Mechanical Systems and Signal Processing 42 (2014) 314–334

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

# Prognostics and health management design for rotary machinery systems—Reviews, methodology and applications

Jay Lee [a], Fangji Wu [b], Wenyu Zhao [a,*], Masoud Ghaffari [a], Linxia Liao [a], David Siegel [a]

[a] NSF I/UCR Center for Intelligent Maintenance System, University of Cincinnati, USA
[b] State Key Laboratory for Manufacturing Systems Engineering, Research Institute of Diagnostics and Cybernetics, Xi'an Jiaotong University, Xi'an 710049, China

ARTICLE INFO

*Article history:*
Received 15 March 2010
Received in revised form
3 October 2012
Accepted 10 June 2013
Available online 29 August 2013

*Keywords:*
Diagnostics
Prognostics and health management (PHM)
Condition based maintenance
Reliability centered maintenance

ABSTRACT

Much research has been conducted in prognostics and health management (PHM), an emerging field in mechanical engineering that is gaining interest from both academia and industry. Most of these efforts have been in the area of machinery PHM, resulting in the development of many algorithms for this particular application. The majority of these algorithms concentrate on applications involving common rotary machinery components, such as bearings and gears. Knowledge of this prior work is a necessity for any future research efforts to be conducted; however, there has not been a comprehensive overview that details previous and on-going efforts in PHM. In addition, a systematic method for developing and deploying a PHM system has yet to be established. Such a method would enable rapid customization and integration of PHM systems for diverse applications. To address these gaps, this paper provides a comprehensive review of the PHM field, followed by an introduction of a systematic PHM design methodology, 5S methodology, for converting data to prognostics information. This methodology includes procedures for identifying critical components, as well as tools for selecting the most appropriate algorithms for specific applications. Visualization tools are presented for displaying prognostics information in an appropriate fashion for quick and accurate decision making. Industrial case studies are included in this paper to show how this methodology can help in the design of an effective PHM system.

Published by Elsevier Ltd.

## 1. Introduction

Both diagnostics and prognostics originally come from the medical field. As machinery maintenance technology emerged, diagnostics and prognostics gradually permeated all areas of mechanical engineering. Nowadays, there are many kinds of professional instruments, such as sensors, meters, controllers and computational devices, for conducting machine diagnostics. These instruments can be used to acquire and analyze signals from a machine or process. More and more sophisticated diagnostics methodologies are available to determine the root causes of machine failure. However, diagnostics, which is conducted when a fault has already occurred, is a reactive process for maintenance decisions and cannot prevent downtime as well as corresponding expense from happening. In order to reduce maintenance cost and maintain machine

* Corresponding author. Tel.: +1 513 5563412; fax: +1 513 5563390.
*E-mail address:* zhaowy@mail.uc.edu (W. Zhao).

0888-3270/$ - see front matter Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.ymssp.2013.06.004

uptime at the highest possible level, maintenance should be carried out in a proactive way. That means a transformation of maintenance strategy from the traditional fail-and-fix practices (diagnostics) to a predict-and-prevent methodology (prognostics).

Prognostics has been applied to the field of maintenance for more than 10 years, however, most of these applications only addresses forecasting, or remaining useful life (RUL) prediction, which is just one facet of prognostics and health management (PHM). As an engineering discipline PHM aims to provide users with an integrated view of the health state of a machine or an overall system. Diagnostics is also included in prognostics and health management. Diagnostics can be summarized as the process of identifying and determining the relationship between cause and effect in that its function is to isolate faults and identify failure root causes. Prognostics can be interpreted as the process of health assessment and prediction, which includes detecting incipient failure and predicting RUL. Health management is the process of taking timely, appropriate maintenance actions and making accurate logistics decisions based on outputs from diagnostics and prognostics, available resources and operational demand. It focuses on assessing impact of failures, and minimizing impact and loss with maintenance management.

An effective PHM system is expected to provide early detection and isolation of the precursor and/or incipient fault of components or sub-elements; to have the means to monitor and predict the progression of the fault; and to aid in making, or autonomously trigger maintenance schedule and asset management decisions or actions. The detected, incipient fault condition should be monitored, trended from a small fault as it progresses to a larger fault, until it warrants some maintenance action and/or replacement. By employing such a system, the health of a machine, component or system can be known at any point in time, and the eventual occurrence of a failure can be predicted and prevented, enabling the achievement of near-zero downtime performance. Unnecessary and costly preventive maintenance can be eliminated, maintenance scheduling can be optimized, and lead-time for spare parts and resources can be reduced—all of which can result in significant cost savings.

This paper reviews various methodologies and techniques in PHM research, and presents a systematic methodology for conducting PHM as applied to machinery maintenance. The remained of this paper is organized as follows: In Section 2, the relationship between diagnostics and prognostics is defined, and the objectives of prognostics are introduced. Section 3 includes the review of developed and applied PHM methods. Section 4 introduces several unmet challenges/issues related to PHM and contains a proposed systematic methodology for the design of an effective PHM system. Industrial application examples are provided in Section 5 to validate this systematic methodology. A conclusion is given in Section 6 with a discussion of future development for PHM.

## 2. Development of PHM

### *2.1. Diagnostics and prognostics*

Although the issue of diagnostics and prognostics has been addressed in the literature, the topic has not been covered thoroughly. The impact of diagnostics and prognostics on modeling and reasoning system requirements are explored in [1], and several approaches to diagnostics, prognostics and health management are defined as physical models, reliability models, machine learning models and dependency models. Though the methods and knowledge bases for diagnostics and prognostics may be similar, the way in which each of them is implemented is significantly different.

Diagnostics is conducted to investigate or analyze the cause or nature of a condition, situation, or problem, whereas prognostics is concerned with calculating or predicting the future as a result of rational study and analysis of available pertinent data. In terms of the relationship between prognostics and diagnostics, diagnostics is the process of detecting and identifying a failure mode within a system or sub-system; while prognostics is the process of generating a rational estimation of the remaining useful life and/or remaining performance life until complete failure occurs. Prognostic, in its simplest form, is to monitor and detect the initial indications of degradation in a component, and be able to consistently make accurate predictions [2].

Fig. 1 shows a long degradation process of an impending fault in a machine, where an initial defect continues to proliferate, and eventually reaches a critical condition that causes the machine failure. We can conceptualize the task of diagnostics as an in-depth exploration of the failure to identify the leading cause after it has occurred, while prognostics is

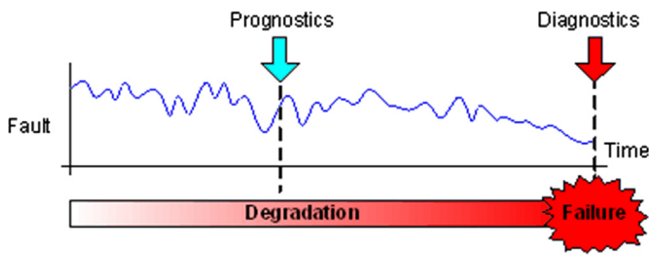



**Fig. 1.** Differencing perception of diagnostics and prognostics.

to investigate the problem taking time factor into account during the degradation period and make prediction. The main aim of prognostics is to predict an event before its possible occurrence. Time is thus a critical variable in prognostics, distinguishing it from diagnostics, in which time plays a less important role, the emphasis being placed more on determining the parameters of an already occurring fault or failure.

The architecture of a diagnostics system framework and that of a prognostics system framework should be different because of their different objectives. A diagnostics system consists of a data collection system, a signal processing and feature extraction module, and a knowledge base of faults, which may be derived from expert knowledge, physical models and historical data. The final determination of what type of failure has occurred, and why it is made by comparing the feature extraction results with the knowledge base. In prognostics, however, several other steps are required. In addition to utilizing feature extraction and a knowledge base of faults, as in diagnostics, performance assessment, degradation models, failure analysis and prediction are employed or carried out in conducting prognostics. When combined, performance assessment and degradation models can describe a machine's relative health status and indicate what kind of degradation patterns may exist. Prediction algorithms, which could be derived from classic time series analysis theories, statistics, or artificial intelligence technologies, can forecast when machine performance will decrease to an unacceptable level as defined by the failure analysis and health management. Hence, the questions that prognostics attempts to answer are

(1) ***How*** is the machine operating now? (Performance assessment).
(2) ***When*** will the machine break down? (Remaining useful life).
(3) ***What*** will be the primary faults that cause downtime?
(4) ***Why*** does the fault occur?

### 2.2. Maintenance transformation and PHM development

The concept and framework of PHM have been developed based on well known maintenance methodologies and diagnostics techniques, such as preventative maintenance (PM), reliability centered maintenance (RCM) and condition based maintenance (CBM). The future development of PHM will be mutually inspired and promoted from various fields besides engineering [3]. The related research topics in Meteorology/Climatology [4], Decision Science/Policy [5], Financial/Economic [6] and other fields can also be followed to expand the vision of PHM.

CBM consists of data acquisition and data processing (condition monitoring), resulting in actionable condition information on which maintenance decision-making can be based, thus avoiding unnecessary maintenance tasks. Currently, more and more research effort has shifted toward prognostics and health management which focuses more on incipient failure detection, current health assessment and remaining useful life prediction. However, in various maintenance scenarios with different system complexity and uncertainty, the maintenance strategies should be different. Fig. 2 is the maintenance transformation map in which diverse maintenance strategies are shown with the system complexity and uncertainty.

CBM can be applied in systems that (1) can be regarded as being deterministic to some extent, (2) is stationary or static, and (3) for which signal variables that can be good health indicators can be extracted, despite low dimensionality. If the system is a probabilistic system for which the output cannot be easily determined with a known relationship model and is conditionally dependent upon the input, output data will not always be repeatable in instances observed at different

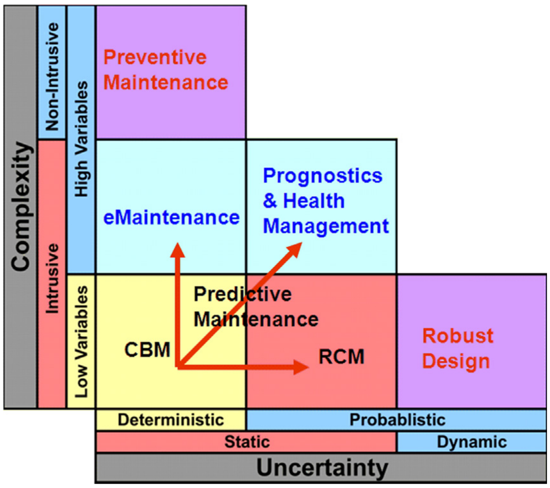



**Fig. 2.** Maintenance transformation map.

timings. Hence, the future behavior cannot be predicted accurately based on the domain knowledge of the system and the historical observations. In such an uncertainty laden system as described, RCM is more suitable. RCM focuses on the ability of a system to have expected reliability in a certain period of time, and utilizes statistical tools such as failure modes and effects criticality analysis (FMECA) to retrieve the information that can help identify failure modes and possible durations before each of the modes can happen. Since RCM relies on statistical estimation of the total operation life expectation, it can reduce unscheduled or unnecessary maintenance if the system is static and the failure modes are well studied. However, RCM is still prone to large deviation of the system dynamic and it lacks significant insight into the actual system performance. If the system uncertainty is more complicated, like in a highly dynamic system in which the behavior varies over time, robust design should be considered. In this scenario, resources should be allocated to the design processes, rather than relying on inspection to ensure quality. As well, the product performance, due to robust design being deployed, should have minimal sensitivity to material, manufacturing, or operation variations.

Along the other axis in Fig. 2, if a system has a high level of complexity and a large number of variables that represent different aspects of the system, such as vibration, position, velocity, stress, current, environment, controller parameters, and so on, eMaintenance is preferred as CBM techniques usually deal with low dimension of data. By using internet and tether-free communication technologies, eMaintenance enables a system to achieve near-zero-breakdown performance on a common platform to integrate information. Moreover, by linking with industrial business systems, eMaintenance is able to align the maintenance process with the business and operations processes to achieve optimal integrated production and asset management. But if the system complexity is even higher so that only non-intrusive approaches can be applied to the system, which means no or only very limited instrumentation can be applied due to the product package, seal, and the concern that externally added components will dramatically affect the precision and efficiency of the products, preventive maintenance may be chosen rather than CBM or eMaintenance which require systems to be heavily instrumented. Preventive maintenance is a time-driven maintenance strategy that schedules maintenance for a machine or component based on experience of the mean time between failures (MTBF). This method follows strong assumptions that the machine is working under deterministic and static conditions, and therefore cannot be applied to system that operates in dynamic working regimes. Hence preventive maintenance may lead to untimely maintenance and non-optimal cost.

PHM can be treated as an evolved form of CBM. CBM techniques can be used to provide input for the prognostics models in PHM and support the timely, accurate decision making that prevents downtime and maximizes profit. For its capability to assess health status and predict occurrence of failure and downtime, PHM is considered to be the foundation, when complemented with other techniques, for advanced areas including self-maintenance, resilient system and engineering immune systems. The disciplines of PHM need to be further developed and extended to help building these areas.

