MACHINE CONDITION PROGNOSTICS: THE STATE OF THE ART

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ABSTRACT

Prognostics is an inherent component of condition-based maintenance. It can assess the current health of a part and predict into the future the health of a part for a fixed time horizon or predict the time to failure. Since this topic has gained popularity in machine learning, however, researchers who applied in machine prognostics (or prognosis) are relatively rare.With the aim of synthesizing and providing the information of these researches for researcher's community, this paper attempts to summarize and classify the recent published techniques in prognostics of rotating machinery. It reviews the papers upon the early 2012. Furthermore, it also discusses the opportunities as well as the challenges for conducting advance research in the field of machine prognostics.

Keywords: Machine Fault, Condition Prognostics

1. INTRODUCTION

In today's highly competitive marketplace, industries strive to minimize their capital and operational cost by trying to utilize the full life cycle of their machinery without sacrificing human, production, or environmental safety. Condition-based maintenance(CBM) is most useful in predicting equipment failure and avoiding unnecessary maintenance activities. Prognostics is an inherent component of condition-based maintenance. It can assess the current health of a part and predict into the future the health of a part for a fixed time horizon or predict the time to failure. Being able to perform reliable prognostics is the key to CBM [1].

The existing prognostics methods can be classified into three categories, which are physical model-based prognostics, knowledge-based prognostics, and data driven prognostics[2]. Table 1 listthe prognostics methods, their advantages and disadvantages.Various techniques and algorithms have been reviewed by this category as follows.

2. PHYSICAL MODEL-BASED APPROACHES

Physical model-based approachesare applicable to where accurate mathematical models can be constructed from physical system.Physical model-based approaches usually employ mathematicalmodels that are directly tied to physical processesthat have direct or indirect effects on health of relatedcomponents. It used for prognostics require specific mechanisticknowledge and theories relevant to the monitoredsystems [2, 3].

Table 1 List of prognostics methods, their advantages and disadvantages

Approaches	Advantages	Disadvantages
Physical Model-Based approaches	• Can be highly accurate • Require less data then data-driven approaches	• Real-life system physics is often too stochastic and complex to model. • Simplifying assumptions need to be examined. • Various physics parameters need to be determined.
Knowledge-based approaches	• Solve problem by mimicking how human expert makes decisions • Can forecast on the future time forboth detected and likely faults, and give suggestions abouthow to control the problem.	• It is difficult to obtain domain knowledge and convert it to rules, and once built, an ES cannot handle new situations that not covered explicitly in its knowledge bases.
Data-driven approaches	• Do not require assumption or empirical estimation of physics parameters • Do not require a priori knowledge	• Generally required a large amount of data to be accurate

Ray and Tangirala employed a non-linear stochastic model of fatigue crack dynamics for real-time computation of the time-dependent damage rate and accumulation in mechanical structures [4].

Li et al. presented a defect propagation model bymechanistic modeling approach for remaining useful life (RUL) estimation ofbearings [5]. Engel et al. discussed some practical issuesregarding accuracy, precision, and confidence of the RULestimates [6].Oppenheiner and Loparo used a physical model for predicting the machine condition in combination with fault strengths to life model based on crack growth law to estimate RUL [7].Chelidze and Cusumano were proposed a general method for tracking the evolution of hidden damage process in the situation that a slowly evolving damage process is coupled to a fast, directly observable dynamical system [8]. Kacprzynski et al. employed statisticalphysics-of-failure models to assess and predict gas turbinecompressor performance degradation rates due to saltdeposit ingestion [9]. Byington et al. developed a specifically configured dynamicmodel for flight actuator fault detection and failureprediction [10]. Other different approaches used physical model-based techniques for prognostics were presented in [11-15].

Thelimitation is their higher costs and component speciality,which means that they cannot be applied to other types ofcomponents [16]. Furthermore, the demerit of physical model-based is difficult to approach the real-life system due to complex and stochastic. In other words, it is very difficult to build agood physical model.

3. KNOWLEDGE-BASED APPROACHES

Knowledge-based approaches solve problem by mimicking how human expert makes decisions. Two typical examples of knowledge-based approaches are expert system and fuzzy logics [2].

Expert system (ES) canbe considered as a computer system that is programmed toexhibit expert knowledge in solving a particular domainproblem. The performance could be evaluated by combiningthe power of computers with the laws of reasoning. ESstores the so-called domain knowledge extracted by humanexperts into computers in the form of rules, simulates theway human experts do thinking and inference, and then uses these rules to generate solutions.

Some approaches used knowledge model-based prognostics were explained as follows. An on-line expert system for fault prognostics,which continuously monitors the health ofan industrialequipment have been developed by Lembessis et al [17]. Butler introduced an expert system-based frameworkfor incipient failure detection and predictivemaintenance [18]. It is comprisedof several expert system-related components and databases by usingthe mathematical and neural network models. On the other hand, design of a prognostic and intelligent monitoring expertsystem that can generate real-time information on theexistence of severity faults were proposed by Biagetti and Sciubba [19].Moreover, it can forecast on the future time forboth detected and likely faults, and give suggestions abouthow to control the problem.

