

Chapter 2

Literature Review

Abstract The thesis title reflects a number of themes, i.e. intelligent system, embedded system, condition monitoring and industrial robot, and previous and recent research in each theme needs to be studied thoroughly; however, there has not been much researches in the field of robot condition monitoring. Thus the purpose of this chapter is to evaluate the condition monitoring methods that have been developed for different machinery with a view to applying the most appropriate one to robots and collectively helps to establish if there is a gap in the area of industrial robot condition monitoring. This chapter will give and describe in its first two sections the necessary background information about the various condition monitoring approaches and techniques. Statistical and Artificial intelligence techniques, such as artificial neural networks (ANN), fuzzy logic system (FLS), genetic algorithm (GA), and support vector machine (SVM), which can be applied to address the issues of fault detection and diagnosis, will also be reviewed. Then, the principle of embedded systems and their application in condition monitoring is reviewed in the third section. The last section of this chapter will discuss the work done in robotics health monitoring and finally the research gap is addressed in the summary section.

2.1 Condition Monitoring Approaches

In machines condition monitoring (CM), fault detection/diagnostic approaches can be classified into two types, dependent on whether the diagnosis evaluation is based on deterministic or stochastic information (e.g., historical, statistical parameters). The first of which has been termed a model-based or “white box” approach, while the second is known as data-driven or “black box” approach (Park and Zak 2003; Kim 2010; Butler 2012). Sections 2.1.1 and 2.1.2 define the principles of these approaches and present a brief overview of previous work based on them.

2.1.1 Model-Based Approach

The model-based fault detection approach employs a mathematical model of the system under observation, by assuming that a fault in the system will lead to deterministic changes in the model parameters. The model-based approach relies on comparing the model outputs with the actual system outputs to generate a residual signal, and based upon the properties of the generated residual signal, potential fault conditions are identified and useful information is extracted (Ding 2008). The basic concept of a typical model-based fault detection approach is illustrated in Fig. 2.1.

As indicated in Fig. 2.1, there are two main stages in this approach, the first of which generates the residual which is then passed to the residual evaluation stage. Throughout the fault-free operation, the magnitude of the residual signal should be approximately zero, indicating that the proposed model is accurately describing the current behaviour of the system. If, however, the value of the residual signal diverges from zero, appropriate processing and analysis techniques are applied to it in order to obtain valuable features related to the present fault. The properly processed residual signal is then forwarded to a decision logic routine to map the behaviour of the residual signal onto a specific fault condition.

The most important aspect in the model-based approach for precise fault detection is the requirement of an accurate and robust mathematical model of the system under study. In such models since they are usually derived from first principles, using ordinary differential equations, different elements of the model are related to actual physical properties. Therefore, the main advantage of model-based techniques is the capability of detecting unanticipated faults as well as the replacement of hardware redundancy by analytical redundancy (Vachtsevanos et al. 2006). However, in many real world applications it is almost impractical to apply model-based diagnostic approaches, since many physical processes are too complex to develop accurate model. This will cause mismatch between the process and model outputs which, in turn, lead to large error signals usually giving rise to false alarms (Ding 2008).

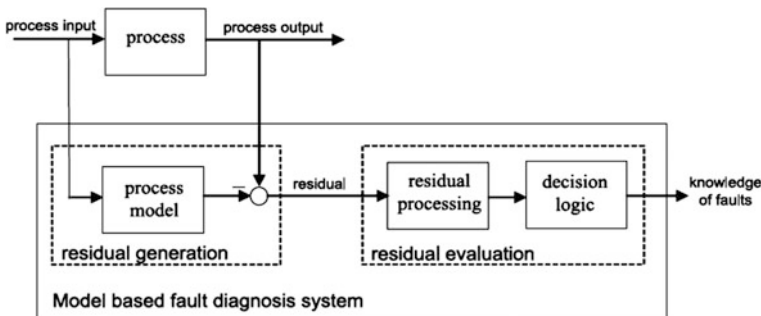
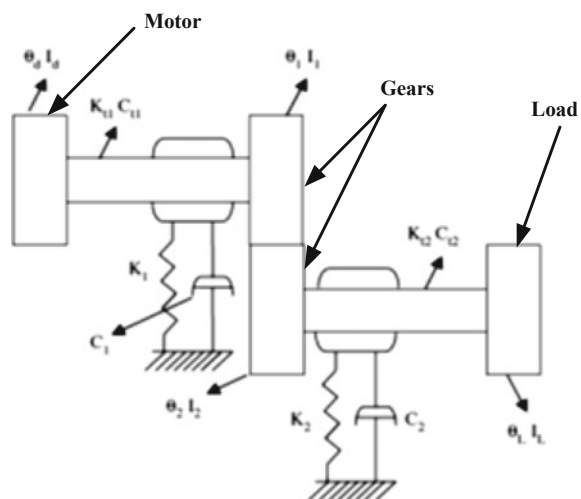


Fig. 2.1 Model-based fault diagnosis flowchart (Ding 2008)

A great amount of work have been undertaken to study the dynamic modelling of, for example gears and bearings, for fault detection. Gears have wide industrial application and unforeseen failures can be enormously damaging, and so research into CM and fault diagnosis in gearboxes is very important. Parey et al. (2006) propose a 6-degree-of-freedom dynamic model for a spur gear pair to simulate and study the effect of lateral–torsional vibration combination on vibration response in the presence of localized tooth defects. The model included two inertial masses representing load and prime mover, two shafts, and bearings, as shown Fig. 2.2. To analyse the simulated signals a multi-resolution signal processing technique was used to break-down the vibration signal to multi-level. Then, statistical parameters such as Crest factor and kurtosis were calculated from each level and utilized to give an early detection of contact surface pitting. Recently, Liang et al. (2015) have developed a dynamic model to simulate the vibration source signals for a planetary gearbox in the healthy and the cracked tooth conditions. The signals were analysed using time- and frequency-domain feature extraction techniques. For model verification experimental work was accomplished and the results were deemed acceptable.

