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Review

Rotating machinery prognostics: State of the art, challenges and opportunities

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A B S T R A C T

Machinery prognosis is the forecast of the remaining operational life, future condition, or probability of reliable operation of an equipment based on the acquired condition monitoring data. This approach to modern maintenance practice promises to reduce downtime, spares inventory, maintenance costs, and safety hazards. Given the significance of prognostics capabilities and the maturity of condition monitoring technology, there have been an increasing number of publications on rotating machinery prognostics in the past few years. These publications covered a wide spectrum of prognostics techniques. This review article first synthesises and places these individual pieces of information in context, while identifying their merits and weaknesses. It then discusses the identified challenges, and in doing so, alerts researchers to opportunities for conducting advanced research in the field. Current methods for predicting rotating machinery failures are summarised and classified as conventional reliability models, condition-based prognostics models and models integrating reliability and prognostics. Areas in need of development or improvement include the integration of condition monitoring and reliability, utilisation of incomplete trending data, consideration of effects from maintenance actions and variable operating conditions, derivation of the non-linear relationship between measured data and actual asset health, consideration of failure interactions, practicability of requirements and assumptions, as well as development of performance evaluation frameworks.

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1. Introduction

Operational safety, maintenance cost effectiveness and asset availability have a direct impact on the competitiveness of organisations and nations. Today's complex and advanced machines demand highly sophisticated and costly maintenance strategies. Domestic plants in the United States spent more than $600 billion to maintain their critical plant systems in 1981 and this figure doubled within 20 years [1]. An even more alarming fact is that one-third to one-half of this expenditure is wasted through ineffective maintenance. The trend is similar in many other countries including Australia [2]. Therefore, there is a pressing need to continuously develop and improve current maintenance programs.

Current maintenance strategies have progressed from breakdown maintenance, to preventive maintenance, then to condition-based maintenance (CBM) managed by experts, and lately towards a futuristic view of intelligent predictive maintenance systems. Breakdown maintenance is the earliest form of maintenance, where no actions are taken to maintain the equipment until it breaks and consequently needs a repair or replacement. To prevent catastrophic failures and emergency shutdowns, preventive maintenance was introduced in the 1950s. A typical preventive maintenance scheme includes setting periodic intervals for machine inspections and maintenance regardless of the machine's health condition. The determination of optimal maintenance interval is critical for this scheme to work effectively. Bazovsky [3] pioneered the use of mathematical optimization methods in preventive maintenance policies. Jardine [4] introduced decision models for determining optimal replacement or overhaul interval by analysing reliability data (e.g. historical breakdown events) and cost data. However, fixed time maintenance policies were not well-received by most practitioners [5]. While these policies do sometimes reduce equipment failures, they are more labour intensive, does not eliminate catastrophic failures and cause unnecessary maintenance. This is where CBM steps in. It was reported that 99% of mechanical failures are preceded by noticeable indicators [6]. CBM attempts to monitor machinery health based on condition measurements that do not interrupt normal machine operation. Over the past few decades, technologies in machine condition monitoring (CM) and fault diagnostics have become more developed. Data such as vibration signatures, acoustic emissions signatures and oil particle counts can be acquired, processed and analysed through state-of-the-art sensors, database software and parallel computation technologies. Nevertheless, new technologies often introduce new types of information that may not have been fully exploited. This development has presented a paramount challenge for the research community to synthesise and integrate the new information into conventional reliability calculations and eventually into maintenance scheduling.

Three key elements of effective CBM are data acquisition (i.e. the collection and storage of machine health information), data processing (i.e. the conditioning and feature extraction/selection of acquired data) and decision making (i.e. the recommendation of maintenance actions through diagnosis and/or prognosis). Increased automation and mechanisation have made computerised diagnostics and prognostics systems a valuable tool for maintenance personnel in making maintenance decisions, or possibly even replace maintenance experts in due time. Today's concept of machine diagnosis comprises the automated detection and classification of faults, whereas machine prognosis is the automated estimation of how soon and likely a failure will occur. Prognostics promises to significantly reduce expensive downtime, spares inventory, maintenance labour costs and hazardous conditions. However, prognostics is a relatively new research area and has yet to receive its prominence compared to the other areas of CBM.

Related reviews on prognostics have been reported in the literature. Pusey and Roemer [7] provided a broad overview of the development in diagnostics and prognostics technologies applicable to high-performance turbo-machines up until year 1999. Jardine et al. [8] provided an overview and a catalogue of publications on data acquisition, data processing, diagnostics and prognostics of various machines up to year 2005. Vachtsevanos et al. [9] defined and described intelligent fault diagnostics and prognostics approaches for engineering systems through examples. Ma [10] discussed the need for a new paradigm shift in CM research for engineering asset management.

This paper focuses on rotating machinery prognostics. Rotating machinery is one of the most common classes of machines. The number of publications on rotating machinery prognosis has been increasing steadily over the past few years. Section 2 aims to place these articles in context, showing how they add to the accumulation of knowledge in the area. Section 3 then discusses the identified challenges and in doing so, alerts researchers to opportunities for advanced research in the field of machinery prognostics.

2. Methods for predicting rotating machinery failures

The existing methods for predicting rotating machinery failures can be grouped into the following three main categories:

1. Traditional reliability approaches—event data based prediction.
2. Prognostics approaches—condition data based prediction.
3. Integrated approaches—prediction based on both event and condition data.

Table 1 lists the existing models under these three approaches and describes their merits and limitations.

Traditional approaches to reliability estimation are based on the distribution of event records of a population of identical units. Many parametric failure models, such as Poisson, Exponential, Weibull, and Log-Normal distributions have been used to model machine reliability. The most popular among them is the Weibull distribution due to its ability to accommodate various types of behaviour including infant mortality in the "bath-tub" curve. Reliability analyses have been extensively studied and developed over the past few decades and numerous books and articles have been published, e.g. [3,11–17]. These classical reliability approaches basically use historical time-to-failure data to estimate the population characteristics (such as mean-time-to-failure and probability of reliable operation). However, these approaches only provide general overall estimates for the entire population of identical units. This type of estimations is useful to manufacturers that produce units in high volumes but are of little value to end users. For example, a maintenance engineer would be more interested in the ongoing reliability information of a particular piece of component currently running in the machine, rather than in the mean-time-to-failure of the whole population of such a component.

