and predicting remaining useful life (RUL) [5]. As opposed to prognostics, diagnostics is retrospective by nature. Its goal is to identify and quantify the damage that has occurred [6], to determine the cause and effect relation searching for root causes, and to isolate faults [5], failure modes or failure conditions [7]. Detection is closely related to diagnostics and aims to detect anomalies in the system. It is binary by nature, indicating either a healthy or a faulty system. Many now-a-day systems are equipped with built-in test sensors and diagnostic tests.

A lot of research is conducted in developing specific models and algorithms. Many academic researchers have discussed or commented on the technical features of these technologies and many techniques are described in the

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literature. For an overview of diagnostic techniques see for example [8-10], for prognostics, see for example [5].

However, many prognostics and health management methods are introduced and applied to solve specific problems without much explanation or documentation given as how or why these methods have been selected [5]. Next to that, as Grubic, Redding [2] suggest, research in this area should embrace both the technological and business aspects of diagnostics and prognostics. Therefore, it is important to guide the asset owner through the process of making the optimal maintenance decision based on the right collection of data and assist in selecting the type of prognostic technology applicable to his situation.

In the current paper, we will introduce a framework which combines and links elements discussed in current literature and guides users of prognostic technologies through the steps from data collection to maintenance decision making for life cycle management decision support. With this framework we envision to use the maintenance analysis to aid business purposes rather than only using it for technical evaluations.

After introducing the framework, the main assumptions and descriptions identified from the described literature are used to construct postulates. These will be confronted with and reflected on industrial practice by means of a multiple case study within different industries in the Netherlands. A case study is appropriate since our main aim is theory building from an exploratory perspective [11]. The results are preliminary as the work is still in progress; more interviews will be conducted to validate those preliminary results. Moreover, not all the possible issues in prognostic techniques for maintenance decision making are included, but only those that the case studies have shed some further light on. At a detailed level, the followed methodology is similar to that of Meredith [12], Veldman, Klingenberg [13], and Braaksma, Klingenberg [14].

2. Advanced maintenance analyses for maintenance decision making

Six postulates will be introduced in three paragraphs of this chapter which are devoted to three consecutive steps of the proposed framework.

After a deliberation on how and why to start an advanced maintenance analysis, multiple routes can be followed through the proposed framework, see Figure 1. The proposed framework links and connects multiple parts of current literature in a new way and connects data gathering with maintenance and life cycle decision making support.

The first step (corresponding to the steps in Figure 1) is to select and gather the (available) input data, from historical records and monitoring systems. In the second step, the type of prognostic analysis is selected and the actual analysis is conducted. This leads to step 3a, the determination of anomalies in the system, the diagnosis of the current state of the system and the prognosis of the expected capabilities, which still is an intermediate technical analysis result. Finally, the detection, diagnosis and prognosis should be used, in step 3b, to support business or life cycle decisions.

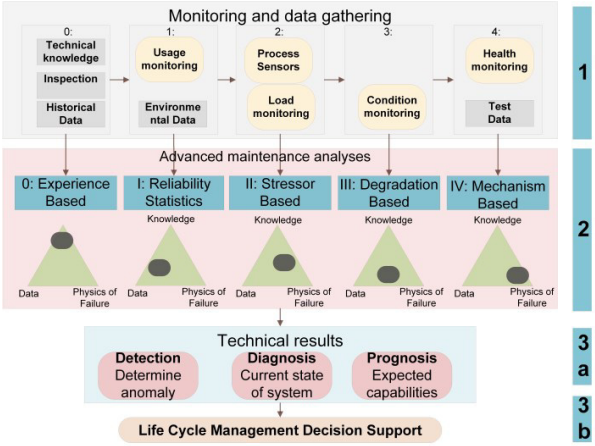

Figure 1, The proposed framework: routes to maintenance decision making, based on Jardine, Lin [15], Coble and Hines [16], Dibsdale [17].

Boundaries are created by internal and external laws and regulations e.g. setting norms for the accuracy of the prediction or by limiting the possibilities of data gathering.