However, it is difficult to obtain domain knowledge andconvert it to rules,and once built, an ES cannot handlenew situations that not covered explicitly in its knowledgebases[2, 20].

Fuzzy logic (FL) is a problem-solving methodology that provides asimple way to arrive at a definite conclusion based uponvague, ambiguous, imprecise, noisy, or missing inputinformation. FL is widely used in various systems rangingfrom simple, small, embedded microcontrollers to large, networked PC or workstation-based data acquisition andcontrol systems.

Usually ES,kalmanfilter, and artificial neuralnetwork (ANN) are techniques that incorporated with FL application. Choi etal. proposed alarm filtering and diagnostic system as anon-line fuzzy expert system[21]. On the other hand, Frelicot developed a prognostic adaptive system based on fuzzypattern recognition principles[22]. The fault detection is achieved by a fuzzy classificationrule including membership rejection (nondetection) and ambiguity rejection (multiple detections).

4. DATA-DRIVEN APPROACHES

Data driven approaches are based upon statistical and learning techniques, most of which originated from the theory of pattern recognition. Data-driven techniques are also known as data mining techniques or machine learning techniques. They utilize and require large amount of historical failure data to build a prognostic model that learns the system behavior [3].

Widely used data driven methodologies are ANN, bayesian-related method, hidden markov models (HMM) and hidden semi-markov models (HSMM), hazard rate (HR), and proportional HR. Byington et al. have developed a neural network methodology for remaining life prediction of aircraft actuator components [23]. Gebraeel et al. developed Bayesian updating methods that use real-time condition monitoring information to develop a closed-form residual-life distribution for the monitored device [24]. Huang and Xi deal with a new scheme for the prediction of a ball bearing's remaining useful life based on self-organizing map and back propagation neural network methods [25]. Gebraeel and Lawley used a neural network-based degradation model to compute and continuously update residual life distributions of partially degradated components [26].Baruah and Chinnam employed HMM for modeling sensor signals emanating from the machine, and in turn, identify the health state of the cutting tool as well as facilitate estimation of remaining useful life [27]. Liao et al. presented the proportional hazards model and logistic regression model, which relates the multiple degradation features of sensor signals to the specific reliability indices of the unit, and enable us to predict its RUL [28]. However, disadvantages of the above methodologies are hard to fit domain knowledge to ANN, need model retraining if operating conditions change, need a lot of historical state transition and fatal data, and the model is complicated.

A. Widodo and B.S Yang have developed support vector machine and relevance vector machine for machine degradation assessment [29-31]. These models with survival probability were employed for bearing prognostics. V. T. Tran and B.S. Yang have successfully applied regression tree for machine condition prognostics with one-step-ahead as well as multi-step-ahed prediction [32-34]. Other works by G. Niu and B.S. Yang proposed dempster-shafer regression and data-fusion strategy toward data-driven machinery prognostics [35-36]. Sequential montecarlo method as a robust tool for prognostics has been presented by W. Caesarendra and B.S. Yang. They also applied relevance vector machine and logistic regressionformachine degradation assessment [37-41]. Other methods for prognostics such as nonlinear autoregressive model and autoregressive moving average model have proposed by H.T. Pham and B. S. Yang [42-43].

Among the data driven approaches, grey model which have been successfully used in other domains before, has been introduced to deal with prognostics. Ku and Huang explored the application of grey model for predicting and monitoring production processes [44]. Subsequently, Gu et al. successfully developed grey prediction model in the failure prognostics for electronics [45]. Moreover, S. Tangkuman and B. S. Yang have analyzed application of grey model for machine degradation prognostics [46].

This new theory, grey model, was originally proposed by Deng [47]. The advantages from the use of grey model are it can be applied to circumstances with the minimum data down to some observations, and utilizes a first-order differential equation to characterize a system [48]. On the other hand, nowadays it is desirable to develop a RUL estimation model based on very few data situations [49]. Grey model can be a promising model to respond this current challenge. It is able to work with four input data [46]. So far, rare application of grey prediction model has been reported in machine prognostics. Therefore, for that reasons grey model was developed in this work.

5. CHALLENGES AND OPPORTUNITIES OF MACHINE PROGNOSTICS

Techniques for maintenance decision support in a CBM program can be divided into two main categories: diagnostics and prognostics. Diagnostics focuses on detection, isolation and identification of faults when they occur. Prognostics, however, attempts to predict faults or failures before they occur. Diagnostics is posterior event analysis, and prognostics is priorevent analysis. Prognostics is much more efficient than diagnostics to achieve zero-downtime performance.

Clearly, the architecture of intelligent CBM is shown in Fig.1 [50].A CBM system comprises a number of functionalmodules: sensing and data acquisition, signal processing, featureextraction and feature selection, condition monitoring and healthassessment, diagnostics, prognostics, decision reasoning, andhuman system interface.Most ofthese approaches focus on fault diagnostics and prognostics.