Bearings are of paramount importance in most types of machinery, and bearing failure is one of the foremost causes of breakdown in machines. A generic scheme for health monitoring of rolling element bearings was proposed by Jiang and Zhang (2012). The approach incorporates vibration modelling and online fault dimension estimation. Offline training was applied to obtain the parameters of the vibration model. The trained model is then used online in parallel with a real system (in service) to realize model-based fault detection and diagnosis. To address noise and uncertainties problems associated with fault dimension estimation, an extended Kalman filter was used to increase the accuracy of diagnosis. The proposed system was validated on a case study of rolling element bearing health monitoring and experimental results demonstrated the efficiency of the proposed method. An earlier

Fig. 2.2 Schematic of modelled spur gear pair (Parey et al. 2006)



paper introduced a dynamic modelling for a gearbox test rig to investigate the effect of a defect in gears and bearings on the vibration signal (Sawalhi and Randall 2008). Two damage types in the gears, spalls and cracks, and inner race, outer race and rolling elements faults in the bearings were adopted in this study. To detect these faults, diagnostic techniques such as spectrum comparison, spectral kurtosis analysis and envelope analysis were applied to the vibration signal for both experimental and simulation work.

2.1.2 *Data-Driven or Model-Free Approach*

Data-driven approaches depend on the features extracted from the measured process data for building a model that represents the process, and these are categorised into two types; statistical based methods and those based on artificial intelligence (AI) techniques (Jardine et al. 2006; Yadav and Kalra 2010). Within these categories, a huge range of techniques have been employed to handle a wide variety of fault detection problems. The suitability for usage a data-driven monitoring strategy is for processes in which an explicit mathematical model is difficult to construct because of shortage of knowledge or information related to the process (Yadav and Kalra 2010). In the following subsections, an overview of these methods and their applications are presented.

2.1.2.1 Statistical Based Approaches

The concept of model-free based fault detection and diagnosis has stimulated the interest of using *novelty detection* for condition monitoring, which focuses on identifying any deviations between the features extracted from the recent measured data and the data measured under normal (healthy) operating conditions. The features obtained from a machine in its undamaged state will have a distribution with an associated mean and variance. However, a variation in the mean and/or variance will appear if the machine is damaged.

Statistical control charts (SCCs) provide a framework for monitoring the distribution of the features and detection if they are inconsistent with the past healthy state, and any change in the distribution characteristics of the features will indicate damage, termed *outlier* analysis. SCCs are one of the earliest statistical fault detection techniques dating back to 1931 (Yadav and Kalra 2010). Starting with the advent of Shewhart control charts for averaging, usually called X-bar ($\bar{X}$) chart, which is normally used in combination with a range chart (R chart) or standard deviation chart (S chart) (Montgomery and Runger 2014). Further modification to Shewhart charts have resulted in cumulative sum (CUSUM) and the exponentially weighted moving average (EWMA) charts in the early 1950s (Yadav and Kalra 2010). Because these charts are easy to construct, implement, and interpret, they received a large acceptance in the field of machines and processes monitoring.

Techniques based on SCCs can be classified to two approaches: the univariate and multivariate approaches. In the former method each characteristic of interest is monitored independently whereas in the latter the concurrent monitoring of characteristics is accomplished, considering the correlation that may exist among the various characteristics (Yadav and Kalra 2010; Kisić et al. 2013). Despite their acceptance, the main disadvantage of control charts is that their purpose is for the detection of damage, rather than its quantification and location.

Baydar et al. (2001) presented a multivariate statistical methodology for helical gears monitoring. The gathered time-domain vibration signals were employed to form a reference condition model using principle component analysis (PCA). The T-square control chart, type of multivariate SCCs, was adopted as health condition indicator. Researchers concluded that when tooth failures occur, the probability density function (PDF) of the measured signal will change which gives good indication about the health condition. Another paper applied two statistical techniques for wind turbine gearbox CM (Zhang et al. 2012). The first technique was based on data-mining algorithms used to build a statistical model for predicting the jerk indicated by the vibration excitement of the gearbox. This model was utilized in conjunction with experimentally captured vibration signal to produce residual signals. Two control charts, X-bar and EWMA charts, were constructed to evaluate the residual and fault prediction.

Another application, amongst others, of statistical control charts is for roller bearings condition monitoring. Niknam et al. (2013) at University of Tennessee investigate the use of CUSUM chart for detecting bearing failures, such as unbalance, based on acoustic emission signal analysis. Similarly, Zhou et al. (2008) presented an approach for in situ induction motor bearing fault detection by combining noise cancellation and X-bar chart. In this work the motor current signature was analysed to extract features related to bearings deterioration. Two control charts were developed based on Shewhart average chart to identify the initial start point of the bearing defect (Wang and Zhang 2008). These charts are named adaptive moving average chart, and adaptive Shewhart average level charts. Based on these charts the researchers were able to produce warning and action limits, as shown in Fig. 2.3. The findings of this study suggest that the adaptive Shewhart average level chart overcomes the drawback of adaptive moving average charts by working out the limits using all the bearings' data.

