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Prognosis of Rotating Machinery Using Artificial Neural Network [A Review]

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Abstract

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. Research in the Condition Based Monitoring (CBM) area grows rapidly. Hundreds of papers in this area, including theory and practical applications, appear every year in academic journals, conference proceedings and technical reports. This paper attempts to summarise and review the recent research and developments in prognostics of rotating mechanical systems.

Key words : Condition monitoring , Prognosis, Artificial neural network.

1. Introduction

Machine maintenance has played more and more important role in the modern industry. An inadequate maintenance strategy may lead to unnecessarily high downtime or accidental breakdown of machine that lose a lot of money, and even human life. In maintenance approaches, the condition based maintenance (CBM) is assessed as the most effective technology that can identify incipient faults before they become critical to enable more accurate planning of maintenance, while the others such as corrective and predetermined approach have shown to be costly in many applications due to, e.g., lost production, cost of keeping spare parts, quality deficiencies, etc. Fault diagnosis and prognosis, which can estimate and forecast the machine states, have significant roles in a CBM system. Finding an excellent model of fault diagnosis and prognosis is the key to enable CBM system to be more useful in practical applications. In order to evaluate the states of machine, the condition monitoring data must be acquired and processed by using appropriate signal processing techniques before being applied in diagnosis or prognosis model. The measured data could be vibration, acoustic, oil analysis, temperature, pressure, moisture, etc. Among of them, vibration data are considered to be easy to measure and to analyse signal and are also used to show the ability of the proposed approach. Vibration-based machine condition monitoring system has been widely examined by many researchers. The fault identification or fault diagnosis, a major part of condition monitoring system, has been most commonly investigated in many ways.

2. Definition of Prognosis

Prognosis corresponds to the “estimation of the time to failure and the risk for one or more existing and future failure modes”. It’s the art or act of predicting future conditions on the basis of present signs and symptoms. The implementation of prognosis system results in an optimal maintenance schedule. Prognostic activity aims at anticipating the failure date by predicting the future health state of a system and its Remaining Useful Life (RUL) estimation. Most of the research related to CBM is mainly focused on fault diagnostic. Failure prognostic is a new research domain and there is a wide scope to develop methods, tools and applications for effective prognostic system.

Remaining useful life (RUL)

RUL, also called remaining service life, residual life or remnant life, refers to the time left before observing a failure given the current machine age and condition, and the past operation profile. It is defined as the conditional random variable

$$T - t | T > t, Z(t),$$

Where T denotes the random variable of time to failure, t is the current age and Z(t) is the past condition profile up to the current time. Since RUL is a random variable, the distribution of RUL would be of interest for full understanding of the RUL. In the literature, a term ''remaining useful life estimate (RULE)'' is used with double meanings. In some cases, it means finding the distribution of RUL. In some other cases, however, it just means the expectation of RUL, i.e.,

$$E[T - t | T > t, Z(t)].$$

Note here that proper definition of failure is crucial to correct interpretation of RUL. Although there is a controversy in current industrial practice, a formal definition of failure can be found in many reliability textbooks. To do prognosis, in addition to knowledge (or data) on the fault propagation process, knowledge (or data) on the failure mechanism must be available.

Prognostic methods can be classified into three main approaches as shown in the Fig. 1.

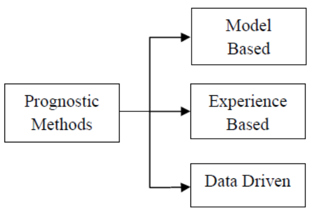

Fig.1. Classification of Prognostic Methods

2.1 Model-Based Prognostic Methods

Model-based prognostic methods are applicable to where the accurate mathematical models can be constructed based on the physical fundamentals of a system. These approaches use residuals as features, which are the outcomes of consistency checks between the sensed measurements of system and the outputs of a mathematical model .However, these techniques are merely applied for some specific components and each requires a different mathematical model. Changes in structural dynamics and operating conditions can affect the mathematical model as it is impossible to model all real-life conditions. Furthermore, a suitable model is difficult to establish to mimic the real life.