## 3. PHM methodologies—a review

Historically, PHM concept was first introduced in medical field. Medical prognostics is defined as the prediction of the future course and outcome of disease processes, which may either concern their natural course or their outcome after treatment [7]. Derived from the same concept as medical prognostics, a lot of prognostics methods and systems have been developed for machinery maintenance in the past 10 years. Vibration signature analysis and oil analysis, because of their excellent capabilities in describing machine performance, have been employed for prognostics for a long time, and many applications are still based on this classic method [8–12]. Other techniques, such as temperature analysis, acoustic emissions [13], and ultrasonics are being widely employed as well. Sensor fusion techniques are commonly used due to their inherent superiority to merge and interpret the diverse information from multiple sensors [14–17]. Table 1 gives an introductory summary of PHM tools for common critical components, regarding the components' issues and possible failure modes, characteristics, common available data types, common features and algorithms applied for diagnostics and prognostics.

Current prognostic approaches can be categorized into three classes, namely model-based, data-driven and hybrid prognostics approaches. A typical model-based approach includes data generated from simulated models under nominal and degraded conditions [118]. Prediction of system remaining life is subject to simulation of system's multiple operational modes and generated by mixing the prediction from each mode weighted with time-averaged model probabilities. If a reliable or accurate system model is not available, the data-driven prognostics approach is used to determine the remaining useful life by trending the trajectory of a developing fault and predicting the amount of time before it reaches a predetermined threshold level. Two well-known tracking and prediction tools, Alpha–Beta–Gamma tracking filter and Kalman filter have been applied to gearbox prognostics [119–121]. Both filters have been investigated for their ability to track and smooth features from gearbox vibration data. The literature presents additional discussions on using Kalman filters to track changes in features like vibration levels, mode frequencies, and other waveform signature features, and estimate future failure hazard, probability of survival and remaining useful life [122,123]. A hybrid prognostics approach, which fuses the outputs from model-based approach and data-driven approach, was proposed in [15], in which prognostics results are claimed to be more reliable and accurate.

Currently, the development of neural networks has added new dimensions to overcome the existing problems of prognostics and diagnostics. In a case focusing on a centrifugal pump, comparison of the results using the signal identification technique reveals the various merits of neural nets including the ability to handle multivariate wear parameters in a much shorter time [124]. A helicopter transmission prognostic application was presented in [125] in which fault detection, isolation, and estimation were conducted by a polynomial neural network. A fuzzy logic-based

**Table 1**
Introductory summarization of PHM tools of critical components.

| Component | Issue & failure | Characteristic | Common measures | Common features | Common algorithms used |
|---|---|---|---|---|---|
| Bearing | Outer-race, inner-race, roller, and cage failures | Raw data does not contain insightful information; low amplitude; high noise | Vibration, oil debris, acoustic emission | Vibration characteristic frequency, time domain statistical characteristics, metallic debris shape, size, quantity, sharp pulses and rate of development of stress-waves propagation | Fourier Transform (FT) [18,19], Short Time Frequency Transform (STFT) [20], Wavelet Transform (WT) [21], Empirical Mode Decomposition (EMD) [22], Bispectrum [23], Autoregression (AR) Frequency Spectra [24], Hilbert Spectrum [25], Instantaneous Power Spectrum [26], Hilbert–Huang Transform (HHT) [27], Neural Networks (NN) [28–30], Hidden Markov Modeling (HMM) [31], Fuzzy Logic [32], Support Vector Machine (SVM) [33], Genetic Algorithm (GA) [34,35], Rough Set [36], Autoregressive Moving Average (ARMA) [37], Stochastic Model [38,39], Principal Component Analysis (PCA) [40] |
| Gear | Manufacturing error, tooth missing, tooth pitting/spall, gear crack, gear fatigue/wear | High noise; high dynamic; signal modulated with other factors (bearing, shaft, transmission path effect); gear specs need to be known | Vibration, oil debris, acoustic emission | Time domain statistical features, vibration signature frequencies, oil debris quantity and chemical analysis | FT [41], STFT [42,43], WT [44,45], EMD [46–48], HHT [48–50], NN [51–54], Fuzzy Logic [55], Neuro-Fuzzy Hybrid Model [56], Energy Index Analysis [57], Kalman Filter [58–60], SVM [61], Autoregressive Model [62,63], Particle Filter [64] |
| Shaft | Unbalance, bend, crack, misalignment, rub | Vibration signal is relatively clean and harmonic frequency components of rotating speed can indicate the defects | Vibration | Vibration characteristic frequency, time domain statistical characteristics, system modal characteristics | FT [65], WT [66], Wigner–Ville Transforms (WVT) [67], EMD [68,69], Analytical or Numerical Models [70,71], NN [72–74], Fuzzy Logic [75], Support Vector Regression (SVR) [76], GA [77,78], ARMA [79,80] |
| Pump | Valve impact, score, fracture, piston slap, defective bearing and revolving crank, hydraulic problem | Pump's dynamic responses, generated by a wide range of possible impulsive sources, are very complex; nonlinear, time-varying behavior | Vibration, pressure, acoustic emission | Vibration characteristic frequency, pressure time domain statistical characteristics, sharp pulses and rate of development of stress-waves propagation | FT [81], STFT [72–84], WT [85], Envelop Analysis [86], NN [87–89], Fuzzy Logic [90,91], Neuro-Fuzzy Hybrid Model [92], Rough Set [93], PCA [94] |
| Alternator | Stator faults, rotor electrical faults, rotor mechanical faults | Currents and voltages are preferred for noninvasive and economical testing | Stator currents and voltages, magnetic fields and frame vibrations | Specific harmonic components, sideband components | FT [95], WT [96–99], Instantaneous Power Fourier Transform [100], Bispectrum [101,102], High Resolution Spectral Analysis [103,104], Expert Systems [105,106], NN [107–109], HMM [110], Fuzzy Logic [111–113], GA [113], Higher Order Statistics [114], Park's Current Vector Pattern [115], Petri Net [116], Kalman Filter [117] |

neural network and decision tree were applied to the prediction of paper web breakage in a paper mill in [126]. Yet another prognostic application, presented in [127], involves an integrated prognosis system using a dynamically linked ellipsoidal basis function neural network coupled with an automated rule extractor to develop a tree-structured rule set that closely approximates the classification of the neural network. This method allows assessment of trending from the nominal class to each of the identified fault classes, which means quantitative prognostics is built into the network functionality.

Garga et al. [128] introduced a hybrid reasoning method for prognostics, which integrates explicit domain knowledge and machinery data. In this approach, a feed-forward neural network is trained using explicit domain knowledge to get a parsimonious representation of the explicit domain knowledge. Vachtsevanos and Wang [129] present a prognostic approach that is based on the concept of a dynamic wavelet neural network and virtual sensors. The method's feasibility was demonstrated on an example involving bearing failure. Vachtsevanos collaborated with Wang and Khiripet to describe a fault predictor based on the dynamic wavelet neural network (DWNN) [130]. DWNN is used as a dynamic predictor which receives fault data from the diagnostic module and determines the allowable time window during which machine maintenance must be performed to preserve the integrity of the process. The output of the dynamic predictor, which is either the remaining useful life or time to failure, is dynamically updated as more information becomes available from the diagnostics outputs. Jaw [131] used neural networks for model-based prognostics to improve the fidelity of the models used onboard aerospace systems to facilitate PHM.

The concept of PHM has been deployed in multiple applications, resulting in the development of many diverse tools, techniques and methodologies. Several information fusion systems for engine prognostics and health management have been introduced which integrate various applicable data and suitable technologies [132,133]. By utilizing a combination of health monitoring data and model-based techniques, comprehensive component prognostic capabilities can be achieved throughout a component's life [134,135]. A method using the ARMA model to carry out future performance prediction in an elevator door system is presented in [136] while using logistic regression for performance assessment. Model-based prognosis methods for wheeled mobile robots are surveyed in [137]. An electronics prognostics method, which uses thermal data for modeling stress and damage in electronic parts and structures, is introduced in [138]. A methodology for prognosis of electronics which enables the assessment of exploited usage based on phase growth rate and an estimate of residual life has been demonstrated in [139]. A model-based PHM technique for avionics utilizing embedded life models and environmental information obtained from aircraft mounted sensors is presented in [140]. With the proliferation of battery applications in different industries, data-driven methods have been developed for the demand of battery health monitoring (BHM). These methods utilize voltage, current, temperature and other measurements [141], and employ Bayesian techniques, such as Particle Filters, to estimate battery RUL by incorporating the collected measurements with the system dynamics [142].

Some research activities concerning the architecture of prognostic systems have also been reported. Hess and Fila introduced issues such as levels of maintenance, inventory policies and supply chain management need to be tackled for advanced logistics infrastructure for PHM activity [143]. From 1998 to 2000, the US army logistics integration agency funded a project entitled “Prognostics Framework” [144]. The project aimed to provide an overall architecture to manage the information provided by individual prognostic techniques. This prognostics framework is generic, open architecture, horizontal technology, and customizable, and was integrated with embedded diagnostics to provide a “total health management” capability.

## 4. Improved PHM design using a systematic methodology

Besides the recognition that PHM is desirable and technically feasible, a number of success stories have already drawn credence and anticipation for this discipline. However, to make PHM more methodical and influential, there are still several key issues to be addressed.

(1) Most of the developed PHM approaches are application or equipment specific. A clear systematic way to design and implement PHM does not exist.
(2) Currently, many PHM methods are introduced and applied to solve specific problems without much explanation or documentation given as to how or why these methods have been selected.
(3) There is a lack of visualization tools for PHM information dissemination or decision making support.

### *4.1. Systematic PHM design and implementation—5S approach*

To conduct step-by-step design and deployment of a PHM system, 5S approach is adopted to convert multivariate data to abstract prognostics information, utilizing different computing tools for different steps [145]. 5S, as shown in Fig. 3 stands for Streamline, Smart Processing, Synchronize & See, Standardize, and Sustain.

The first “S”, Streamline, focuses on identifying critical components and prioritizing data to ensure the accuracy of the second “S”, which is Smart Processing. Identifying the critical components for which the prognostics should be performed is the first key step of smart processing by determining which components' degradation or failure has the most significant impact on a system in terms of performance and/or cost of downtime. In real world applications, data collected from multiple sensors are not necessarily in a readily usable form due to issues such as missing data, redundant data, noise or even sensor degradation problems. Therefore it is necessary to sort, filter and/or prioritize the raw data before processing it. Critical component identification will be further described in Section 4.2.

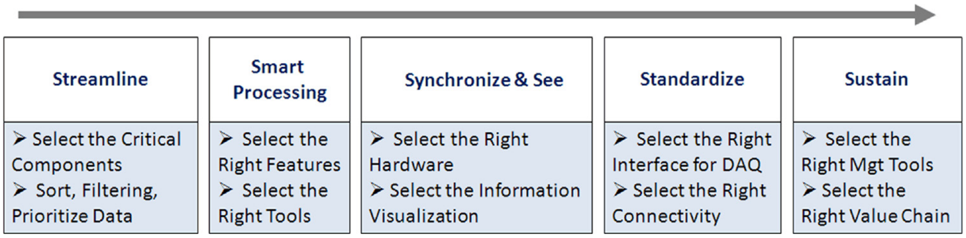



**Fig. 3.** 5S approach.

The second "S", Smart Processing, focuses on utilizing computing tools to convert data to information for different purposes, such as health degradation evaluation, performance trend prediction and potential failure diagnosis. Currently, most manufacturing, mining, farming, and service machines (e.g., elevators) are actually quite "smart" on their own; many sophisticated sensors and computerized components are capable of delivering data concerning status and performance. In many situations, a large amount of data is available, but it is often not known which prognostics technologies should be applied. A systematic methodology for the design of a PHM system should include a means of selecting and combining a set of data-to-information conversion tools to convert machine data into performance-related information to provide real-time health indicators/indices for decision makers to effectively understand the current performance and make maintenance decisions before potential failures occur. This would prevent waste in terms of time, spare parts and personnel, and ensures the maximum uptime of equipment, resulting in significant cost-savings. This tool selection method will be further described in Section 4.3.

Synchronize & See is the third "S" of the 5S methodology. It integrates the results of the first two S's (Streamline and Smart Processing) to enable the selection of the right hardware solutions and software platforms to most effectively facilitate data-to-information conversion and information transmission. Advanced technologies, such as embedded agents and tether-free communication, are considered to realize prognostics information transparency between manufacturing operations, maintenance practitioners, suppliers and customers. Prognostics information is demonstrated using information visualization tools. These tools allow decision makers to use decision support tools, based on the delivered information, to assess and predict the performance of machines in order to make the right maintenance decisions before failures can occur. Prognostics information can be further integrated into an enterprise asset management system, which can greatly improve productivity and asset utilization by providing a direct link between machine status and support availability. The selection of information visualization tools will be introduced in Section 4.4.