To estimate the current condition of an operating unit, a more "engineering" approach to reliability based on the actual change in unit health is necessary. Recent developments in CM technologies have enabled the collection of non-intrusive degradation measurements of a unit in operation. These CM data are a rich source of information in reliability evaluation of individual units. Consequently, the research community has started to develop prognostics models that estimate the future health of a monitored unit based on acquired CM data. This second category of failure prediction models are reviewed in Section 2.1. While CM data are corroborative data that reflect the current health of an operating item, they do not replace reliability data that reflect population characteristics. The last category comprises models that integrate reliability data into prognostics and is reviewed in Section 2.2.

2.1. Prognostics approaches—condition-based prediction

Most of the existing prognostics models can be divided into two main categories: physics-based models and data-based models.

2.1.1. Physics-based prognostics models

Physics-based models typically involve building technically comprehensive mathematical models to describe the physics of the system and failure modes, such as crack propagation and spall growth. These models attempt to combine system-specific mechanistic knowledge, defect growth formulas and CM data to provide "knowledge-rich" prognosis output.

A common physics-based approach is crack growth modelling. Li et al. [19,20] related rolling element bearing defect growth rate to the instantaneous defect area size and material constants based on Paris' formula. Li and Choi [21], and Li and Lee [22] used Paris' law to model spur gear crack growth. A 2D Finite Element Analysis (FEA) model was integrated to calculate stress and strain fields based on gear tooth load, geometry and material properties. Oppenheimer and Loparo [23] modelled rotor shaft crack growth using the Forman law of linear elastic fracture mechanics. However, since knowledge of the instantaneous defect area size is usually unavailable without interrupting the machine operation, these crack growth models assumed that defect area size could be directly estimated from vibration data.

Orsagh et al. [24,25] used a stochastic version of the Yu-Harris bearing life equation to predict spall initiation and the Kotzalas-Harris progression model to estimate the time to failure. Kacprzynski et al. [26] enhanced the above system by proposing a framework for physics-based prognostics integrating material-level models, system-level data fusion algorithms and parameter tuning techniques. A spiral bevel pinion gear of a helicopter gearbox was used as a case study. It was stated that uncertainty in factors such as gear geometry, contact, load and material properties limit the reliability of prognostics systems. Information such as statistical variation of fatigue and fracture properties, as well as compressive stresses, has a dominant impact on the prediction accuracy of physics-based models.

Sentient Corporation developed a programme called Contact Analysis for Bearing Prognostics (CABPro) [27], which uses FEA to calculate material stress field and then determines the cycles to failure based on damage mechanics principles. Qiu et al. [28] considered the rolling element bearing system as a single-degree-of-freedom vibratory system. The failure natural frequency and the acceleration amplitude were related to the running time and failure time established from damage mechanics. Like other physics-based models, these techniques require the estimation of various physics parameters.

Table 1
List of rotating machinery health prediction methods and their merits and limitations

Approach	Merits	Limitations
1. Reliability—use event data, e.g. replacement/failure times of historical units		
Traditional reliability models (e.g. Weibull, Poisson, Exponential, Log-Normal distributions, see e.g. [3,11–17])	• Population characteristics information enable longer-range forecast • Do not require CM	• Only provide general, overall estimates for the entire population of identical units—not necessarily accurate for individual operating units
2. Prognosis—use CM data, e.g. vibration measurements of operating units		
(i) Physics-based prognostics models	• Can be highly accurate if physics of models remain consistent across systems • Require less data than data-driven techniques	• Real-life system physics is often too stochastic and complex to model • Defect-specific
Paris' law crack growth modelling [19,20]	• Least-square scheme enables adaptation of model parameters to changes in condition	• Defect area size is assumed to be linearly correlated to vibration RMS level • Least-square scheme similar to single-step adaptation in time series prediction • Material constants to be determined empirically
Paris' law crack growth modelling with FEA [21,22]	• FEA enables material stress calculation based on bearing geometry, defect size, load and speed.	• Performance relies on the accuracy of crack size estimation based on vibration data • Computationally expensive
Forman law crack growth modelling [23]	• Relates CM data and crack growth physics to life models	• Simplifying assumptions need to be examined • Model parameters yet to be determined for complex conditions (e.g. in shaft loading zone and plastic zones)
Fatigue spall initiation and progression model [24–26]	• Calculates the time to spall initiation and the time from spall initiation to failure • Cumulative damage since installation is estimated with consideration of operating conditions	• Various physics parameters need to be determined
Contact analysis for bearing prognostics [27]	• FEA enables material stress calculation based on bearing geometry, defect size, load and speed	• Various physics parameters need to be determined • Computationally expensive
Stiffness-based damage rule model [28]	• Relates bearing component natural frequency and acceleration amplitude to the running time and failure time	• Least-square scheme similar to single-step adaptation in time series prediction • Various material constants need to be determined
(ii) Data-driven prognostic models	• Do not require assumption or empirical estimation of physics parameters	• Generally required a large amount of data to be accurate
Simple trend projection models [29–31]	• Ease of calculation	• Rely on past degradation pattern and can lead to inaccurate forecasts in times of change
Time series prediction using ANNs [33,38–42]	• Fast in handling multivariate analysis • Provide non-linear projection • Do not require a priori knowledge	• Assume that condition indices deterministically represent actual asset health • Assume that failure occurs once the condition index exceeds a presumed threshold • Short prediction horizon
Exponential projection using ANN [43]	• Estimates actual failure time instead of condition index at future time steps • Longer prediction horizon	• Assumes that all bearing degradation follow an exponential pattern • Requires training one ANN for each historical dataset
Data interpolation using ANN [44]	• Longer prediction horizon	• Requires training one ANN for each historical dataset
Particle filtering [45]	• Provides non-linear projection	• Poor performance with high dimensional data
Regression analysis and fuzzy logic [46]	• Emphasizes the most recent condition information • Fuzzy logic enables condition classification based on histories	• Does not provide indication of time to failure or probability of failure