2.2 Experience-Based Prognostic Methods

Experience-based prognostic methods require the component failure history data or operational usage profile data. They involve in collecting statistical information from a large number of component samples to indicate the survival duration of a component before a failure occurs and use these statistical parameters to predict the RUL of individual components. Generally, they are the least complex forms of prognostic techniques and their accuracy is not high because they base solely on the analysis of the past experience.

2.3 Data-Driven Methods

In these methods an online data is captured with the help of sensors and converted into relevant information. It is then used to study the degradation phenomenon based on different models and tools like (neuronal networks, Bayesian networks, Markovian processes, etc.) or statistical methods, to learn the degradation model and to predict the future health state and the corresponding RUL of the system. Data-Driven Methods have advantage over both of the above methods i.e. model-based prognostic methods and experience-based prognostic methods as in one hand, in real industrial applications getting reliable data is easier than constructing physical or analytical behavior models. And in the other hand, the generated behavioral models from real monitoring data lead to more precise prognostic results than those obtained from experience feedback data.

The dataset for the prognostic or RUL of Machine are publicly available in following websites:-

National Aeronautics and Space Administration (NASA) http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/ collection of data sets that have been donated by various universities, agencies, or companies. The data repository focuses exclusively on prognostic data sets, i.e., data sets that can be used for development of prognostic algorithms.

1) Milling data set Experiments on a milling machine for different speeds, feeds, and depth of cut. Records the wear of the milling insert, VB. The data set was provided by the BEST lab at UC Berkeley.

2) Bearing data set Experiments on bearings. The data set was provided by the Centre for Intelligent Maintenance Systems (IMS), University of Cincinnati.

3) Battery data set Experiments on Li-Ion batteries. Charging and discharging at different temperatures. Records the impedance as the damage criterion. The data set was provided by the Prognostics CoE at NASA Ames.

4) Turbofan engine degradation simulation data set Engine degradation simulation was carried out using C-MAPSS. The data set was provided by the Prognostics CoE at NASA Ames.

5) PHM08 Prognostics Data Challenge dataset from the data challenge competition held at the 1st international conference on Prognostics and Health Management (PHM08) is being made publicly available.

6) IGBT accelerated aging data set is provided by the Prognostics CoE at NASA Ames.

7) Trebuchet data set of different types of balls launched from a trebuchet with varying counter weights.

8) FEMTO Bearing Data Set Experiments on bearings' accelerated life tests provided by FEMTO-ST Institute, Besançon, France.

9) UCI Machine Learning Repository. CalIt2 Building People Counts Data Set. http://archive.ics.uci.edu/ml/datasets/CalIt2+Building+People+Counts.

10 IEEE PHM 2012 Prognostic Challenge. Scoring of results and application procedure. http://www.femto-st.fr/f/d/IEEE-Challenge-Appli.pdf.

Table 1 :List of Rotating Machinery Health Prediction methods and their Merits and Limitations.

Approach	Merits	Limitations
1. Reliability-use event data, Traditional reliability models (e.g Weibull poisson, exponential , log normal distribution.)	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 system. Require less data than data-driven techniques	Real-life system physics is often too stochastic and complex to model. Defect- specific
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
Time series prediction using Artificial Neural Network (ANN)	Fast in handling multivariate analysis	Assumes that condition indices deterministically Represent actual asset health
Exponential projection using ANN	Estimates actual failure time instead of condition index at future time steps.	Assumes that all bearings degradation follow an exponential pattern
Data interpolation using ANN	Longer prediction horizon	Requires training one ANN for each historical dataset

3. The review of prognosis consists of following stages.

3.1 Dataset

In this we have considered two categories, First one being , the dataset taken from websites, second one from the test rig setup by the authors.