The fourth "S", Standardize, has great impacts for enterprises, especially in terms of deploying large scale information technology applications. The interface for acquiring prognostic information from the Synchronize & See stage and importing the information into enterprise business systems, such as supply chain management (SCM) and enterprise resource planning (ERP) systems, needs to be constructed. The implementation of those applications can benefit from a standardized open architecture, information sharing interface and plant operation flow, which brings cost-effective information integration between different systems that can aide in realizing the implementation of e-Manufacturing.

The fifth "S", Sustain, aims to technically enable a sustainable closed-loop product life-cycle. To accomplish this, management tools need to be selected and value chains need to be defined. Product information, such as product usage profiles, historical data, middle-of-life (MOL) and end-of-life (EOL) service data, can be provided as feedback to designers and life-cycle management systems.

### 4.2. *Critical component identification*

Identifying critical components is the first step in developing a PHM system. The goal of this procedure is to understand which components have the most significant impact on a system in terms of performance and/or cost of downtime. A powerful method for identifying critical components is to create a four quadrant chart as shown in Fig. 4 that displays the frequency of failure vs. the average downtime associated with failure for relevant components [146]. When the data is graphed in this way, the effectiveness of the current maintenance strategy can be seen. The horizontal and vertical lines that divide the graph to four quadrants are determined by user based on their demands on production and/or maintenance. The resulting quadrants are numbered 1–4 starting with the upper right and moving counter clockwise. Quadrant 1 contains the components that not only fail most frequently, but whose failure also results in extensive downtime. Typically, there should not be any components in this quadrant because such issues should have been noticed and fixed during the design stage. However, there could be instances in which a manufacturing defect in, or continued improper use of, a particular component could result in repetitive failures and significant downtime. Quadrant 2 contains components with a high frequency of failure, but a short length of downtime for each component. The maintenance recommendation for such components is to have an adequate number of spare parts on hand. Quadrant 3 contains components with a low frequency of failure and low average duration of downtime per failure, which means that the current maintenance practices are working for these components and no changes are required. In Quadrant 4 lie the most critical components as their failures, though infrequent, cause the most downtime per occurrence. For components such as these, prognostics should

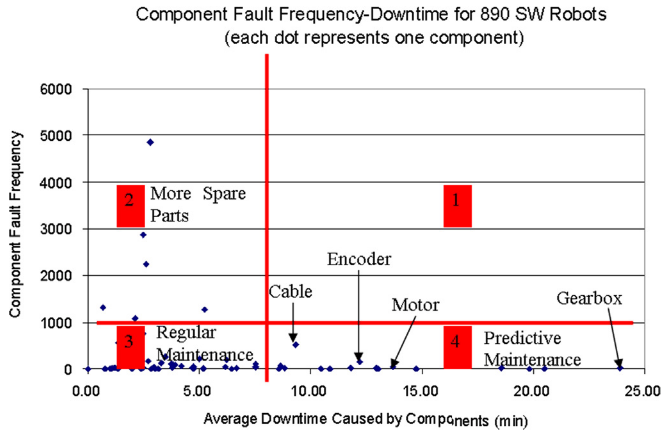



**Fig. 4.** Four quadrant chart for identifying critical components.

be employed. An example is shown in Fig. 4, which indicates, for this specific situation, that cable, encoder, motor and gearbox are critical components on which prognostics should be focused.

### 4.3. PHM tool selection method

In a systematic approach to apply prognostics and health management methodologies to traditional or novel areas, the analytical procedure mostly originates with processing of available data. Before certain algorithms are employed, it is necessary and beneficial to understand the characteristics of the data and possible causality between these characteristics, and the nature of the system in terms of the operating condition, service intensity, system dynamics and all other applicable attributes. No matter what type of data is available (vibration or acoustic emissions, environmental parameters, PLC, etc.), the ascertained data characteristics will be fundamental to subsequent steps in designing an effective methodology with the appropriate combination of algorithms, and to achieve solutions with dependable accuracy.

Some categories in the field of PHM are widely recognized and investigated including signal processing, feature extraction and reduction, fault diagnosis, health assessment, performance prediction and so on. Along with the continuous progress in these categories, numerous algorithms have been introduced, developed and benchmarked to process signals, classify them in a supervised or unsupervised manner, estimate the state of the object in question and predict future states for different prognostics purposes. These algorithms are studied in multiple disciplines and interdisciplinary areas. Some algorithms can be applicable to more than one category depending on the adaptability. Researchers usually have different algorithm preferences depending on the application and available infrastructure. Table 2 lists the most commonly used algorithms and gives a brief summary for each of them, including their applications, strengths and weaknesses in the field of PHM.

A crucial step for constructing an effective PHM system is to select the most appropriate algorithms, based on system properties, data characteristics and corresponding algorithm applicability, and eventually have confidence in the final outputs of algorithm selection. This can be performed in a heuristic way that relies on researchers' experience and expertise to meet users' requirement. However, such an approach is not best for situations in which there is a lack of expert knowledge, and could be extraordinarily time-consuming for complex problems or systems. In order to provide quantified selection criteria, enable automatic benchmarking, and recommend the appropriate tool(s) for an application, it is necessary to formulate a selection scheme that compares the suitability of each algorithm by taking into accounts not only the application attributes, but also the proficiency and unique requirements of the user. A feasible solution can be a numerical comparison based ranking of algorithm scores for each category so that the top algorithms can be selected.

Quality function deployment (QFD) [147] is a suitable ranking method for algorithm selection. QFD is best known as a tool for product design, quality management, customer need analysis and decision making purposes [148]. In traditional QFD, a House of Quality (HOQ) is constructed to combine engineering attributes and customer needs (and their assigned weights), and transform them into design specifications and controllable parameters. For algorithm selection, data characteristics, corresponding algorithm suitability and user inputs are integrated to give a ranking of all algorithm candidates in each category. The process of applying QFD for algorithm selection can be presented as follows. First, according to the application and available knowledge of the data, all criteria related to the application should be selected. Second, the properties of each criterion should be indentified in order to describe the available data in a detailed manner. These criteria do not have to be binary as long as ambiguity can be avoided, so users can classify the level of the characteristic specifically and therefore with high confidence. Furthermore, a quantified description is recommended in this step, for example, low, medium and high stationarity can be presented by ascending integers like 1, 3 and 5. Third, eligible algorithms for each characteristic are compared in a pair-wise way based on algorithm applicability. Analytical Hierarchy Process (AHP) [149], employed in this step, is a decision making tool which is able to compare every paired combination of

**Table 2**
Characteristics of commonly used algorithms.

| Algorithm | What is it used for? | Advantage | Disadvantage |
|---|---|---|---|
| Time Domain Analysis [150] | – Directly uses the waveform to compare different signals | – Immediately shows the difference of the signals | – Cannot provide enough information (e.g., frequency domain features) for further analysis |
| Fourier Transform [151] | – To represent a waveform in frequency domain<br>– Decomposes or separates the waveform into a sum of sinusoids of different frequencies | – Appropriate for stationary signals<br>– Presents signal with good spectrum resolution | – Lack of the temporal information<br>– Not appropriate for non-stationary signals |
| Short-time Fourier Transform (STFT)/ Wigner–Ville Distribution (WVD) [152,153] | – To represent signals with both time and frequency information simultaneously | – Provides both temporal and spectral information<br>– Present signal with picture-based information<br>– Appropriate for non-stationary signals | – High-load computation is needed<br>– Resolution is not scalable |
| Wavelet/Wavelet Packet Energies [154,155] | – To represent the time signals in terms of a finite length or fast decaying oscillating waveform which is scaled and translated to match the input signals | – Very powerful for non-stationary signal analysis<br>– Achieves better resolution than time–frequency analysis (scalable resolution) | – Not easy to determine the optimal parameters for the wavelet filter<br>– May compromise signal mathematical properties |
| Hilbert–Huang Transform (HHT) [156,157] | – To decompose complicated signals into a finite number of intrinsic mode functions (IMFs) within<br>– The time domain and to represent signals with time–frequency–energy distribution | – Adaptive and unsupervised method<br>– Useful for analyzing non-stationary, nonlinear signals | – An empirically based data analysis method with the difficulty of laying a firm theoretical foundation.<br>– High-load computation |
| Principal Component Analysis (PCA) [158,159] | – To reduce the dimensionality by transforming the original features into a new set of uncorrelated features | – Reduces multi-dimensional data sets to lower dimensional data sets | – Its performance varies for different applications<br>– Linear transformation |
| Fisher Linear Discriminant [160] | – To reduce the dimensionality by seeking a projection that best separates the data in a least-squares sense | – Reduces multi-dimensionality<br>– Keep the information that is efficient for discrimination | – Linear approach |
| Gaussian Mixture Model (GMM) [161] | – A type of density model which comprises a number of Gaussian functions which are combined to provide a multimodal density<br>– To fuse information | – Mixture of Gaussians can be utilized to approximate an arbitrary distribution within an arbitrary accuracy | – The optimization parameters are sensitive to the initialization methods<br>– Not easy to determine the number of mixtures |
| Logistic Regression (LR) [162,163] | – To find the best fitting model to describe the relationship between the input multiple variables and the output variable | – Especially appropriate when the output is constrained between 0 and 1 | – Not feasible unless normal feature domain description and unacceptable behavior are both available<br>– Not appropriate when the output is unbounded |
| Statistical Pattern Recognition (SPR) [164,165] | – A method to calculate the overlap between the current feature distribution and the normal mode | – Applicable when only normal feature domain description is available | – Not feasible when the feature distribution is not approximately Gaussian (normal distribution) |
| Gaussian Process Regression/Prediction [166] | – To fit models to data and recover underlying process form noisy observed data based on a particularly effective method for placing a prior distribution over the space of functions<br>– To perform prediction with Gaussian | – Can adapt to environments and learn from experience | – Need to determine covariance function<br>– Only suitable for Gaussian likelihood |

**Table 2** (*continued* )

| Algorithm | What is it used for? | Advantage | Disadvantage |
|---|---|---|---|
| | Processes | | |
| Particle Filter [167] | – Another Bayesian approach to obtain state estimation that represents the probability distribution function of the tracked state by sampling particles recursively | – Applicable for non-linear system and non-Gaussian noise<br>– Higher accuracy than other existing filtering algorithms<br>– Sequential importance sampling helps increase accuracy and avoid degeneracy | – Equations governing system dynamic and measurement model need to be defined<br>– Higher dimension system or more particles require too much computation cost |
| Kalman Filter [168,169] | – A Bayesian technique that estimates the state of a process and minimizes the covariance of the estimation by incorporating with measurement related to the state | – Able to estimate the current state and also predict the future state<br>– Corrects the estimate with latest measurement to maintain minimal state error covariance | – System model and measurement model need to be defined<br>– Noise levels in both models could affect the performance and stability of the algorithm<br>– Only works with linear system and Gaussian noise |
| Feature map pattern matching (Self-organizing Maps) [170,171] | - To represent multidimensional feature space in a low dimensional space while preserving the topological properties of the input space | – Unsupervised learning methods (no prior output is needed)<br>– Very good visualization capability | – Lack of standard algorithm to determine the structure and shape of the map |
| Bayesian Networks [172,173] | – A directed acyclic graph tool to present the structure of conditional interdependency relations and probability distributions between variables in one domain system | – Reduces number of parameters to learn a domain structure by marginalizing conditional probability distributions<br>– Visualizes the dependency links between each pair of variables | – Learning an unknown structure can be complex and costly<br>– Relies on certain amount of prior knowledge of the domain |
| Neural Network [174,175] | – A model that simulate the structures and functions of biological neural networks<br>– Can learn the knowledge by modeling complex relationships between inputs and outputs and find patterns in data | – For complex systems which involve non-linear behavior and unstable processes<br>– Adaptive system | – No standard method to determine the structure of the network<br>– Requires sufficient computational resources |
| Decision Trees [176] | – Make decision or classify data item by starting at the root node of tree and following the assertions down until reach a terminal node (leaf of tree)<br>– A special form of a rule set, characterized by hierarchical organization of rules | – Good visualization, easy interpretation and quick analysis ability for decision making | - Need high level experience and knowledge to formulate the tree structure |
| ARMA [177] | – Consists of two parts—the autoregressive (AR) part and the moving average (MA) part for modeling and predicting future values in a time series of data | – Applicable to linear time-invariant systems whose performance features display stationary behavior<br>– Utilizes a small amount of historical data | – Cannot provide good long term prediction<br>– Limited for non-stationary and dynamic processes |
| Fuzzy Logic [178,179] | – To represent and process uncertainty to make system complexity manageable.<br>– Tolerate uncertainty and can utilize language-like vagueness to offer robust, noise tolerant models or predictions where precise input in unavailable or too expensive | – Can deal with incomplete, nosy or imprecise data<br>– Helpful in developing uncertain models of data<br>– More compatible with human reasoning process than traditional symbolic approach<br>– Appropriate for complex/ unknown system | – Not feasible in the situation that membership functions are complicated to be determined<br>– Linguistic terms may compromise the accuracy of the model |
| Rough Sets [180,181] | – A formal framework for the automated transformation of data into knowledge.<br>– For rule induction, fault diagnosis and feature selection | – Useful for rule induction from incomplete data sets.<br>– Mathematically relatively simple<br>– No assumptions about the independence of the attributes are necessary nor is any background | – Cannot be applied to continuous values.<br>– Determination of thresholds may not be reliable |