2.1. Step 1: Monitoring and data gathering

Two main categories of asset data can be distinguished: (i) event data, and (ii) condition monitoring data [18]. The latter will be collected via condition and health monitoring sensors, usage and load monitoring systems [19]. Event data is gathered from historical records and enterprise resource planning (ERP) systems.

Postulate 1: *The collected data is often not useful for advanced maintenance analyses*

In the literature, it is often implicitly assumed that the collected data can be used for maintenance analyses. However, in real world applications, data collected from multiple sensors are not necessarily in a readily usable form due to issues such as missing data, redundant data, noise or even sensor degradation problems [5].

Postulate 2: *The selection of parameters to monitor is not well motivated.*

Suitable sensor placement and selection of sensors requires knowledge about the system's most critical failure mechanisms and the governing loads [20]. However, a common approach is to collect large amounts of data with considerable numbers of sensors, only to discover that essential quantities are missing and non-relevant parameters have been monitored [20]. This is often discovered when the data is interpreted after a certain period of data collection.

2.2. Step 2: Advanced maintenance analyses

Among reviewers within the prognostic field, there is little consensus as to what classifications of prognostics are most appropriate [6]. We therefore adopt two classifications.

In the first categorization we adapt the model proposed by Coble and Hines [16], which was already extended by Dibsdale [17] with category IV. We slightly extend this with

the least mature, experience based route by considering the difference between methods that use historical records and those that only use expert knowledge and the experience of people who operate and maintain the equipment, as they can be regarded as the best source of information [21]. The framework now consists of five maturity levels of prognostics:

(0) Experience based predictions of failure times are based on knowledge and previous experience outside (e.g. Original Equipment Manufacturer) or within the company. Sometimes supported by little or scattered data. Predictions based on e.g. Failure Mode, Effects and Criticality Analyses.

(I) Reliability Statistics prediction analyses are based on historical (failure) records of comparable equipment without considering component specific (usage) differences. Describes population-based failure probabilities accurately. These models estimate the life of an average component operating under historically average conditions. Based on e.g. Weibull or Normal distributions.

(II) Stressor Based predictions are based on historical records supplemented with stressor data, e.g. temperature or humidity, to include environmental and operational variances. Results in expected lifetime of an average system in specific environment. Based on extrapolation of a general path derived from physical models, built in tests, or operating history.

(III) Degradation based predictions are based on the extrapolation of a general path of a prognostic parameter, a degradation measure, to a failure threshold. The prognostic parameter is inferred from sensor readings. The prediction includes the current state of degradation and results in an expected lifetime of a specific system in a specific environment. It also measures symptoms of incipient failure e.g. raise in temperature or vibration.

(IV) Mechanism based predictions are based on direct sensing of the critical failure mechanisms of individual components. It results in an expected lifetime of a specific system in specified conditions. The prognostic parameter is calculated with a physical model of the degradation mechanism. The model uses the sensed variation of loads or usage as input.

The second categorization classifies the maturity levels on the type of input data; data, knowledge or a physical model.

Data driven approaches rely on the assumption that the statistical characteristics of data will remain relatively unchanged unless a malfunction occurs in the system [22]. Its strength is the ability to transform high-dimensional noisy data into lower dimensional information [22]. A drawback is that the efficacy is highly dependent on the quality and quantity of the input data [22].

On the other side are the physical models which require the availability of an accurate mathematical model [22]. The behavior of a failure mode is quantitatively characterized using physical laws [6]. Physical models are especially useful for predicting system response to new loading conditions or new system configurations. Physical models are typically more computationally intensive than data-based models [23].

Finally, knowledge based models accumulate experience from subject matter experts to form rules to apply that knowledge [6]. These models require a high degree of completeness and exactness to be useful [24]. A high amount of in- and outputs can make them rather complex to develop and apply which sometimes can be solved with fuzzy systems.

Postulate 3: *Higher maturity levels of maintenance analyses result in higher value analyses.*

In the first proposed classification of maintenance analyses, from experience based to mechanism based, the latter can be regarded as being more mature. More mature analyses are often more difficult and require more effort to develop, this implicitly suggests that these analyses result in outcomes with a higher added value for the decision maker. However, the metrics to justify the investments in advanced maintenance analyses, as for example a Condition Based Maintenance (CBM) program, may show improvements in a technical sense, like the availability of equipment, but may not reveal that the production line efficiency decreases [25].