More attractive applications of SCC are for induction motors and rotating shafts health monitoring. García-Escudero et al. (2011) proposed a methodology for incipient fault detection in induction motors. They used fast Fourier transform (FFT) and wavelet transform (WT) signal processing techniques to detect significant peaks in the captured current signal. Then, a quality control approach based on multivariate T-square control chart was successfully applied to detect the progressive deterioration of the rotor cage. Another paper proposed the use of CUSMA chart to monitor the misalignment in a rotating shaft (Sun and Chang 2004). The gathered vibration signal was fitted with an autoregressive model and the residuals between the fitted and observed vibration signals used as a monitored parameter. Control chart limits were designed using the healthy baseline residual data. The

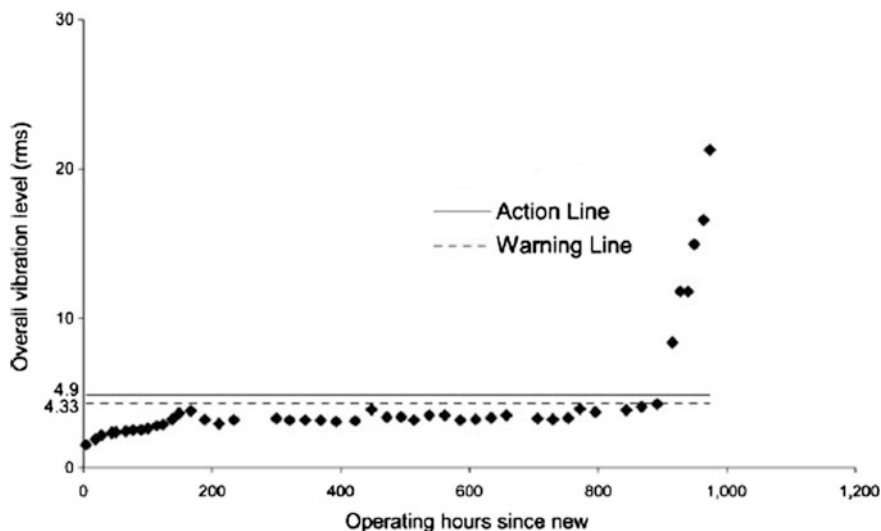


Fig. 2.3 Shewhart rms average chart for bearing fault detection (Wang and Zhang 2008)

results showed that this approach was capable of detecting both mean and variance shifts and also indicate the fault severity.

2.1.2.2 Artificial Intelligence Based Approaches

Artificial intelligence (AI) can be defined as a “computerized approach that employs knowledge, reasoning and/or self-learning to enable machines to perform tasks which humans perform using their intelligence” (Heng 2009). In recent years, AI techniques such as neural networks, fuzzy logic and support vector machines have been widely developed to improve the accuracy and efficiency of fault detection and the diagnosis of machines which can take over some menial and tedious tasks. The intelligent detection and diagnosis begins after data has been collected and important features extracted, as illustrated in Fig. 2.4. The following bulleted sections summarize the fundamental concepts of these methods and their applications to the area of intelligent condition monitoring.

- Artificial Neural Network (ANN):** An artificial neural network (ANN) is a computational structure inspired by the data processing and learning ability of biological neurons in the brain. It is composed of simple computation units called neurons, which integrate the functionality of both memory and computation (Samarasinghe 2007; Dreyfus 2005). ANNs can be employed for a variety of tasks, such as function approximation, classification, pattern recognition, clustering, and forecasting (Samarasinghe 2007). For example, an ANN was applied to fault detection and diagnosis in 4-stroke internal combustion engine

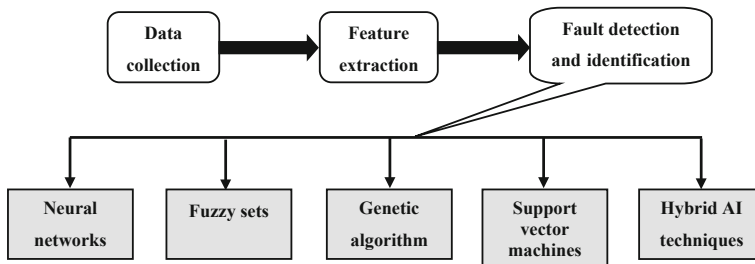


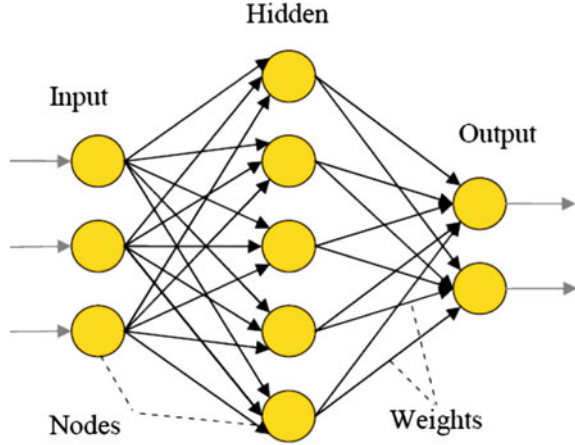
Fig. 2.4 Some of artificial intelligence techniques used for condition monitoring

by depending on a minimum number of sensory data (Chandroth et al. 1999). Cylinder pressure and vibration data were acquired from the engine. By using features of the collected data, two sets of artificial neural nets were trained separately. Experimental work was carried out using a twin cylinder diesel engine, and it was demonstrated that it is possible to detect and diagnose the most common component faults in the engine using either cylinder pressure or vibration amplitude. Such a system would thus require fewer sensors. Neural networks are commonly arranged in layers, and each layer has an array of interconnected elements. Each element receives an input signal, manipulates it, and then output signals are forwarded to the other connected elements in other layers. There are many different forms of neural networks depending on their connection patterns. However, the main classes of neural networks are the feed-forward neural network, whose signal direction is from the input to output layer without any feedback connection. That means the past signals are not used for processing the new signals, as illustrated in Fig. 2.5a. The recurrent (Feedback) Neural Network, which has a feedback connection, and utilizes past signals for identifying the new features, Fig. 2.5b.

