Prognostics: design, implementation and challenges

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Paper presented at CM2015/MFPT2015, the Twelfth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, Oxford, UK, June 2015

Prognostics is an essential part of condition-based maintenance (CBM), described as predicting the remaining useful life (RUL) of a system. It is also a key technology for an integrated vehicle health management (IVHM) system that leads to improved safety and reliability. A vast amount of research has been presented in the literature to develop prognostics models that are able to predict a system's RUL. These models can be broadly categorised into experience-based models, data-driven models and physics-based models. Therefore, careful consideration needs to be given to selecting which prognostics model to take forward and apply for each real application. Currently, developing reliable prognostics models in real life is challenging for various reasons, such as the design complexity associated with a system, the high uncertainty and its propagation in the degradation, system level prognostics, the evaluation framework and a lack of prognostics standards. This paper is written with the aim to bring forth the challenges and opportunities for developing prognostics models for complex systems and making researchers aware of these challenges and opportunities.

1. Introduction

Prognostics is an inherent part of condition-based maintenance (CBM). Prognostics is the ability to predict the future health of a given component/system, for a fixed time horizon or to predict the time to failure, and its remaining useful life (RUL).

Large amounts of literature covering prognostics models have already been published by researchers[1-8]. These models can be broadly categorised into experience-based models, data-driven models and physics-based models, as shown in Figure 1. Experience-based models correlate knowledge and engineering experience with the observed monitoring data to infer the RUL from historical measurements[1]. Data-driven models rely only on learning the system's behaviour directly from collected raw monitoring data to predict the projection of a system's state or to match similar patterns in the history to infer the RUL. Data-driven models include, but are not limited to, statistical models, reliability functions and artificial intelligence models[2]. Physics-based models quantitatively characterise the behaviour of a failure mode using physical laws to estimate the RUL[3]. More recently, hybrid prognostics approaches have been presented, attempting to leverage the advantages of combining the prognostics models in the aforementioned different categories for a better capability of managing the uncertainty related to system complexity and data availability to achieve more accurate RUL estimations. However, hybrid prognostics models can have a higher computational cost, which leads to more difficulties in some applications. Hybrid prognostics models can be mainly categorised into experience-based and data-driven models[4], experience-based and physics-based models[5], data-driven and data-driven models[6], data-driven and physics-based models[7] and experience-based, data-driven and physics-based models[8]. Moreover, hybrid modelling can be performed in two approaches, namely the series approach and the parallel approach[9]. The main challenge of a hybrid prognostics approach is choosing the right category, which depends on the available data and information, and choosing the appropriate fusion mechanism for developing the hybrid model.

The performance of a prognostics model can suffer due to different factors, such as inherent uncertainties associated with the deterioration process, a lack of sufficient quantities of run-to-failure data, sensor noise, unknown environmental and operating conditions and engineering variations. Obviously, in such situations it could be quite hard to precisely infer the exact state of degrading machinery and to further predict the evolution of degradation from the collected data.

Prognostics appears to be a very promising maintenance activity because it improves safety, maintenance planning and reduces maintenance costs and downtime. However, developing a reliable prognostics model in industrial applications is challenging because the design complexities associated with a system reduce the effectiveness of prognostic techniques, which are developed based on assumptions and simplifications, and a redundancy in data collection and recording increase the inefficiency in computation for prognosis and data selection and analysis strategies to identify the right data for the execution of prognostics models.

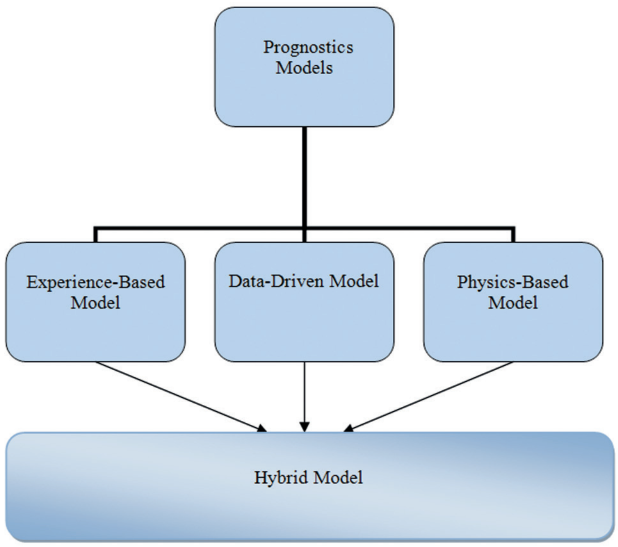

Figure 1. Classification of prognostics models

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2. Prognostics challenges and opportunities

Prognostics has impressive benefits, but it is still not mature in real applications. In this section, we will briefly address the challenges facing the implementation of prognostics in real applications.

