Diagnosis and Prognosis of Mechanical Components Using Hybrid Methods

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Abstract. Diagnosis and prognosis of mechanical components are important for critical rotating machinery found in the power generation, mining, and aviation industries. Data-driven diagnosis and prognosis methods have much potential; however, their performance is dependent on the quality of historical data . Usually only limited historical data are available for newly commissioned parts and for parts that do not go through a full degradation cycle before being replaced. Physics-based diagnosis and prognosis methods require assumptions of the underlying physics; the governing equations need to be derived and solved; and the model needs to be calibrated for the underlying system. Physics-based methods require extensive domain knowledge and could have modelling biases due to missing physics. Hybrid methods for diagnosis and prognosis of mechanical components have the potential for improving the accuracy and precision of remaining useful life (RUL) estimation when historical fault data are scarce. This is because hybrid methods combine data-driven and physics-based models to alleviate the shortcomings of the respective methods. For these reasons, hybrid methods are getting more attention in the condition monitoring community as a solution for diagnosis and prognosis tasks. Therefore, in this chapter, we present a review of the state-of-the-art implementations of physics-based, data-driven, and hybrid methods for diagnosis and prognosis. The methods are organised using a condition monitoring framework and contributions of various techniques are discussed. We identify gaps in the hybrid diagnosis and prognosis field that could be the focus of future research projects.

Keywords: Hybrid methods · Diagnosis · Prognosis · Remaining useful life

1 Introduction

Mechanical components such as bearings, gears or turbomachine blades are affected by different degradation mechanisms. These degradation mechanisms include, but are not limited to creep, wear, and fatigue crack growth (Cubillo et al. 2016). Remaining useful life (RUL) is defined as the time or number of cycles the damage in a component will remain within the specified limits set by the engineer ("ISO 13381-1" 2015). RUL is one of the most important aspects of predictive maintenance. In predictive maintenance strategies engineers need to know the condition of the component and the RUL of the component to make decisions that either (i) ensure safety against unplanned failure or (ii)

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maximise the component's use before unnecessarily replacing the component (Saxena 2010). Condition monitoring is collection of techniques that use sensors to determine the damage of a component while the component is in operation. It forms an integral part of diagnosis and prognosis. Lee et al. (2018) reviewed different condition monitoring techniques applied to rotating mechanical components. The focus of this review was on vibration sensors and acoustic emission sensors. According to the review, vibration-based condition monitoring methods are the most popular for mechanical components (Lee et al. 2018).

Methods for estimating the condition and the RUL of mechanical components from condition monitoring data are often categorised into either (i) physics-based, or (ii) data-driven methods (An et al. 2015). Physics-based methods use first principles to model the damage in the component and to model the response of the system. In contrast, data-driven methods only rely on the available data to find relationships between the different correlated variables and do not account for the underlying physical mechanisms that generate the data. Both physics-based methods and data-driven methods have their limitations (Khan and Yairi 2018). Physics-based can contain model errors, while data-driven methods require historical fault data. Hybrid methods can improve existing methods by addressing the drawbacks of the other methods.

In this chapter, we organise the contribution of different authors into a generalised framework and highlight the applications of hybrid methods in this framework. The objective of this chapter is to present the state-of-the-art methods in diagnosis and prognosis of mechanical components. We identify areas that still need to be addressed, which are presented in Sect. 4 of this chapter.

2 Diagnosis and Prognosis Using Condition Monitoring Data

Figure 1 presents a summary of the condition monitoring process and the various parts that are required to estimate RUL. The most common vibration-based condition monitoring techniques are broadly categorised as (i) machine learning techniques or (ii) Fourier-based methods (Lee et al. 2018). The purpose of these methods is to relate the characteristics of the vibration of the system to the condition of the component.

Diagnosis refers to the identification, localisation, and quantification of the damage. Identification and localisation (otherwise known as anomaly detection) refer to detecting the damaged component, the degradation mechanism, and the exact location of the damage. Anomaly detection is usually performed in early stages of the component's condition monitoring process (Carden and Fanning 2004). Wang et al. (2016) demonstrated the use of spectral kurtosis as an anomaly detection method for determining faults in gear teeth from accelerometer data. Quantification refers to an estimation of the extent of the damage (e.g., the crack length in a steam turbine blade). An accurate estimate of the damage severity is essential for making the appropriate maintenance decisions. The accuracy of the estimate can be quantified by its bias and its variance. The estimate's variance is influenced by electrical, mechanical, and environmental noise sources. The bias is typically influenced by incorrect measurement models (i.e., the model that relates the underlying state to the measured data). Continuous condition monitoring applications enable the implementation of Bayesian filtering algorithms to update and improve the