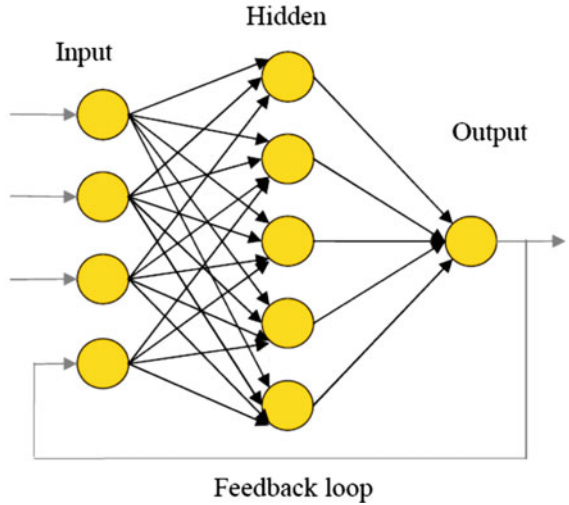
There has been significant interest in applying artificial neural networks to identify and diagnose faults in machinery. Kudva et al. (1992) used multilayer perceptron neural networks to deduce the size and location of damage in smart structures using measured strain values at different locations. More recently, and in contrast, Parhi and Dash (2011) applied the same technique for structural monitoring, but vibration signatures were used instead. Both studies achieved acceptable levels of prediction of crack locations.

Lopes Jr et al. (2000) implemented impedance techniques and neural networks to detect, locate, and characterize structural damage. The advantages of smart materials technology and the characteristics of neural network were combined in proposing a self-diagnostic procedure. Experimental investigations were successfully carried out to locate and identify damage in a quarter-scale bridge section. It was concluded that this technique can be applied to complex structures. In another study, a 2-step neural network was used to design a predictive fault detection and diagnosis model for the monitoring of nuclear power plants (Bae et al. 2006). The

Fig. 2.5 The main categories of artificial neural network (Heng 2009)



(a) Feed-forward network



(b) Recurrent network

main role of the first network was to classify failure type, and then failure severity was determined using the second network. The results showed that this model was suitable for failure detection, but additional work was needed to increase its accuracy. Another study conducted by Zhang et al. (2007) looked at fault diagnosis in a steam turbine generator by applying of an integrated neural network based on combined information. The aim of this method was to overcome the problem of multi-failure mode diagnosis in a single neural sub-network, which normally requires many learning samples. The preliminary diagnosis of faults was implemented using one sub-neural network, after which the sub-neural networks were

merged to yield the final decision. It was found that there are many advantages to this approach as system accuracy and reliability are increased, and the uncertainty of system information is reduced.

- **Fuzzy Logic (FL):** Fuzzy logic or fuzzy set theory is an important technique first introduced by Zadeh in the 1960s to deal with vague, imprecise and uncertain knowledge and data. It is especially suitable for systems with a mathematical model which is difficult to drive. FL is composed of four elements (Marwala 2012): a fuzzy set, which is applied to achieve a flexible representation of the elements in the fuzzy system; a membership function, which shows the level of possibility that an object is an element of a certain class; logical operators, which are used to find new fuzzy sets from the existing fuzzy sets; and fuzzy rules, which show the conditional articulations used to perform the input–output relationships of the system, which can include human descriptive judgments such as:

IF speed is high THEN stopping-distance is long
IF speed is low THEN stopping-distance is short

Decisions in FL can be made with estimated values and incomplete information. A decision might be changed at a later time when extra information is available, or when it may not be correct. For instance, if the input parameter values of a system might be ‘fuzzy’ or incomplete, the conclusions drawn will be incomplete or incorrect as well (Munakata 2008). The major advantages of fuzzy systems are their robustness and flexibility, since they are not restricted to a true or false approach, and they are ideal where system information is limited and unclear (Lim 2009). The application of fuzzy systems in CM has recently been studied in building reliable monitoring systems. For example, Navarro et al. (2010) successfully designed a FL system for monitoring of electric motor bearings. The researchers used more than one signal to accurately detect bearing failures. These included vibration, stator current, bearing frequency, and acoustic emission. In another paper, a computer system-based fuzzy tool was developed to monitor an induction motor by measuring its vibration signal (Janier and Fazrin Zaim Zaharia 2011). The information received from the vibration sensors was used to determine whether or not faults had occurred and actions would then take place to protect the motor from further damage.

Aliustaoglu et al. (2009) developed a fusion approach based on a two-stage fuzzy system and sensor readings for tool wear monitoring. The machine acoustic emission, thrust force, and vibration signals were used to drive the statistical parameters by applying the first stage of the proposed approach, using a Mamdani fuzzy model, as demonstrated in Fig. 2.6. The output values from the first stage were taken as the input parameters of the second stage, which applies the Takagi-Sugeno fuzzy model. Then, the final decision was made using the threshold function and depending on the output values from the second stage as illustrate in Fig. 2.7. The authors mentioned that the performance of this approach can be improved by using electric motor current as a fourth input parameter to the fuzzy system, in addition to using various classifiers.

