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Review

# A review on machinery diagnostics and prognostics implementing condition-based maintenance

Andrew K.S. Jardine*, Daming Lin, Dragan Banjevic

*CBM Lab, Department of Mechanical and Industrial Engineering, University of Toronto, 5 King's College Road, Toronto, Ont., Canada M5S 3G8*

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**Abstract**

Condition-based maintenance (CBM) is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring. It consists of three main steps: data acquisition, data processing and maintenance decision-making. Diagnostics and prognostics are two important aspects of a CBM program. Research in the CBM area grows rapidly. Hundreds of papers in this area, including theory and practical applications, appear every year in academic journals, conference proceedings and technical reports. This paper attempts to summarise and review the recent research and developments in diagnostics and prognostics of mechanical systems implementing CBM with emphasis on models, algorithms and technologies for data processing and maintenance decision-making. Realising the increasing trend of using multiple sensors in condition monitoring, the authors also discuss different techniques for multiple sensor data fusion. The paper concludes with a brief discussion on current practices and possible future trends of CBM.


*Keywords:* Diagnostics; Prognostics; Condition monitoring; Condition-based maintenance; Signal processing; Sensor data fusion

**Contents**



*Corresponding author. Tel.: +1 416 978 2921; fax: +1 416 946 5462.
*E-mail addresses:* jardine@mie.utoronto.ca (A.K.S. Jardine), dlin@mie.utoronto.ca (D. Lin), banjev@mie.utoronto.ca (D. Banjevic).

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## 1. Introduction

Reliability has always been an important aspect in the assessment of industrial products and/or equipments. Good product design is of course essential for products with high reliability. However, no matter how good the product design is, products deteriorate over time since they are operating under certain stress or load in the real environment, often involving randomness. Maintenance has, thus, been introduced as an efficient way to assure a satisfactory level of reliability during the useful life of a physical asset.

The earliest maintenance technique is basically breakdown maintenance (also called unplanned maintenance, or run-to-failure maintenance), which takes place only at breakdowns. A later maintenance technique is time-based preventive maintenance (also called planned maintenance), which sets a periodic interval to perform preventive maintenance regardless of the health status of a physical asset. With the rapid development of modern technology, products have become more and more complex while better quality and higher reliability are required. This makes the cost of preventive maintenance higher and higher. Eventually, preventive maintenance has become a major expense of many industrial companies. Therefore, more efficient maintenance approaches such as condition-based maintenance (CBM) are being implemented to handle the situation. Martin [1] briefly summarised the history of maintenance technique development for machine tools. Indeed, the history applies to other types of machines and systems as well.

CBM is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behaviours of a physical asset. A CBM program, if properly established and effectively implemented, can significantly reduce maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations.

A CBM program consists of three key steps [2] (see Fig. 1):

1. Data acquisition step (information collecting), to obtain data relevant to system health.
2. Data processing step (information handling), to handle and analyse the data or signals collected in step 1 for better understanding and interpretation of the data.
3. Maintenance decision-making step (decision-making), to recommend efficient maintenance policies.

Diagnostics and prognostics are two important aspects in a CBM program. Diagnostics deals with fault detection, isolation and identification when it occurs. Fault detection is a task to indicate whether something is going wrong in the monitored system; fault isolation is a task to locate the component that is faulty; and fault identification is a task to determine the nature of the fault when it is detected. Prognostics deals with fault

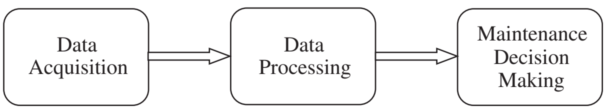


Fig. 1. Three steps in a CBM program.

prediction before it occurs. Fault prediction is a task to determine whether a fault is impending and estimate how soon and how likely a fault will occur. Diagnostics is posterior event analysis and prognostics is prior event analysis. Prognostics is much more efficient than diagnostics to achieve zero-downtime performance. Diagnostics, however, is required when fault prediction of prognostics fails and a fault occurs. A CBM program can be used to do diagnostics or prognostics, or both. No matter what the objective of a CBM program is, however, the above three CBM steps are followed.

The literature on machinery diagnostics and prognostics is huge and diverse primarily due to a wide variety of systems, components and parts. Hundreds of papers in this area, including theories and practical applications, appear every year in academic journals, conference proceedings and technical reports. This paper reviews the research on diagnostics and prognostics of mechanical systems implementing CBM with an emphasis on models, algorithms and technologies for data processing and maintenance decision-making. Some published reviews or overviews related to this topic with emphasis on specific kinds of systems (or components) are [1,3–10].

The remaining part of the paper is organised as follows. Section 2 briefly describes the data acquisition step in order to accomplish diagnostics and prognostics. Section 3 reviews models and methods for data processing that is essential to diagnostics and prognostics. Section 4 reviews the ideas and methodologies for maintenance decision-making, the final step to accomplish diagnostics and prognostics. Finally, Section 5 concludes the paper by summarising a short list of references to provide introductory familiarity with ideas and methodologies in this area, pointing out some existing problems in diagnostics and prognostics, and addressing research directions needed for the next generation of diagnostic and prognostic systems and possible future development trends of diagnostics and prognostics.

## 2. Data acquisition

Data acquisition is a process of collecting and storing useful data (information) from targeted physical assets for the purpose of CBM. This process is an essential step in implementing a CBM program for machinery fault (or failure, which is usually caused by one or more machinery faults) diagnostics and prognostics. Data collected in a CBM program can be categorised into two main types: the so-called event data and condition monitoring data. Event data include the information on what happened (e.g., installation, breakdown, overhaul, etc., and what the causes were) and/or what was done (e.g., minor repair, preventive maintenance, oil change, etc.) to the targeted physical asset. Condition monitoring data are the measurements related to the health condition/state of the physical asset.

Condition monitoring data are very versatile. It can be vibration data, acoustic data, oil analysis data, temperature, pressure, moisture, humidity, weather or environment data, etc. Various sensors, such as micro-sensors, ultrasonic sensors, acoustic emission sensors, etc., have been designed to collect different types of data [11,12]. Wireless technologies, such as Bluetooth, have provided an alternative solution to cost-effective data communication. Maintenance information systems, such as computerised maintenance management systems (CMMS), enterprise resource planning systems, etc., have been developed for data storage and handling [13]. Collection of event data usually requires manual data entry to the information systems. With the rapid development of computer and advanced sensor technologies, data acquisition facilities and technologies have become more powerful and less expensive, making data acquisition for CBM implementation more affordable and feasible.

This paper will not cover the details of data acquisition techniques. One point the authors would like to make is that event data and condition monitoring data are equally important in CBM. In CBM practice, however, people tend to put more emphasis on the collection of the condition monitoring data and sometimes neglect the collection of event data. The overlooking of event data may result from the erroneous belief that event data are not valuable as long as the condition indicators (or features) seem to be working well in reducing equipment failures. This belief is incorrect since the event data are at least helpful in assessing the performance of current condition indicators (or features), and can even be used either as feedback to the system designer for consideration of system redesign or improvement of condition indicators (or features). The overlooking may also result from the fact that event data collection usually requires manual data entry. Once a human is involved, everything becomes more complicated and error-prone. A solution might be to implement and automate event data collection and reporting in the maintenance information system.

## 3. Data processing

The first step of data processing is data cleaning. This is an important step since data, especially event data, which is usually entered manually, always contains errors. Data cleaning ensures, or at least increases the chance, that clean (error-free) data are used for further analysis and modelling. Without the data cleaning step, one may get into the so-called "garbage in garbage out" situation. Data errors are caused by many factors including the human factor mentioned above. For condition monitoring data, data errors may be caused by sensor faults. In this case, sensor fault isolation [14] is the right way to go. In general, however, there is no simple way to clean data. Sometimes it requires manual examination of data. Graphical tools would be very helpful to finding and removing data errors. Data cleaning is, indeed, a big area. It is beyond the scope of this paper and will not be discussed in detail here.

The next step of data processing is data analysis. A variety of models, algorithms and tools are available in the literature to analyse data for better understanding and interpretation of data. The models, algorithms and tools used for data analysis depend mainly on the types of data collected.

