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Review Paper

Machine Fault Diagnosis and Prognosis: The State of The Art

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Abstract

Machine fault diagnostic and prognostic techniques have been the considerable subjects of condition-based maintenance system in the recent time due to the potential advantages that could be gained from reducing downtime, decreasing maintenance costs, and increasing machine availability. For the past few years, research on machine fault diagnosis and prognosis has been developing rapidly. These publications covered in the wide range of statistical approaches to model-based approaches. 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 diagnosis and prognosis of rotating machinery. Furthermore, it also discusses the opportunities as well as the challenges for conducting advance research in the field of machine prognosis.

Keywords: Rotating Machinery, Fault Diagnosis and Prognosis.

1. Introduction

A failure in industrial equipment results in not only the loss of productivity but also timely services to customers, and may even lead to safety and environmental problems. This emphasizes the need of maintenance in manufacturing operations of organizations. Maintenance is of great importance in keeping availability and reliability levels of production facilities, product quality, etc. Unfortunately, compared with production and manufacturing problems which have received great interest from researchers and practitioners, maintenance gained much less attention in the past. This might be one of the reasons that leads to low maintenance efficiency in industry at present. As pointed out by Mobley [1], one-third of all maintenance costs is wasted as the result of unnecessary or improper maintenance activities. Furthermore, maintenance cost is one of the main expenditure items. According to study, maintenance cost can reach 15-40% of production costs, varying depending on the type of industry. For instance, it is estimated to be more than 600,000 million dollars spent on maintenance in a selected group of companies in 1989 [2-3]; maintenance cost as a percentage of total value-added costs could be 20-50% for mining, 15-25% for primary metal and 3-15% for processing and manufacturing industries [4]. Additionally, with the augment of mechanization and automation, many modern plants have installed flexible computer-controlled automatic and unmanned equipments, the maintenance cost has been increased substantially. Therefore, maintenance has been historically regarded as a necessary evil by the various management functions.

Today, the role of maintenance is changing from a "necessary evil" to a "profit contributor" and toward a "partner" of organizations to achieve world-class competitiveness [5]. Consequently, research on maintenance area is on the rise in which hundreds of papers have been published and represents an opportunity for making significant contribution to academics over the past few years. In these publications, maintenance strategies have progressed from breakdown maintenance to preventive maintenance, then to condition-based maintenance (CBM), 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. It can restore the functional operation of failed components by repairing the defect or replacing them with new ones. However, random stoppage of equipment can limit the machine usage capacity and has serious impacts on productivity and product quality. Consequently, breakdown maintenance often results in high equipment downtime, high cost of restoring equipment, high penalties associated with the loss production, high spare part inventory level, and extensive unscheduled repair time [6]. To prevent catastrophic failures and emergency shutdowns, preventive maintenance was introduced in the 1950s. A preventive maintenance scheme includes setting periodic intervals for machine inspections and maintenance regardless of the machine's health condition. This helps prevent functional failures by replacing critical components at regular intervals before the end of their expected useful lives. Even though preventive maintenance reduces the frequency of unplanned breakdown and increases the reliability of equipment, it is costly due to the frequent replacements of expensive components before the end of their

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useful lives and the reduction of the availability of the equipments. Furthermore, it may create other unrelated failures due to the removal and replacement of parts, which is inappropriate for specific tolerances and human errors. There is where CBM steps in. CBM, which includes diagnostic and prognostic modules, attempts to monitor machinery health based on condition measurements that do not interrupt normal machine operations. It is based on the actual condition and can assess whether the equipment is in need of maintenance or not; and if it is necessary, determine when the maintenance actions need to be executed. Moreover, by incorporating prognosis, an alarm level can be set when the predicted values and the actual fault symptom of failure fall within the warning region. This will provide adequate time for the system operators to take remedial actions and inspect the condition of the equipment and conduct a repair on the defect before the catastrophic failure occurs.