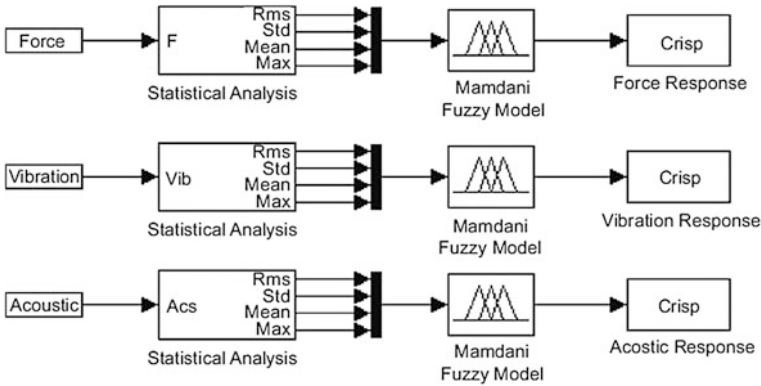


Fig. 2.6 First stage of proposed Fuzzy-sensor model (Aliustaoglu et al. 2009)

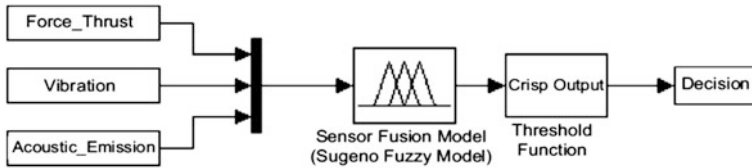


Fig. 2.7 Second stage of proposed Fuzzy-sensor model (Aliustaoglu et al. 2009)

- Genetic Algorithm (GA):** The genetic algorithm was first introduced by John Holland in the early 1970s. It can be defined as a computational technique that mimics the genetic processes of biological organisms in order to solve search and optimization problems (Negnevitsky 2005; Munakata 2008; Marwala 2012). To apply a GA to any problem, several key steps have to be followed (Goldberg 1989; Marwala 2012). Firstly, a number of possible individual solutions containing a number of chromosomes are randomly generated. Then, the fitness value of each individual current solution has to be computed, the purpose of which is to evaluate the performance of each chromosome. Once the fitness values have been calculated, a new population will be generated by applying crossover and mutation operations to the individuals. When a convergence criterion is reached, the algorithm stops; and if not, this process is repeated from the second step.

Genetic algorithms have since been adopted in many different disciplines, such as for automatic programming, missing-data estimation, finite-element analysis, and condition monitoring (Marwala 2012). For example, GA was successfully applied in the bearing monitoring process to select the most important features from a large set of vibration signals (Jack and Nandi 2000), where in one set of experiments the GA was capable of selecting a subset of six inputs from a set of 156 features. In a similar study, a GA-based optimization method was applied to select the optimal

cutting conditions for each pass of a turning operation, with consideration given to the effect of overall progressive tool wear on machining performance (Pal et al. 2011). The optimization process showed precisely that cutting parameters are not constant when tool wear is taken into account, from which it was concluded that the GA has very good classification accuracy. In other studies, a two-stage process was utilized to detect structural damage (Chiang and Lai 1999; Moslem and Nafaspour 2002), where in the first stage the residual force method was applied to initially locate damage. The GA was then used in the second stage to evaluate the damage in the identified structure.

Differences in the natural frequencies of force vibration are most frequently represented as a potential damage indicator (Ostachowicz et al. 2002). However, changes in the first four frequencies have been used to identify the exact location and magnitude of an added concentrated mass on a simply supported, isotropic plate. A GA model was developed which showed good ability in finding the accurate location and value of added mass. Meruane and Heylen (2011) have presented a technique based on model properties and a GA to detect faults in a tri-dimensional space-frame structure. Two damage scenarios were adapted in this work to verify this technique. The findings showed that this method was capable of detecting and quantifying three simultaneous instances of damages.

- **Support Vector Machines (SVM):** Support vector machines are a type of artificial intelligence methodology applied mostly for the classification and regression of data. SVMs were first introduced by Vapnik in the late 1990s and are supervised learning methods derived from statistical learning theory, as in most neural network systems. Supervised learning methods refer to machine learning methods which try to generate a clear map between the inputs and outputs in the training data. SVMs are suitable for two-class classification, but there are a number of extensions which enable this technique to be used for multi-class classification problems (Marwala 2012; Lim 2009).

SVMs have gained significant importance recently because of their superior ability to generate an accurate representation of the relationship between the input and output from a small amount of training information (Sharma 2008). For example, if there is a two-class dataset, a SVM will classify them by finding a separating plane that will divide the space containing the data. All points at each side of the hyper-plane will belong to a specific class. The best separating plane can be a linear boundary in the input feature space, however, in some cases a non-linear boundary could be used to separate the target classes where a linear boundary might not be able to separate them adequately, as shown in Fig. 2.8 (Fulcher 2006).

Nowadays, SVMs are applied in many research fields, such as biological sequence analysis, text classification, data mining, facial recognition and mechanical fault diagnosis, and the results are promising (Lim 2009; Zhang et al. 2009). In terms of fault detection, SVMs have been applied to detect the location of damage in rigid structures (Shimada and Mita 2005; Shimada et al. 2006). Changes in the natural frequencies of the structure were used first as training data for the SVMs,