Table 1 (*continued*)

Approach	Merits	Limitations
Recursive Bayesian technique [47]	• Estimates reliability using CM data of individual assets, rather than event data	• Accuracy relies strongly on the correct determination of thresholds for various trending features
Hidden Markov Model and Hidden Semi-Markov Model [48,49]	• Can be trained to recognise different bearing fault types and states	• Lack of relation of the defined health-state change point to the actual defect progression since it is often impractical to physically observe a defect in an operating unit. • Prognosis projection relies on a failure threshold
Bearing dynamics model using system identification [50]	• Tracks defect severity based on features that are not affected by operating condition and nearby equipments	• Reasonably accurate only when the signal-to-noise ratio is high, e.g. damage is severe and running speed is relatively high
3. Integration of reliability and prognosis—use both event and CM data		
Models combining reliability and prognostics	• Utilise available information more fully for increased accuracy • Longer-range prediction	• Require both event and condition data to be accurate
IP and PF interval representation using Weibull distribution [51]	• Combines reliability and CM data to narrow down the time-to-failure window	• Assumes an underlying distribution
EXAKT (combining Proportional Hazards Models, transition probability and a cost model) [52–55,60,61]	• Combines economic considerations with failure prediction in aiding maintenance decision • Identifies the order of significance of trending data features	• Accurate transition probability calculation required a relatively large amount of CM histories • PHM assumes that hazard changes proportionately with covariates and the proportionality constant is the same at all time
Proportional covariates model [62]	• Can be used in cases of sparse or no historical failure data	• Assumes that hazard changes proportionately with covariates and the proportionality constant is the same at all time
Conditional residual time distribution model and proportional residual model [63,64]	• Considers the whole CM history rather than only the current information	• Requires the determination of a threshold level that indicates defect initiation, which is hard to identify and seldom recorded in practice
Symptom reliability model [66]	• Defines reliability in “symptom” domain • Can include system and operating parameters in reliability modelling to permit more precise prediction	• Yet to be validated since sufficiently large database of symptoms and covariates is scarce in practice
Intelligent product-limit estimator [67]	• Uses ANN recognise the nonlinear relationship between actual asset health and measured condition data • Non-parametric—avoids potentially large errors due to incorrect assumptions about the underlying failure distribution	• Requires sufficient CM histories for ANN training

For most industry applications, physics-based models might not be the most practical solution since the fault type in question is often unique from component to component and is hard to be identified without interrupting operation. However, physics-based models may be the most suitable approach for cost-justified applications in which accuracy outweighs most other factors and physics models remain consistent across systems, such as in air vehicles [18]. They also generally require less data than data-driven models.

2.1.2. Data-driven prognostics models

Data-driven approaches attempt to derive models directly from routinely collected CM data instead of building models based on comprehensive system physics and human expertise. They are built based on historical records and produce prediction outputs directly in terms of CM data.

The conventional data-driven methods include simple projection models, such as exponential smoothing [29] and autoregressive model [30]. One major advantage of these techniques is the simplicity of their calculations, which can be carried out on a programmable calculator. However, most of these trend forecasting techniques assume that there is some underlying stability in the monitored system. They also rely on past patterns of degradation to project future degradation.

This reliance could lead to inaccurate forecasts in times of change. Most of these models follow the changing pattern with a time lag of at least one observation. Cempel [31] introduced the Tribo-vibroacoustical (TVA) model, which can estimate the time to failure of a machine as well as forecasting the vibration amplitude or condition. The model was compared with a constant trend parabolic model, an exponential trend model and an adaptive trending model in predicting a rolling bearing's peak vibration acceleration. It was reported that none of the forecasting techniques was able to predict the sudden change in the life curve.

Artificial neural network (ANN) is currently the most commonly found data-driven technique in the prognostics literature. An ANN consists of a layer of input nodes, one or more layers of hidden nodes, one layer of output nodes and connecting weights. The network learns the unknown function by adjusting its weights with repetitive observations of inputs and outputs. Numerous studies across various disciplines have demonstrated the merits of ANNs, including the abilities to (a) perform faster than system identification techniques in multivariate prognosis [32]; (b) perform at least as good as the best traditional statistical methods, without requiring untenable distributional assumptions [33,34]; and (c) capture complex phenomenon without a priori knowledge [35]. A widely known limitation of ANNs is the lack of transparency, or rather the lack of documentation on how decisions are reached in a trained network. However, it was argued in Ref. [35] that increase in model complexity reduces the transparency of both traditional statistical models and ANN models. It is just that ANNs are more capable in modelling complex phenomenon and consequently need a more complex structure to represent the phenomenon. Rules can actually be extracted from trained ANNs to explain how decisions are reached, see e.g. [36,37].

The most simple ANN-based machinery prognostics approach was time series prediction models. Tse and Atherton [33] and Yam et al. [38] used recurrent neural networks (RNNs) to trend CM indices and forecast successive index value at the next time step. Wang and Vachtsevanos [39] developed a recurrent wavelet neural network (RWNN) to predict rolling element bearing crack propagation. The network performed satisfactorily in trending an artificially seeded and manually enlarged crack, provided that sufficient data points were used and network retraining was carried out after each time step. Wang et al. [40] used a Neuro-Fuzzy (NF) network to predict spur gear condition value one step ahead. The fuzzy interference structure is determined by experts, whereas the fuzzy membership functions are trained by the neural network. The NF system performed much better than RNN when there was sufficient training data. However, it could not predict well when the train-set was small or when there were fast dynamic fluctuations, such as during the chipping of gear tooth surface material or just prior to gear failure. An adaptive training technique was later proposed by Wang [41] to improve the NF model. The addition of feedback links to the NF model was able to increase the forecasting accuracy. However, further work is needed to extend the prediction horizon from single step to multiple steps ahead. Feed forward neural network (FFNN) has also been used to perform single-step-ahead prediction of rolling element bearing condition by Shao and Nezu [42]. Multiple-step-ahead predictions were also performed simply by feeding the predicted value back into the network input until the desired prediction horizon was reached. The authors also proposed some rules to vary the data sampling period according to the change ratio of consecutive condition index values.