**Table 2** (*continued* )

| Algorithm | What is it used for? | Advantage | Disadvantage |
|---|---|---|---|
| | | knowledge about the data | |
| Match Matrix [182] | – An enhanced ARMA model which utilizes the historic data from different operations for robust prediction | – Dealing with high dimensional feature space<br>– Provides better long term prediction than ARMA<br>– Feasible for non-stationary processes | – Not appropriate unless sufficient historical data from different operation cycles is available<br>– Historical data must contain degradation data |
| Support Vector Machine (SVM) [183,184] | – To project feature space into a higher dimensional space by a kernel function<br>– To find an optimized separation hyperplane in the projected space to maximize the decision boundary | – Achieves better decision accuracy in special cases because of the maximized decision boundary<br>– Efficient for large dataset and real-time analysis | – No standard method to choose the kernel function which is the key process for SVM |
| Hidden Markov Model (HMM) [185,186] | – A statistical model where the system being modeled is assumed to be a Markov process with unknown state space parameters | – Can be used for fault and degradation diagnosis on non-stationary signals and dynamic systems<br>– Appropriate for multi-failure modes | – Not appropriate when the failure state is observable<br>– Large amount of data is needed for accurate modelling |

algorithms and provide final applicability indices for all algorithms for each specific characteristic. In the fourth step, an HOQ can be established for each one of the algorithm categories to aggregate all the indices from the previous step for all characteristics in order to generate an overall weight, based on which a final rank of algorithms can be decided for this category. Therefore, a procedure can be established for the user to execute an effective, systematic PHM approach with the top ranked algorithms from each category.

Fig. 5 illustrates the QFD algorithm selection tool using the gears of a wind turbine as an example application. Rotary components of a wind turbine system such as rotor blades, bearings, shafts and gears are working under dynamic loads and are more susceptible to failure than other components. The aforementioned systematic methodology can be referenced to explore and develop fundamental techniques to aid in establishing a prognostics and health management system for wind turbines under varying environmental, operational and aging processes. In this case, only vibration data is available, and the applicability of each relevant algorithm is defined by assigning an importance to different characteristics using a scale ranging from 1 to 5 (5 being the most important). The rankings are structured so that in each catalog the algorithm with lowest ranking is the most recommended one. The tool selection for each of the other critical components can be performed in this fashion.

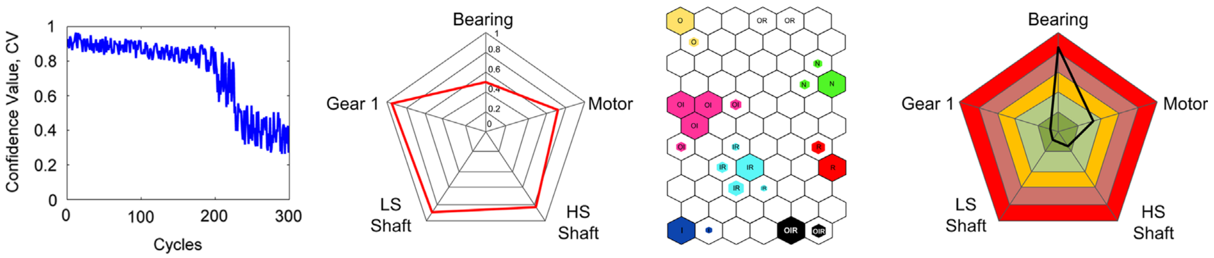
### 4.4. Visualization tools

After the selected algorithms have digested the data, prognostics information is ready for further utilization to support the decision making process. One valuable objective of PHM is to enable a support system to convey the right information to right person so that right decisions can be made at the right time. Therefore, visualization tools are essential part of a PHM methodology. Four frequently used visualization tools, Degradation Chart, Performance Radar Chart, Problem Map and Risk Radar Chart, can be designed to present prognostics information as shown in Fig. 6. The functionalities of the presented visualization tools are described as follows [146]:

- *Degradation Chart*—If the confidence value (0—unacceptable, 1—normal, between 0 and 1—degradation) of a component drops to a low level, a maintenance practitioner can track the historical confidence value curve to find the degradation trend. The confidence value curve shows the historical, current and predicted confidence value of the equipment. An alarm will be triggered when the confidence value drops under a preset threshold.
- *Performance Radar Chart*—A maintenance practitioner can look at this chart to get an overview of the performance status of each component. Each axis on the chart corresponds to the confidence value of a specific component.
- *Classification and Fault Map*—A Classification and Fault Map is used to determine the root causes of degradation or failure. This map classifies different failure modes of the monitored components by presenting different failure modes in clusters, each indicated by a different color.
- *Risk Chart*—A Risk Chart is a visualization tool for plant-level maintenance information management that displays risk values, indicating equipment maintenance priorities. The risk value of a machine (determined by the product of the

| Customer Requirements and Application Conditions | | Importance | Algorithms | Ranking | Catalog | Suggested Tools |
|---|---|---|---|---|---|---|
| **Available Signal** | Vibration | 5 | Fourier Transform Analysis | 4 | Signal Processing & Feature Extraction | **Wavelet Packet Decomposition** |
| | Acoustic Emission | 1 | STFT Analysis | 2 | | |
| | Oil Debris | 1 | Wavelet Packet Decomposition | 1 | | |
| **Working Condition** | Load Magnitude: Heavy | 3 | Autoregressive Modeling | 3 | | |
| | Load Magnitude: Light | 1 | Logistic Regression | 3 | Performance Assessment | **Statistical Pattern Recognition** |
| | Load: Constant | 1 | Feature Map | 2 | | |
| | Load: Variate | 5 | Statistical Pattern Recognition | 1 | | |
| | Speed: High | 3 | Hidden Markov Model | 5 | | |
| | Speed: Low | 1 | Particle Filter Performance Assessment | 4 | | |
| | Speed: Constant | 1 | Feature Map | 2 | Diagnostics | **Neural Network** |
| | Speed: Variate | 5 | Hidden Markov Model | 5 | | |
| **System Dynamic** | Stationary | 1 | Bayesian Belief Network | 4 | | |
| | Dynamic | 5 | Neural Network | 1 | | |
| | | | Support Vector Machine | 3 | | |
| **Historic Data & Expert Knowledge Availability** | Sufficient | 3 | Autoregressive Moving Average | 3 | Prognostics | **Elman Neural Network Prediction** |
| | Insufficient | 1 | Match Matrix Prediction | 2 | | |
| **Other Process Property** | Multi-stage | 1 | Fuzzy Logic Prediction | 4 | | |
| | Single-stage | 5 | Elman Neural Network Prediction | 1 | | |
| | High Frequency Signal | 1 | | | | |
| | Low Frequency Signal | 3 | | | | |

**Fig. 5.** Tool selection for wind turbine gear.




Degradation Chart    Performance Radar Chart    Classification and Fault Map    Risk Chart

**Fig. 6.** Four visualization tools for PHM.

degradation rate and the value of the corresponding cost function) indicates how important the machine is to the maintenance process. The higher the risk value, the higher the priority given to that piece of equipment for requiring maintenance.

## 5. Industrial case studies

A few case studies have been selected to illustrate above mentioned methodology and tools as follows.

### 5.1. Case study 1—alternator component health assessment

A vehicle alternator's overall function is to charge the vehicle battery as well as power the electrical auxiliaries; an alternator that is degraded or failed will ultimately result in the inability to use these additional auxiliaries and an increased potential for a dead battery and stalled car. Considering the importance of the alternator in the overall functioning of the vehicle and perhaps in particular for military vehicles for which mission success is dependent on the use of surveillance equipment or other features that require a properly functioning vehicle electrical system; knowledge of the health status of the alternator is useful information that can support logistical, tactical and maintenance planning efforts [187]. The vehicle alternator is essentially a rotating machine that generates a 3-phase alternating current that is rectified by a set of diodes in order to produce a DC current with low ripple content; the vehicle alternator shares many similarities with a generator, and to some degree electrical motors, and in turn some of the common health monitoring and prognostic techniques, as well as common failure modes, for motors and generators are applicable.

Considering the similarity between vehicle alternators, electric motors and generators, a general methodology for assessing the health of rotating electro-mechanical components was developed and demonstrated for an automotive alternator component. The approach, which is shown in Fig. 7, applied domain specific knowledge, along with processing the data and extracting features from the time domain signal, as well as the order spectrum, to train machine learning algorithms, such as statistical pattern recognition, logistic regression, or a self-organizing map to assess the health of the vehicle alternator. For this particular case study, three components of the alternator were monitored, the alternator bearings, stator windings and diodes, with respective features from the electrical or vibration signals that are correlated to the degradation of each of those components. The processing of the alternator tachometer signal and the vibration and electrical signals into the order spectrum provides a way to extract relevant information that is indicative of bearing, diode and stator health. Three health assessment algorithms were highlighted for this particular study with both the logistic regression method and the self-organizing map method performing quite well with the logistic regression technique having a type I and II error of 5% [188]. The overall framework utilized in this case could be extended to other applications, and assessing the component health over time is a pre-requisite for prognostics in which further work could look at developing a remaining useful life prediction technique for vehicle alternators.

### 5.2. Case study 2—airport chiller predictive maintenance

A chiller is a complicated system which contains many components such as a compressor, a condenser/evaporator, a water pump and others. Considering that the working load is subjected to change in different working conditions, the monitoring of overall health status of a chiller system is not a trivial task.

A systematic method called Fixed Cycle Features Test (FCFT) was employed to identify the incipient faults of the chiller before it completely shuts down. Instead of acquiring data $24 \times 7$, the chiller is run through several possible work conditions (e.g., 25%, 50%, 75% and 100% load) for 2 min every day and the overall health condition of different components will be assessed by comparing the readings acquired during these periods to the baseline.

The data acquisition system used in this project consisted of six accelerometers (IMI 623C01) installed on the housing of 6 bearings on the chiller. In addition, a National Instruments PXI-4472 was used to obtain data from the 6 accelerometers simultaneously. The data logging system also obtained data from the Johnson Controls Object-linking-and-embedding for Process Control (OPC) server of the chiller system through an Ethernet connection.

As the working load is subject to change, the proposed method focused on identifying system behaviors during the transient period between different working loads. Wavelet Packet Analysis (WPA) method was applied to extract

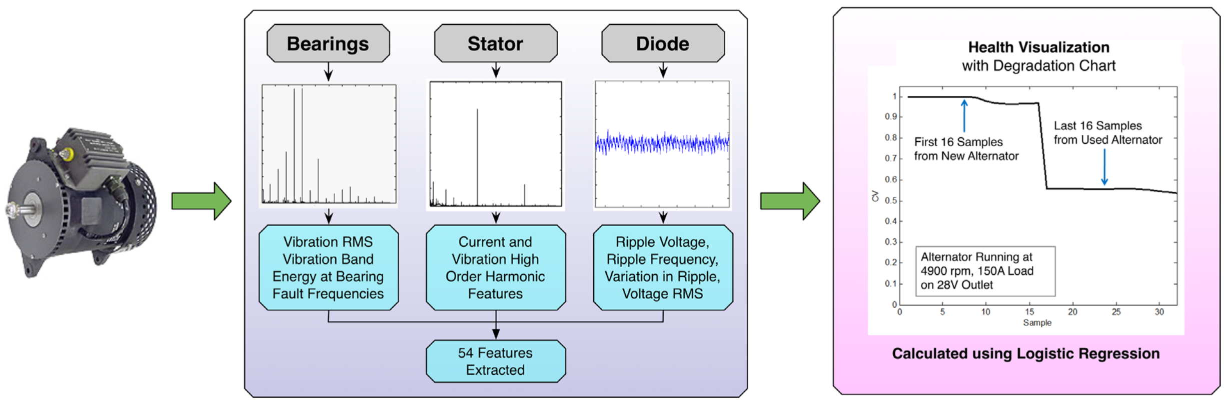



**Fig. 7.** Health assessment of alternator components.

component health related features from the non-stationery vibration data obtained during this transient period. Gaussian Mixture Model (GMM) was used as the health assessment model to calculate the confidence value (CV) of the different components of the chiller. The same method was also used to analyze the data obtained from the Johnson controller. Hence, a CV (using a 0–1 scale, 0 being unacceptable or faulty and 1 being normal) was derived from both acceleration data and OPC data were converted into 0–1 (0—unacceptable or faulty; 1—normal) information to indicate the health condition of the chiller components. Finally, a radar chart, as shown in Fig. 8, was generated to show the health condition of all the components, including the shaft, four bearings, the evaporator, the condenser, the compressor oil and the refrigerant circuit. A drop in confidence value was displayed close to the center of the radar chart, which indicated an unexpected fault was likely to happen. The method employed successfully detected the abnormal health condition of the chiller during validation. For more detailed information, please refer to [189].