Postulate 4: *The predictive performance of the prognostic systems improves in time, they are evolving systems.*

Prognostic systems can be validated and improved during their lifetime because more and more data, for example failure or costing data, is collected during its utilization. Especially knowledge based models should be updated since they require a high degree of completeness and exactness to be useful [24].

Postulate 5: *The selection of the type of advanced maintenance analysis is not well motivated.*

In the literature, many advanced maintenance analyses are developed and proposed, as has been mentioned before. However, most Prognostics and Health Management (PHM) approaches are application or equipment specific. A clear systematic way to design and implement PHM does not exist [5]. Moreover many PHM methods are introduced and applied without much explanation or documentation given as to how or why these methods have been selected [5]. Typically, the balance between physics-based models and data-based techniques will depend on the amount of relevant data available and the level of confidence in the predictive accuracy of the physics-based models [23] and the amount of knowledge of the monitored system.

2.3. Step 3: Technical results and life cycle management decision making support

When dealing with complex systems with interrelating failure modes, human made decisions are often not sufficiently reliable or accurate [6]. The technical result in step 3a of Figure 1, should be used to improve life cycle decisions in step 3b. Decision support systems (DSS) can be used in step 3b to aid this decision making process. Studies show that model based decision making is superior to human based decision making [26]. A typical DSS consists of (i) a databank which provides logical data structures, (ii) a model that translates data into useful information. And finally, (iii) a dialog generating and management system which provides insight and gives recommendations to the manager [26, 27].

Postulate 6: *The quality level of current analyses is not sufficient to improve maintenance decisions.*

To be able to use the analyses effectively for decision making, the remaining useful lifetime forecast, the prognostic distance [28], should be equal to or larger than the lead time for the decision-maker to take preventive actions prior to a failure [29]. This is also called the flexibility phenomenon [30]. A prognostic system with high prognostic distance is expensive and probably less accurate. Too little prognostic distance prohibits users to schedule preventive maintenance and wait for spares. Grubic, Redding [2] found that only a low percentage of companies have adopted decision support systems and suggest that in most of the cases the data is not readily available and integrated with a company's operational system. This can hinder decision support, since the analyses, especially the data driven methods, rely on the quality and quantity of input data [22].

3. Case study results

The case studies presented in this section show a range of maintenance technologies, organizational arrangements, industries, products, and maturity levels. Thus, they form a good range for evaluating existing knowledge developed in this research field. Most insights gained from the postulates provided additional knowledge about current practice of applying prognostic techniques and showed how companies use these for maintenance decision making. In some cases, only insights in a number of topics were obtained and not all postulates could be fully evaluated. A specific selection of unique cases within four companies was made based on industries where prognostics is applied, the type of assets, the lifecycle of the assets, and the degree to which companies consider maintenance as an important area. Below, we will introduce the case companies. For confidentiality issues, the numbers assigned to the companies do not correspond with the letters assigned to the interviewees.

3.1. Multiple case study: case company description

Company 1 is an owned subsidiary of a large transportation company for which it conducts maintenance, repair and overhaul activities of rolling stock. A large part of the asset fleet is equipped with sensory systems which are used in a real-time diagnostic system, usable for prognostic analyses.

Company 2 surveillances and monitors the sea, it provides safety on seas all over the world. Condition monitoring systems are installed on a small part of the fleet of vessels. A major part of the maintenance is predefined by the OEM.

Company 3 provides disaster relief and ensures safety from the air all over the world. A larger part of the fleet of aircraft is equipped with health and usage monitoring systems (HUMS). The system on which we focus is being operated in highly demanding and varying environments. The company has already applied several techniques effectively.

Company 4 provides transportation for people from and to vessels. The organization contributes to the efficient and safe handling of shipping traffic. *4* operates in multiple regions in the Netherlands, in any weather.