So far all the ANN models mentioned above only produced estimates of the future asset condition indices. Gebraeel et al. [43] attempted to predict the actual bearing failure time instead of the future condition index. Their thrust bearing prognosis was based on the assumption that all bearing degradation signals possess an inherent exponential growth, and FFNNs were used to project the degradation by computing exponential parameters that give the best exponential fit. Remaining useful life was then found by solving for the projected failure time at the predetermined failure threshold. Ninety-two percent of the failure time predictions were within 20% of the actual bearing life. Huang et al. [44] built on the above method and used an FFNN to predict the failure time of single-row deep-groove ball bearings based on 100 interpolated points. It was stated that 85% of the failure time predictions were within 20% of the actual bearing lifetime. It was pointed out that the features effective for trending the degradation of thrust bearings in Ref. [43] either have low sensitivity to incipient faults or are not effective for trending the degradation of single row, deep groove ball bearings under highly accelerated tests.

Particle filtering has also been employed to provide non-linear projection in forecasting the growth of a crack on a turbine engine blade [45]. The current fault dimension was estimated based on the knowledge of the previous state of the process model. The *a priori* state estimate was then updated using new CM data. To extend this state estimation to multi-step-ahead prediction, a recursive integration process based on both Importance Sampling and Kernel probability density function approximation was applied to generate state predictions to the desired prediction horizon.

Jantunen [46] used high-order regression functions to mimic bearing fault development and also to save trending data in a compact form. Fuzzy classification limits were set to define eight classes of predicted conditions or health states of a rolling element bearing. Simplified fuzzy logic was then used to classify the bearing health state. Indication of time to failure or probability of failure was not provided.

Zhang et al. [47] proposed a recursive Bayesian technique to calculate failure probability based on the joint density function of different CM data features. This method enabled reliability analysis and prediction based on the degradation process of historical units, rather than on failure event data. The prediction accuracy of this model relied strongly on the correct determination of thresholds for the various trending features.

The use of Hidden Markov Models (HMMs) in bearing fault prognosis was investigated by Zhang et al. [48]. In an HMM, a system is modelled to be a stochastic process in which the subsequent states have no causal connection with previous states. In the work of Zhang et al., one HMM was trained to recognise one type of cone-and-cup bearing faults based on the corresponding vibration data. The HMMs were also trained to estimate the fault states, such as "normal", "nick", "scratches", "more nicks" and "failure". The similarity between current state and failure state was used as the bearing degradation index, which was then extrapolated to estimate the time of exceeding a predetermined failure threshold. HMMs do not represent temporal structure adequately since their state durations follow an exponential distribution. Dong and He [49] have thus proposed a segmental Hidden Semi-Markov Model (HSMM). Unlike HMMs, which generate a single observation for each state, HSMMs generate a segment of observations and estimate the durations from training data. However, the other possible limitations of HMMs remain. One example limitation is the difficulty in relating the defined health-state change point to the actual defect progression since it is often impractical to physically observe a defect in an operating unit.

Li and Shin [50] argued that it is often impractical to estimate bearing fault severity directly from vibration data because such data can be affected by many factors other than defect severity, such as machine operating conditions and vibrations from nearby machine components. They proposed a system identification method to identify a bearing dynamics model using measured bearing vibration. This dynamics model was then inverted to recover the impact impulse response of the measured vibration signal. The estimated relative severity index was reasonably accurate only when the signal-to-noise ratio was high with a relatively high running speed.

Data-driven models may often be the more available solution in many practical cases in which it is easier to gather data than to build accurate system physics models.

2.2. Integrated approaches—prediction based on both reliability and condition data

The previous section presented conventional reliability models as well as condition-based prognostics models made possible by the new CM technologies. While CM data are a rich source of information for fault/failure prediction, it should be noted that they do not render reliability data unnecessary. Several valuable models have considered integrating reliability data into prognostics.

Goode et al. [51] proposed a statistical method to predict the remaining useful life of pumps in a hot strip steel mill. Alarm limits were first determined using the Statistical Process Control (SPC) theory, with the assumption that healthy state data follow a normal distribution. The "Installation to Potential failure" (IP) and the "Potential failure to Functional failure" (PF) intervals were then represented using Weibull distribution. Time to failure was calculated in the PF interval taking into account vibration data. This work presented a relatively simple approach to forecasting failure with utilisation of both reliability and CM data.

Jardine et al. [52–55] applied the Proportional Hazards Model (PHM) to forecasting the reliability of rolling element bearings and engines. PHMs assume that hazard changes proportionately with covariates (asset condition in this case) and that the proportionality constant is the same at all time. The use of PHM for incorporating CM information in reliability calculation started in the 1980s [56–59]. Jardine et al. used Weibull distribution to model the baseline hazard function in PHM. The covariates were assumed to follow a non-homogeneous Markov stochastic process [60,61]. A software called EXAKT [61] was developed to calculate the optimal maintenance or replacement time intervals based on historical event and condition data, as well as cost data.

Sun et al. [62] pointed out that the change in CM covariates is a response to the change in system hazard. Therefore, system hazard should be modelled as the "explanatory variable" in the proportional hazards theory, where as CM information should be modelled as the "response variables". A Proportional Covariates Model (PCM) was thus proposed. PCM can be used to estimate hazard functions of mechanical components or systems in cases of sparse or no historical failure data, provided that the covariates are proportional to the hazard. A suggested research direction was to use PCM for reliability prediction based on both failure/covariates data and online CM data.

Wang [63] and [64] stated that models like PHM and PCM only use the current asset condition information (or functions of current information), rather than the whole monitoring history, to predict future asset health. Therefore, he modelled a conditional residual time distribution to estimate the residual life distribution of rolling element bearings based on the stochastic filtering theory [65]. All the test bearings were initially assumed to follow the Weibull delay time distribution modelled, and as more CM information became available, the distribution was updated. However, this model required the determination of a threshold level to indicate defect initiation point, which is hard to identify and seldom recorded in practice.