Three key components of 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). Diagnosis and prognosis are the two important aspects in a CBM system. Diagnosis is the ability to detect fault, isolate and identify which component is failure, and decide on the potential impact of failed component on the health of the system. Fault detection is a task to indicate whether something is going wrong in the monitored system; fault isolation is a task to locate the component that is faulty; and fault identification is a task to determine the nature of the fault when it is detected. Prognosis is the capability to use available observations to predict upcoming states of machine or forecast the fault before it occurs.

The literature on machine fault diagnosis and prognosis is huge and diverse primarily due to a wide variety of systems, components and parts. This paper reviews the research on fault diagnosis and prognosis of rotating machinery implementing CBM to provide the information for research's community. Furthermore, it also discusses the opportunities, the challenges for conducting advanced research in this field.

2. Machine Fault Diagnosis

Several methods have been proposed in order to solve the fault detection and fault diagnosis problems. The most commonly employed solution approaches for fault diagnosis system include (a) model-based, (b) knowledge-based, and (c) pattern recognition-based approaches [7]. Generally, analytical model-based methods can be designed in order to minimize the effect of unknown disturbance and perform the consistent sensitivity analysis; knowledge-based methods are used when there is a lot of experience but not enough details to develop accurate quantitative models; and pattern recognition methods are applicable to a wide variety of systems and exhibit real-time characteristics. The applications of these methods to machine fault diagnosis are reviewed as follows:

2.1 Model-Based Approaches

The model-based methods perform fault diagnosis relied on analytical redundancy in which the consistency between the measurements and expected behavior of the process is checked by analytical models. These analytical models could be physical specific or explicit mathematical model of the monitored machine. Based on this explicit model, residual generation methods such as Kalman filter, system identification, and parity relations are used to obtain signals - so called residuals which is indicative of fault presence in the machine. Finally, the residuals are evaluated to achieve fault detection, isolation and identification. This process is illustrated in Fig. 1.

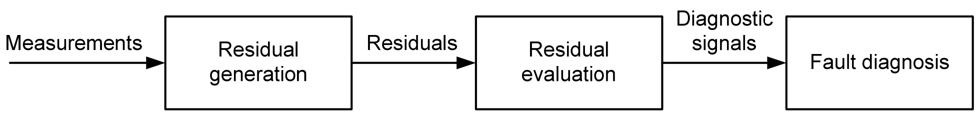

Fig. 1 General flowchart of model-based approach

Different approaches for fault detection using mathematical models have been developed [8-14]. A variety of models have been examined including linear system models [15], graph models [16, 17], process models [18], component models [19], and behavioral models [20, 21]. Furthermore, model-based methods have been successfully applied for diagnosing the faults of components of mechanical system such as gearboxes [22, 23], bearings [24-26], rotors [27, 28] and cutting tools [29]. Bartelmus [30, 31] used mathematical model and computer simulation as a tool for aiding signal processing and interpretation of gearbox diagnosis. Hansen et al. [32] proposed an approach to a more robust diagnosis of meshing gears based on the fusion of sensor-based and model-based information. Vania and Pennacchi [33] developed some methods to measure the accuracy of the results obtained from model-based techniques aiming to identify faults of generator. The information provided by these methods was shown to be very useful in having more precise fault identification along with evaluating the confidence of a diagnostic decision.

Recently, model-based techniques for diagnosis have been examined in the artificial intelligence (AI) community under the title of model-based reasoning. Furthermore, the use of AI techniques or the combination of conventional techniques and AI techniques has greatly enhanced the efficiency of model-based approaches in fault diagnosis. For example, Su and Chong [34] used neural network model as an analytical method in fault diagnosis of induction motor to avoid the ineffectiveness of traditional methods due to their non-adaptation with vibration signal. Liang and Du [35] combined a model-based fault detection and diagnosis method with support vector machine technique and successfully used this integrated technique for diagnosing the fault of heating, ventilation and air conditioning systems.

Generally, model-based approaches can be more effective if a correct and accurate model is built. However, explicit mathematical models may not be feasible for complex systems since it would be very difficult or even could not be established for such systems.