Being able to perform preciseand reliable prognostics is the key of CBM for anengineering system, and it is also critical for improvingsafety, planning missions, scheduling maintenance, reducingmaintenance costs, and down time. Even though it ishard to do a prognostics with an acceptable precise,prognostic methodologies based on CBM have attracted alot of attentions recently. Eventually, prognostics method has been an active area of research and developmentin aerospace, automotive, nuclear, process controls, andnational defense fields. In many instances, these modelscould be loosely built based on the analysis of signalscollected from system. Some review works on prognostics have beendone recently.

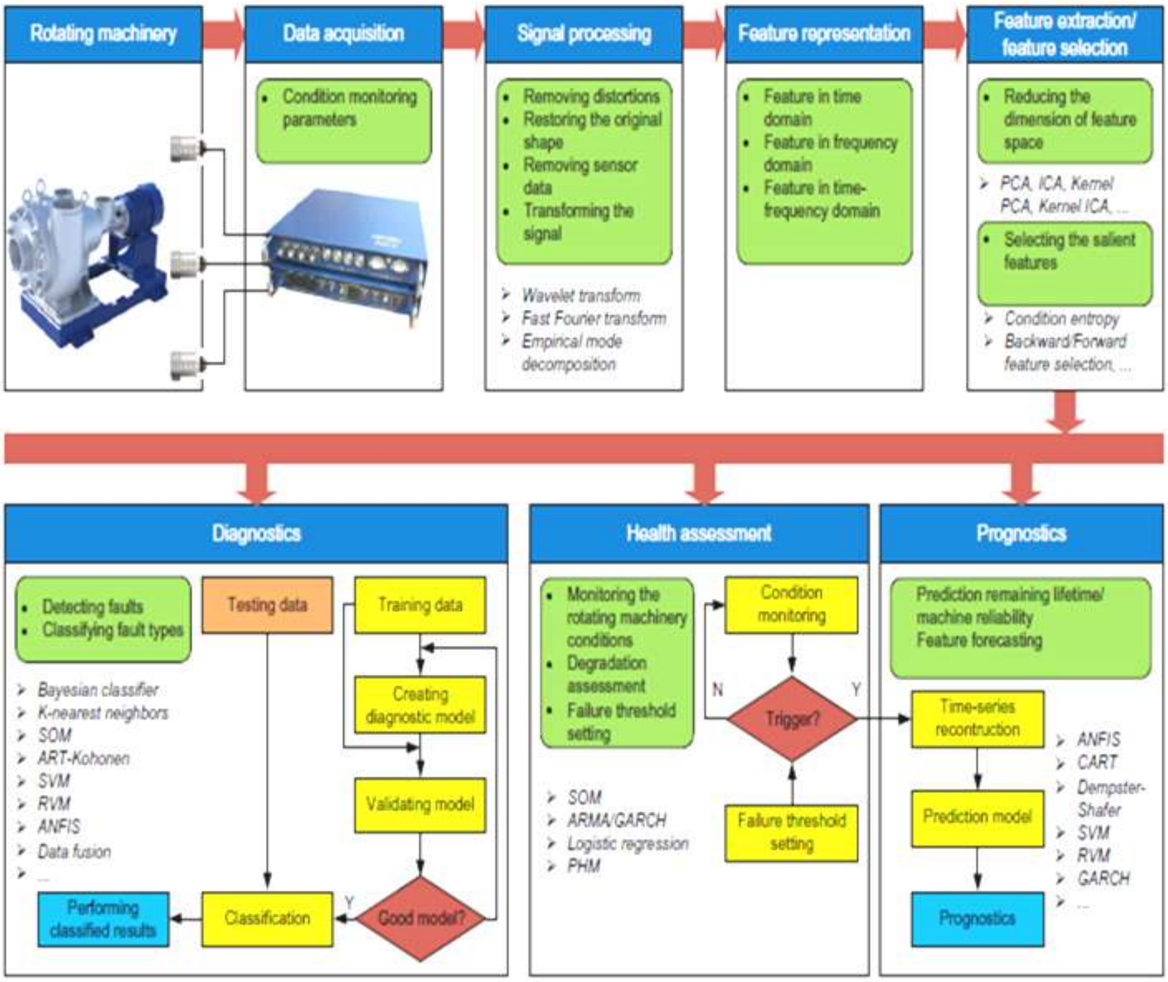

Fig.1 The architecture of I-CBM platform [50]

6. CONCLUSION

This papertries to review the techniques andalgorithms that appeared in recent research literatureinvolved in machine prognostics for implementing CBM.Various techniques and algorithms have been proposed that distinguished among model-based approaches, knowledge-based approaches, and data driven approaches.

Some theories and algorithms such as grey model have been introduced to prognostics. They have some advantages in accordance with data processing or condition monitoring system. They also can improve the accuracy of prediction, and may reduce the complexity of calculation.

Combination models are considered more and more to deal with prognostics. Combination model usually combines two or moretheories and algorithms to model the system in orderto eliminate the disadvantages of each individual theory.

Until the early 2012, it can be concluded that machine fault diagnosis and prognosis are tending to develop towards expertise orientation and problem-oriented domain. Furthermore, the challenges and opportunities in the field of rotating machinery fault prognostics are also discussed in this paper.

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