### 5.3. Case study 3—spindle bearing health monitoring

Bearings are critical components in rotary machines; therefore the detection of incipient faults and the implementation of prognostics for bearings have been gaining importance in the literature. Bearing failures are subject to failure modes such as inner-race, out-race, and rotating element defects. A method which can differentiate a number of bearing degradation and failure patterns from the normal operating condition was designed in this case study.

For data taken for each failure mode, the vibrations can be treated as stationary signals since the machine is rotating at a constant speed with a constant load. A plot of the vibration data acquired while the machine is operating in a normal condition, as well as plots of seven different combinations of the failure modes identified, is shown in Fig. 9(a). The designed method includes two steps,

(1) Feature extraction using fast Fourier transform (FFT)—by using FFT, the time domain vibration data was transformed into a frequency spectrum. The energy in each of the sub-bands (centered at bearing defect frequencies such as Ball Passing Frequency Inner-race (BPFI), Ball Passing Frequency Outer-race (BPFO), Ball Spin Frequency (BSF) and Foundation Train Frequency (FTF)) was computed and passed on to the health assessment algorithm in next step.
(2) Health diagnosis using SOM—After training the SOM, a so called health map, as shown in Fig. 9(b), was obtained. The map showed eight areas which were labeled by 'N', 'RF', 'IF', 'OF', 'OR', 'OI', 'IR' and 'OIR,' indicating the normal status, roller defect, inner-race defect, outer-race defect, outer-race & roller defect, outer-race & inner-race defect, inner-race & roller-defect and outer-race & inner-race & roller defect, respectively. The input vector of a specific bearing defect was represented by the Best Matching Unit (BMU) on the map indicating by a "hit point". By looking at the area pointed by the "hit point", the failure mode of the bearing was determined. For more detailed information, please refer to [190].

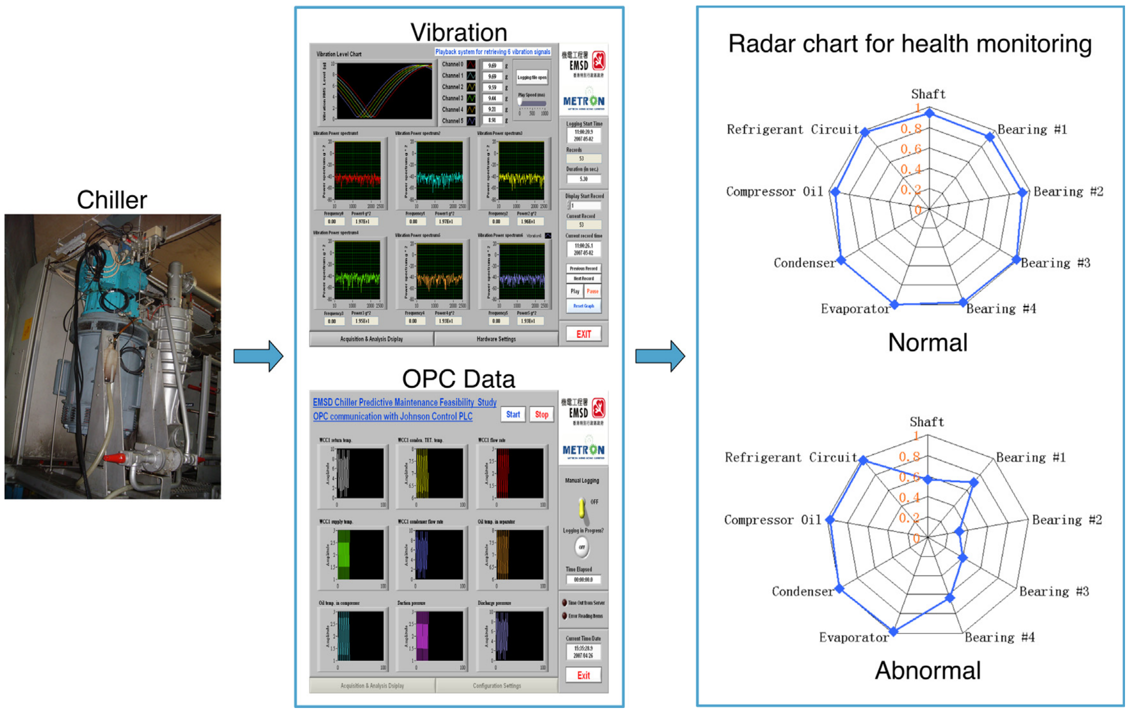



**Fig. 8.** Radar chart for chiller health monitoring in predictive maintenance.

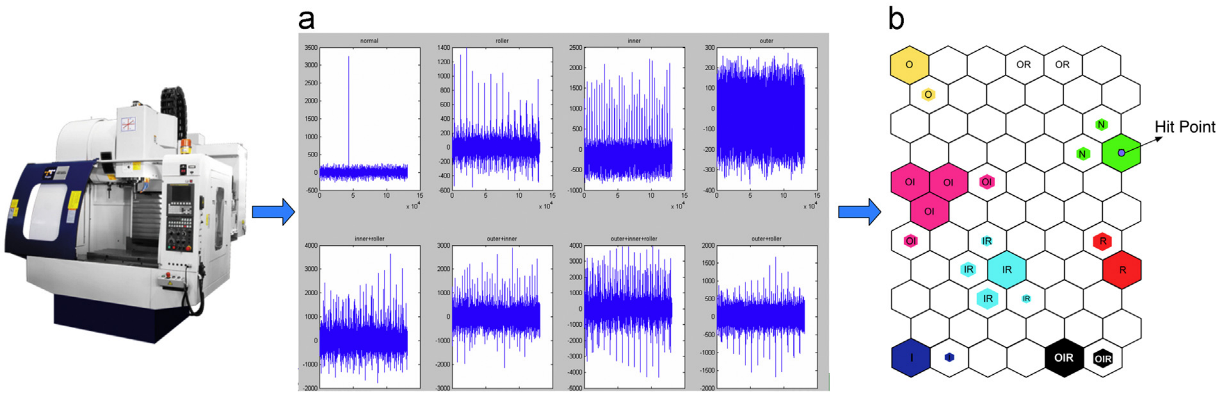



**Fig. 9.** (a) Vibration signals for bearing defects and (b) health map for different bearing failure modes.

### *5.4. Case study 4—engine risk management*

Engine risk management is critical for engine manufacturers to support their customers and for deciding several product life-cycle activities, including repair and maintenance scheduling. This will have a positive impact on the quality of their aftermarket services if the company is able to predict the types of failure that can happen on each machine, or is able to estimate the remaining life of the main components. For engine risk management, historical data related to a certain number of selected engines from customer sites were sampled from the company's database. This historical data includes condition-based operating data of engines and also engines replacement data available in a central knowledge database. Data acquisition was conducted by a remote monitoring system for heavy equipment. The data was observed and signals were collected by an on-board computer from sensors installed on the engine, transmission and the pump of each machine. The data consists of equipment characteristics identification data, operating data (engine on/off and physical variables), event data (failure and maintenance history) and environmental and condition data (location and payload history). Autoregression moving average model (ARMA) was used to estimate missing data during the pre-study and predict the evolution of the decision variables. Bayesian belief network was used to evaluate and predict the occurrence of a failure event based on information. Fuzzy logic enables fast decision making based on short term history data. Health information for all engines was processed locally on-board and sent back to the design center. For visualization of results, risk radar chart as shown in Fig. 10 was developed for maintenance information management that displays risk values, indicating equipment maintenance priorities [191].

## 6. Future trends of PHM

PHM is a generic way of dealing with a certain degree of system uncertainty and complexity. To further the discussion of Fig. 2 in Section 2.2, in situations in which system uncertainty and complexity further increase, self-maintenance abilities, resilient systems and engineering immune systems are necessary and should be developed, as shown in Fig. 11. Systems, with high uncertainty and are applicable to non-intrusive approaches only, require solutions that are more advanced than preventive maintenance in order to avoid untimely maintenance and non-optimal cost. Self-maintenance could be a suitable approach to this problem.

Self-maintenance refers to the ability to carry out regular quality and safety checking by machine itself, to detect anomaly, and to make immediate repairs when needed by using stocked spare parts to avoid potential catastrophic loss. Based on the PHM functions such as current health assessment and RUL prediction, self-maintenance will be achievable. High complexity and dynamic are noticeable challenges for current PHM techniques. Resilient system could be the solution to this situation.

Resilient systems can manage functions across multiple possible states, resist different types of disorder and gradually return to the equilibrium state. Compared with the concept of robustness of a system which mainly refers to a static behavior of the system, resilience means the system is capable to dynamically survive different unforeseen impacts and adaptive to disturbance to reach a new stable status at a steady rate. Resilience is one of many qualities to be integrated into future system with the support of advanced PHM techniques.

Beyond self-maintenance and resilient system, engineering immune system (EIS) will be the next-generation PHM. EIS is an analogy of the biological immune system which protects against invasion and infection by identifying and killing the pathogens. It can address the machine maintenance issues in highly complex and uncertain environment. The goal of having an EIS is to achieve efficient near-zero breakdown performance with minimal human intervention. EIS should be robust in diverse and dynamic environment, adaptive to learn and respond to new infections, adaptive to retain memory to facilitate future responses, and autonomous for self-controlled ability with no requirement of external control. Currently, artificial immune system has already been developed to enable computing system to manage itself and adjust to accommodate

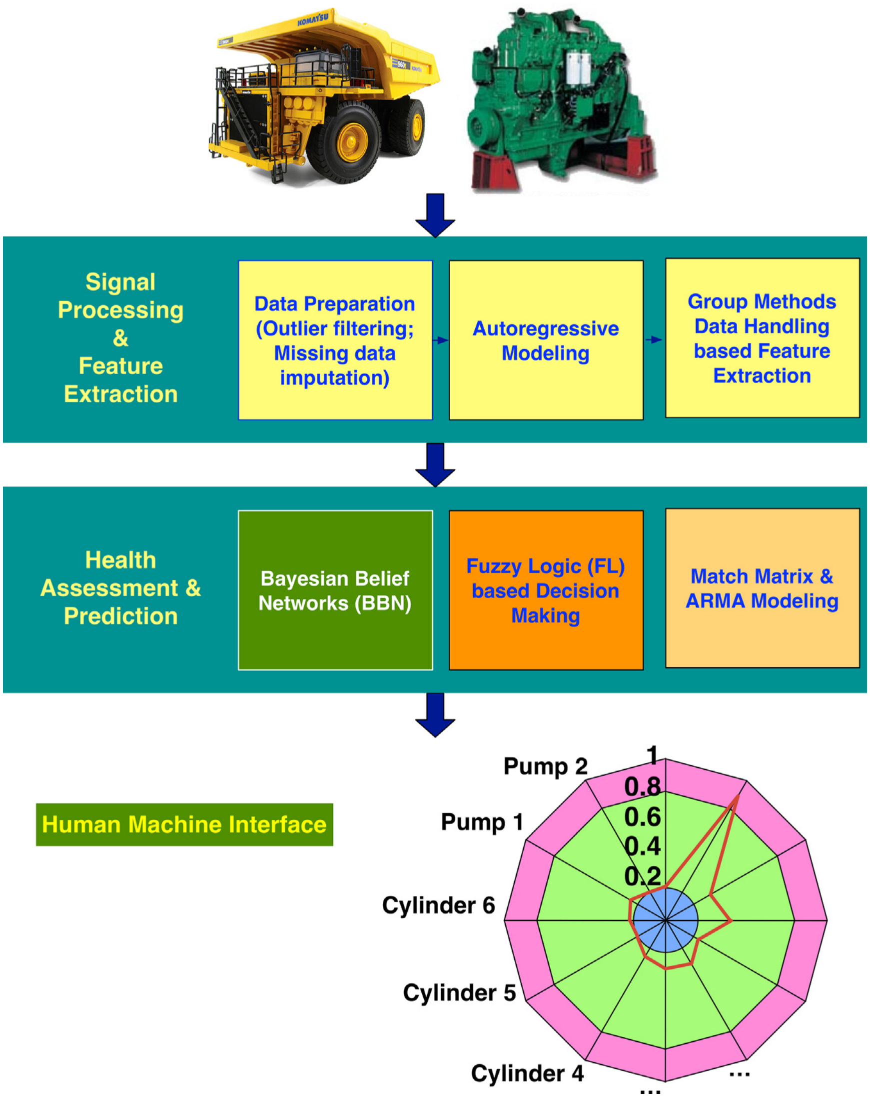



**Fig. 10.** Engine risk management system.

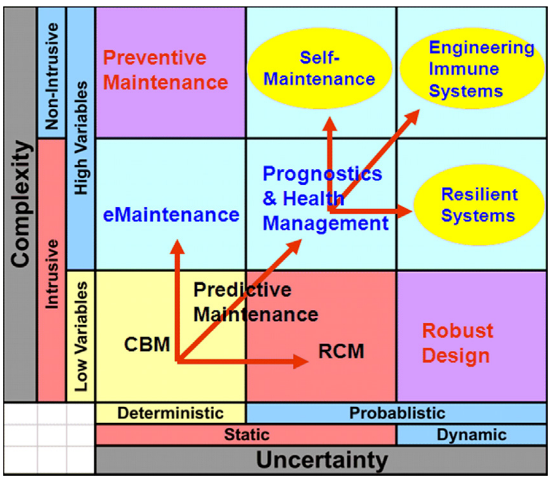



**Fig. 11.** PHM transformation and future trends.

varying circumstances with minimized interference from human operator. To improve the prognostics performance of the rotary machinery system, further development of EIS is essential.