Abd Kadir Mahamada et al.[1] the authors used the vibration signals which were provided by the Center for Intelligent Maintenance Systems (IMS), University of Cincinnati. Zhigang Tian et al. [2] conducted the experiment using gearbox test rig at the Reliability Research Lab of the University of Alberta, Canada. Nagi Gebraeel et al. [3] developed an experimental setup to perform accelerated bearing tests where vibration information is collected from a number of bearings that are run until failure. Samanta et al. [4] the authors used sunspot activity data from the RWC Belgium World Data Center,(5).

3.2. Feature Selection

The vibration data are used to design a suitable signal that captures the evolution of the bearing's degradation. This signal can be used to predict the bearing's residual life. A good degradation signal must capture the physical transitions that the bearing undergoes during different stages of its life Second; it must possess a trend that reflects the deteriorating condition of the bearing. Third, the signal should possess a low signal-to-noise ratio and must be easy to compute since it is frequently updated in real time. Finally, it must be possible to define a reasonable failure threshold, signal amplitude that indicates failure.

Abd Kadir Mahamada et al.[1] proposed ANN to achieve accurate RUL of a predicted machine failure. To achieve this objective, the ANN model uses time and fitted measurements Weibull hazard rates of RMS and kurtosis from its present and previous points as input and normalized life percentage as output. By doing that, the noise due to degradation from a target bearing can be minimized and the accuracy of the prognosis can be improved. In the reference [2] Zhigang Tian et al. the authors has observed that the root mean square (RMS) value for gear data is relatively flat in the beginning , and then it starts to increase, suggesting a degradation process of the gearbox. So the vibration data at data points 90 to 141 , were used for training ERNN for health condition prediction as shown in Fig 2. The RMS plot with only these data points is shown .The authors used data points 90 to 135, represented by "o" in Fig.2 to train Extended Recurrent Neural Network (ERNN). Data points 136 to 141, represented by "Δ", are used to test the prediction performance of the ERNN based approach. The Vibration Data With a Weibull Failure rate function based approach were used for processing validation data because , the Weibull distribution is the most powerful, flexible lifetime distribution, and it is flexible enough to model the "wear out" portion of a piece of equipment's life.

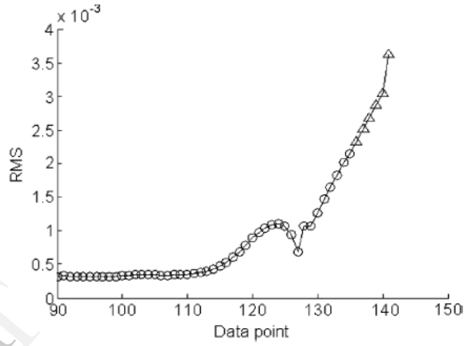

Fig. 2. The RMS data points 90 to 141.

Nagi Gebraeel et al. [3] the degradation signal developed in this work consists of the average amplitude of the defective frequency and its first six harmonics as shown in Fig 3. The degradation signal is composed of two distinct parts corresponding to normal and defective bearing operation.

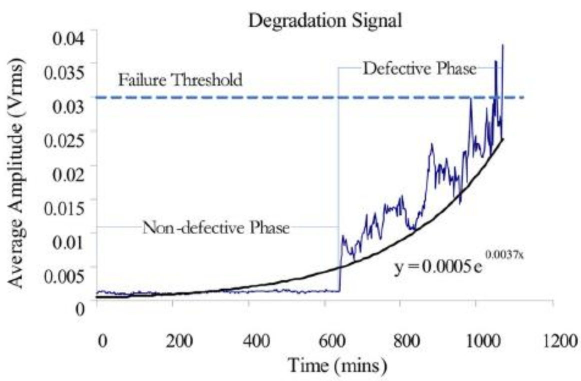

Fig. 3. Vibration based degradation signal

Samanta et al. [4] the authors have developed suitable monitoring Index for training purpose. A monitoring index based on energy concentration of the residual signal, obtained through continuous wavelet transform of typical gear faults, namely wear, chipping and crack, was used.