Cempel et al. [66] defined reliability in "symptom (S)" (condition data) domain, assuming the symptom of a set of continuously operating units was measured periodically and had a uniform limit value and breakdown value. Hazard function was defined as the relative number of units reaching breakdown value per unit increment of symptom. A logistic vector containing covariates such as system foundation stiffness and running load was also introduced into the reliability model to permit more precise determination of the system condition and symptom limit value. The model, though not yet been applied to rotating machinery, provided a unique concept in estimating reliability based on condition data. The model can only be validated when a sufficiently large database of real-life symptoms and covariates are available. Methods for assessing the covariate function needed for logistic vector implementation also remain an open question.

Heng et al. [67] introduced an intelligent reliability model called the Intelligent Product Limit Estimator, which was able to include suspended CM data in machinery fault prognosis. The accurate modelling of suspended data was found to be of

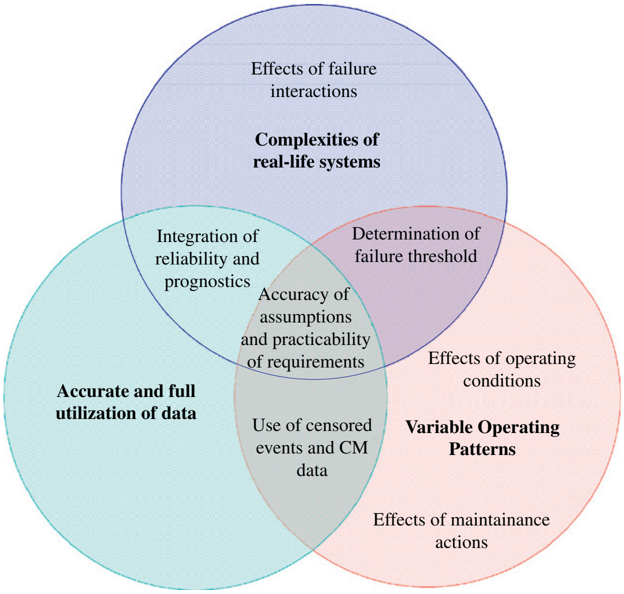

Fig. 1. Challenges in rotating machinery prognostics.

great importance, since in practice machines are rarely allowed to run to failure and data are commonly suspended. The model consists of an FFNN whose training targets are asset survival probabilities estimated using a variation of the Kaplan–Meier estimator and the true survival status of historical units. This work presented a concept of utilising available information more fully and accurately, and of providing longer-range prediction in a probabilistic sense with minimal assumptions.

All of the models reviewed in this subsection combined reliability and condition information in failure prediction. They generally produce longer-range failure forecasts than models that only use individual asset condition information.

Fig. 1.

Other papers related to machinery prognostics are listed in Refs. [32,68–77].

3. Challenges and opportunities

This section discusses how the previous studies, though they have aided the advancement of the discipline, have made only a limited contribution to developing an effective prognostics model. Several aspects need to be further investigated before prognostics systems can be reliably applied in real-life situations. Firstly, methods for utilising available data more fully and accurately need to be explored. Secondly, real-life machines are often subject to variable operating patterns, which include repairs and change of operating parameters. The effects of these operational complexities, if not properly considered, may greatly reduce the accuracy of prognosis output. Thirdly, the inherent structural complexity of real-life machines also hinders practical applications of many prognostics models, which are only designed to predict a specific failure mode of a component without considering the interaction of the component with other components or with the operating environment. Several challenges stem from one or more of the three issues mentioned above. To suggest the many opportunities for prognostics research, we list eight areas in need of new ideas and improvement: the incorporation of CM data into reliability analyses; the utilisation of incomplete trending data; the consideration of effects from maintenance actions and variable operating conditions; the deduction of the non-linear relationship between measured condition and actual degradation; the considerations of failure interactions; the accuracy of assumptions and practicability of requirements, as well as the development of performance measurement frameworks. These challenges are depicted in Fig. 2 and discussed in the following sections.

3.1. Integration of reliability and prognostics

As mentioned in Section 2 of this review, reliability models based solely on event data have been reasonably well developed for machinery life estimation. However, these approaches only provide general or average estimates for the entire population of identical units to facilitate time-based maintenance. Maintenance or repair at pre-established intervals tends to incur even higher scheduled downtime. Besides, failure behaviour of each unit is a function of changes in work schedule, operating environment and other duty parameters, and of failure interaction between components. Therefore, current condition of an operating unit needs to be monitored online. Nevertheless, CM data, though reflect the state of

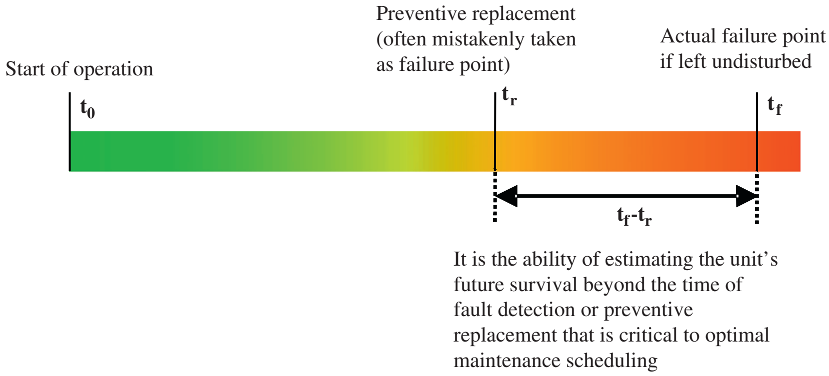

Fig. 2. Timeline of the operational life of an asset.

individual operating units, do not replace reliability data that reflect population characteristics. CM data mainly provide information for short-term condition prediction only. Several data-driven prognostics models [33,38–42] enabled machine prognosis using time series prediction. These models mainly performed single-step-ahead predictions to estimate the vibration signal feature value at the next immediate time step. These techniques require further research because prognosis with such short a prediction horizon is not of much help for optimal maintenance scheduling. Sufficiently long lead time is often needed for effective and economical preparation of spares and human resources. A longer prediction horizon is also necessary for deciding whether a unit will last until the next maintenance opportunity (such as the end of a batch production or the next scheduled inspection).