As mentioned above, condition monitoring data collected from the data acquisition step are versatile. It falls into three categories:

*Value type*: Data collected at a specific time epoch for a condition monitoring variable are a single value. For example, oil analysis data, temperature, pressure and humidity are all value type data.
*Waveform type*: Data collected at a specific time epoch for a condition monitoring variable are a time series, which is often called time waveform. For example, vibration data and acoustic data are waveform type.
*Multidimension type*: Data collected at a specific time epoch for a condition monitoring variable are multidimensional. The most common multidimensional data are image data such as infrared thermographs, X-ray images, visual images, etc.

Data processing for waveform and multidimensional data is also called signal processing. Various signal processing techniques have been developed to analyse and interpret waveform and multidimensional data to extract useful information for further diagnostic and prognostic purpose. The procedure of extracting useful information from raw signals is the so-called feature extraction.

Signal processing for multidimensional data such as image processing is similar to but more complicated than waveform signal processing due to one more dimension involved. In practice, raw images are usually very complicated and immediate information for fault detection is unavailable. In these cases, image processing techniques are powerful to extract useful features from raw images for fault diagnosis—see [15,16] for descriptions and discussions on image processing tools and algorithms. Image processing seems unnecessary when raw images provide sufficient and clear information to identify patterns and detect faults. However, image processing can still help in extracting features for automatic fault detection in such situations. In addition to raw images obtained via data acquisition, some waveform processing techniques such as time–frequency analysis also produce images. In these situations, image processing can be combined with waveform processing to obtain better results. Usually, low-level signal processing is good enough to obtain satisfied results. As such, there is little research applying advanced image processing in machinery diagnostics and prognostics. A few examples of applying image processing techniques in condition monitoring and fault diagnosis and prognosis are Wang and McFadden [17], Utsumi et al. [18], Heger and Pandit [19] and Ellwein et al. [20].

In the following sections, signal processing techniques for waveform data are reviewed and then data analysis techniques for other types of data are discussed.

### 3.1. Waveform data analysis

There are numerous signal processing techniques and algorithms in the literature for diagnostics and prognostics of mechanical systems. Case-dependent knowledge and investigation are required to select appropriate signal processing tools among a number of possibilities.

The most common waveform data in condition monitoring are vibration signals and acoustic emissions. Other waveform data are ultrasonic signals, motor current, partial discharge, etc. In the literature, there are three main categories of waveform data analysis: time-domain analysis, frequency-domain analysis and time–frequency analysis.

#### 3.1.1. Time-domain analysis

Time-domain analysis is directly based on the time waveform itself. Traditional time-domain analysis calculates characteristic features from time waveform signals as descriptive statistics such as mean, peak, peak-to-peak interval, standard deviation, crest factor, high-order statistics: root mean square, skewness, kurtosis, etc. These features are usually called time-domain features. A popular time-domain analysis approach is time synchronous average (TSA). The idea of TSA is to use the ensemble average of the raw signal over a number of evolutions in an attempt to remove or reduce noise and effects from other sources, so as to enhance the signal components of interest. TSA is given by

$$\bar{s}(t) = \frac{1}{N}\sum_{n=0}^{N-1} s(t+nT), \quad 0 \leqslant t < T,$$

where $s(t)$ denotes the signal, $T$ is the averaging period and $N$ is the number of samples for averaging. Details on TSA will not be discussed in this paper. References on details about TSA can be found in the references of [21,22]. A brief review of TSA was given by Dalpiaz et al. [21] and some drawbacks of TSA were pointed out by Miller [22].

More advanced approaches of time-domain analysis apply time series models to waveform data. The main idea of time series modelling is to fit the waveform data to a parametric time series model and extract features based on this parametric model. The popular models used in the literature are the autoregressive (AR) model and the autoregressive moving average (ARMA) model. An ARMA model of order $p, q$, denoted by $ARMA(p, q)$, is expressed by

$$x_t = a_1 x_{t-1} + \cdots + a_p x_{t-p} + \varepsilon_t - b_1 \varepsilon_{t-1} - \cdots - b_q \varepsilon_{t-q},$$

where $x$ is the waveform signal, $\varepsilon$'s are independent normally distributed with mean 0 and constant variance $\sigma^2$, and $a_i, b_i$ are model coefficients. An AR model of order $p$ is a special case of $ARMA(p, q)$ with $q = 0$. Poyhonen et al. [23] applied AR model to vibration signals collected from an induction motor and use the AR model coefficients as extracted features. Baillie and Mathew [24] compared the performance of three AR time series modelling techniques: AR model, back propagation (BP) neural networks and radial basis function networks. Garga et al. [25] proposed an approach that uses AR modelling followed by dimension reduction. Recently, Zhan et al. [26] used a state space model representation of an AR model to analyse vibration signals. In practice, however, application of the AR or ARMA models is difficult due to the complexity in modelling, especially the need to determine the order in the model.

There are many other time-domain analysis techniques to analyse waveform data for machinery fault diagnostics. Some of them are briefly mentioned as follows without detailed discussions. Wang et al. [27] discussed three non-linear diagnostic methods, known as pseudo-phase portrait, singular spectrum analysis and correlation dimension, based on the signal time series and time series analysis theory. Other works on application of these methods are: [28] for pseudo-phase portrait and [29,30] for correlation dimension. Zhuge and Lu [31] proposed a modified least mean square algorithm to model the non-stationary impulse-like signals. Baydar et al. [32] investigated the use of a multivariate statistical technique known as principal component analysis (PCA) for analysis of the time waveform signals in gear fault diagnostics.

#### 3.1.2. Frequency-domain analysis

Frequency-domain analysis is based on the transformed signal in frequency domain. The advantage of frequency-domain analysis over time-domain analysis is its ability to easily identify and isolate certain frequency components of interest. The most widely used conventional analysis is the spectrum analysis by means of fast Fourier transform (FFT). The main idea of spectrum analysis is to either look at the whole spectrum or look closely at certain frequency components of interest and thus extract features from the signal (see, e.g., [33–35]). The most commonly used tool in spectrum analysis is power spectrum. It is defined as $E[X(f)X^*(f)]$, where $X(f)$ is the Fourier transform of signal $x(t)$, $E$ denotes expectation and "$*$" denotes complex conjugate. Some useful auxiliary tools for spectrum analysis are graphical presentation of spectrum, frequency filters, envelope analysis (also called amplitude demodulation) [36–38], side band structure analysis [39], etc. Hilbert transform, which is a useful tool in envelope analysis, has also been used for machine fault detection and diagnostics [36,40]. Descriptions of the above-mentioned techniques for FFT-based spectrum can be found in textbooks such as [41,42] and will not be discussed in detail here.

Despite the wide acceptance of power spectrum, other useful spectra for signal processing have been developed and have been shown to have their own advantages over FFT spectrum in certain cases. Cepstrum has the capability to detect harmonics and sideband patterns in power spectrum. There are several versions of definition of cepstrum [42]. Among them, power cepstrum, which is defined as the inverse Fourier transform of the logarithmic power spectrum, is most commonly used. A modified cepstrum analysis was proposed in [43]. High-order spectrum, i.e., bispectrum or trispectrum, can provide more diagnostic information than power spectrum for non-Gaussian signals. In the literature, high-order spectrum is also called high-order statistics [44]. This name comes from the fact that bispectrum and trispectrum are actually the Fourier transforms of the third- and fourth-order statistics of the time waveform, respectively. But this name could be confused with the time-domain high-order statistics. Bispectrum analysis has been shown to have wide application in machinery diagnostics for various mechanical systems such as gears [45], bearings [46], rotating machines [30,47] and induction machines [48,49]. Li et al. [50] investigated the application of bispectrum diagonal slice to gear fault diagnostics. Yang et al. [46] used both bispectrum diagonal slice and bicoherence (the normalised bispectrum) diagonal slice, summed bispectrum and summed bicoherence for bearing fault diagnostics. Application of both bispectrum and trispectrum to bearing fault diagnostics was discussed in [51]. A new technique called holospectrum was introduced by Qu et al. [52] to integrate all the information of phase, amplitude and frequency of a waveform signal. Application of holospectrum to vibration signals was also studied in [53,54]. A review on holospectrum and its applications was given by Qu and Shi [55].