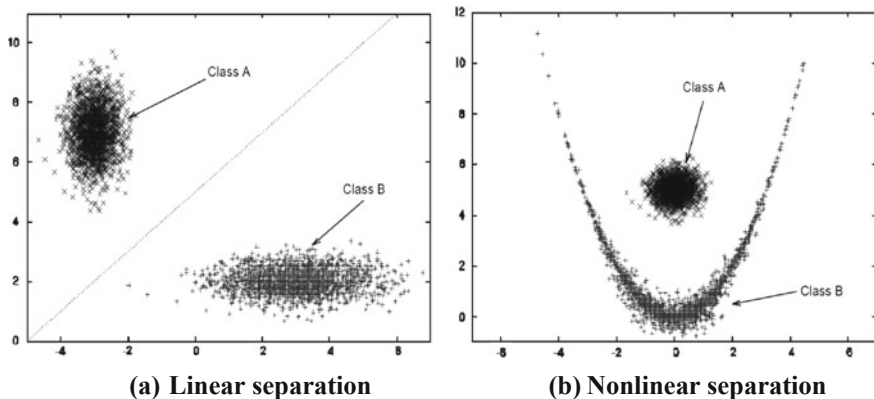


Fig. 2.8 SVMs for data classification (Fulcher 2006)

and then to detect damage location. The main goal of this study was to reduce the number of sensors used to collect important data from the structure. The authors pointed out that this technique effectively decreased the possibility of incorrect damage detection. A comparison study of artificial neural networks (ANNs) and support vector machines (SVMs) has been presented which compares their performance in gear fault detection (Samanta 2004). Vibration signals in the time-domain were used in this research for feature extraction. Moreover, the number of nodes in the hidden layer in the case of ANNs and kernel parameters in the case of SVMs were optimized using GAs. The researchers used experimental data for a known machine to train the ANNs and SVMs. The findings showed that the classification accuracy of SVMs is better than that of ANNs without GA, and the performance of both classifiers increased when GA was used. Additionally, Zhong et al. (2010) used SVMs for the intelligent diagnosis of gearbox faults. An experimental test rig was designed to simulate the most common faults occurring in the gearbox, such as imbalance and misalignment. It was concluded that the SVMs are able to precisely recognize different fault types and their severity.

A research study was conducted using SVMs technique to detect and classify of faults in rolling bearings depending on vibration signals in the time-domain (Rojas and Nandi 2006). Four bearing faults were simulated in this study: an inner race fault, outer race fault, rolling element fault and cage fault. It was found that the accuracy of SVMs is minimized if there is a limited amount of training data. Furthermore, this technique has been utilized for the purpose of rotor failure assessment (Yan et al. 2009). It was found that the SVM was reasonable and effective assessment of machinery degradation especially in complicated operating conditions since it does not have limits of input parameters, and the computational required time is also short. On the other hand, Caccavale et al. (2009) reported that “the main drawback of the SVMs is the absence of control over the number of data points selected as SVs by the learning algorithm. This may lead to a heavy computational load in the presence of a large number of training data”. From the above

it can be concluded that SVMs for condition monitoring is still under development and requires further investigation.

- **Hybrid systems:** A hybrid intelligent system is a combination of at least two of the intelligent approaches mentioned previously to achieve more accurate results and better performance. A hybrid system can combine the advantages of different technologies. The main concept of hybrid systems is to create new approaches where the components complement each other's weakness (Lim 2009; Negnevitsky 2005; Munakata 2008). Recently, there has been an explosive growth in the use of hybrid intelligent systems in condition monitoring, in particular, for instance, in Neural- and Genetic-Fuzzy systems.

Neural networks have the capabilities of learning, memorizing, and recognizing patterns in a way the fuzzy systems do not. In contrast, the strength of fuzzy logic lies in its ability to model the decision-making of humans. So, the synergetic integration of neural networks and fuzzy logic can complement each other (Munakata 2008; Negnevitsky 2005). A growing number of researchers have constructed and examined different forms of neural-fuzzy or fuzzy-neural networks. Yen and Meesad (2001) developed a classification algorithm based on fuzzy-neural networks called the incremental learning fuzzy neural (ILFN) network. This technique has the capability of learning new information without forgetting old information. The authors concluded that this approach in classification is better than many recognized classifiers. Additionally, an evaluation study has been conducted to discuss the usability of three artificial intelligence (AI) methods in lathe turning tool wear estimation (Balazinski et al. 2002). These methods were the feed-forward back-propagation neural network, a fuzzy decision support system, and neural network-based-fuzzy inference system with moving consequents in If-Then rules. All three methods gave similarly acceptable results, but there were differences in the training time required. The neural network and fuzzy logic systems needed a considerable amount of training data. On the other hand, the training time was very short for the neural-fuzzy system, making it easy to optimize and use in industry.

In another study, a neural-fuzzy system was applied for the detection of faults in alternating current (AC) motors (Sainz Palmero et al. 2005). This method was tested using an AC motor, and 15 non-destructive fault types were generated. The results showed good levels of detection and classification. Moreover, the knowledge extracted by a fuzzy rule set had an acceptable degree of interpretability. A multiple adaptive neural-fuzzy inference system (MANFIS) methodology has also been applied to detect cracks in dynamic structures (Parhi and Dash 2011). The input layer of the controller was the fuzzy layer and the other layers were neural layers. The relative deviation of the first three frequencies and mode shapes were used as inputs to the fuzzy layer, and the outputs of this layer were used as inputs to the neural layer. The final findings from the use of this method were relative crack depth and relative crack location, showing good agreement with experimental results collected using an aluminium beam with transverse cracks.

A genetic algorithm has a perfect machine learning capability and satisfactory global search ability, whereas its drawback is chance-dependent outcomes and lengthy computation time. When combined with the benefits of fuzzy logic mentioned earlier, it introduces flexible and robust inference methods under high possibility of imprecision and uncertainty. An improved artificial intelligence technique called a genetic-fuzzy system (GFS) can be developed by the hybridization of a genetic algorithm and fuzzy logic. The genetic-fuzzy system combines the learning ability of the genetic algorithm with the uncertainty representation characteristics of fuzzy logic (Munakata 2008; Pawar and Ganguli 2003).