## References

[1] A. Mathur, K.F. Cavanaugh, K.R. Pattipati, P.K. Willett, T.R. Galie, Reasoning and modeling systems in diagnosis and prognosis, in: Proceedings of SPIE—The International Society for Optical Engineering, Orlando, FL, USA, vol. 4389 (2001) pp. 194–203.
[2] A. Hess, Prognostics, from the need to reality—from the fleet users and PHM system designer/developers perspectives, in: Proceedings of the IEEE Aerospace Conference, Big Sky, MT, USA, vol. 6 (2002) pp. 2791–2797.
[3] 〈http://www.phmsociety.org/sites/phmsociety.org/files/Luminary_Engel_PHM09.pdf〉.
[4] 〈http://www.phmsociety.org/sites/phmsociety.org/files/Luminary_Johnson_PHM09.pdf〉.
[5] 〈http://www.phmsociety.org/sites/phmsociety.org/files/Luminary_Stewart_PHM09.pdf〉.
[6] 〈http://www.phmsociety.org/sites/phmsociety.org/files/Luminary_Nickelsburg_PHM09.pdf〉.
[7] A. Abu-Hanna, P.J.F. Lucas, Prognostic models in medicine—AI and statistical approaches, Methods of Information in Medicine 40 (2001) 1–5.
[8] R.C. Kemerait, New cepstral approach for prognostic maintenance of cycle machinery, in: Proceedings of the IEEE Southeast Conference (1987) pp. 256–262.
[9] C. Fisher, N.C. Baines, Multi-sensor condition monitoring systems for gas turbines, Journal of Condition Monitoring 1 (1988) 57–68.
[10] D. Muir, B. Taylor, Oil debris monitoring for aeroderivative gas turbine, ASME Power Division (Publication) PWR 32 (1997) 547–553.
[11] C.S. Byington, M.J. Watson, J.S. Sheldon, G.M. Swerdon, Shaft coupling model-based prognostics enhanced by vibration diagnostics, Insight: Non-Destructive Testing and Condition Monitoring 51 (2009) 420–425.
[12] R. Orsagh, M. Roemer, J. Sheldon, A comprehensive prognostics approach for predicting gas turbine engine bearing life, in: Proceedings of ASME Turbo Expo, Vienna, Austria, vol. 2, 2004, pp. 777–785.
[13] C.K. Tan, P. Irving, D. Mba, A comparative experimental study on the diagnostic and prognostic capabilities of acoustics emission, vibration and spectrometric oil analysis for spur gears, Mechanical Systems and Signal Processing 21 (2007) 208–233.
[14] M.J. Roemer, G.J. Kacprzynski, R.F. Orsagh, Assessment of data and knowledge fusion strategies for prognostics and health management, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2001) pp. 62979–62988.
[15] R.J. Hansen, D.L. Hall, S.K. Kurtz, New approach to the challenge of machinery prognostics, Journal of Engineering for Gas Turbines and Power 117 (1995) 320–325.
[16] K.M. Reichard, M.V. Dyke, K. Maynard, Application of sensor fusion and signal classification techniques in a distributed machinery condition monitoring system, in: Proceedings of SPIE—The International Society for Optical Engineering, Orlando, FL, USA, vol. 4051 (2000) pp. 329–336.
[17] E.C. Crow, K. Reichard, C. Rogan, J. Callen, E. Seifert, Integrated Multi-Sensor Package (IMSP) for unmanned vehicle operations, in: Proceedings of SPIE—The International Society for Optical Engineering, Florence, Italy, vol. 6736 (2007).
[18] P.D. McFadden, M.M. Toozhy, Application of synchronous averaging to vibration monitoring of rolling element bearings, Mechanical Systems and Signal Processing 14 (2000) 891–906.
[19] C.K. Mechefske, J. Mathew, Fault detection and diagnosis in low speed rolling element bearings Part I: the use of parametric spectra, Mechanical Systems and Signal Processing 6 (1992) 297–307.
[20] R.B. Randall, Applications of spectral kurtosis in machine diagnostics and prognostics, Key Engineering Materials 293–294 (2005) 21–32.
[21] H. Qiu, J. Lee, J. Lin, G. Yu, Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics, Journal of Sound and Vibration 289 (2006) 1066–1090.
[22] Y. Lei, Z. He, Y. Zi, Q. Hu, Fault diagnosis of rotating machinery based on multiple ANFIS combination with GAs, Mechanical Systems and Signal Processing 21 (2007) 2280–2294.
[23] D.-M. Yang, A.F. Stronach, P. Macconnell, J. Penman, Third-order spectral techniques for the diagnosis of motor bearing condition using artificial neural networks, Mechanical Systems and Signal Processing 16 (2002) 391–411.
[24] G. Wang, Z. Luo, X. Qin, Y. Leng, T. Wang, Fault identification and classification of rolling element bearing based on time-varying autoregressive spectrum, Mechanical Systems and Signal Processing 22 (2008) 934–947.
[25] D. Yu, J. Cheng, Y. Yang, Application of EMD method and Hilbert spectrum to the fault diagnosis of roller bearings, Mechanical Systems and Signal Processing 19 (2005) 259–270.
[26] P. Chen, M. Taniguchi, T. Toyota, Z. He, Fault diagnosis method for machinery in unsteady operating condition by instantaneous power spectrum and genetic programming, Mechanical Systems and Signal Processing 19 (2005) 175–194.
[27] V.K. Rai, A.R. Mohanty, Bearing fault diagnosis using FFT of intrinsic mode functions in Hilbert–Huang transform, Mechanical Systems and Signal Processing 21 (2007) 2607–2615.
[28] R. Huang, L. Xi, X. Li, C.R. Liu, H. Qiu, J. Lee, Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods, Mechanical Systems and Signal Processing 21 (2007) 193–207.
[29] R.C.M. Yam, P.W. Tse, L. Li, P. Tu, Intelligent predictive decision support system for condition-based maintenance, International Journal of Advanced Manufacturing Technology 17 (2001) 383–391.
[30] P. Wang, G. Vachtsevanos, Fault prognostics using dynamic wavelet neural networks, Artificial Intelligence for Engineering Design, Analysis and Manufacturing 15 (2001) 349–365.
[31] H. Ocak, K.A. Loparo, F.M. Discenzo, Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: a method for bearing prognostics, Journal of Sound and Vibration 32 (2007) 951–961.
[32] B. Satish, N.D.R. Sarma, A Fuzzy BP approach for diagnosis and prognosis of bearing faults in induction motors, in: Proceedings of the IEEE Power Engineering Society General Meeting, vol. 3 (2005) pp. 2291–2294.
[33] J. Yang, Y. Zhang, Y. Zhu, Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension, Mechanical Systems and Signal Processing 21 (2007) 2012–2024.
[34] F.-Z. Feng, D.-D. Zhu, P.-C. Jiang, H. JIang, GA-SVR based bearing condition degradation prediction, Key Engineering Materials 413–414 (2009) 431–437.
[35] Z. Li, Z. He, Y. Zi, H. Jiang, Rotating machinery fault diagnosis using signal-adapted lifting scheme, Mechanical Systems and Signal Processing 22 (2008) 542–556.
[36] W.-Y. Ling, M.-P. Jia, F.-Y. Xu, J.-Z. Hu, B.-L. Zhong, Optimizing strategy on rough set neural network fault diagnosis system, Proceedings of the Chinese Society of Electrical Engineering 5 (2003) 98–102.
[37] F.A. Galati, B.D. Forrester, S. Dey, Application of the generalised likelihood ratio algorithm to the detection of a bearing fault in a helicopter transmission, Australian Journal of Mechanical Engineering 5 (2008) 169–175.
[38] W. Wang, A model to predict the residual life of rolling element bearings given monitored condition information to date, IMA Journal of Management Mathematics 13 (2002) 3–16.
[39] Y. Li, T.R. Kurfess, S.Y. Liang, Stochastic prognostics for rolling element bearings, Mechanical Systems and Signal Processing 14 (2000) 747–762.
[40] X. Zhang, C.K.R. Xu, S.Y. Liang, Q. Xie, L. Haynes, An integrated approach to bearing fault diagnostics and prognostics, in: Proceedings of the American Control Conference, vol. 4 (2005) pp. 2750–2755.
[41] F. Choy, V. Polyshchuk, J. Zakrajsek, R. Handschuh, D. Townsend, Analysis of the effects of surface pitting and wear on the vibration of a gear transmission system, Tribology International 29 (1996) 77–83.