Generally speaking, there are two classes of approaches for power spectrum estimation. The first one is the non-parametric approaches that estimate the autocorrelation sequence of the signal and then apply Fourier transform to the estimated autocorrelation sequence. For details, see [56]. The second class includes the parametric approaches that build a parametric model for the signal and then estimate power spectrum based on the fitted model. Among them, AR spectrum [57–59] and ARMA spectrum [60] based on AR model and ARMA model, respectively, are the two most commonly used parametric spectra in machinery fault diagnostics.

#### 3.1.3. *Time–frequency analysis*

One limitation of frequency-domain analysis is its inability to handle non-stationary waveform signals, which are very common when machinery faults occur. Thus, time–frequency analysis, which investigates waveform signals in both time and frequency domain, has been developed for non-stationary waveform signals. Traditional time–frequency analysis uses time–frequency distributions, which represent the energy or power of waveform signals in two-dimensional functions of both time and frequency to better reveal fault patterns for more accurate diagnostics. Short-time Fourier transform (STFT) or spectrogram (the power of STFT) [61,62] and Wigner–Ville distribution [63–66] are the most popular time–frequency distributions. Cohen [67] reviewed a class of time–frequency distributions which include spectrogram, Wigner–Ville distribution, Choi–Williams and others. The idea of STFT is to divide the whole waveform signal into segments with short-time window and then apply Fourier transform to each segment. Spectrogram has some limitation in time–frequency resolution due to signal segmentation. It can only be applied to non-stationary signals with slow change in their dynamics. Bilinear transforms such as Wigner–Ville distribution are not based on signal segmentation and thus overcome the time–frequency resolution limitation of spectrogram. However, there is one main disadvantage of bilinear transforms due to the interference terms formed by the transformation itself. These interference terms make interpretation of the estimated distribution difficult [68]. Improved transforms such as Choi–Williams distribution have been developed to overcome this disadvantage. Gu et al. [69] applied singular value decomposition to extract features from the time–frequency distribution.

Loughlin et al. [70] used a set of conditional time–frequency moments as characteristic features for fault diagnosis.

Another transform for time–frequency analysis is the wavelet transform. Unlike a time–frequency distribution, which is a time–frequency representation of a signal, wavelet transform is a time-scale representation of a signal. Wavelet theory has been rapidly developed in the past decade and has wide application [71]. A continuous wavelet transform is defined as

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-b}{a}\right) \mathrm{d}t,$$

where $x(t)$ is the waveform signal, $a$ is the scale parameter, $b$ is the time parameter and $\psi(\cdot)$ is a wavelet, which is a zero average oscillatory function centred around zero with a finite energy, and "*" denotes complex conjugate. Commonly used wavelets are Morlet, Mexican hat, Haar, etc. Similar to Fourier transform, wavelet transform has also its discrete form which is obtained by discretising $a$ and $b$, and expressing $x(t)$ in discrete form. Similar to FFT, a fast wavelet transform is also available for the calculation.

Wavelet analysis of a waveform signal expresses the signal in a series of oscillatory functions with different frequencies at different time by dilations via the scale parameter $a$ and translations via the time parameter $b$. Similar to power spectrum and phase spectrum in Fourier analysis, a scalogram defined as $|W(a,b)|^2$ and a wavelet phase spectrum defined as the phase angle of the complex variable $W(a,b)$ are used to interpret the signal. One main advantage of wavelet transform is its ability to produce a high frequency resolution at low frequencies and a high time resolution at high frequencies for signals with long duration low frequencies and short duration high frequencies. Another advantage of wavelet transform is its ability to reduce noise in raw signals.

Wavelet transform has been successfully applied to waveform data analysis in fault diagnostics of gears [72,73], bearings [74,75] and other mechanical systems [76,77]. Dalpiaz and Rivola [78] assessed and compared the effectiveness and reliability of wavelet transform to other vibration signal analysis techniques. Baydar and Ball [79] applied wavelet transform to both acoustic signals and vibration. Addison et al. [80] investigated the use of low-oscillation complex wavelets, Mexican hat and Morlet wavelets, as feature detection tools. Wavelet analysis using Haar wavelet was considered in [81,82]. Miller and Reichard [83] used a wavelet basis as a comb filter to decompose vibration signals. A graphical tool called wavelet polar maps to display wavelet amplitude and phase was proposed in [84] and was applied to gear fault diagnostics in [85]. Wavelet transform combined with Fourier transform to enhance feature extraction capability was proposed in [86]. A more advanced transform, known as wavelet packet transform, was studied in [87–89]. A new technique known as basis pursuit based on a general wavelet packet dictionary was applied to analyse the vibration signals for rolling element bearing fault diagnostics in [90]. It was shown that basis pursuit has some advantages over other commonly used wavelet analysis approaches. Lin et al. [91] used wavelet threshold de-noising technique to extract faulty information from the noisy signals. A recent review with more extensive discussions and more references on the applications of wavelet transform for signal processing in machine condition monitoring and fault diagnostics was given in [92].

### 3.2. *Value type data analysis*

Value type data include both raw data obtained via data acquisition and feature values extracted from raw signals via signal processing. Value type data look much simpler than waveform and image data. However, complexity lies in the correlation structure when the number of variables is large. Multivariate analysis techniques such as PCA and independent component analysis (ICA) are very useful to handle data with complicated correlation structure. For example, Stellman et al. [93] applied PCA to spectroscopic data to monitor the condition of a lubricant in helicopter rotary gearboxes. Allgood and Upadhyaya [94] performed PCA on certain descriptive statistics in DC motor diagnostics and prognostics. ICA is an extension of PCA and will be discussed later. When the number of variables is large, dimension reduction techniques such as PCA and project pursuit can be used for data reduction. For a review on dimension reduction techniques, see [95]. An example of applying dimension reduction techniques in machine fault diagnostics is given in [25].

Trend analysis techniques such as regression analysis and time series model are commonly used techniques for analysing value type data. For example, Grimmelius et al. [96] developed a prototype condition monitoring and diagnostics system for compression refrigeration plants using a regression analysis model to predict healthy system behaviour. Yang et al. [97] established an ARMA model to extract features from on-line data in power equipment diagnosis. Sinha [98] applied both polynomial regression and an ARMA model to predict the trend of vibration peak amplitude.

### 3.3. Data analysis combining event data and condition monitoring data

Data analysis for event data only is well known as reliability analysis, which fits the event data to a time between events probability distribution and uses the fitted distribution for further analysis. In CBM, however, additional information—condition monitoring data—is available. Thus, it is beneficial to analyse event data and condition monitoring data together. This combined data analysis can be accomplished by building a mathematical model that properly describes the underlying mechanism of a fault or a failure. The model built based on both event and condition monitoring data is the basis for maintenance decision support—diagnostics and prognostics, which will be discussed in Section 4.

A time-dependent proportional hazards model (PHM), which is a popular model in survival analysis, is suitable for analysing both event and condition monitoring data together. The merit of a time-dependent PHM is its ability to relate the failure probability to both age and condition variables, so that one can assess the failure probability with given machine condition at any specified age. A time-dependent PHM has a hazard function of the form

$$h(t) = h_0(t)\exp(\gamma_1 x_1(t) + \cdots + \gamma_p x_p(t)),$$

where $h_0(t)$ is a baseline hazard function, $x_1(t), \ldots, x_p(t)$ are covariates which are functions of time and $\gamma_1, \ldots, \gamma_p$ are coefficients. The baseline hazard function $h_0(t)$ can be in non-parametric or parametric form. A commonly used parametric baseline hazard function is the Weibull hazard function, which is the hazard function of the Weibull distribution. A PHM with Weibull baseline hazard function is called Weibull PHM. The covariates $x_1(t), \ldots, x_p(t)$ can be any condition variables such as health indicators and features in condition monitoring. Maximum likelihood estimation is usually used to build a PHM from event data and condition monitoring data. Modelling a PHM is more or less like the process of regress analysis: a set of significant covariates is finally found and only these significant covariates are included in the model. However, PHM modelling differs from regular regression analysis in that there are no observations for the "dependent" variable $h(t)$ and instead observations are available as event data. Jardine et al. [99] proposed using a Weibull PHM to analyse the aircraft and marine engine failure data together with the metal concentration measurements of the engine oil. Other works applying PHM in CBM will be discussed in Section 4. An extension of PHM is the proportional intensity model (PIM), which adopts a stochastic process setting and assumes a similar form to the intensity function of the stochastic process. Vlok et al. [100] studied the application of PIM to analyse failure and diagnostic measurement data from bearings.

