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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.

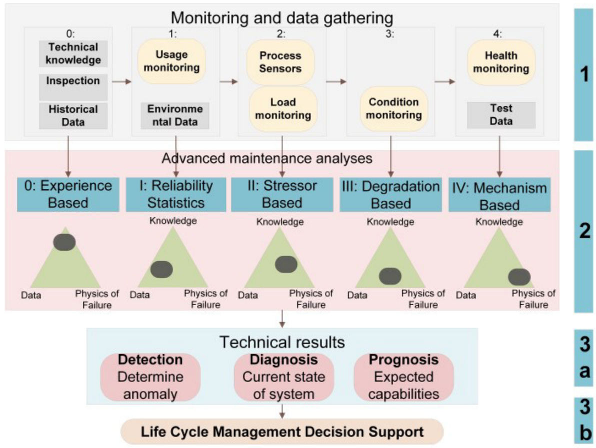

Figure 1, The proposed framework: routes to maintenance decision making, based on Jardine, Lin [15], Coble and Hines [16], Dibsdale [17].

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