3.3 Artificial Neural Network

Abd Kadir Mahamada et al.[1] author proposed ANN model uses the fitted measurement values as inputs instead of real measurement values. The fitted measurement use the Weibull hazard rate function which is a very powerful function to represent the reliability of machine failure, for output of ANN, the life percentage (normalized) is preferred and is denoted as Ti as shown in Fig 4 . The life percentage (normalized) is the best option in mapping the bearing's health condition, which is proportional to time. This means that the bearing is totally damaged when it reaches 100% of the life percentage.

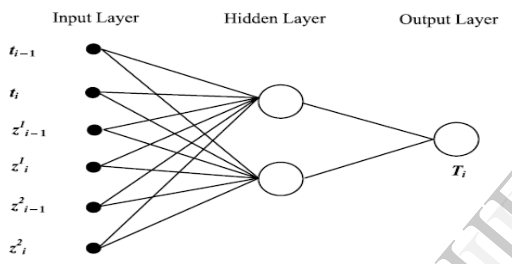

Fig 4. Structure of the proposed ANN model

Zhigang Tian et al. [2] proposed the ERNN model, a new recurrent neural network prediction mode. The structure of the proposed ERNN is shown in Fig. 5.

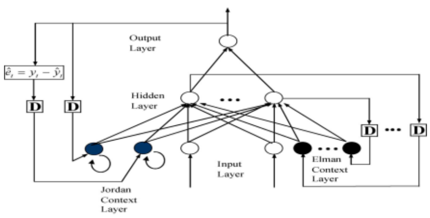

Fig 5. The structure of ERNN.

author used the gearbox dataset obtained from the previous section to investigate the performance of the ERNN based approach in predicting the gearbox health condition, and perform a comparative study between the ERNN and FCRNN based methods. Nagi Gebraeel et al. [3] developed the neural network model in this work which consists of a group of feed-forward back-propagation neural networks that undergo supervised training. Each network is used to model the degradation process of a single bearing using the history of its vibration signals. Samanta et al [4] used time-series prediction capabilities of artificial intelligence [AI] and soft computing [SC] techniques like adaptive neuro-fuzzy inference system (ANFIS) and support vector regression (SVR) are utilized for machinery prognostics.

3.4 Conclusions

Abd Kadir Mahamada et al.[1] the proposed ANN gave good performance in predicting RUL of a bearing failure. In this paper the authors did not take into account the failure threshold, which many other researchers proposed. The bearing will fail after it reaches 100% of its life percentage. Zhigang Tian et al. [2] authors concludes that the ERNN based approach for producing satisfactory health condition prediction results and also demonstrates ERNN as an effective neural network model for health condition prediction. Nagi Gebraeel et al. [3] results of the prediction errors were compared with results from two benchmark policies. The first benchmark utilized conditional reliability, while the second benchmark utilized a degradation model. The proposed methodology had a mean prediction error of 7.56% compared with the first and second benchmarks that had prediction errors 26.3% and 32.3%, respectively. In the reference [4] Samanta et al. as a result they used both ANFIS and SVR performed quite well for the test cases. The performance of SVR was found to be better than that of ANFIS. However, the training time of SVR was much higher than for ANFIS.

In this paper, we have attempted to summarise recent research and development in machinery (gear and bearing) prognosis implementing CBM. The emphasis has been put on various prognosis methods used for both gear and bearings. Although lot of work has been carried out in the area of fault diagnosis but area of prognostics need to be explored to estimate correctly RUL of machine. Further development is required particularly for difficult cases of rotating machinery in practical applications, where number of failure modes could be expected due to different loading and operating

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conditions. Accurate prognosis requires signals from several sensors which are costly and difficult to install in already mounted industrial machines. Also number of methodologies discussed above needs further study, in order to verify their application to industrial problems with varied experimental conditions.

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