In reliability centred maintenance [101], the concept known as P-F interval is used to describe the failure patterns in condition monitoring. A P-F interval is the time interval between a potential failure (P), which is identified by a condition indicator, and a functional failure (F). A P-F interval is a useful tool to determine the condition monitoring interval for periodical condition monitoring. A condition monitoring interval is usually set to be the P-F interval divided by an integer. In practice, however, it is usually difficult to quantify the P-F interval. Goode et al. [102] assumed two Weibull distributions for the P-F interval and the I-P interval, i.e., from machine installation to a potential failure. Using the statistical process control (SPC) methods, they separated each machine life cycle in historical data into two zones: stable zone and failure zone. Then the stable zone times in historical data are used to fit the Weibull distribution for the I-P interval, whereas the failure zone times are used to fit the Weibull distribution for the P-F interval. Based on these two fitted distributions and the condition monitoring process, machine prognosis was derived.

Hidden Markov model (HMM) [103,104] is another appropriate model for analysing event and condition monitoring data together. An HMM consists of two stochastic processes: a Markov chain with finite number of states describing an underlying mechanism and an observation process depending on the hidden state. A discrete-time HMM is defined by

$$X_{k+1} = AX_k + V_{k+1},$$
$$Y_k = CX_k + W_k,$$

where $X_k$ and $Y_k$ denote the hidden process and the observation process, respectively, $V_k$ and $W_k$ are noise terms with martingale increments, and $A$ and $C$ are parameters. Event data and condition monitoring data are used to train the HMM, i.e., to estimate model parameters. Since full likelihood function is not available for an HMM, a statistical approach known as EM algorithm is usually used for parameter estimation. For more details on HMM modelling, see [103,104]. Bunks et al. [105] applied an HMM to analyse the Westland helicopter data which consists of gearbox fault class information and vibration measurements with different faults. The fault classes were treated as states in the hidden Markov chain, whereas the vibration measurements were treated as realisations of the observation process. The trained HMM using lab test data was then applied to fault classification for a data set from an operating gearbox. Dong and He [106] proposed a more general model, hidden semi-Markov model, for analysing pump experimental data in pump diagnostics and prognostics.

In condition monitoring, a failure state is usually observable. In this situation, it is inappropriate to use HMM to describe the machine state process up to failure. Lin and Makis [107] proposed using a partially observable stochastic model to describe the underlying failure mechanism of a system undergoing condition monitoring. The proposed model is similar to HMM but it has some distinguishing characteristics: all health states are hidden, the failure state is observable and the partially hidden state process is continuous in time, whereas the observation process in discrete in time. These characteristics are more realistic in periodical condition monitoring phenomenon. The model parameters were estimated using both event and condition monitoring data. The fitted model can be used for further diagnostics and prognostics. A fast recursive parameter estimation procedure for a partially observable stochastic model was given in [108].

Other models appeared in the literature that can be used to analyse both event and condition monitoring data are models using delay-time concept [109] and stochastic process models such as a gamma process [110].

## 4. Maintenance decision support

The last step of a CBM program is maintenance decision-making. Sufficient and efficient decision support would be crucial to maintenance personnel's decisions on taking maintenance actions. Techniques for maintenance decision support in a CBM program can be divided into two main categories: *diagnostics* and *prognostics*. As mentioned earlier, fault diagnostics focuses on detection, isolation and identification of faults when they occur. Prognostics, however, attempts to predict faults or failures before they occur. Obviously, prognostics is superior to diagnostics in the sense that prognostics can prevent faults or failures, and if impossible, be ready (with prepared spare parts and planned human resources) for the problems, and thus save extra unplanned maintenance cost. Nevertheless, prognostics cannot completely replace diagnostics since in practice there are always some faults and failures which are not predictable. Besides, prognostics, like any other prediction techniques, cannot be 100% sure to predict faults and failures. In the case of unsuccessful prediction, diagnostics can be a complementary tool for providing maintenance decision support. In addition, diagnostic is also helpful to improving prognostics in the way that diagnostic information can be useful for preparing more accurate event data and hence building better CBM model for prognostics. Furthermore, diagnostic information can be used as useful feedback information for system redesign. Jardine [111] reviewed and compared several commonly used CBM decision strategies such as trend analysis that is rooted in SPC, expert systems (ESs), and neural networks. Wang and Sharp [112] discussed decision aspect of CBM and reviewed the recent development in modelling CBM decision support.

### *4.1. Diagnostics*

Machine fault diagnostics is a procedure of mapping the information obtained in the measurement space and/or features in the feature space to machine faults in the fault space. This mapping process is also called pattern recognition. Traditionally, pattern recognition is done manually with auxiliary graphical tools such as power spectrum graph, phase spectrum graph, cepstrum graph, AR spectrum graph, spectrogram, wavelet scalogram, wavelet phase graph, etc. However, manual pattern recognition requires expertise in the specific area of the diagnostic application. Thus, highly trained and skilled personnel are needed. Therefore, automatic pattern recognition is highly desirable. This can be achieved by classification of signals based on the information and/or features extracted from the signals. In the following sections, different machine fault diagnostic approaches are discussed with emphasis on statistical approaches and artificial intelligent approaches. Machine diagnostics with emphasis on practical issues was discussed in [113]. Various topics in fault diagnosis with emphasis on model-based and artificial intelligence (AI) approaches were covered in a recent co-authored book [114].

#### 4.1.1. Statistical approaches

A common method of fault diagnostics is to detect whether a specific fault is present or not based on the available condition monitoring information without intrusive inspection of the machine. This fault detection problem can be described as a hypothesis test problem with null hypothesis $H_0$: Fault A is present, against alternative hypothesis $H_1$: Fault A is not present. In a concrete fault diagnostic problem, hypotheses $H_0$ and $H_1$ are interpreted into an expression using specific models or distributions, or the parameters of a specific model or distribution. Test statistics are then constructed to summarise the condition monitoring information so as to be able to decide whether to accept the null hypothesis $H_0$ or reject it. See [115–117] for some examples of using hypothesis testing for fault diagnosis. Recently, a framework for fault diagnosis, called structured hypothesis tests, was proposed for conveniently handling complicated multiple faults of different types [118].

A conventional approach, SPC, which was originally developed in quality control theory, has been well developed and widely used in fault detection and diagnostics. The principle of SPC is to measure the deviation of the current signal from a reference signal representing the normal condition to see whether the current signal is within the control limits or not. An example of using SPC for damage detection was discussed in [119].

Cluster analysis, as a multivariate statistical analysis method, is a statistical classification approach that groups signals into different fault categories on the basis of the similarity of the characteristics or features they possess. It seeks to minimise within-group variance and maximise between-group variance. The result of cluster analysis is a number of heterogeneous groups with homogeneous contents: There are substantial differences between the groups, but the signals within a single group are similar. Application of cluster analysis in machinery fault diagnosis was discussed in [120,121]. A natural way of signal grouping is based on certain distance measures or similarity measure between two signals. These measures are usually derived from certain discriminant functions in statistical pattern recognition [122]. Commonly used distance measures are Euclidean distance, Mahalanobis distance, Kullback–Leibler distance and Bayesian distance. See [123–126] for some examples of using these distance metrics for fault diagnostics. Ding et al. [123] introduced a new distance metric called quotient distance for engine fault diagnosis. Pan et al. [127] proposed an extended symmetric Itakura distance for signals in time–frequency representations such as the Wigner–Ville distributions. Other than distance measures, feature vector correlation coefficient is also a similarity measure commonly used for signal classification in machinery fault diagnosis [126]. Many clustering algorithms are available for determining the signal groups [128]. A commonly used algorithm in machine fault classification is the nearest neighbour algorithm that fuses two closest groups into a new group and calculates distance between two groups as the distance of the nearest neighbour in the two separate groups [129]. The boundary of two adjacent groups is determined by the discriminant function used. A piecewise linear discriminant function was used and thus piecewise linear boundaries were obtained for bearing condition classification in [130]. A technique called support vector machine (SVM) is usually employed to optimise a boundary curve in the sense that the distance of the closest point to the boundary curve is maximised. SVM applied to machine fault diagnosis was considered in [23,131].