[42] C. Kar, A. Mohanty, Technical note: gearbox health monitoring through multiresolution Fourier transform of vibration and current signals, Structure Health Monitoring 5 (2006) 195–200.
[43] W. Bartelmus, R. Zimroz, Vibration condition monitoring of planetary gearbox under varying external load, Mechanical Systems and Signal Processing 23 (2009) 246–257.
[44] Z. Peng, F. Chu, Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography, Mechanical Systems and Signal Processing 18 (2004) 199–221.
[45] J.H. Suh, S.R.T. Kumara, S.P. Mysore, Machinery fault diagnosis and prognosis: application of advanced signal processing techniques, CIRP Annals—Manufacturing Technology 48 (1999) 317–320.
[46] S. Loutridis, Damage detection in gear systems using empirical mode decomposition, Engineering Structures 26 (2004) 1833–1841.
[47] J.-Z. Wang, G.-H. Zhou, X.-S. Zhao, L. S.-X., Gearbox fault diagnosis and prediction based on empirical mode decomposition scheme, in: Proceedings of the Sixth International Conference on Machine Learning and Cybernetics, art. no. 4370302 (2007) pp. 1072–1075.
[48] B. Liu, S. Riemenschneider, Y. Xu, Gearbox fault diagnosis using empirical mode decomposition and Hilbert spectrum, Mechanical Systems and Signal Processing 20 (2006) 718–734.
[49] H. Li, Y. Zhang, H. Zheng, Wear detection in gear system using Hilbert–Huang transform, Journal of Mechanical Science and Technology 20 (2006) 1781–1789.
[50] D. Bri, M. Tomczak, H. Oehlmann, A. Richard, Gear crack detection by adaptive amplitude and phase demodulation, Mechanical Systems and Signal Processing 11 (1997) 149–167.
[51] M. Dellomo, Helicopter gearbox fault detection: a neural network based approach, Journal of Vibration and Acoustics 121 (1999) 265–272.
[52] W. Staszewski, K. Worden, Classification of faults in gearboxes—preprocessing algorithms and neural networks, Neural Computing and Applications 5 (1997) 160–183.
[53] C.S. Byington, M. Watson, D. Edwards, Data-driven neural network methodology to remaining life predictions for aircraft actuator components, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2004) pp. 3581–3589.
[54] T. Khawaja, G. Vachtsevanos, B. Wu, Reasoning about uncertainty in prognosis: a confidence prediction neural network approach, in: Proceedings of the Annual Conference of the North American Fuzzy Information Processing Society, art. no. 1548498 (2005) pp. 7–12.
[55] P. Dempsey, A. Afjeh, Integrating oil debris and vibration gear damage detection technologies using fuzzy logic, Journal of American Helicopter Society 49 (2004) 109–116.
[56] W. Wang, M. Golnaraghi, F. Ismail, Prognosis of machine health condition using neuro-fuzzy systems, Mechanical Systems and Signal Processing 18 (4) (2004) 813–831.
[57] K. Al-Balushi, B. Samanta, Gear fault diagnosis using energy-based features of acoustic emission signals, Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering 216 (2002) 249–263.
[58] J. Wu, C. Huang, R. Huang, An application of a recursive Kalman filtering algorithm in a rotating machinery fault diagnosis, NDT&E International 37 (2004) 411–419.
[59] Y. Zhan, V. Makis, A. Jardine, Adaptive state detection of gearboxes under varying load conditions based on parametric modeling, Mechanical Systems and Signal Processing 20 (2006) 188–221.
[60] R. Houser, J. Sorensen, J. Harianto, H. Wijaya, M. Satyanarayana, Comparison of analytical predictions with dynamic noise and vibration measurements for a simple idler gearbox, VDI Berichte 2 (2002) 995–1002.
[61] B. Samata, Gear fault detection using artificial neural networks and support vector machines with genetic algorithms, Mechanical Systems and Signal Processing 18 (2004) 625–644.
[62] W. Wang, A. Wang, Autoregressive model-based gear fault diagnosis, Journal of Vibration and Acoustics 124 (2002) 172–179.
[63] Z. Chen, Y. Yang, Z. Hu, G. Shen, Detecting and predicting early faults of complex rotating machinery based on cyclostationary time series model, Journal of Vibration and Acoustics 128 (2006) 666–671.
[64] M.E. Orchard, G.J. Vachtsevanos, A particle-filtering approach for on-line fault diagnosis and failure prognosis, Transactions of the Institute of Measurement and Control 31 (2009) 221–246.
[65] L.S. Andres, J.C. Rivadeneira, K. Gjika, C. Groves, G. LaRue, A virtual tool for prediction of turbocharger nonlinear dynamic response: validation against test data, Journal of Engineering for Gas Turbines and Power 129 (2007) 1035–1046.
[66] L. Gao, J. Zhang, L. Cui, Q. Ding, Research on fault diagnosis technology of low speed and heavy duty equipments based on wavelet analysis, Chinese Journal of Mechanical Engineering 41 (2005) 222–227.
[67] B.S. Kim, S.H. Lee, M.G. Lee, J. Ni, J.Y. Song, C.W. Lee, A comparative study on damage detection in speed-up and coast-down process of grinding spindle-typed rotor-bearing system, Journal of Materials Processing Technology 187–188 (2007) 30–36.
[68] W. Yang, P.J. Tavner, Empirical mode decomposition, an adaptive approach for interpreting shaft vibratory signals of large rotating machinery, Journal of Sound and Vibration 321 (2009) 1144–1170.
[69] F. Wu, L. Qu, Diagnosis of subharmonic faults of large rotating machinery based on EMD, Mechanical Systems and Signal Processing 23 (2009) 467–475.
[70] D.B. Stringer, P.N. Sheth, P.E. Allaire, Gear modeling methodologies for advancing prognostic capabilities in rotary-wing transmission systems, Annual Forum Proceedings—AHS International 2 (2008) 1492–1504.
[71] C.M. Stoisser, S. Audebert, A comprehensive theoretical, numerical and experimental approach for crack detection in power plant rotating machinery, Mechanical Systems and Signal Processing 22 (2008) 818–844.
[72] A.C. McCormick, A. Nandi, Neural network autoregressive modeling of vibrations for condition monitoring of rotating shafts, in: Proceedings of the IEEE International Conference on Neural Networks, vol. 4 (1997) pp. 2214–2218.
[73] T. Sahraoui, S. Guessasma, N.E. Fenineche, G. Montavon, C. Coddet, Friction and wear behaviour prediction of HVOF coatings and electroplated hard chromium using neural computation, Material Letters 58 (2004) 654–660.
[74] S. Vijayakumar, S. Muthukumar, Artificial neural network prediction and quantification of damage in impeller shaft using finite element simulation, International Journal of COMADEM 9 (2006) 23–29.
[75] M.A. Jarrah, A.R. Al-Ali, Web-based monitoring and fault diagnostics of machinery, in: Proceedings of the IEEE International Conference on Mechatronics (2004) pp. 525–530.
[76] Omitaomu, Jeong, Badiru, Hines, On-line prediction of motor shaft misalignment using fast Fourier transform generated spectra data and support vector regression, Journal of Manufacturing Science and Engineering 128 (4) (2006) 1019–1024.
[77] H.-W. Cho, Multivariate calibration for machine health monitoring: kernel partial least squares combined with variable selection, International Journal of Advanced Manufacturing Technology 48 (2009) 691–699.
[78] Y. He, Detection and configuration of the shaft crack in a rotor-bearing system by genetic algorithms, Key Engineering Materials 204–205 (2001) 221–230.
[79] X. Wang, V. Makis, Autoregressive model-based gear shaft fault diagnosis using the Kolmogorov–Smirnov test, Journal of Sound and Vibration 327 (2009) 413–423.
[80] B.K. Sinha, Trend prediction from steam turbine responses of vibration and eccentricity, Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy 216 (2002) 97–104.
[81] T.-W. Ha, Y.-B. Lee, C.-H. Kim, Leakage and rotordynamic analysis of a high pressure floating ring seal in the turbo pump unit of a liquid rocket engine, Tribology International 35 (2002) 153–161.
[82] M.R. Hodkiewicz, J. Pan, Identification of transient axial vibration on double-suction pumps during partial flow operation, Acoustics Australia 32 (2004) 25–32.

[83] Q. Du, K. Zhang, Condition monitoring and fault diagnosis of hydraulic pump based on inherent vibration signals, Transactions of the Chinese Society of Agricultural Engineering 23 (2007) 120–123.
[84] Y. Terao, S. Wada, Time–frequency analysis of driving sound and application to electric machinery diagnosis, in: Proceedings of the International Conference on Signal Processing, vol. 1 (2004) pp. 203–206.
[85] H.-R. Li, B.-H. Xu, Fault prognosis of hydraulic pump in the missile launcher, Acta Armamentarii 30 (2009) 900–906.
[86] W. Jiang, S.K. Spurgeon, J.A. Twiddle, F.S. Schlindwein, Y. Feng, S. Thanagasundram, A wavelet cluster-based band-pass filtering and envelope demodulation approach with application to fault diagnosis in a dry vacuum pump, Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science 221 (2007) 1279–1286.
[87] E. Liang, R.J. Rodriguez, A.A. Husseiny, Prognostics/diagnostics of mechanical equipment by neural network, Neural Networks 1 (1988) 33.
[88] M. Gibiec, Prediction of machines health with application of an intelligent approach—a mining machinery case study, Key Engineering Materials 293–294 (2005) 661–668.
[89] T. Engin, Prediction of relative efficiency reduction of centrifugal slurry pumps: empirical- and artificial-neural network-based methods, Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy 221 (2007) 41–50.
[90] A. Sozen, E. Arcaklioglu, A. Erisen, M.A. Akçayol, Performance prediction of a vapour-compression heat-pump, Applied Energy 79 (2004) 327–344.
[91] S. Perovic, P.J. Unsworth, E.H. Higham, Fuzzy logic system to detect pump faults from motor current spectra, in: Conference Record—IAS Annual Meeting, vol. 1 (2001) pp. 274–280.
[92] H. Esen, M. Inalli, A. Sengur, M. Esen, Modelling a ground-coupled heat pump system using adaptive neuro-fuzzy inference systems, International Journal of Refrigeration 31 (2008) 65–74.
[93] J.R. Li, L.P. Khoo, S.B. Tor, RMINE: a rough set based data mining prototype for the reasoning of incomplete data in condition-based fault diagnosis, Journal of Intelligent Manufacturing 17 (2006) 163–176.
[94] Y. Chen, L. Lan, A fault detection technique for air-source heat pump water chiller/heaters, Energy and Buildings 41 (2009) 881–887.
[95] J. Sottile, F. Trutt, A. Leedy, Condition monitoring of brushless three-phase synchronous generators with stator winding or rotor circuit deterioration, IEEE Transactions on Industry Applications 42 (2006) 1209–1215.
[96] F. Wan, Q. Xu, S. Li, Vibration analysis of cracked rotor sliding bearing system with rotor–stator rubbing by harmonic wavelet transform, Journal of Sound and Vibration 271 (2004) 507–518.
[97] Z. Wang, H. Jiang, Robust incipient fault diagnosis methods for enhanced aircraft engine rotor prognostics, in: Proceedings of the Second International Conference on Innovative Computing, Information and Control, art. no. 4428097 (2007) pp. 455–458.
[98] W.G. Zanardelli, E.G. Strangas, S. Aviyente, Failure prognosis for permanent magnet AC drives based on wavelet analysis, in: Proceedings of the IEEE International Conference on Electric Machines and Drives, art. no. 1531320 (2005) pp. 64–70.
[99] H. Xie, G. Wen, Long-term vibration trend prediction of rotor system state based on support vector regression and Discrete Wavelet Decomposition, in: Proceedings of the 2009 International Workshop on Intelligent Systems and Applications, art. no. 5072946 (2009) pp. 1–4.
[100] Z. Liu, X. Yin, Z. Zhang, D. Chen, W. Chen, Online rotor mixed fault diagnosis way based on spectrum analysis of instantaneous power in squirrel cage induction motors, IEEE Transactions on Energy Conversion 19 (2004) 485–490.
[101] L. Wang, P. Ye, J. Wang, S. Yang, Bispectrum characteristics of the faults of rubbing rotor system based on experimental study, Journal of Vibration Engineering 15 (2002) 339–344.
[102] T. Chow, G. Fei, Three phase induction machines asymmetrical faults indentification using bispectrum, IEEE Transactions on Energy Conversion 10 (1995) 688–693.
[103] M.E.H. Benbouzid, M. Vieira, C. Theys, Induction motors' faults detection and localization using stator current advanced signal processing techniques, IEEE Transactions on Power Electronics 14 (1999) 14–22.
[104] X. Hou, Z. Wu, L. Xia, Method for detecting rotor faults in asynchronous motors based on the square of the Park's vector modulus, Proceedings of the Chinese Society of Electrical Engineering 23 (2003) 137–140.
[105] R. Schoen, B. Lin, T. Habetler, J. Schlag, S. Farag, An unsupervised, on-line system for induction motor fault detection using stator current monitoring, IEEE Transactions on Industry Applications 31 (1995) 1280–1286.
[106] R.J. Bankert, V.K. Singh, H. Rajiya, Model based diagnostics and prognosis system for rotating machinery, American Society of Mechanical Engineers GT-252 (1995) 5.
[107] J. Penman, C. Yin, Feasibility of using unsupervised learning, artificial neural networks for the condition monitoring of electrical machines, IEEE Proceedings: Electric Power Applications 141 (1994) 317–322.
[108] F. Filippetti, G. Franceschini, C. Tassoni, Neural networks aided on-line diagnostics of induction motor–rotor faults, IEEE Transactions on Industry Applications 31 (1995) 892–899.
[109] C.S. Byington, M. Watson, D. Edwards, Dynamic signal analysis and neural network modeling for life prediction of flight control actuators, Annual Forum Proceedings—American Helicopter Society 1 (2004) 928–937.
[110] X. Wu, Y. Li, T.D. Lundell, A.K. Guru, Integrated prognosis of AC servo motor driven linear actuator using hidden semi-Markov models, in: Proceedings of the IEEE International Electric Machines and Drives Conference (2009) pp. 1408–1413.
[111] R.J.B. Sepe, J.M. Miller, A.R. Gale, Intelligent efficiency mapping of a hybrid electric vehicle starter/alternator using fuzzy logic, in: Proceedings of the AIAA/IEEE Digital Avionics Systems Conference, vol. 2 (1999) pp. 8.
[112] P. Vas, AI-based Electrical Machines and Drives: Application of Fuzzy, Neural, Fuzzy-Neural, and Genetic-Algorithm-Based Techniques, Oxford University Press, New York, 1999.
[113] F. Filippetti, G. Franceschini, C. Tassoni, P. Vas, Recent developments of induction motor drives fault diagnosis using AI techniques, IEEE Transactions on Industrial Electronics 47 (2000) 994–1004.
[114] N. Arthur, J. Penman, Induction machine condition monitoring with higher order spectra, IEEE Transactions on Industrial Electronics 47 (2000) 1031–1041.
[115] H. Nejjari, M. Benbouzid, Monitoring and diagnosis of induction motors electrical faults using a current Park's vector pattern learning approach, IEEE Transactions on Industry Applications 36 (2000) 730–735.
[116] B. Yang, S. Jeong, Y. Oh, A. Tan, Case-based reasoning system with Petri nets for induction motor fault diagnosis, Expert Systems with Applications 27 (2004) 301–311.
[117] S.K. Yang, An experiment of state estimation for predictive maintenance using Kalman filter on a DC motor, Reliability Engineering and System Safety 75 (2002) 103–111.
[118] J. Luo, N. Madhavi, K.R. Pattipati, L. Qiao, M. Kawamoto, S. Chigusa, Model-based prognostic techniques, in: Proceedings of the IEEE AUTOTESTCON (2003) pp. 330–340.
[119] K.T. McClintic, Feature prediction and tracking for monitoring the condition of complex mechanical systems (Ph.D. Thesis), The Pennsylvania State University, University Park, PA, USA, December 1998.
[120] R.J. Ferlez, D.C. Lang, Gear-tooth fault detection and tracking using the wavelet transform, in: Proceedings of the 52nd Meeting of the MFPT Society (1998).
[121] K.P. Maynard, Interstitial processing: the application of noise processing to gear fault detection, in: Proceedings of the International Conference on Condition Monitoring, University of Wales Swansea (1999) pp. 77–86.
[122] D.C. Swanson, A general prognostic tracking algorithm for predictive maintenance, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2001) pp. 62971–62977.
[123] D.C. Swanson, J.M. Spencer, S.H. Arzoumanian, Prognostic modelling of crack growth in a tensioned steel band, Mechanical Systems and Signal Processing 14 (2000) 789–803.