2.1 Redundancy in data collection and recording

Data collection is a key part of prognostics. Therefore, inaccurate measurements will lead to an inaccurate estimate of the RUL of the system. Moreover, a redundancy in data collection and recording increases the inefficiency in computation for prognosis. Furthermore, high noise in collected data reduces the sensitivity of diagnostic techniques, consequently increasing the impact of abnormal operating conditions on the prognostic algorithms by decreasing the accuracy of prediction. Data collection is required by sensors and, therefore, the selection of the type and location of the sensor should be carefully considered for an accurate measurement of the change in the parameters linked to the degradation indicators. One source of redundancy in data collection and recording is ignoring the possibility of the sensor, which needs to be taken into account to improve the reliability of the sensor and consequently the accuracy of the prediction.

Currently, industries are facing a significantly complex challenge during the integration of data recorders inside platforms due to the tremendous amount of data generated by the monitored components/subsystems. This challenge is often referred to as the management of big data and includes, but is not limited to, capturing, processing, mining, analysis, integration and visualisation data. This challenge needs to be solved by developing advanced automated data selection and analysis strategies to identify the right data for the execution of prognostics models. This strategy can help to ease the management of big data by identifying only data having features of interest for the assessment of the component/subsystem/system's prognosis.

2.2 Design complexity

Prognostics models face a big challenge in meeting industrial expectations. This can be due to the highly complex and non-linear operational environment of industrial machinery, which makes it hard to establish efficient prognostics approaches that are robust enough to tolerate uncertainty and reliable enough to show acceptable performance under diverse conditions. In addition, the applicability of prognostics approaches is also necessary to meet industrial constraints and requirements. Finally, prognostics approaches should be enhanced by handling, simultaneously, all three challenges: robustness, reliability and applicability, which are still open areas.

2.3 System-level prognostics

All reported prognostics applications raise fundamental challenges since most of the applications so far have been 'point solutions'. It has focused on predicting the RUL of a single component/subsystem, but not on predicting the RUL of the entire system in which these components/subsystems reside[10]. Prognostics at a system level is a relatively new concept in the aerospace sector. As a consequence, there are very few research groups working on this concept. Currently, prognostics at a system level are mainly implemented at a research level; very few systems actually have prognostics built in and these prognostics are based on basic trend and history data. The literature shows very little information about prognostics at a system level in a real application.

Developing prognostics at a system level can be challenging due to the complexity of the system, the lack of exchanged information between the components/subsystems within the system and the relative lack of efficiency of classical prognostics techniques. The system level of prognostics consists of multiple interconnected components/subsystems to perform a given function. Failure of an individual component/subsystem may or may not cause the whole system to fail, but its consequences could propagate through the system causing additional components/subsystems to fail, eventually compromising the system's functional capacity. At the system level, measurements from several components/subsystems may be combined to interpret overall system degradation. In addition, prognostics at the system level will require models to capture the interdependence and cross-coupling effects between components/subsystems within the system.

A distributed solution for addressing the problem of system level prognostics has been addressed in[11]. This solution is based on the concept of structural model decomposition. The system model of a four-wheeled rover simulation test-bed is decomposed into dependent sub-models. Then, independent local prognostics sub-problems are formed based on these local sub-models. This structure results in a scalable, efficient and flexible distributed approach to the prognostics problem at system level. The results proved that the system-level prognostics problem can be efficiently solved in a distributed framework.

Recently, research[12] has considered the problem of system-level prognostics in the cloud. This research has considered the transformation of application systems from system centric architecture to cloud-based systems that leverage shared computational resources to reduce cost and maximise reach.