HMM described earlier can also be used for fault classification. Early applications of HMM in fault classification and diagnostics treated the real machine faulty states and the machine normal state as the hidden states of the HMM [105,132]. Two recent applications of HMM in fault classification assumed an HMM with hidden states having no physical meaning for each machine condition (normal and faulty) [133,134]. The trained HMMs are then used to decode an observation with unknown machine condition for fault classification. Xu and Ge [135] presented an intelligent fault diagnosis system based on an HMM. Ye et al. [136] considered application of two-dimensional HMM based on time–frequency analysis for fault diagnosis.

#### 4.1.2. AI approaches

AI techniques have been increasingly applied to machine diagnosis and have shown improved performance over conventional approaches. In practice, however, it is not easy to apply AI techniques due to the lack of efficient procedures to obtain training data and specific knowledge, which are required to train the models. So far, most of the applications in the literature just used experimental data for model training. In the literature, two popular AI techniques for machine diagnosis are artificial neural networks (ANNs) and ESs. Other AI techniques used include fuzzy logic systems, fuzzy–neural networks (FNNs), neural–fuzzy systems and evolutionary algorithms (EAs). A review of recent developments in applications of AI techniques for induction machine stator fault diagnostics was given by Siddique et al. [137].

An ANN is a computational model that mimics the human brain structure. It consists of simple processing elements connected in a complex layer structure which enables the model to approximate a complex non-linear function with multi-input and multi-output. A processing element comprises a node and a weight. The ANN learns the unknown function by adjusting its weights with observations of input and output. This process is usually called training of an ANN. There are various neural network models. Feedforward neural network (FFNN) structure is the most widely used neural network structure in machine fault diagnosis [138–141]. A special FFNN, mulitlayer perceptron with the BP training algorithm, is the most commonly used neural network model for pattern recognition and classification, and hence machine fault diagnostics as well [46,142,143]. The BP neural networks, however, have two main limitations: (1) difficulty of determining the network structure and the number of nodes; (2) slow convergence of the training process. A cascade correlation neural network (CCNN) does not require initial determination of the network structure and the number of nodes. CCNN can be used in cases where on-line training is preferable. Spoerre [144] applied CCNN to bearing fault classification and showed that CCNN can result in utilising the minimum network structure for fault recognition with satisfied accuracy. Other neural network models applied in machine diagnostics are radial basis function neural networks [24], recurrent neural networks [145,146] and counter propagation neural networks [147]. The above ANN models usually use supervised learning algorithms which require external input such as the a priori knowledge about the target or desired output. For example, a common practice of training a neural network model is to use a set of experimental data with known (seeded) faults. This training process is supervised learning. In contrast to supervised learning, unsupervised learning does not require external input. An unsupervised neural network learns itself using new information available. Wang and Too [44] applied the unsupervised neural networks, self-organising map (SOM) and learning vector quantisation to rotating machine fault detection. Tallam et al. [148] proposed some self-commissioning and on-line training algorithms for FFNN with particular application to electric machine fault diagnostics. Sohn et al. [117] used an autoassociative neural network to separate the effect of damage on the extracted features from those caused by the environmental and vibration variations of the system. Then a sequential probability ratio test was performed on the normalised features for damage classification.

In contrast to neural networks, which learn knowledge by training on observed data with known inputs and outputs, ESs utilise domain expert knowledge in a computer program with an automated inference engine to perform reasoning for problem solving. Three main reasoning methods for ES used in the area of machinery diagnostics are rule-based reasoning [149–151], case-based reasoning [152,153] and model-based reasoning [154]. Another reasoning method, negative reasoning, was introduced to mechanical diagnosis by Hall et al. [155]. Stanek et al. [156] compared case-based and model-based reasoning and proposed to combine them for a lower-cost solution to machine condition assessment and diagnosis. Unlike other reasoning methods, negative reasoning deals with negative information, which by its absence or lack of symptoms is indicative of meaningful inferences.

ESs and neural networks have their own limitations. One main limitation of rule-based ESs is combinatorial explosion, which refers to the computation problem caused when the number rule increases exponentially as the number of variables increases. Another main limitation is consistency maintenance, which refers to the process by which the system decides when some of the variables need to be recomputed in response to changes in other values. Two main limitations of neural networks are the difficulty to have physical explanations of the trained model and the difficulty in the training process. Obviously, combination of both techniques would significantly improve the performance. For instance, Silva et al. [157] used two neural networks, SOM and adaptive resonance theory (ART), combined with an ES based on Taylor's tool life equation to classify tool wear state. DePold and Gass [158] studied the applications of neural networks and ESs in a modular intelligent and adaptive system in gas turbine diagnostics. Yang et al. [159] presented an approach for integrating case-based reasoning ES with an ART-Kohonen neural network to enhance fault diagnosis. It was shown that the proposed approach outperforms the self-organising feature map-based system with respect to classification rate.

In condition monitoring practice, knowledge from domain specific experts is usually inexact and reasoning on knowledge is often imprecise. Therefore, measures of the uncertainties in knowledge and reasoning are required for ES to provide more robust problem solving. Commonly used uncertainty measures are probability, fuzzy member functions in fuzzy logic theory and belief functions in belief networks theory. An example of applying fuzzy logic to machine fault classification was given in [160] to classify frequency spectra representing various rolling element bearing faults. A comparison between conventional rule-based ESs and belief networks applied to machine diagnostics was given in [161]. Du and Yeung [162] introduced an approach called fuzzy transition probability, which combines transition probability (Markov process) as well as the fuzzy set, to monitoring progressive faults. The application of fuzzy logic is usually incorporated with other techniques such as neural networks and ES. For example, Zhang et al. [163] developed an FNN for fault diagnosis of rotary machines to improve the recognition rate of pattern recognition, especially in the case when sample data are similar. Lou and Loparo [126] employed an adaptive neural–fuzzy inference system as a diagnostic classifier for bearing fault diagnosis. Liu et al. [164] applied fuzzy logic and ESs to build a fuzzy ES for bearing fault detection. Chang et al. [165] built a system for decision-making support in a power plant using both rule-based ES and fuzzy logic.

Neural networks and ESs have also been combined with other AI techniques to enhance machine diagnostic systems. Garga et al. [166] proposed a hybrid reasoning approach combining neural network, fuzzy logic and ES to integrate domain knowledge and test and operational data from the machine for machine diagnostics and prognostics. EAs [167], which mimic the natural evolution process of a population, have also been shown to have merits in applications to machine diagnostics. Genetic algorithms (GAs) are the most widely used type of EA. Sampath et al. [168] proposed a GA-based optimisation approach to gas turbine diagnostics. Several examples of ANN incorporating GA and other EA algorithms for machine fault classification and diagnostics are [169–171].

#### 4.1.3. Other approaches

Another class of machine fault diagnostic approaches is the model-based approaches [172,173]. These approaches utilise physics specific, explicit mathematical model of the monitored machine. Based on this explicit model, residual generation methods such as Kalman filter, parameter estimation (or system identification) and parity relations are used to obtain signals, called residuals, which is indicative of fault presence in the machine. Finally, the residuals are evaluated to arrive at fault detection, isolation and identification. This general procedure is illustrated in Fig. 2. Model-based approaches can be more effective than other model-free approaches if a correct and accurate model is built. However, explicit mathematical modelling may not be feasible for complex systems since it would be very difficult or even impossible to build mathematical models for such systems.