Therefore, other than the unit-specific, online condition information measured, the prediction of remaining useful life should also be dependent on the operational age or time that the unit has survived, as well as on the general characteristics of the population to which the unit belongs. For example, given the same condition information, a bearing that is in its early operating period and is from a family with a long nominal life should have a longer remaining useful life than a bearing that is in the wear-out period from a family with a much shorter nominal life. Although several models have attempted to use CM information for reliability estimation as discussed in Section 2, the integration of CM information with reliability analysis has not been well explored. Some valuable literature [78–82] outside the research area of rotating machine prognostics has proposed some very interesting approaches. For example, Knezevic [78] estimated the probability density of the condition parameter values of all historical units at a certain operational age. The probability of reliable operation at that instant of operational age was represented by the instantaneous probability that the condition parameter values fell below the failure threshold. Most of these approaches [78–81] are theoretical formulations and the opportunities here lie in adapting and validating these techniques in the area of rotating machinery prognostics.

3.2. Use of censored event data and censored CM data

Many prognostics models, especially data-driven models, require abundant historical event data such as the time of failures. In practice, however, industrial and military communities would rarely allow their assets to run to failure. Most of the time, once a defect is detected in a unit, the unit is replaced or overhauled before it fails. Therefore the cut-off point at which the unit will cease to function is not always known or recorded. It is only known that the unit has survived up to the time of replacement or repair but there is no information as to when it would have failed if left undisturbed. Data of this sort are called censored or suspended data. Publications related to the modelling of suspended CM data in existing prognostics models are very limited.

When all the historical suspension times are treated as historical failure times, the prognostics model will produce biased estimates (underestimation) of the time to failure. Since in many instances a unit is replaced/overhauled once a fault is detected, treating the replacement/overhaul times as failure times defeats the purpose of prognosis because it is the duration the failing unit can survive beyond this point that is of interest (Fig. 2). It is not uncommon that a machine component's remaining useful life (from the point where a defect is detected) is substantially more than its nominal life. A prognostics specialist's goal is to recommend a maintenance schedule that does not interrupt production or wastefully replace units that still have useful remaining life. It is the ability to estimate this remaining lifetime that is critical to optimal maintenance scheduling.

On the other hand, prediction models that carefully omit suspended data from the training examples will worsen the problem of data unavailability. Degradation data are already scarce due to irregular measurement recording and/or the huge amount of time they take to accumulate. For example, a bearing may last several years even under harsh operating conditions. Therefore, a good prognostics model must be able to maximise the use of available data. The survival probability of a historical unit after suspension may be estimated based on the population characteristics. Recently Heng et al. [67] demonstrated an approach of including both suspended CM data and suspended event data in training an intelligent prognostics model. This concept aims to stimulate thoughts on utilising available prognostics information more fully and accurately and opens up new opportunities for the development of more robust variations of the proposed approach.

3.3. Effects of maintenance actions

One of the main objectives of implementing CBM is to optimise maintenance schedules and actions. This optimisation can be achieved through the estimation of asset life and the effectiveness of maintenance actions. Therefore, it is necessary to extend prognostics research effort to monitor the change in unit condition after a maintenance action and estimating the consequent change in unit reliability. Maintenance actions, such as repairs and re-lubrication, do not always restore the health of a unit to "as good as new" conditions. Besides, the unit may sometimes deteriorate at a different rate after such maintenance actions. These effects need to be considered when developing a prognostics model.

In the field of Reliability Centered Maintenance (RCM), the reliability of repairable systems has been extensively modelled. Monga and Zuo [83] introduced a time variable parameter to define the different start points of a system hazard function after different repairs. They also proposed a failure rate deterioration factor and modelled system reliability to be inversely proportional to the number of repairs [84]. Several Markovian models and Poissonian process models have been proposed to model the reliability of repairable systems. Markov models [85–90] were developed to model a repairable unit as a system with a finite state space. They described events such as repairs, failures and standby as different states and assumed that the transition between these states to be a stochastic process with Markov property. Poissonian process models [91–96] generally assume that failures of repairable systems can be considered as a series of random discrete events that follow a Poisson's distribution. Sun et al. [97,98] also developed a split system approach to model imperfect repairs. The basic concept of the split system approach is to separate repaired and unrepaired components within a system when modelling the system reliability after maintenance activities, since not all the components of a system are repaired during each maintenance action. A comprehensive review of existing reliability models and maintenance policies can be found in [99].

Considerable research effort needs to be contributed to developing prognostics models that can account for the effects of maintenance actions. One way of responding to this opportunity is by enhancing the above-mentioned reliability models that account for maintenance effects with CM information such as the past examples of post-maintenance changes in condition indices.

3.4. Effects of operating conditions

In most real-life situations, machines are subject to varying operating conditions. This form of variation is a major contribution to the change in the energy of measured CM signals. In machining processes for example, non-uniformity of raw material causes the load on the tooling system to vary [100]. This load variation is transmitted to the output shaft of the gearing system and is manifested as energy variation in vibration sensor signals. Therefore, an effective prognostics system should only be sensitive to the changes in condition measurements caused by the deterioration of a monitored unit, and insensitive to the influence of any non-deterioration source of variation. Prognostics models found in the literature have not directly considered the effects of varying operating conditions. For example, Qiu et al. [28,101] related remaining bearing life to bearing stiffness, which decreases as the spall grows. However rotor stiffness is a function of many factors, such as speed, load, lubrication and temperature, which are rarely constant in practice. Thus the model might only function well under controlled experimental conditions and requires further research for practical applications. A more general example is when an increase in operating speed causes the machine vibration amplitudes to rise. A prognostics model might perceive this rise in vibration as increased degradation of the monitored unit. Conversely, if the operating speed is decreased when a monitored unit is deteriorating, a prognostics model might recognise this effect as a decrease in machine hazard even though a failure is imminent. It is not uncommon that the speed of a machine changes continuously during normal operation, whether it is an electric machine being fed by a variable speed drive or an induction machine operating under variable load conditions. This change in speed, if not taken into account, might result in errors in life predictions.