A genetic-fuzzy system has been utilized for damage detection in a cantilever beam and helicopter blades (Pawar and Ganguli 2003). This method was used to find the existence, location, and extent of damage. In order to calculate changes in beam frequencies because of structural damage, a finite element model of a cantilever beam was applied. These changes in frequencies were used to generate the fuzzy system, and rule-base and membership function optimized by a genetic algorithm. It was concluded that this system allows easy rule generation for different structures. The same technique was used in a similar study by the same research group to detect cracks in a thin-walled hollow circular cantilever beam, which was made of composite material and used as part of a helicopter structure (Pawar and Ganguli 2005). It was found that the effectiveness of this method depends on the number of parameters, such as crack density and noise level. Furthermore, it was observed that the genetic-fuzzy system showed reasonable performance in damage detection and isolation.

Genetic algorithms have also been used for optimizing fuzzy system parameters. This technique has been applied to monitor the performance of a cutting machine (Gallova 2010). A simulation study was conducted along with experimental work for result validation. The findings from the experimental work showed good accuracy with theoretical results, and it was concluded that the proposed technique is suitable for large-scale problems because of the ability of genetic algorithm to extract the most effective features from a considerable number of parameters. Furthermore, this hybrid technique has been used in medical diagnosis applications to achieve correct disease classifications (Di Nuovo and Catania 2007). The authors' main aim of this study was to obtain an efficient diagnostic system and at the same time reliable and easy for practitioners to use. The approach was applied to three real-world benchmarks and compared with relevant work to show its effectiveness.

2.2 Condition Monitoring Techniques

In the past few decades and with the development of sensing technologies, different CM techniques have been utilized for the purpose of gears and bearings (or other machines) health monitoring. These techniques, but not limited to, are vibration; sonic emission; motor current; wear debris and lubricant analysis; and thermal

monitoring. Each one of these techniques has its unique advantages and disadvantages and may suit one application but not another. For instance, wear debris monitoring technique requires measuring and analysing the wear particles and contaminants inside the used oil, and needs advanced and expensive laboratory equipment, human expert inspection of the wear debris samples, and is very time consuming (Ebersbach et al. 2006). In this section, a brief description of the first three techniques with a review of previously and recently achieved work based on them will be given, as they are the most applicable techniques to the work reported in this thesis.

2.2.1 Vibration Condition Monitoring

When a defect is developed in a rotating machine while it is in operation, the result is usually an increase in vibration level. Each component of a machine has its own characteristic frequencies determined by its geometry and the rotational speed of the machine. Therefore, by establishing the relationship between the measured frequencies and expected defects, either by theoretical modelling of the machine or by measurement, the defect along with its cause and severity can be determined by performing a detailed vibration signal analysis. Vibration signals analysis has been extensively used for machines fault detection and diagnosis in various industrial applications (Gelman et al. 2011). Gear defect diagnosis based on the analysis of vibration signals using multi-scale statistics was introduced by Loutridis (2008). Experimental investigation to test the capability of this statistical technique was carried out by analysing the vibration data recorded from a single stage gearbox with a pair of spur gears. The fault was simulated on the gear by removing approximately 10 % of the tooth material from the root. Wind turbine gearboxes are one of the most important and fault-critical components in the turbines because of the complicated alternating loads from wind turbulence. Empirical mode decomposition (EMD) signal analysis technique has been used for analyzing the vibration signal of a wind turbine gearbox (Teng et al. 2014), and intrinsic information from the vibration signal of a field gearbox has been extract using EMD.

Huang et al. (2014) published a spur bevel gear fault diagnosis method based on vibration signal analysis by employing wavelet analysis. To test the performance of the proposed method, an experimental study was undertaken of two different faults (tooth breakage and tooth surface wear) in the pinion gear. This paper analysed the variations of gear fault vibration signal using time- and frequency-domain signal analysis methods and then fault attributes were extracted using wavelet analysis. Vibration signal analysis is widely used for planetary gearbox fault detection. Recently, a research proposes two features, namely, accumulative amplitudes of carrier orders and energy ratio based on difference spectra for gear and bearing monitoring of a planetary gearbox (Lei et al. 2015). Vibration data acquired from a gearbox test rig has been used to demonstrate the effectiveness of the proposed features. The vibration data is measured under different motor speeds.

A comparison has been made with those reported in the literature, and has been reported that the proposed features are more successful than others in monitoring and diagnosing gearbox faults.

Randall (2004) used the vibration signature of bearing faults to separate gear from bearing signals in a helicopter gearbox. This technique was based on the different statistical properties of bearings and gears, which were the main factors in the fault diagnosis approach. An illustration was conducted using case history data collected from the US, and Australian Navies. Shao and Nezu (2005) developed an early bearing fault detection technique based on vibration signal de-noising. This technique consists of an adaptive noise-cancelation filter and a wavelet-based estimator. The researchers concluded that, using this method can improve the signal-to-noise ratio when the signal is contaminated by noise and thus faults can be detected efficiently.