Various model-based diagnostic approaches have been applied to fault diagnosis of a variety of mechanical systems such as gearboxes [174,175], bearings [176–178], rotors [179,180] and cutting tools [181]. Bartelmus

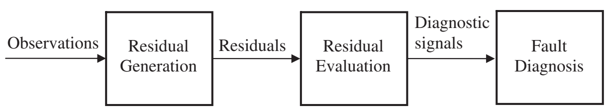


Fig. 2. General flowchart of a model-based approach.

[182,183] used mathematical modelling and computer simulation to aid signal processing and interpretation. Hansen et al. [184] proposed an approach to more robust diagnosis based on the fusion of sensor-based and model-based information. Vania and Pennacchi [185] developed some methods to measure the accuracy of the results obtained with model-based techniques aimed to identify faults in rotating machines. The information provided by these methods was shown to be very helpful to having more precise fault identification along with evaluating the confidence of a diagnostic decision.

Petri nets, as a general purpose graphical tool for describing relations existing between conditions and events [186], have recently been applied to machine fault detection and diagnostics. Propes [187] used a fuzzy Petri net to describe operating mode transition and to detect mode change event for fault detection of diagnostics of complex systems. Yang [188] proposed a hybrid Petri-net modelling method coupled with fault-tree analysis and Kalman filtering for early failure detection and fault isolation. Yang et al. [189] introduced an approach for integrating case-based reasoning with Petri net for fault diagnosis of induction motors. The integrated approach was shown to outperform the conventional case-base reasoning ES.

## 4.2. Prognostics

Compared to diagnostics, the literature of prognostics is much smaller. There are two main prediction types in machine prognostics. The most obvious and widely used prognostics is to predict how much time is left before a failure occurs (or, one or more faults) given the current machine condition and past operation profile. The time left before observing a failure is usually called remaining useful life (RUL). In some situations, especially when a fault or a failure is catastrophic (e.g., nuclear power plant), it would be more desirable to predict the chance that a machine operates without a fault or a failure up to some future time (e.g., next inspection interval) given the current machine condition and past operation profile. Actually, in any situation, the probability that a machine operates without a fault until next inspection (or condition monitoring) interval could be a good reference for maintenance personnel to determine whether the inspection interval is appropriate or not. Most of the papers in the literature of machine prognostics discuss only the first type of prognostics, namely RUL estimation. Only few papers addressed the second type of prognostics [107,190]. In the following sections, we focus on discussions of RUL estimation, prognostics incorporating maintenance actions or policies, and the determination of condition monitoring interval.

### 4.2.1. Remaining useful life

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

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

where $T$ denotes the random variable of time to failure, $t$ is the current age and $Z(t)$ is the past condition profile up to the current time. Since RUL is a random variable, the distribution of RUL would be of interest for full understanding of the RUL. In the literature, a term "remaining useful life estimate (RULE)" is used with double meanings. In some cases, it means finding the distribution of RUL. In some other cases, however, it just means the expectation of RUL, i.e.,

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

Note here that proper definition of failure is crucial to correct interpretation of RUL. Although there is a controversy in current industrial practice, a formal definition of failure can be found in many reliability textbooks. To do prognosis, in addition to knowledge (or data) on the fault propagation process, knowledge (or data) on the failure mechanism must be available. The fault propagation process is usually tracked by a trending or forecasting model for certain condition variables. There are two ways in describing the failure mechanism. The first one assumes that failure depends only on the condition variables, which reflect the actual fault level, and the predetermined boundary. The most commonly used failure definition in this case is simple: failure occurs when the fault reaches a predetermined level. The second one builds a model for the failure mechanism using historical data available. In this case, different definitions of failure can be used. A failure can be defined as the event that the machine is operating at an unsatisfactory level, or it can be a functional failure when the machine cannot perform its intended function at all, or it can be just a breakdown when the machine stops operating, etc. Similar to diagnosis, the approaches to prognosis fall into three main categories: *statistical approaches*, *artificial intelligent approaches* and *model-based approaches*.

Goode et al. [102] used SPC to separate the whole machine life into two intervals, the I-P (Installation-Potential failure) interval in which the machine is running correctly and the P-F (Potential failure-Functional failure) in which the machine is running with a problem. Based on two Weibull distributions assumed for the I-P and P-F time intervals, respectively, failure prediction was derived in the two intervals and the RUL was estimated. Yan et al. [191] employed a logistic regression model to calculate the probability of failure for given condition variables and an ARMA time series model to trend the condition variables for failure prediction. Then a predetermined level of failure probability was use to estimate the RUL. Phelps et al. [192] proposed to track sensor-level test-failure probability vectors instead of the physical system or sensor parameters for prognostics. A Kalman filter with an associated interacting multiple model was used to perform the tracking.

Two statistical models in survival analysis, PHM and PIM, are useful tools for RUL estimation in combination with a trending model for the fault propagation process. Banjevic and Jardine [193] discussed RUL estimation for a Markov failure time process which includes a joint model of PHM and Markov property for the covariate evolution as a special case. Vlok et al. [100] applied PIM with covariate extrapolation to estimate bearing residual life. HMM, a stochastic process model discussed earlier, is also a powerful tool for RUL estimation [194,195]. Lin and Makis [196] introduced a partially observable continuous-discrete stochastic process model to describe the hidden evolution process of the machine state associated with the observation process. RUL estimation, as one of the prediction tasks, was given based on the model. Wang et al. [110] proposed a stochastic process, called gamma process, with hazard rate as its mean for prediction of residual life. The condition information considered was the expert judgement based on vibration analysis. Wang [109] used the residual delay-time concept and stochastic filtering theory to derive the residual life distribution.

AI techniques applied to RUL estimation have been considered by some researchers. Zhang and Ganesan [197] used self-organising neural networks for multivariable trending of the fault development to estimate the residual life of a bearing system. Wang and Vachtsevanos [198] applied dynamic wavelet neural networks to predict the fault propagation process and estimate the RUL as the time left before the fault reaches a given value. Yam et al. [199] applied a recurrent neural network for predicting the machine condition trend. Dong et al. [200] utilised a grey model and a BP neural network to predict machine condition. Wang et al. [201] compared the results of applying recurrent neural networks and neural–fuzzy inference systems to predict the fault damage propagation trend. Chinnam and Baruah [202] presented a neural–fuzzy approach to estimating RUL for the situation where no failure data and no specific failure definition model are available, but domain experts with strong experiential knowledge are available.

Model-based approaches to prognosis require specific mechanistic knowledge and theory relevant to the monitored machine. Ray and Tangirala [203] used a non-linear stochastic model of fatigue crack dynamics for real-time computation of the time-dependent damage rate and accumulation in mechanical structures. Li et al. [204,205] introduced two defect propagation models via mechanistic modelling for RUL estimation of bearings. Oppenheimer and Loparo [179] applied a physical model for predicting the machine condition in combination with a fault strengths to life model based on crack growth law to estimate RUL. Chelidze and Cusumano [206] proposed a general method for tracking the evolution of hidden damage process in the situation that a slowly evolving damage process is coupled to a fast, directly observable dynamical system. Luo et al. [207] introduced an integrated prognostic process based on data from model-based simulations under nominal and degraded conditions. Kacprzynski et al. [208] proposed fusing physics of failure modelling and relevant diagnostic information for helicopter gear prognosis. A different way of applying model-based approaches to prognosis is to derive the explicit relationship between the condition variables and the lifetimes (current lifetime and failure lifetime) via mechanistic modelling. Two examples of research along this line are [209] for machines considered as energy processors subject to vibration monitoring and [210] for bearings with vibration monitoring. Lesieutre et al. [211] developed a hierarchical modelling approach for system simulation to assess RUL. Engel et al. [212] discussed some practical issues regarding accuracy, precision and confidence of the RUL estimates.

#### 4.2.2. Prognostics incorporating maintenance policies

The aim of machine prognosis is to provide decision support for maintenance actions. As such, it is natural to include maintenance policies in the consideration of the machine prognostic process. This makes the situation more complicated since extra effort is needed to describe the nature of maintenance policies. Maintenance in this situation is the so-called CBM discussed in the introduction. Compared to conventional maintenance, mathematical models applicable to the CBM scenario are much fewer [213]. See also [214] for more recent references on maintenance modelling.