2.2 Knowledge-Based Approaches

Knowledge-based system (KBS) or expert system (ES) for fault diagnosis is performed based upon the evaluation of on-line monitored data according to a rule set which is determined by expert knowledge. This knowledge includes the locations of input and output process variables, patterns of abnormal process conditions, fault symptom, operational constraints, and performance criteria. The operators and engineers' intelligence related to the specific process systems can be implemented into this approach. Their knowledge can help to recognize the potential faults based on previous experiences. This approach can reduce the difficulties on exact numeric information and automates the human intelligence for process supervision.

Although KBSs are expensive and time-consuming during implementation, they are dedicated to machine fault diagnosis that was reported in the literatures [36-41]. In [40], an ES including adaptive order tracking technique and artificial neural networks (ANNs) for fault diagnosis in internal combustion engines is introduced. This system consisted of two stages. In the first stage, the engine sound emission signals were recorded and treated as the tracking of frequency-varying bandpass signals. Then the sound energy diagram was utilized to normalize the features and reduce computation quantity. In the second stage, the probability neural network was used to train the signal features and engine fault conditions. Similarly, an expert system using order tracking technique in combination with fuzzy logic inference was presented to fault diagnosis of scooter platform [41]. The fuzzy-logic inference was used in this system for developing the diagnostic rules of the data base in the present fault diagnosis system.

Data mining techniques were also applied to KBS as tools extracted diagnosis knowledge from data base. A decision tree, which is a method in data mining technology, was developed from the information gathered from the machine maintenance manual, electrical prints, and a human expert. The information from the decision tree was then used to develop the rules that represent the knowledge base. Yang et al. [42] proposed an expert system, namely VIBEX, to aid plant operators in diagnosing the cause of abnormal vibration for rotating machinery. Decision tree in their work was used as an acquisition of structured knowledge to obtain the diagnosing rules from decision table which was built by the cause-symptom matrix.

Evolutionary algorithms (EAs) are also utilized for domain expert knowledge in a computer program with an automated inference engine to perform reasoning for solving problem. Three main reasoning methods for ES used in the area of machinery diagnostics are rule-based reasoning [43-45], case-based reasoning [46-47] and model-based reasoning [48]. Another reasoning method, negative reasoning, was introduced to mechanical diagnosis by Hall et al. [49]. Unlike other reasoning methods, negative reasoning deals with negative information, of which absence or lack of symptoms is indicative of meaningful inferences. Stanek et al. [50] compared case-based and model-based reasoning and then proposed a combination of these methods for a lower-cost solution of machine condition assessment and diagnosis.

Other examples of diagnostic ESs were used for hydraulic system [51, 52] in mining areas. Petri nets, as a general purpose graphical tool for describing relations between conditions and events, have recently been applied to machine fault detection and diagnosis. Propes [53] used a fuzzy Petri net to describe an operating mode transition and to detect a mode change event for fault detection of diagnostics of complex systems. Yang [54] proposed a hybrid Petri-net modeling method coupled with fault tree analysis and Kalman filtering for early failure detection and fault isolation. Yang et al. [55] introduced an approach for integrating case-based reasoning with Petri net for fault diagnosis of induction motors. The integrated approach was shown to outperform the conventional case-based reasoning expert system.

Compared with model-based approaches, knowledge-based approaches are particularly suitable for large industrial plants since those non-linear real plants are extremely difficult to be modeled and the linear approximation of the model results in large errors. In addition, knowledge-based approaches are able to reduce the complexity when implementing the corresponding safety system and make it flexible, easy to understand and follow. Combining knowledge-based fault diagnosis methods with real-time process variables monitoring will improve the efficiency and reliability of detecting fault behavior and overall effectiveness of the system.

2.2 Pattern Recognition-Based Approaches

Pattern recognition is a process of mapping the information obtained from the measurement space and/or features from the feature space to machine faults in the fault space. Traditionally, pattern recognition is manually done by auxiliary graphical tools such as power spectrum graph, phase spectrum graph, cepstrum graph, autoregressive spectrum, spectrogram, wavelet phase graph, etc. However, manual pattern recognition requires expertise in the specific area of diagnosis application. Thus, highly trained and skilled personnel are necessary. Therefore, automatic pattern recognition is exceedingly desirable. This can be achieved by classification of signals based on the information and feature extracted from the signals.