In a comparison of vibration amplitudes of healthy and damaged bearings, Stack et al. [102] observed that vibration amplitude fluctuations due to speed variations under normal operating conditions are less pronounced and usually go unnoticed when a rolling element bearing is healthy. But as bearing health degrades, these variations in vibration amplitudes become quite significant. The authors suggested obtaining measurements at the same machine speed and comparing them to baseline values when performing fault detection. In practice, multiple variables often need to be accounted for. Marble and Morton [27] ran multiple bearings to failure under various speeds and loads. It was observed that the effect of speed on spall propagation was much smaller than that of load. It was also shown that the accrued run time prior to damage (spall) initiation had a significant effect on the spall propagation rate.

The effects of variations in operating conditions have not been properly explored and modelled for fault prognosis. This issue limits the application of prognostics models to real-life machines and thus needs to be addressed. One possible solution may be to use condition data features that are less dependent on operating conditions. In the literature on fault detection, load-independent techniques have been proposed. McFadden [103] performed a Hilbert transform on band-pass filtered, time synchronously averaged signals for gear fault detection. This technique cancelled out vibration amplitude through phase modulation and therefore was independent of load condition. Parker Jr. et al. [104] studied the use of bispectrum-based statistical change detection algorithms for gear and bearing fault monitoring. It was found that the bicoherence function reduced the variation in the bispectrum across different torque levels and loads. Stander et al. [105] proposed order tracking and time synchronously averaging gearbox vibration data to compensate for the variation in rotational speed induced by fluctuating loads. A pseudo-Wigner-Ville distribution was then applied to the data to identify the influence of the fluctuating load. These load-independent fault detection techniques need to be explored and extended for application in prognostics. For example, the load demodulation normalisation technique proposed by Stander and Heyns [105] was validated using limited data recorded at several inspections. To determine the suitability of this technique for fault prognostics, the performance or stability of this method over a full cycle of fault progression needs to be investigated. It is also helpful to express remaining useful life in number of cycles/revolutions, instead of calendar time such as minutes or days. The variation in speed or operation schedule changes the time taken by a rotating machine to complete the same number of revolutions. Other useful references include papers on accelerated life tests [106–108], which involve collecting data under several conditions and then extrapolating the results for other possible conditions. Simple stress-life models such as Arrhenius or the Power Law may be combined with a life distribution model [106]. One difficulty of in accelerated life tests is the large number of unknown parameters in the equations. A simple 2-stress, 4-level test may lead to a series of simultaneous non-linear equations with 10 or more unknowns. Another consideration is the associated costs.

3.5. Non-linear relationship between CM indices and actual asset health

CM data are commonly taken to indicate the health of a monitored unit. However, the measured condition indices do not always deterministically represent the actual health of the monitored unit. The challenges and opportunities here lie in developing prognostics models that recognise the non-linear relationship between a unit's actual survival condition and the measured CM indices.

Most of the existing prognostics techniques use CM indices to represent the health of the monitored unit and then use methods such as regression or time series prediction to estimate the unit's future health, or rather the future CM indices. In these techniques, a threshold for the CM data is predefined to represent a failure (as depicted in Fig. 3). The prediction accuracy then relies strongly on the assumption that failure takes place at the instant of time when the relevant CM index exceeds the predetermined threshold. However, it is not uncommon that a system fails when its condition measurement is still below a predefined failure threshold or even temporarily decreasing. Conversely a system may still be performing its required function when its condition measurements already fall outside the tolerance range. Missed alarms and false alarms are significant issues in practical applications of prognostics systems. Several methods have been proposed for determining thresholds for fault detection based on mathematical models instead of solely on the asset suppliers' suggestions or maintenance personnel's past experiences. Decoste [109] proposed a dynamic threshold approach to set limits that can adapt to different normal baseline conditions. The variable threshold was modelled by parametric functions which can be learnt and adapted from historical condition trending data.

In the field of prognostics, more thought should be devoted to developing prognostics models that can deduce the non-linear relationship between a unit's actual survival condition and the measured CM indices. Artificial intelligence models can be trained to learn from past examples. Hence, there are research opportunities to use the past measured condition data as model training input and the actual unit health as target output. By repetitively presenting various pairs of training input and target to the intelligent models, the models may learn to recognise how unit degradation is veiled in the non-deterministic changes in CM measurements and disregard fluctuations caused by non-deterioration factors.

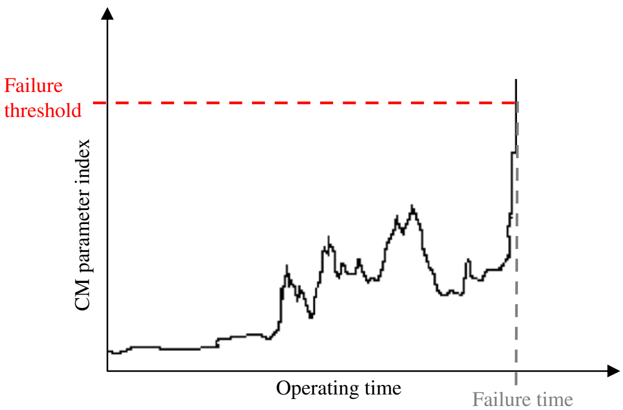

Fig. 3. Assumption that failure takes place at the instant of time when the condition index exceeds a predefined threshold.

3.6. Effects of failure interactions

Given that a machine often consists of multiple components or subsystems, the ability to monitor and predict the degradation of one component might not be sufficient to predict overall machinery failures. For example, the degradation of a component may initiate or accelerate the failure of another component and vice versa. In critical cases, this phenomenon can result in catastrophic consequences. Literature on prognostics models for multi-component systems appear to be absent. In the field of reliability however, there have been several attempts to model interactive failures [97,110–113]. For example, Greig [110] proposed a method for modelling multiple sequential failures in a system. According to this model, the failure of a component changes the system topology and consequently increases the failure probabilities of the other components in the system. Sun et al. [113] proposed an analytical model where the interactive failure rate of a component was estimated by its independent failure rate plus a portion of the failure rates of its influencing components. It was stated that the failure rate of a component accelerates when the failure rates of its influencing components increase. If this type of failure interaction effects is not considered, the probability of failure will be underestimated.

As CBM systems mature and provide data that actually reflect the health state of individual operating units, it is important to combine this new information with the existing wealth of knowledge on interactive failures.