3.2. Step 1: Monitoring and data gathering

Postulate 1: *The collected data is not useful for advanced maintenance analyses*

From the case studies, it can be observed that the more mature companies tend to have more structured and accessible data. Especially the less mature companies seem to experience difficulties with fractured data, e.g. stored in multiple systems, local desktops, and data which is difficult to access, e.g. data in legacy systems, data stored in text format (i.e. word or pdf), or incomplete data.

"Some maintenance operators just refuse to enter the correct data in the maintenance system as they find it difficult to work with new and complex programs. Our first step has been to create a culture change and to improve the ease of data input." - Maintenance manager company C

On the other hand, the two more mature companies have their data systems better in place. In these cases, event logs and sensor data are automatically sent to integrated data systems and are well accessible for analysis. Furthermore, the quality of the data input is often higher as described by the maintenance engineer of company B:

"All equipment from this fleet collects sensor data, which is uploaded in real-time to a central data warehouse."

However, as this same engineer continues, even the mature systems are as strong as the weakest link.

"..when we want to access this data, we have to ask a particular person who works there for a specific data query. These files are really large, therefore he has to send us the files on a USB stick with the postal service.. Once, I even had to wait for two weeks. We are working on a solution for that."

It seems that the maturity of the companies determines the acceptance of this postulate. Therefore, the outcome of the postulate remains undetermined. For the higher mature companies, the postulate is rejected, for companies with a lower maturity the postulate is accepted.

Postulate 2: *The selection of parameters to monitor is not well motivated.*

The case studies show that when monitoring systems are purchased or installed, it is not exactly known what parameters should be measured. A solution followed for this seems to be that companies try to measure many parameters.

"Together with a consultancy firm, we developed a data collection system which measures many parameters. We intend to use these for future analyses."

This approach reported by the engineer of company A, is analogue to the situation the maintenance engineer of company B describes: *"When the assets are purchased, we don't exactly know what to measure. We just use the pre-installed sensors, which are determined by the OEM. The solution is that we measure a lot."*

In the latter solution, it isn't clear for the asset owner how the OEM determined what should be measured. Moreover, some sensors aren't placed on the correct locations to use them effectively. Initially, when installing the sensory systems, companies lack the knowledge to select the proper parameters. The case study companies gain knowledge on the parameters to measure in a trial and error process. The length

of this process seems dependent on the knowledge level of the company. In hindsight, the motivation of the parameters seems marginal since a trial and error process is followed. This influences the success of the outcomes, which are possibly suboptimal. Considering the current case studies, this postulate can be accepted.

3.3. Step 2: Advanced maintenance analyses

Postulate 3: *Higher maturity levels of analyses result in higher value analyses.*

Companies experience difficulties in expressing the value of the maintenance analyses. As the maintenance engineer of company B reacted to this postulate: *"Yes, I hope so! It's hard to show that"*. However, this maintenance engineer adds to this that it doesn't always seem to be true that more difficult and more mature analyses are better and adding more value to the company than experience of operators:

"People hear, smell, and see all the strange things. Sensors only measure very specific parameters."

These parameters which are referred to, are very specific readings from sensors. Operators will notice various different abnormalities when inspecting a system. To equal this would require a vast amount of sensors and prior knowledge of possible faults.

The added value of the analyses is not only present in the direct prevention of faults, but also in the obtained knowledge about the system's state before it comes into the workshop.

"The major part of our maintenance consists of inspections. The highest potential to add value lies in knowing what is wrong with our equipment before it comes into the workshop." - Maintenance Engineer company B

The reason for companies to invest in maintenance analyses is often based on an incentive to lower cost, but it is hard to create a rigid business case since the outcomes of the analyses are unknown on forehand. Companies therefore rely on the trust of management to invest in these techniques. This postulate can be rejected, it is not true that higher mature analyses always result in higher value for the company.

Postulate 4: *The predictive performance of the prognostic system improves in time, they are evolving systems.*

In the early lifetime of the monitoring system, companies use prognostic techniques to learn about the monitored system instead of directly predicting failures.