The main idea of prognostics incorporating maintenance policies is to optimise the maintenance policies according to certain criteria such as risk, cost, reliability and availability. Risk is defined as the combination of probability and consequence. Usually, consequence can be measured by cost. In this case, risk criterion is equivalent to the cost criterion. However, there are some cases, e.g., critical equipments in a power plant, in which consequence cannot be estimated by cost. In these scenarios, probability or reliability criterion would be more appropriate. Since cost criterion applies to most situations, it is not surprising that the literature in CBM optimisation is dominated by cost-based CBM optimisation. The consequence analysis technique discussed in [215] is a general risk evaluation tool for CBM optimisation based on various kinds of criteria.

In condition monitoring, no matter what machines are monitored, they fall into two categories: *completely observable systems* and *partially observable systems*. For a completely observable system, the machine state can be completely observed or identified. The information collected from this system is called direct information. For a partially observable system, the machine condition cannot be fully observed or identified. The information obtained from this system is called indirect information, which is somehow related to the real machine state. In the text to follow, we discuss various models and methods for these two types of systems, respectively.

First, we consider completely observable systems. Wang [216] developed a CBM model based on a random coefficient growth model where the coefficients of the regression growth model are assumed to follow known distribution functions. The model was used to determine the optimal critical level and inspection interval in CBM in terms of a criterion of interest, which can be cost, downtime or reliability. In a series of works [217–219], a stochastic model, gamma process, was used to describe the deterioration process; the system was considered as failed if its condition jumps above a pre-set failure level; sequential (or non-periodic) inspection interval was assumed. Then Grall et al. [217] assumed a multi-level control-limit rule replacement policy and obtained the optimal thresholds and inspection scheduling by minimising the expected maintenance cost per unit time. Castanier et al. [218] assumed a multi-level control-limit rule repair/replacement policy and obtained optimal thresholds and inspection scheduling based on a cost criterion and an availability criterion as well. Dieulle et al. [219] assumed a one-level replacement policy and a sequentially chosen inspection interval using a maintenance scheduling function, and obtained the optimal threshold and inspection scheduling by minimising the global cost per unit time. Amari and McLaughlin [220] utilised a Markov chain to describe the CBM model for a deterioration system subject to periodic inspection. The optimal inspection frequency and maintenance threshold were found to maximise the system availability.

Berenguer et al. [221] presented a CBM structure for continuously deteriorating multi-component systems, which allows cost savings by performing simultaneous maintenance actions. Barata et al. [222] used Monte-Carlo simulation to model continuously monitored deteriorating systems, non-repairable single components or multi-component repairable systems. Then optimal degradation thresholds of maintenance intervention were found to minimise the expected total system cost over a given mission time by a direct search. Marseguerra et al. [223] used GA to find the optimal thresholds in the previous work by simultaneously optimising two typical objectives of interest, profit and availability. Hosseini et al. [224] employed generalised stochastic Petri nets to represent a CBM model for a system subject to deterioration failures and Poisson failures. It was assumed that deterioration failures are restored by major repair and Poisson failures are restored by minimal repair. The optimal maintenance policy and inspection interval were then found to maximise system throughput.

Now we consider partially observable systems. Ohnishi et al. [225] applied a Markov decision process model for a discrete-time deterioration system to find the optimal replacement policy in which minimal repair is used to restore a failure if the decision is not to replace. Hontelez et al. [226] formulated the decision process as a discrete Markov decision problem based on a continuous deterioration process to find the optimum maintenance policy with respect to cost. Aven [227] presented a counting process approach to determining the replacement policy minimising the long-run expected cost. Barbera et al. [228] proposed a CBM model assuming exponential failures with failure rate depends on the condition variables, and fixed inspection intervals. The optimal maintenance action was then found to minimise the long-run average cost of maintenance actions and failures. Barbera et al. [229] extended the previous work to the case of two-unit series systems. Christer et al. [230] used a state space model and the Kalman filter to predict the erosion condition of the inductors in an induction furnace conditional on the indirect measurements to date. Then a replacement cost model was developed to obtain the optimal replacement policy given all available information. Kumar and Westberg [231] proposed a reliability-based approach for estimating the optimal maintenance time interval or the optimal threshold of the maintenance policy to minimise the total cost per unit time. The authors used PHM to identify the importance of monitored variables and a total time on test plot to find the optimal solution. Makis and Jardine [232] established a CBM model using a Markov process to describe the evolution process of condition variables and a PHM to describe the failure mechanism that depends both on age and condition variable. This CBM model was further elaborated in [233]. The optimal replacement policy of the hazard control-limit type was then determined by minimising the long-run expected total cost per unit time. Makis et al. [234] applied optimal stopping theory to find the replacement policy maximising the total expected profit during the machine life where no assumption of monotonicity of the signal process is made. Makis and Jiang [235] presented a framework for CBM optimisation based on a continuous-discrete stochastic model. The evolution of the hidden machine state was described by a continuous-time Markov process, and the condition monitoring process was described by a discrete-time observation stochastic process which depends on the hidden machine state. Then the optimal replacement policy was found to minimise the long-run expected cost per unit time using optimal stopping theory. Wang [236] applied a stochastic recursive control model for CBM optimisation based on the assumptions that the item monitored follows a two-period failure process with the first period of a normal life and the second one of a potential failure. A stochastic recursive filtering model was used to predict the residual, and then a decision model was established to recommend the optimal maintenance actions. The optimal condition monitoring intervals were determined by a hybrid of simulation and analytical analysis. Okumura and Okino [237] constructed a generalised CBM model, in which residual life loss and replacement preparation lead-time are included. The optimal inspection time vector and warning level of the target maintained system under a constraint preventive replacement probability were obtained by minimising the long-run average incurred cost per unit time. Barros et al. [238] considered an optimal CBM policy for a two-unit parallel system of which unit-level monitoring information is imperfect and/or partial.

#### *4.2.3. Condition monitoring interval*

There are two types of condition monitoring: continuous and periodic. By continuous monitoring, one continuously monitors (usually by mounted sensors) a machine and triggers a warning alarm whenever something wrong is detected. Two limitations of continuous monitoring are: (1) it is often expensive; (2) to continuously monitor raw signals with noise produces inaccurate diagnostic information. Periodic monitoring is, therefore, used due to it being more cost effective and providing more accurate diagnosis using filtered and/or processed data. Of course, the risk of using periodic monitoring is the possibility of missing some failure events which occur between successive inspections ([41], p. 131).

The main issue relevant to periodic monitoring is the determination of the condition monitoring interval. Optimal design of the condition monitoring interval (or inspection interval) has been studied together with optimal threshold design in some of the works discussed in the previous section [216–220,224,231,236,237]. The following research works considered condition monitoring interval determination only. Christer and Wang [239] derived a simple model to find the optimal time for next inspection based upon the wear condition obtained up to current inspection. The criterion is to minimise the expected cost per unit time over the time interval between the current inspection and the next inspection time. Okumura [240] used a delay-time model to obtain the optimal sequential inspection intervals of a CBM policy for a deteriorating system by minimising the long-run average cost per unit time. Goode et al. [241] used the model developed in [102] to determine the length of the next condition monitoring interval for a given risk level. Wang [242] developed a model for optimal condition monitoring intervals based on the failure delay-time concept and the conditional residual time concept. Condition monitoring is assumed to be performed at a fixed condition monitoring interval over the whole life and at a dynamic condition monitoring interval as well in the failure delay-time period realising that more frequent monitoring might be needed in this later period. A hybrid of simulation and analytical procedure was used to find the optimal intervals based on one of five cost criterion functions.

## 5. Multiple sensor data fusion

For a complex system, a single sensor is incapable of collecting enough data for accurate condition monitoring, fault diagnosis and prognosis. Multiple sensors are needed in order to do a better job. With the rapid development of computer science and advanced sensor technology, there has been an increasing trend of using multiple sensors for condition monitoring, fault diagnosis and prognosis. When multiple sensors are used, data collected from different sensors may contain different partial information about the same machine condition. Now the problem is how to combine all partial information obtained from different sensors for more accurate machine diagnosis and prognosis. The solution to this problem is known as multisensor data fusion.