Pattern recognition approaches, which include artificial intelligent (AI) techniques, have been increasingly applied to machine diagnosis and have shown superior performance over conventional approaches. However, it is not easy to apply AI techniques in practice due to the lack of efficient procedures for obtaining training data and specific knowledge that are necessary for training the models. Thus far, most of the applications in the literatures just used experimental data for training models. Popular AI techniques for machine diagnosis are ANNs, fuzzy logic systems, fuzzy-neural networks (FNNs), and neural-fuzzy systems. A review of recent developments in applications of AI techniques for induction machine stator fault diagnostics was given in [56].

ANNs mimic the human brain structure which consists of simple arithmetic units connected to complex layer architecture. They are capable of representing highly nonlinear functions and performing multi-input, multi-output mapping. The ANNs learn the unknown function by adjusting its weights with observations of input and output. This process is usually called training process of an ANN.

There have been various neural network models applied to pattern recognition. Feed forward neural network (FFNN) structure is widely used neural network structure in machine fault diagnosis [57-60]. Multilayer perceptron with the back propagation (BP) training algorithm, which is a special FFNN, is also employed for pattern recognition and classification as well as machine fault diagnostics [61-63]. However, the BP neural networks have two main limitations which are difficult to determine the network structure and the number of nodes; and slow convergence of the training process. Cascade correlation neural network (CCNN) is alternative which does not require initial determination of the network structure and the number of nodes. CCNN can be used in case that on-line training is preferable. CCNN was applied to bearing fault classification and showed that it can result in the minimum network structure for fault recognition with acceptable accuracy [64]. Other neural network models including radial basis function neural networks, recurrent neural networks, and counter propagation neural networks were also applied in machine diagnostics [65-68].

The ANN models mentioned above usually use supervised learning algorithms which require external input such as a priori knowledge about the target or desired output. For example, a common practice is to utilize a set of experimental data with known faults to generate a neural network model. Conversely, unsupervised learning does not require the external input. The unsupervised neural network learns itself by using the new available information. The applications of unsupervised neural network for fault diagnosis were introduced in [69-71]. In [69], faults of rotating machine were detected by using self-organizing map (SOM) and learning vector quantization. Tallam et al. [70] proposed some self-commissioning and on-line training algorithms for FFNN with particular application to electrical machine fault diagnostics. Sohn et al. [71] employed an auto associative neural network to separate effects of damages caused by the environmental and vibration variations of the system. Then a sequential probability ratio test was performed on the normalized features for damage classification.

The combination of neural networks and other techniques would be a significant alternative to improve the performance of machine diagnosis. For instance, Silva et al. [72] used two neural networks, which are SOM and adaptive resonance theory (ART), in association with an ES based on Taylor's tool life equation to classify tool wear state. DePold and Gass [73] studied the applications of neural networks and ESs in a modular intelligent and adaptive system in gas turbine diagnostics. Yang et al. [74] presented an approach for integrating case-based reasoning ES with an ART-Kohonen neural network to enhance fault diagnosis. It showed that the proposed approach outperforms the self-organizing feature map-based system with respect to classification rate. Garga et al. [75] proposed a hybrid reasoning approach combining neural network, fuzzy logic and ES to integrate domain knowledge and test operation data from the machine for machine diagnostics and prognostics.