"Yes, the predictive performance is improving during the lifetime. However, that has merely to do with our understanding of this system and that we gain better knowledge about how we should interpret the output of the prognostic system"

Thus, as this maintenance engineer of company B continues, it is not always possible to have accurate predictions from the start of the monitoring system.

"I even think that you aren't able to draw conclusions when the equipment is new. Well you can make statements, but you don't know if it is true."

These preliminary results indicate that the knowledge base for understanding the predictions is improved during the lifetime of the prognostic system, this aids the predictive performance. Therefore, this postulate can be accepted.

Postulate 5: *The selection of the type of advanced maintenance analysis is not well motivated.*

Companies experience difficulties in the selection of the maintenance analysis. For the less mature companies, the selection is rather straightforward as they seem to limit their selves to less advanced analyses

"Advanced analyses? We don't do advanced analyses. We use FMECA and common sense" - Maintenance Chef D

However, when companies have enough knowledge to be able to conduct multiple analyses, it seems again (just as with the choice for a certain parameter) to be a process of trial and error.

"Sometimes, we just try a particular method. When this doesn't work, we will try another method. The reason we chose some methods was that we already had some experiences with it, we found a nice software package which enables its use, or we heard from others that they have achieved good results with it." - Maintenance Engineer B

This postulate can be accepted. Companies do not know beforehand what they should measure and therefore ad-hoc choose a suitable method. In hindsight the motivation seems marginal since a trial and error process is followed.

3.4. Step 3: Technical results and life cycle management decision making support

Postulate 6: *The quality level of current analyses is not sufficient to improve maintenance decisions.*

The precision of current analyses of the case study companies was often low, therefore, companies experience difficulties in using these analyses for maintenance decision making, especially for events in the distant future.

"Our FMECAs are used for long term prediction. Resulting maintenance intervals are rather conservative, therefore maintenance is often conducted too early."

As the maintenance engineer of company B reports, long term predictions are often difficult with the current maintenance analyses. However, the step to short term predictions is often made:

"The alerts triggered by the diagnostic system are sufficient to guarantee the safety of the crew. The system is however not yet really effective to aid maintenance decision making."

Nevertheless, as this engineer of company A continues, even in data rich environments, the translation from data to maintenance decisions cannot always be made.

"With our health and usage monitoring systems we are not yet able to translate the measurements of pressure, temperature or altitudes into signs of incipient failure like crack size or use these for failure predictions. This information is sufficient , but we lack a methodology to extend maintenance intervals"

Detection and diagnostic analyses seem to be sufficient to warn in case of emergency and to be able to reduce (safety) risks. Therefore, corrective repairs can be prevented by conducting preventive maintenance. However, for the long

term, the step to better informed maintenance decision making is often not made, the analyses are exclusively used for short term decisions because accurate analyses with a long prognostic distance are missing.

We could only find limited support for this postulate, it seems that the horizon of the maintenance decision is of influence for the acceptance of the postulate.

4. Discussion and conclusion

The large amount of literature devoted to advanced maintenance analyses indicates that this is an important topic in maintenance management. This study shows that several implicit assumptions (post. 1, 3 and 6) found in the literature cannot be supported in the current case studies. As opposed to a large part of the literature which implicitly assumes that selecting and applying the developed techniques is a trivial task, companies experience multiple difficulties in selecting and applying the right prognostic technique for their situation, this is especially true for the implementation of more mature maintenance analyses. It seems that companies often start with experience based methods which are enriched with data from historical failure records (post. 1). Subsequently, companies aim to develop more mature analyses with a trial and error approach which is started with collecting data of many different parameters. For the companies it seems very difficult to determine beforehand the relevant methods and parameters (post. 2 and 5) and they therefore experience a long and costly implementation process. Thus, more guidance is needed on the selection of the methods to be used and the parameters that should be monitored. The presented framework can provide a start to further research the choice of methods and parameters.

Another problem we found in the case studies, partly due to the trial and error approach, is the difficulty to connect and support business aspects of maintenance to the technical features of the maintenance analyses (post. 6), Therefore, more research on the business case for the use of (advanced) prognostic techniques is needed.

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