There are many techniques to multisensor data fusion. They can be grouped into three main approaches: (1) data-level fusion, (2) feature-level fusion and (3) decision-level fusion. For more discussion on these three approaches, see [243,244]. Heger and Pandit [19] used a data-level fusion approach to fuse images obtained by multidirectional illumination to generate an image with a high degree of relevant information for grinding tool condition monitoring and fault diagnostics. Liu and Wang [245] briefly reviewed some applications of these three multisensor data fusion approaches to machine diagnosis and prognosis, and applied a feature-level fusion approach called CCNN for rotating imbalance diagnosis. Diagnostics based on the multisensor data fusion was shown to outperform diagnostics based on a single sensor. Wang and Wang [246] used a decision-level data fusion approach called Dempster–Shafer evidence theory for diesel engine fault diagnosis. Kozlowski et al. [247] proposed a model-based approach to battery predicted diagnostics using decision-level data fusion. Byington et al. [248] explored the methods to fuse non-commensurate oil and vibration features for better gearbox fault diagnostics and prognostics. Mannan et al. [249] applied a radial basis function neural network to fuse the features extracted from images of machined surfaces and sound generated during the machining process for condition monitoring and diagnostics of cutting tools. Hannah et al. [250] discussed frameworks in data fusion applications for condition monitoring and diagnostic engineering. Data fusion combined with CBM optimisation was studied in [251,252]. Assessment and evaluation of data and information fusion strategies were discussed in [253,254]. Wang and Wang [255] discussed the reliability and self-diagnosis of sensors in a multisensor data fusion diagnostic system.

In a mechanical system with multiple sensors installed, data collected from each sensor may be a complicated mixture of data from several sources. But only some of the sources are related to a particular machine condition of interest. Now the problem is how to separate different sources for better machine diagnosis and prognosis by fusing the observed multisensor data. The technique for solving this problem is known as blind source separation (BSS) [256]. Recently, BSS has received increasing attention in the area of machine fault diagnostics and prognostics. The general idea of BSS is shown in Fig. 3. It is assumed that the source signals $S(t) = [s_1(t), \ldots, s_n(t)]$, generated from $n$ unknown independent sources, and the noise signals $N(t)$ independent of the source signals, are combined together by an unknown mixing process. The mixed result is observed at the channel output as an $m$-dimensional ($m \geqslant n$) signal $X(t) = [x_1(t), \ldots, x_m(t)]$. A formula for the mixing process can be written as

$$X(t) = f(S(t), N(t)),$$

where $f$ is generally a non-linear, time-dependent function. A commonly used form for the mixing process separates the signal and noise, i.e., $X(t) = f(S(t)) + N(t)$. The objective of BSS is to find a separating function that is applied to the observed signals $X(t)$ to obtain an estimate of the source signals $S(t)$.

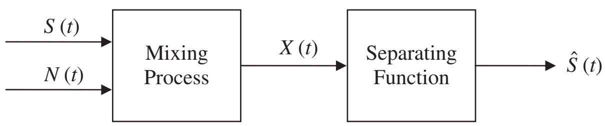


Fig. 3. General idea of BSS.

In the literature, there are two categories of mixing process: instantaneous and convolutive mixing process. A mixing process is instantaneous if $f(\cdot)$ is a time-independent (memoryless) function, and convolutive otherwise. Convolutive mixing process is more common especially for mechanical systems. Instantaneous mixing model is also called ICA model, which is a natural extension of PCA. For a survey on ICA theory and methods, see [257]. Several authors applied ICA together with other signal processing techniques for condition monitoring and machine fault diagnosis [258–261]. Tian et al. [262] used ICA in frequency domain and wavelet filtering for gearbox fault diagnostics. Zhang et al. [263] studied ICA for partially BSS of diagnostic signals for bearing faults with prior knowledge. For a convolutive mixing process, BSS is more complicated. Gelle et al. [264] compared two approaches, namely a temporal approach and a frequency approach, to solving the BSS problem of rotating machine signals for monitoring and diagnosis purpose. They [265] further studied the application of the temporal approach to bearing fault diagnostics. Tse and Zhang [266] applied the BSS-based method of second-order statistics to separate aggregated vibration signals generated from a number of mechanical components for machine fault diagnostics. Vilela et al. [267] used the temporal de-correlation approach to separate the mixed acoustic signals for machine monitoring and fault diagnosis. Serviere and Fabry [268] applied BSS to separate noisy harmonic signals for rotating machine diagnostics on a semi-blind mixing basis.

## 6. Concluding remarks

In this paper, we have attempted to summarise recent research and development in machinery diagnostics and prognostics implementing CBM. Various techniques, models and algorithms have been reviewed following the three main steps of a CBM program, namely data acquisition, data processing and maintenance decision-making, with emphasis on the last two steps. Different techniques for multiple sensor data fusion have also been discussed.

Realising that the reference list is extensive for a novice in the CBM area to browse through, we summarise here a short list of references to provide an introductory familiarity with the ideas and methodologies in this area. Moubray [101] and Williams et al. [113] are good books for an introduction to the general ideas and concepts of CBM. Collacott [269] can be used as an introductory book for various data acquisition techniques used in condition monitoring. Allen and Mills [270] is a good book providing an introduction to the theory of signal analysis. In this book, time-domain analysis, frequency-domain analysis and time–frequency analysis are covered. For an introduction to signal analysis of random signals, see the book by Hayes [56]. A recent review on the application of wavelet transform in vibration signal processing for machine diagnostics is given in [92]. For an introduction to various methods for fault detection and diagnostics, see books [114,172,173]. For prognostics and CBM models incorporating maintenance policies, see [212,213]. Hall and Llinas [243] and Hall and McMullen [244] are good books for an introduction to multiple sensor data fusion.

Although advanced maintenance techniques have been available in the literature, there are still two common extremes in current industry. One extreme is to always adopt a run-to-failure (breakdown) policy. The other extreme is to always apply an as-frequent-as-possible maintenance policy. Of course, the two conventional maintenance policies, namely the run-to-failure policy and the time-based preventive maintenance can be applied to some special cases with satisfactory results. However, in many situations, especially when both maintenance and failure are very costly, CBM is absolutely a better choice than the conventional ones. Expert knowledge in both the application field and the reliability and maintenance theory is required for choosing the best maintenance policies.

Reasons that advanced maintenance technologies have not been well implemented in industry might be: (1) lack of data due to incorrect data collecting approach, or even no data collection and/or data storage at all; (2) lack of efficient communication between theory developers and practitioners in the area of reliability and maintenance; (3) lack of efficient validation approaches; (4) difficulty of implementation due to frequent change of design, technologies, business policies and management executives.

Next generation diagnostic and prognostic systems will likely focus more on various aspects of continuous monitoring and automatic diagnostics and prognostics. We believe that the following research directions are required for the next generation of diagnostic and prognostic systems.

1. Enhancement of CMMS systems to collect accurate information, especially event information. This information would be invaluable for model building, and model validation as well.
2. Development of advanced sensor techniques for robust on-line data acquisition.
3. Development of methods or tools for extraction, processing and interpretation of knowledge type information.
4. Development of efficient and fast on-line signal processing algorithms.
5. Development of robust fault detection and fault diagnostics approaches for complex systems.
6. Development of fast and precise prognostic approaches.
7. Development of CBM models incorporating more categories of maintenance actions.
8. Establishment of efficient validation approaches.

With the rapid development of the micro-electro-mechanical systems technology, a future trend of CBM research and developments would be the design of intelligent device which has the capability of continuously monitoring its own health using on-line data acquisition, on-line signal processing and on-line diagnostic tools (see, e.g., [271]). Fast and robust on-line signal processing algorithms are crucial to the design of intelligent device. This would no doubt stimulate increasing research interest in this area. Another trend of CBM research would be the collaboration of CBM research groups to produce integrated platforms for enhancing diagnostics and prognostics of a CBM program (see [2] for an application of this idea), since each CBM research group has its own specialty and focus in the CBM area.

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