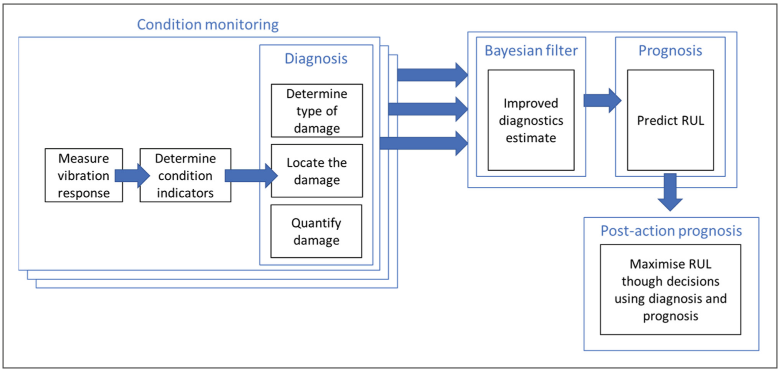

Fig. 1. Condition-based maintenance process from sensor data collection to RUL estimation of critical mechanical components

estimate of the damage severity over time (Jouin et al. 2016). The purpose of a Bayesian filtering algorithm is to improve the diagnosis using a known degradation model, which is critical for RUL prediction.

Prognosis, refers to the estimation of RUL. Sankararaman and Goebel (2014) emphasise the treatment of uncertainty when RUL is estimated and the ways that uncertainty is represented and interpreted from the models. Physics-based models, for instance, are deterministic in nature. Uncertainty can be introduced in these methods by implementing an ensemble of physics-based methods. Data-driven methods, on the other hand, can measure the RUL uncertainty only when enough representative data are collected. RUL estimates from physics-based methods and data-driven methods are limited by the models and data that capture the uncertainty of the component's degradation.

3 Hybrid Methods for Diagnosis and Prognosis of Mechanical Components

Lei et al. (2018) highlight that one of the largest drawbacks of data-driven methods is the availability of run-to-failure data for mechanical components. Mechanical systems are becoming more complex as requirements for flexible manufacturing become more prevalent. As a result, prognostics has reached a tipping point where insufficient data are available for training, particularly for newly commissioned components. Physics-based models, on the other hand, require data to validate their accuracy since they are limited by the modelling assumptions (An et al. 2015). Model inadequacy, where the model does not capture all of the physics of the system, could also be detrimental to the performance of physics-based methods. Liao and Köttig (2014) suggest the use of hybrid techniques for cases where data are scarce and simplified physics-based models are available. We distinguish between hybrid combination frameworks (that is, combinations of different model types for unique purpose in a condition monitoring framework); and hybrid fusion models (that is, different types of models that are combined for the same purpose). An example of a hybrid fusion model is illustrated by Coppe et al. (2012) whereby physics-based crack growth models (e.g. Paris' law) are combined with data-driven observations of the crack length to form a hybrid crack growth prediction model. Most of the models that Liao and Köttig (2014) propose are hybrid combination frameworks. An example of a hybrid combination framework is exhibited by Sanchez et al. (2016) for determining the RUL of wind turbine blades. Sanchez et al. (2016) proposes a physics-based method for determining the stiffness of a blade from the blades' vibration characteristics and a data-driven method for predicting the changes in the blades' stiffness due to crack growth at the root of the blade.

3.1 Diagnosis: Estimating Current Damage

Diagnosis requires condition indicators that unique identify the component and the damage mechanism present in the component (Lei et al. 2018). Incorrect identification may cause all other methods to fail and could result in unnecessary maintenance costs. Hence, anomaly detection methods often form part of the diagnosis procedure. Serafini et al. (2019) use simulated data to detect localised stiffness reduction of helicopter blades from strain gauge measurements.

Physics-based diagnosis models, model the relationship between the condition indicator and the damage using a first-principles approach. Zeng et al. (2018) demonstrated using finite element simulations that there is a comparable difference in the vibration characteristics of a compressor rotor blade with and without a crack. Elshamy et al. (2018) used the first three natural frequencies of a cantilever beam to uniquely identify the depth and location of cracks. Corrado et al. (2018) expanded on this idea to diagnose multiple cracks and the locations of these crack from only the mode shape. The methods only use finite element simulations to construct these models.