In condition monitoring practice, knowledge from domain specific experts is usually inaccurate and reasoning on knowledge is often imprecise. Therefore, measures of the uncertainties in knowledge and reasoning are required for ES to provide more robust problem solving. Unremarkably used uncertainty measures are probability, fuzzy member functions in fuzzy logic theory and belief functions in belief networks theory. An example of applying fuzzy logic to machine fault classification was given in [76] to classify frequency spectra representing various rolling element bearing faults. Du and Yeung [77] introduced an approach, so-called fuzzy transition probability which combined transition probability with the fuzzy set, to monitor progressive faults. Fuzzy logic is also incorporated with other techniques such as neural networks and ES for fault diagnostic application. For example, Zhang et al. [78] developed an FNN for fault diagnosis of rotary machines to improve the recognition rate of pattern recognition, especially in the case that sample data are similar. Lou and Loparo [79] employed an adaptive neural-fuzzy inference system as a diagnostic classifier for bearing fault diagnosis. Liu et al. [80] applied fuzzy logic and ESs to build a fuzzy ES for bearing fault detection. Chang et al. [81] built a system for decision-making support in a power plant using both rule-based ES and fuzzy logic. Genetic algorithms (GAs), which are the most ordinarily used type of EA, have been applied to machine diagnostics. Several examples of ANN incorporating GA and other EAs for machine fault classification and diagnostics are [82-84]. A technique called support vector machine (SVM) is a new general machine learning tool based on the structural risk minimization principle. It has received much consideration in recent times due to its high accuracy and good generalization capabilities. The use of SVM and its extension for machine fault diagnosis were summarized in [85].

Adaptive neuro-fuzzy inference system (ANFIS) which is an integration of ANNs and fuzzy logic system has been widely used for automated detection and diagnosis of machine condition. It takes advantage of good learning capability of ANN and human knowledge representation of fuzzy logic. Successful implementations of ANFIS in fault diagnosis were reported in [86-89]. Shukri et al. [86] applied ANFIS for fault detection and diagnosis of three-phase induction motor. Lou and Loparo [87] used combined method for the diagnosis of localized defects in ball bearings in which wavelet transform was used to process the accelerometer signals and to generate feature vectors; and ANFIS was trained and utilized as diagnostic classifier. Tran et al. [88] used the integration of classification and regression and ANFIS for diagnosing the faults of induction motors. In [89] and [90], multiple ANFIS algorithm and its combination with GAs were employed for detecting rotor bar breakage, air gap eccentricity faults of three-phase induction motor and rolling bearings, respectively. Other applications of ANFIS for machine fault diagnosis were introduced in [91-94].

3. Machine Fault Prognosis

The literatures of prognosis are much smaller in comparison with those of fault diagnosis. The most obvious and normally used prognosis is to use the given current and past machine condition to predict how much time is left before a failure occurs. The time left before observing a failure is usually called remaining useful life (RUL). In order to predict the RUL, data of the fault propagation process and/or the data of the failure mechanism must be available. The fault propagation process is usually tracked by a trending or forecasting model for certain condition variables.

There are two ways in describing the failure mechanism. The first one assumes that failure only depends on the condition variables, which reflect the actual fault level, and the predetermined boundary. The definition of failure is simply defined that the failure occurs when the fault reaches a predetermined level. The second one builds a model for the failure mechanism using available historical data. In this case, different definitions of failure can be defined as follows: (a) an event that the machine is operating at an unsatisfactory level; or (b) it can be a functional failure when the machine cannot perform its intended function at all; or (c) it can be just a breakdown when the machine stops operating, etc. The approaches to prognosis fall into three main categories: statistical approaches, model-based approaches, and data-driven based approaches. Table 1 lists the published methods, their advantages and disadvantages.

Table 1 List of prognosis methods, their advantages and disadvantages

Approaches	Advantages	Disadvantages
Statistical approaches [95-103]	• Do not require condition monitoring • Population characteristics information enable longer-range forecast • Can be trained to recognize the types of faults	• Only provide general, overall estimates for the entire population of identical units
Model-based approaches [104-114]	• 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.
Data-driven approaches [115-122]	• 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