3.7. Accuracy of assumptions and practicability of requirements

Since prognosis involves projecting into the future and that the future cannot be determined with absolute certainty, assumptions and simplifications are often inevitable in prognostics modelling. Nevertheless, care must be taken to minimise these assumptions and simplifications.

Physics-based approaches can be very accurate when a correct and accurate model is available. However, the characteristics and relationships of all related components in a system and its environment are often too complicated to be modelled [32]. It has been reported that the wear of rotating machinery components is still not fully understood at present [114,115]. One of the main issues with empirical or physics-based models is thus their inherent uncertainty due to the large amount of accompanying assumptions. It was shown in numerical simulation tests and bearing life tests that physics-based models without parameter fine-tuning is unable to capture and adapt to the stochastic characteristics of defect growth [19,20]. It was also shown that a small amount of parameter difference results in large prediction errors with the increase of bearing running cycles. Currently most physics-based prognostics methods focus on the prediction of crack propagation. However, in many cases other failure modes tend to dominate and the maintenance engineer needs to correctly identify the fault type in question. Even if that has been accomplished, defect growth is not a deterministic process. Virkler et al. [116] showed that even under well-controlled experimental conditions, crack growths of a set of identical components were vastly different. Crack growth models are also difficult to apply in practice because they require knowledge of the exact geometry or/and orientation of the crack, which are usually very irregular and cannot be identified without disassembling the machine component. Some models have attempted to account for these uncertainties by adopting a stochastic or adaptive component such as a recursive least-squares scheme. Such adaptation techniques are similar to the adaptation in data-driven time series prediction.

Gebraeel et al. [43] based their rolling element bearing prognosis on the assumption that all bearing degradation signals possess an inherent exponential growth. It is unclear that if these complex ANN models offer analysis more accurate than that provided by exponential curve fitting and extrapolation methods. Exponential extrapolations often have a large region of uncertainty. Due to the probabilistic nature of bearing integrity and operating condition, defect propagation rates tend to be stochastic. If the growth of a bearing defect differs from the assumed exponential pattern, the bearing degradation will be poorly extrapolated. Even for proper assumptions about the exponential defect growth, the prediction confidence interval of extrapolations often diverges to unrealistic values. Extrapolating beyond that range can lead to misleading results. Besides, successive prediction outputs may vary vastly and seem confusing. Without probability indication, it is rather difficult for maintenance personnel to make maintenance decisions based on these prediction outputs. It is however noted that, although mathematical prognostics models have yet to prove entirely satisfactory in practice, those used for processing and managing reliability information are critical for reliability prediction work.

Considerations should also be made in order to find the optimum trade-off between accuracy and costs. For example, FEA methods might be able to calculate the stress on the material surrounding a fault based on component geometry and operating conditions, but are very expensive in terms of modelling and computational time.

It is important to keep assumptions and simplifications realistic because real-life machines are complex and fault propagation is probabilistic in nature. Affordability in terms of computation time, accuracy, memory and data storage should also be considered at all stages including model design stage.

3.8. Performance evaluation

The literature on prognostics is continually growing. The standardisation of prognostics performance measures, however, has not matched this growth. Vachtsevanos [117] has defined a possible class of performance metrics that stems primarily from the main objectives of prognosis and the uncertainty of prognostics algorithms. The metrics include prediction-to-failure times, prediction accuracy, precision and confidence, as well as sensitivity to input changes. More effort is required in the development of measurement frameworks for supporting prognostics performance evaluation. Opportunities here include developing frameworks that consider various real-life requirements and include both quantitative and qualitative metrics. Quantitative metrics may include the average difference between the predicted failure time and the actual failure time, as well as the average computational time. Example qualitative metrics include the practicability of model requirements and the ability to provide confidence level indication. Studies on the issues of performance measurement errors and uncertainties, as well as the pros and cons of different measurement strategies, also make contributive investigations.

4. Concluding remarks

The ability to forecast machinery failure is vital to reducing maintenance costs, operation downtime and safety hazards. This paper synthesised the progress in the research and development of rotating machinery prognostics. The review indicates that most of the existing prognostics studies were conducted in research laboratories. It is often easy to neglect certain practical considerations when developing models in laboratory environments, where access to insights into real-life situations is often lacking. Nevertheless, the ultimate goal remains—to establish reliable prognostics systems that can be applied in real-life situations and benefit industry. To realise the greatest economic and social benefits, it is important to design every aspect of a prognostics system by considering the asset manager's perspective.

The challenges remaining in the field of rotating machinery prognostics were discussed in this paper. The occurrences of machinery failures are difficult to predict due to the inherent structural and operational complexities of real life systems. Failure interaction between components, the probabilistic nature of fault symptoms and growth, as well as varying operating conditions and duty parameters also add to the complexity of data. To suggest the many opportunities for prognostics research, we discussed eight areas in need of solution and improvement: (1) the integration of CM and reliability data, (2) the proper utilisation of incomplete trending data, (3) the consideration of the effects from maintenance actions, (4) the consideration of varying operating conditions, (5) the deduction of the non-linear relationship between condition data and asset health, (6) the consideration of failure interactions, (7) the practicability of requirements and assumptions, and (8) the development of a uniform performance measurement framework.

It should also be noted that one of the most overlooked measures in the development of maintenance applications has been the degree of user-friendliness. These applications can be complex and overwhelming to the users, who often do not have in-depth knowledge about the underlying system physics or model algorithms. The review presented in this paper also suggests that, as is true in so many aspects of life, a single tool is usually incapable of solving all problems. One also has to content with a wide variety of applications, with different deterioration mechanisms, operating conditions, data dimensions, computation costs, as well as memory and storage capacities. Collaboration between research groups from different areas of expertise should be encouraged. The lack of effective capture and management of field data also places a huge constraint on the research and development of intelligent maintenance systems. Common datasets consisting of relevant CM data, maintenance event records and cost data may be made available to all researchers in the field. In this way, the technical and economic feasibility of each prognostics model can be evaluated and compared consistently. Researchers should agree on adopting a uniform set of benchmark criteria for convenient model comparison. This practice will significantly accelerate the advancement of prognostics research.

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