2.4 Evaluation framework

Prognostics performance evaluation has gained significant attention in the Prognostics Health Management (PHM) Society during the last few years. From the literature, several metrics have been proposed to measure unique characteristics of prognostics, such as accuracy, precision, timeliness and prediction-confidence attributes of the prediction of a prognostic algorithm[13-15]. However, there are no universally-accepted methods to quantify the benefit of prognostics methods[13]. Also, less attention has been paid towards determining the correct approach for evaluating and interpreting prognostic performance under various uncertainty sources, such as state uncertainty, predicting uncertainty and modelling uncertainty. Generally, the performance metrics of prognostics can be divided into the following four groups (Figure 2):

1. **Algorithm performance:** In this group, the performance of the prognostics algorithm will be evaluated based on the calculated error between the ground truth and the estimated RUL. Such evaluation is not only inequitable but, sometimes, it may lead to incorrect conclusions.
2. **Computational performance:** In this group, the performance of the prognostics model will be evaluated based on its computation. This evaluation plays an important role in prognostics model development in the case of critical systems that require less computational time for decision making. For example, CPU time or elapsed time can be used to measure the computational performance of a prognostics model.
3. **Cost benefit risk:** In this group, the performance of the prognostics algorithm will be evaluated based on the cost benefits of the prognostics model that are influenced by the accuracy of RUL estimates. In other words, the operational costs will be reduced if the estimated RUL values are accurate. The ratio of mean time to failure and mean time between unit replacements and return on investment are examples of the evaluation metrics for a prognostics model in this group.
4. **Ease of algorithm certification:** In this group, the metrics

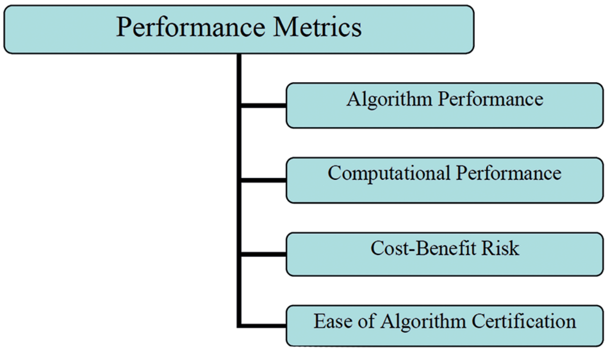

Figure 2. Classification of prognostics metrics[13]

are related to the assurance of an algorithm for a specific implementation.

In addition to the above classification, a list of offline metrics is also proposed by[13-15] to assess prognostics models before they are applied to a real application, such as prognostics horizon, prediction spread, horizon/prediction ratio, and so on.

2.5 Standards for prognostics techniques

Different organisations, such as SAE International, the International Organization for Standardization (ISO) and the United States Army (US Army), have published standards related to prognostics, see Table 1. These entire published standards provide general guidance for prognostics because there is no universal methodology. For example, ISO 13381-1 provides users with general guidelines, approaches and concepts for failure prognostics on engineering systems[16]. It also defines the main four stages of prognosis as the pre-processing phase, existing failure modes, future failure mode and post-action prognosis. In addition, ISO 13381-1 gives a definition of some terms, such as prognosis, root cause, confidence level and estimated time to failure. Moreover, the standard specifies a set of mathematical models for the modelling of degradation mechanisms. An explanation of the presented process of failure prognostics in the ISO 13381-1 standard through an electromechanical example has been presented in[17].

Table 1. Prognostics standards

Organisation	Committee/ Subcommittee	Standard
ISO	TC 108/SC 5	ISO 13379-2
ISO	TC 108/SC 5	ISO 13381-1
ISO	TC 108/SC 5	ISO 18129
ISO	TC 184/SC 5	ISO 22400-1
ISO	TC 184/SC 5	ISO 22400-2
SAE International	E-32	
SAE International	HM-1	
US Army	Aviation Engineering	

Based on the lessons learned from the current prognostics standards, we can conclude that the current prognostics standards are valuable as a general guideline for prognostics. However, there is a lack in the prognostics' standards due to the challenges in developing a universal and reliable prognostics approach across various application domains. Therefore, there is an urgent need for a new generation of prognostics standards because prognostics has become an essential part in the CBM strategy.

3. Conclusions

In this paper, a brief revision of the available prognostics models in the literature is presented. Also, the open challenges and opportunities for prognostics are discussed. In general, the prognostics domain is lacking in standardised concepts and is still evolving to attain a certain level of maturity for real industrial applications. The computational complexity of existing prognostics techniques makes it virtually impossible to apply them from a system-level perspective. Therefore, there is a need to develop a generic framework for prognostics at a system level. New methodologies and tools for prognostics techniques in state estimation, fault and failure modelling and prediction can help to tolerate uncertainty. Developing an automated data collection strategy with the capability to analyse large amounts of data from distributed and heterogeneous sources will be a help to ease the management of data with features of interest for prognosis.

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