[124] E. Liang, R.J. Rodriguez, A.A. Husseiny, Prognostics/diagnostics of mechanical equipment by neural network, Neural Networks 1 (1988) 33.
[125] J.B. Eugene Parker, T.M. Nigro, M.P. Carley, R.L. Barron, D.G. Ward, H.V. Poor, D. Rock, T.A. DuBois, Helicopter gearbox diagnostics and prognostics using vibration signature analysis, in: Proceedings of the SPIE—The International Society for Optical Engineering, vol. 1965 (1993) pp. 531–542.
[126] P.P. Bonissone, K. Goebel, Soft computing applications in equipment maintenance and service, in: Proceedings of the IFSA World Congress and 20th NAFIPS International Conference, Vancouver, BC, Canada, vol. 5 (2001) pp. 2752–2757.
[127] T. Brotherton, G. Jahns, J. Jacobs, D. Wroblewski, Prognosis of faults in gas turbine engines, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2000) pp. 163–172.
[128] A.K. Garga, K.T. McClintic, R.L. Campbell, C.-C. Yang, M.S. Lebold, T.A. Hay, C.S. Byington, Hybrid reasoning for prognostic learning in CBM systems, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2001) pp. 2957–2969.
[129] P. Wang, G. Vachtsevanos, Fault prognostics using dynamic wavelet neural networks, Artificial Intelligence for Engineering Design, Analysis and Manufacturing 15 (2001) 349–365.
[130] G. Vachtsevanos, P. Wang, Prognostication: algorithms and performance assessment methodologies, in: Proceedings of the ATP Fall National Meeting Condition-Based Maintenance Workshop, San Jose, California (1999) pp. 15–17.
[131] L.C. Jaw, Neural networks for model-based prognostics, in: Proceedings of the IEEE Aerospace Applications Conference, Snowmass at Aspen, CO, USA, vol. 3 (1999) pp. 21–28.
[132] A.J. Volponi, T. Brotherton, R. Luppold, Development of an information fusion system for engine diagnostics and health management, Collection of Technical Papers, in: Proceedings of the AIAA 1st Intelligent Systems Technical Conference, vol. 2 (2004) pp. 873–886.
[133] H.E.G. Powrie, C.E. Fisher, Engine health monitoring: towards total prognostics, in: Proceedings of the IEEE Aerospace Applications Conference, vol. 3 (1999) pp. 11–20.
[134] R.F. Orsagh, J. Sheldon, C.J. Klenke, Prognostics/Diagnostics for Gas Turbine Engine Bearings, in: Proceedings of the IEEE Aerospace Conference, vol. 7 (2003) pp. 3095–3013.
[135] M.J. Roemer, C.S. Byington, Prognostics and health management software for gas turbine engine bearings, in: Proceedings of the ASME Turbo Expo: Power for Land, Sea, and Air (GT2007), Montreal Canada, vol. 1 (2007) pp. 795–802.
[136] J. Yan, M. Koc, J. Lee, Predictive algorithm for machine degradation detection using logistic regression, in: Proceedings of the 5th International Conference on Managing Innovations in Manufacturing, Milwaukee, USA (2002) pp. 172–178.
[137] M. Luo, D. Wang, M. Pham, C.B. Low, J.B. Zhang, D.H. Zhang, Y.Z. Zhao, Model-based fault diagnosis/prognosis for wheeled mobile robots: a review, in: Proceedings of the 31st Annual Conference of IEEE Industrial Electronics Society (2005) pp. 2267–2272.
[138] N. Vichare, M. Pecht, Enabling electronic prognostics using thermal data, in: Proceedings of the 12th International Workshop on Thermal Investigation of ICs and Systems, Nice, Côte d'Azur, France (2006).
[139] P. Lall, M.N. Islam, M.K. Rahim, J.C. Suhling, Prognostics and health management of electronic packaging, IEEE Transactions on Components and Packaging Technologies 29 (2006) 666–677.
[140] C. Wilkinson, D. Humphrey, B. Vermeire, J. Houston, Prognostic and health management for avionics, in: Proceedings of the IEEE Aerospace Conference, vol. 5 (2004) pp. 3435–3447.
[141] J.F. Rufus, S. Lee, A. Thakker, Health monitoring algorithms for space application batteries, in: Proceedings of the 2008 International Conference on Prognostics and Health Management, Denver, CO, USA (2008) pp. 1–8.
[142] B. Saha, K. Goebel, Modeling Li-ion battery capacity depletion in a particle filtering framework, in: Proceedings of the Annual Conference of the Prognostics and Health Management Society (2009).
[143] A. Hess, L. Fila, The Joint Striker Fighter (JSF) PHM concept: potential impact on aging aircraft problems, in: Proceedings of the IEEE Aerospace Conference, vol. 6 (2000) pp. 3021–3026.
[144] L.P. Su, M. Nolan, G. deMare, D.R. Carey, Prognostics framework [for weapon systems health monitoring], in: Proceedings of the IEEE Systems Readiness Technology Conference (1999) pp. 661–672.
[145] J. Lee, L. Liao, E. Lapira, J. Ni, L. Li, Informatics platform for designing and deploying e-manufacturing systems, in: L. Wang, A. Nee (Eds.), Collaborative Design and Planning for Digital Manufacturing, Springer, London, 2009, pp. 1–35.
[146] L. Wang, A.Y.C. Nee, Collaborative Design and Planning for Digital Manufacturing, Springer, London, 2009.
[147] J.B. ReVelle, J.W. Moran, C.A. Cox, The QFD Handbook, John Wiley & Sons, New York, 1998.
[148] L.-K. Chan, M.-L. Wu, Quality function deployment: a literature review, European Journal of Operational Research 143 (2002) 463–497.
[149] N. Bhushan, K. Rai, Strategic Decision Making: Applying the Analytic Hierarchy Process, Springer, London, 2004.
[150] G.E.P. Box, G.M. Jenkins, G.C. Reinsel, Time Series Analysis: Forecasting and Control, Prentice Hall; New Jersey, 1994.
[151] E.O. Brigham, The Fast Fourier Transform and its Applications, Prentice Hall; New Jersey, 1988.
[152] B.G. Ferguson, B.G. Quinn, Application of the short-time Fourier transform and the Wigner–Ville distribution to the acoustic localization of aircraft, Journal of the Acoustical Society of America 96 (1994) 821–827.
[153] W. Martin, P. Flandrin, Wigner–Ville spectral analysis of nonstationary process, IEEE Transactions on Acoustics, Speech, and Signal Processing ASSP-33 (1985) 1461–1470.
[154] S.G. Mallat, A theory for multiresolution signal decomposition: the wavelet representation, IEEE Transactions on Pattern Analysis and Machine Intelligence 11 (1989) 674–693.
[155] O. Rioul, M. Vettereli, Wavelets and signal processing, IEEE Signal Processing Magazine 8 (1991) 14–38.
[156] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.-C. Yen, C.C. Tung, H.H. Liu, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, Proceedings of the Royal Society of London 454 (1998) 903–995.
[157] N.E. Huang, S.S. Shen, Hilbert–Huang Transform and its Applications, World Scientific; Singapore, 2005.
[158] I.T. Jolliffe, Principal Component Analysis, Springer; New York, 2002.
[159] Q. Guo, W. Wu, D.L. Massart, C. Boucon, S.D. Jong, Feature selection in principal component analysis of analytical data, Chemometrics and Intelligent Laboratory Systems 61 (2002) 123–132.
[160] R.O. Duda, P.E. Hart, D.G. Stork, Pattern Classification, John Wiley & Sons, USA, 2001.
[161] D.A. Reynolds, A Gaussian mixture modeling approach to text-independent speaker identification (Ph.D. Thesis), Georgia Institute of Technology (1992).
[162] D.W. Hosmer, S. Lemeshow, Applied Logistic Regression, John Wiley & Sons, New York, 2000.
[163] J. Yan, J. Lee, Degradation assessment and fault modes classification using logistic regression, Journal of Manufacturing Science and Engineering 127 (2005) 912–914.
[164] K. Fukunaga, Introduction to Statistical Pattern Recognition, Academic Press; San Diego, 1990.
[165] H. Sohn, C.R. Farrar, N.F. Hunter, K. Worden, Structural health monitoring using statistical pattern recognition, Journal of Dynamic Systems, Measurement and Control 123 (2001) 706–711.
[166] C.E. Rasmussen, C.K.I. Williams, Gaussian Processes for Machine Learning, the MIT Press; Cambridge, 2006.
[167] M.S. Arulampalam, S. Maskell, N. Gordon, T. Clapp, A tutorial on particle filters for online nonlinear/non-Gaussian–Bayesian tracking, IEEE Transaction on Signal Processing 50 (2002) 174–188.
[168] R.E. Kalman, A new approach to linear filtering and prediction problems, Journal of Basic Engineering, Transaction of ASME 82 (1960) 35–45.
[169] S.J. Julier, J.K. Uhlmann, A new extension of the Kalman filter to nonlinear systems, in: Proceedings of the AeroSense: 11th International Symposium Aerospace/Defense Sensing, Simulation and Controls (1997) pp. 182–193.
[170] T. Kohonen, The self-organizing map, Neurocomputing 21 (1998) 1–6.
[171] T. Voegtlin, Recursive self-organizing maps, Neural Networks 15 (2002) 979–991.

[172] F.V. Jensen, An Introduction to Bayesian Networks, Springer; New York, 1996.
[173] K. Murphy, Dynamic Bayesian networks: representation, inference and learning (Ph.D. Thesis), University of California, Berkley (2002).
[174] P.D. Wasserman, Neural Computing: Theory and Practice, Van Nostrand Reinhold, New York, 1989.
[175] D. Mandic, J. Chambers, Recurrent Neural Networks for Prediction: Architectures, Learning Algorithms and Stability, Wiley; New York, 2001.
[176] J.R. Quinlan, Induction of decision trees, Machine Learning 1 (1986) 81–106.
[177] S. Pandit, S. Wu, Time Series and System Analysis with Applications, John Wiley & Sons, New York, 1983.
[178] G. Klir, B. Yuan, Fuzzy Sets and Fuzzy Logic: Theory and Applications, Prentice Hall, New Jersey, 1995.
[179] T.J. Ross, Fuzzy Logic with Engineering Applications, Wiley; New York, 2004.
[180] Z. Pawlak, Rough Sets: Theoretical Aspects of Reasoning About Data, Kluwer Academic Publishers; Norwell, 1991.
[181] Z. Pawlak, Rough set theory and its applications in data analysis, Cybernetics and Systems: An International Journal 29 (1998) 661–688.
[182] J. Liu, D. Djurdranovic, J. Ni, N. Casoetto, J. Lee, Similarity based method for manufacturing process performance prediction and diagnosis, Computers In Industry 58 (2007) 558–566.
[183] C. Cortes, V. Vapnik, Support-vector networks, Machine Learning 20 (1995) 273–297.
[184] C.J.C. Burges, A tutorial on support vector machines for pattern recognition, Data Mining and Knowledge Discovery 2 (1998) 121–167.
[185] L.R. Rabiner, B.H. Juang, An introduction to hidden Markov models, IEEE Transactions on Acoustics, Speech and Signal Processing Magazine 3 (1986) 4–16.
[186] L.R. Rabiner, A tutorial on hidden Markov models and selected applications in speech recognition, Proceedings of the IEEE 77 (1989) 257–285.
[187] D. Siegel, M. Ghaffari, J. Lee, Failure prediction of critical components in military vehicles, in: Proceedings of the Society for Machinery Failure Prevention Technology (2008).
[188] D. Siegel, Evaluation of health assessment techniques for rotating machinery (Master Thesis), University of Cincinnati, Cincinnati, OH, USA (2009).
[189] L. Liao, J. Lee, A novel method for machine performance degradation assessment based on fixed cycle features test, Journal of Sound and Vibration 326 (2009) 240–252.
[190] L. Liao, H. Wang, J. Lee, Bearing health assessment and fault diagnosis using the methods of Self-organizing Map, in: Proceedings of the 61st Machinery Failure Prevention Technology (2007).
[191] J. Lee, C. Deng, C. Tsan, M. AbuAli, Product life cycle knowledge management using embedded infotronics: methodology, tools and case studies, International Journal of Knowledge Engineering and Data Mining 1 (2010) 20–36.