3.1 Statistical Approaches

Statistical approaches, which are the simplest forms of prognosis techniques, collect statistical information from a large number of component samples to indicate the survival duration of component before failure occurs and uses these statistics to predict the RUL of individual components. Yan et al. [95] used a logistic regression model to calculate the probability of failure for given condition variables and an autoregressive moving average time series model to trend the condition variables for failure prediction. Then a predetermined level of failure probability was used to estimate the RUL. Phelps et al. [96] proposed to track sensor-level test-failure probability vectors instead of the physical system or sensor parameters for prognosis. A Kalman filter with an associated interacting multiple models was used to perform the tracking. The proportional hazards models (PHM) and proportional intensity model (PIM), which are two statistical models in survival analysis, are useful tools for RUL estimation in combination with a trending model for the fault propagation process. Banjevic and Jardine [97] discussed RUL estimation for a Markov failure time process which includes a joint model of PHM and Markov property for the covariate evolution as a special case. Vlok et al. [98] applied PIM with covariate extrapolation to estimate bearing residual life. Hidden Markov model is also a powerful tool for RUL estimation [99,100]. Lin and Makis [101] introduced a partially observable continuous-discrete stochastic process model to describe the hidden evolution process of the machine state associated with the observation process. Wang et al. [102] proposed a stochastic process with hazard rate for predicting of residual life. The condition information was the expert judgment based on vibration analysis. Wang [103] used the residual delay-time concept and stochastic filtering theory to derive the residual life distribution.

3.2 Model-Based Approaches

Model-based prognostic approaches are applicable to where accurate mathematical models can be constructed from physical system. These methods use residuals as features, which are the outcomes of consistency checks between the sensed measurements of system and the outputs of a mathematical model. Ray and Tangirala [104] used a non-linear stochastic model of fatigue crack dynamics for real-time computation of the time-dependent damage rate and accumulation in mechanical structures. Li et al. [105, 106] introduced two defect propagation models via mechanistic modeling for RUL estimation of bearings. Oppenheiner and Loparo [107] applied a physical model for predicting the machine condition in combination with fault strengths to life model based on crack growth law to estimate RUL. A general method was purposed by Chelidze and Cusumano [108] 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. Some different approaches used model-based techniques for prognosis were proposed in [109-114]. However, model-based 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, it is difficult to establish the suitable model to mimic the real life.

3.3 Data-Driven Based Approaches

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. Among these techniques, artificial intelligence was regularly used because of its flexibility in generating appropriate model. Several of the existing approaches used ANNs to model the systems and estimate the RUL. Most of ANN approaches were time series forecasting models in which single-step ahead was considered. Zhang and Ganesan [115] used self-organizing neural networks for multivariable trending of the fault development to estimate the residual life of bearing system. Wang and Vachtsevanos [116] proposed an architecture for prognosis applied to industrial chillers. Their prognostic model included dynamic wavelet neural networks, reinforcement learning, and genetic algorithms. This model was used to predict the failure growth of bearings based on the vibration signals. SOM and back propagation neural networks (BPNN) methods using vibration signals to predict the RUL of ball bearing were applied by Huang et al. [117]. Wang et al. [118] utilized and compared the results of two predictors, namely recurrent neural networks and ANFIS, to forecast the damage propagation trend of rotating machinery. In [119], Yam et al. applied a recurrent neural network for predicting the machine condition trend. Dong et al. [120] employed a grey model and a BPNN to predict the machine condition. Recently, other approaches that used regression trees in association with time series techniques to forecast the conditions of mechanical system were reported in [121].

However, further work is essential to extend from single-step-ahead to multi-step-ahead. This assists the RUL estimation to be easier. Liu et al. [122] used neuro-fuzzy system as a multi-step-ahead prediction model to forecast the behavior of dynamic system. In this approach, a hybrid of training algorithm, which involves the recursive Levenberg-Marquardt and recursive least square estimate, was used to enhance the forecasting convergence and to accommodate time-varying system conditions. Altogether, multi-step-ahead prediction is still a difficult and challenging task in time series prediction domain due to the growing uncertainties arising from unrelated sources, such as, accumulation errors and insufficient information. Generally speaking, the data-driven techniques are the promising and effective techniques for machine condition prognosis.