Data-driven diagnosis, on the other hand, apply machine learning techniques to quantify the damage mode and the extend of the damage. Here we refer to the data as collections of the condition indicators and the damage histories. Kaloop and Hu (2015) detected and localised faults in stayed-cable bridges from accelerometer data. Jia et al. (2016) and Zhang et al. (2018) demonstrated the use of deep neural networks and convolutional neural networks respectively for classifying types and severity of faults in bearings from raw accelerometer data. The accuracy of the data-driven diagnosis method surpasses the accuracy of most physics-based diagnostics models (Khan and Yairi 2018). This is because the performance of data-driven methods scale well with the size of the data (Bishop 2006). The more data that is available, the less likely a complex model will overfit the data.

There is however a gap in the literature for methods that diagnose the damage from condition indicators using hybrid fusion models. In a *hybrid fusion diagnosis* model, the physics-based diagnosis and data-driven diagnosis models are combined to improve the quantification of the damage during condition monitoring. That is, after determining the condition indicators from vibration sensors a diagnostics model should quantify the damage and estimate the uncertainty of this quantification. There is presently very limited literature on hybrid fusion diagnostics models. This may be attributed to Bayesian filtering techniques that are used to update the estimation of the current damage from known degradation models. As a result, most researchers deem it unnecessary to improve the quantification of the current damage twice. We discuss these Bayesian filtering techniques next.

3.2 Improved Diagnosis: Bayesian Inference Methods

It has become standard practice to use Bayesian filtering methods in condition monitoring methods (Corbetta et al. 2018a, b) . The purpose of Bayesian filtering is outlined by Jouin et al. (2016): A Bayesian filtering method is only used for improving state estimation and has no predictive capabilities. Since, models that describe the rate of degradation are often a function of damage in the component (Cubillo et al. 2016) it is important to improve the diagnostics obtained from regular condition monitoring to improve RUL estimation.

Let x_k denote the hidden health state estimate at the k^{th} condition monitoring step. The condition indicators at all condition monitoring steps are denoted $y_{1:k}$. A Bayesian filter typically consists of two steps. Firstly, predict the probability of the health state at the using the k^{th} condition monitoring step with

$$p(x_k|y_{1:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|y_{k-1})dx_{k-1} \tag{1}$$

This is also called the Chapman-Kolmogorov equation. Secondly, update the probability distribution of the health state using all the condition monitoring measurements until step k using Bayes' rule

$$p(x_k|y_{1:k}) = \frac{p(y_k|x_k)p(x_k|y_{1:k-1})}{p(y_k|y_{1:k-1})} \tag{2}$$

The normalising constant is determined from

$$p(y_k|y_{1:k-1}) = \int p(y_k|x_k)p(x_k|y_{1:k-1})dx_k \tag{3}$$

Jouin et al. (2016) show that there are analytical and approximate solutions to these equations. Corbetta et al. (2018a, b) used particle filter-based methods for performing Bayesian filtering. Particle filters are approximate inference methods that solve the update and predict equation, using Monte Carlo methods. These particle filters can be degenerate under some modelling assumptions. Therefore, using non-additive process noise is advised. Valeti and Pakzad (2017) and Zaidan et al. (2015) applied particle filtering methods to cracks in wind turbine blades and aerospace gas turbine engines.

3.3 Prognosis: Estimating RUL

RUL is estimated from the posterior distribution of the Bayesian filter. The estimated damage at the last condition monitoring step is propagated using a degradation model. Cubillo et al. (2016) presented an extensive summary of physics-based degradation models for creep, wear, and fatigue crack growth. These models are mostly derived in the form of a differential equation

$$\frac{dx}{dt} = f(x, u(t)) \tag{4}$$

where $f(x, u)$ denotes the non-linear function that describes degradation rate from the currently estimated damage x, and the future operating condition $u(t)$. The Paris-Erdogan law is an example of this model where $x = a$ denotes the crack length and $u(t) = \Delta S(N)$ denotes the stress amplitude as a function of the number of loading cycles, N, instead of time, t. The equation

$$\frac{da}{dN} = C(\Delta K)^m = C\big(F(a)\Delta S(N)\sqrt{\pi a}\big)^m \tag{5}$$

predicts the crack growth rate from material parameters C and m, and the geometric factor $F(a)$. Keprate et al. (2017) presented a Gaussian processes regression surrogate model to quickly evaluating the stress intensity factor range ΔK, in offshore pipelines. Typically, finite element simulations or empirical formulas are used for determining the stress intensity factor range using a physics-based approach. Integrating the degradation model analytically or numerically will solve the degradation path (that is, the damage as a function of time). When the degradation path crosses the fault-specification-limit, the RUL is recorded.