Recently, with the advance of internet and tether-free technologies, a new method for machine maintenance, namely e-maintenance, appears. E-maintenance, which is based on intelligent prognosis, addresses the fundamental needs of predictive intelligence tools to monitor the degradation rather than to detect the faults in a network environment and, ultimately to optimize the asset utilization in the facility [123]. According to Lee et al. [123], intelligent prognostics is defined as a systematic approach that can continuously track health degradation and extrapolating temporal behavior of health indicators to predict risks of unacceptable behavior over time as well as pinpointing exactly which components of a machine are likely to fail. These authors also introduced an intelligent maintenance system and its key components depicted in Fig. 2. In addition, several of methods, hardware and software for machine condition monitoring, fault diagnosis and prognosis could be found in [125], which one of the maintenance research center with the goals that is to enable products and systems to achieve and sustain near-zero breakdown performance, and ultimately transform machine condition data to useful information for improved productivity and asset utilization.

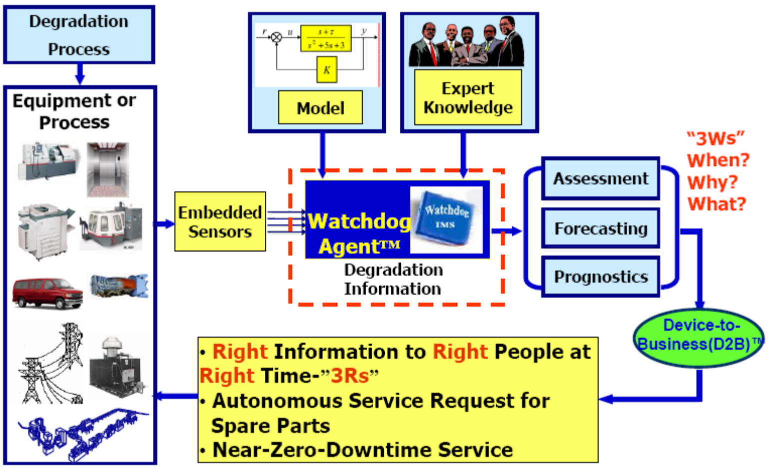

Fig. 2 Intelligent maintenance system and its key components [123, 124]

3.4 Challenges and Opportunities of Machine Prognosis

Obviously, machine fault prognosis plays a crucial role for the foreseeable future of condition-based maintenance. However, further researches in several aspects on machine fault prognosis involved statistical-based, driven-based, and model-based are necessary to be considered. Even though prognosis techniques based data-driven devote their flexibility to generate the prediction model, the improvement of predicting accuracy is the issue needed to pursue so that these techniques can be employed for real industrial applications.

As mentioned in several published approaches, the model-based techniques give the high potential for fault prognosis even though they are challenging to obtain the precise mathematic model for mimicking the dynamic system behavior. The hybridization of model-based and data-driven based techniques is a novel approach to fault prognosis area. This hybrid technique will inherit the advantages from each technique so that the reliability and accuracy of prediction model is significantly gained.

Furthermore, there have been some issues to be considered before the machine prognosis system can be reliably applied to real-life situations. Real-life machines are often subjected to variable operating patterns, which include repairs and change of operating parameters. The effects of these operational complexities may greatly reduce the accuracy of prognosis output. Additionally, the inherent structure complexity of real-life machine also hinders practical applications of many prognosis models, which are only designed to predict a specific failure mode of a component.

4. Conclusion

This paper synthesizes the progress in research and development of machine fault diagnosis and prognosis. It reviews the articles upon the year of 2008 by using a keyword index *machine fault diagnosis* and *machine fault prognosis*. Since this topic has gained popularity in machine learning, however, researchers who applied in machine diagnosis and prognosis are relatively rare. Until 2008, 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 diagnosis and prognosis are also discussed in this paper, especially for machine prognosis. From that, some suggestions for further improvement are proposed, such as hybrid of model-based techniques and data-driven based techniques to increase the reliability and accuracy of prediction ability, the consideration of the effects from maintenance actions, the consideration of the effects of operating condition, etc. so that prognosis system is reliable and can be applied to real-life industrial application.

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