Wang et al. (2020) present a collection of data-driven methods that do not directly measure the condition of the component. The methods estimate the RUL from the condition indicators directly using a relevance vector machine. Data-driven prognostics methods often use run-to-failure data to predict RUL directly from condition indicators without a diagnosis of the component. Khan and Yairi (2018) demonstrate the capabilities of data-driven methods that can perform classification and regression from very little understanding of the data. However, these models do not address uncertainty, which is a critical aspect for RUL estimation.

Hybrid-fusion-based prognostics methods have become popular since the introduction of damage propagation model parameters as part of the Bayesian filter step. Coppe et al. (2010, 2012) first introduced the concept by introducing Paris's law parameters as part of the hidden state to model cracks in a large plate. When introducing the model parameters as part of the hidden state, a posterior probability distribution of the model parameters can be inferred from regular diagnosis. Thus, a physics-based model is augmented with condition monitoring data to improve the model. Corbetta et al. (2018a, b) applied a similar technique to multi-degradation modes of fibre reinforced laminates with matrix cracks and delamination. Corbetta et al. (2018a, b), further termed these types of models as artificial dynamics models. (Chen et al. 2018; Saidi et al. 2018) applied the artificial dynamics approaches to attachment lugs and wind turbine bearings, respectively.

4 Future Aspects of Hybrid Methods

In Fig. 2 we present our hypothesis for the performance of hybrid techniques for RUL predictions. Performance metrics of RUL estimation refer to the accuracy, precision, consistency and robustness of estimating the true RUL of a mechanical component (Saxena et al. 2010); hence, we omit the scale of the dependent axis in Fig. 2. Physics-based models that do not rely on the data for model updating do not change in performance. A Bayesian approach to hybrid diagnosis and prognosis is expected to use physics-based models as a prior model and augment the model with data. Thus, it is expected that hybrid methods will have increased performance compared to physics-based models.

Data-driven methods, on the other hand, are also expected to increase with the accumulation of data. After a certain amount of data is collected data-driven methods will meet the performance of hybrid methods since the likelihood will be very localised and therefore most dominant in the posterior probability of the RUL (Khan and Yairi 2018).

Future applications of condition monitoring methods will require automated diagnosis and prognosis of critical assets. Even though data-driven models could theoretically enable automatic diagnosis and prognosis, mechanical assets typically do not have representative failure data available to properly train data-driven models. This means that the machines will operate on the left end of the graph in Fig. 2 and therefore hybrid methods will be essential for future diagnosis and prognosis tasks.

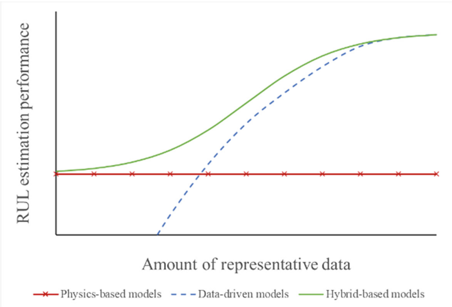

Fig. 2. A hypothesis of the performance of hybrid methods compared to data-driven and physics-based methods.

Corbetta et al. (2017) and Le et al. (2015) investigated hybrid prognostics frameworks for co-existing damage modes. Treatment of degradation modes on an individual basis has some severe consequences since the co-existing damage modes ‘fuel’ the degradation process and consequently the component may fail earlier than predicted. Cubillo et al. (2016) mentioned that fatigue crack growth and creep are stimulated by one-another. Therefore, future work in diagnosis should not only identify a single fault in a component but also identify when multiple failures occur simultaneously.

The future development of hybrid methods is, however, not limited to improvements of diagnosis and prognosis. Sikorska et al. (2011) presented a review of prognostics options for industry and listed many limitations of practically implementing these methods. Most of these problems have since then been addressed. However, possible actions that maximise the RUL of a component based on diagnosis and prognosis is still a developing field. Methods for optimising the RUL by proposing potential actions that could stop, remove, or slow down the failure rate of the component. Gao and Liu (2021) refer to these techniques as resilient control strategies and propose the use of RUL estimation in control systems to reduce the rate of crack growth in wind turbine blades.

5 Conclusion

In this chapter, we presented a review of hybrid methods using a condition monitoring framework. Hybrid methods are identified at the different steps of the frameworks. It is emphasised that the purpose of hybrid methods is to improve the estimation of the health state and the RUL. Two potential gaps for future research are identified namely (i) the effect that hybrid-fusion-based diagnosis has on the RUL estimation of a component and (ii) suggesting actions based on the diagnosis and prognosis to maximise the RUL of the component.

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