A time-frequency analysis technique was adopted for real-time bearing fault diagnosis and prognosis (Aliustaoglu et al. 2008). For frequency analysis, the Fast Fourier transform (FFT) method was used, and experimental work carried out on the bearing-shaft mechanism of an AC electric motor. A schematic diagram of the experimental setup is shown in Fig. 2.9. A current sensor was fixed to the phase line of the motor in order to measure the electric current passing through the driver of the motor, while two accelerometers were placed on the bearing housing to

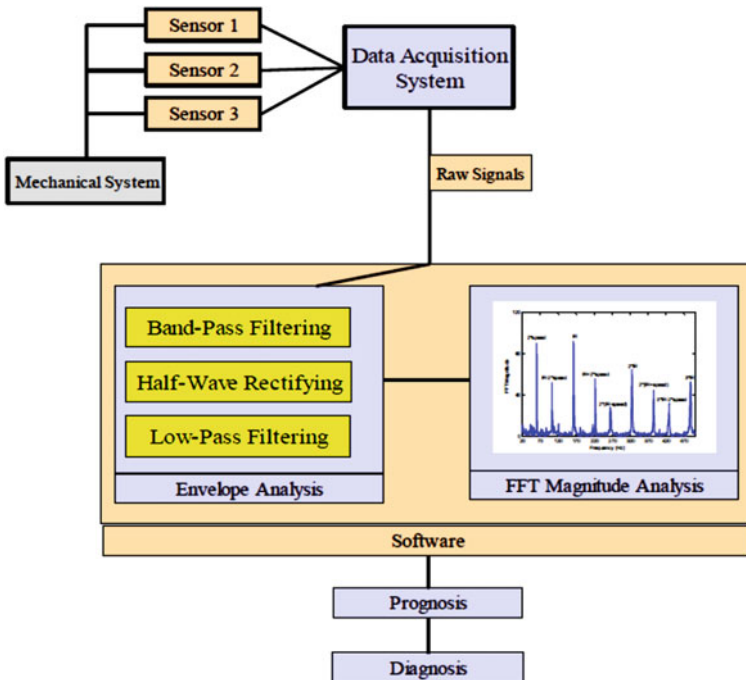


Fig. 2.9 Bearing fault diagnosis and prognosis system (Aliustaoglu et al. 2008)

measure vibration. To analyze bearing status and the progress of any existing faults, vibration and current data were gathered and digitized using a National Instruments data acquisition card. A technique of envelope analysis was applied to separate the modulation signal from the carrier frequency. The authors developed software to perform signal processing task, and six types of defects were defined in this software. The authors claimed that this technique is better than most other advanced techniques, and it could be easily adopted for real-time bearing fault diagnosis.

2.2.2 Noise, Ultrasound and Acoustic Emission (AE) Condition Monitoring Techniques

Acoustics is the study of the generation, propagation, and reception of sound that is heard by a human being (Mohanty 2015). The sounds are classified as desirable or undesirable, which is traditionally known as noise. Human ears are able to hear only sound waves within a specific frequency range, which is known as the audible frequency range (20 Hz to 20 kHz), whereas frequencies above 20 kHz are known as ultrasonic. The acoustic emission (AE) technique deals with signals in the high-frequency range from 100 kHz to 1 MHz (Stamboliska et al. 2015; Mohanty 2015).

Almost all machines under normal operating conditions emit sonic signatures and any variation in these signatures can indicate the start of deterioration of some components. An online gearbox monitoring system based on the LabView program was developed by Wei et al. (2011). This system has the capability to analyze data online and offline, and to query historical data. The authors concluded that the noise detection system can effectively reflect the gearbox's operation status, fault type and location by using spectral analysis. They added that this technique has more advantages than vibration measurement. However, the application of noise measurements in CM is not practical because of the unpreventable noisy background from other neighbouring machines operating in the site which reduces the accuracy of fault detection.

An experimental study was conducted to compare the effectiveness of the ultrasound and vibration measurement technique for the CM of low-speed bearings (Kim et al. 2008). To precisely identify the presence and severity of defects from measured signals, the researchers developed a type of signal processing analysis called the peak ratio (*PR*), suggested by Shiroishi as shown in Eq. (2.1) (Shiroishi et al. 1997):

$$PR = \frac{N \sum_{j=1}^n P_j}{\sum_{k=1}^N S_k} \quad (2.1)$$

where, P_j is the amplitude value of the peak located at the defect frequency and harmonics, S_k is the amplitude at any frequency, N is the number of points in the spectrum, and n is the number of harmonics in the spectrum. The modified PR (mPR) is shown in the following equation, and it depends on disparities between the peak defect frequencies and the average value over the whole spectrum:

$$mPR = 20 \log_{10} \frac{\sum_{j=1}^n (P_j - A_s)}{A_s} \quad (2.2)$$

$$A_s = \frac{\sum_{k=a}^b S_k}{(b - a)} \quad (2.3)$$

where, A_s is the average spectrum amplitude in the frequency band from a to b . It was observed that the ultrasound technique was more effective than common vibration measurements for fault detection. Recently, this opinion has been supported by another research group (Wei et al. 2011).

The AE technique has been increasingly used for condition monitoring of different machinery and structures. For example, Ogbonah (2007) applied AE and wavelet signal analysis techniques for gear fault diagnosis and prognosis. The result of the gearbox health change over time was presented in statistical properties of amplitude, and corresponding frequency and energy changes. A linear relationship between AE amplitude, gearbox running time, and pit progression was shown in this study. An intelligent health monitoring system for power transmission systems (Onsy 2009), included fault prediction and classification, using AE, vibration and oil debris analysis were combined using fuzzy logic. The aim of this was to monitor two modes of gear fatigue failure; the progression of gear surface and bending fatigue failure in helical gears. The progression of micro-pitting was monitored using the AE average signal level, vibration signal root mean square (RMS), and the mass of ferrous debris, whilst tooth-bending failure was monitored using the AE peaks, the vibration kurtosis and oil debris mass rate.

As mentioned earlier the AE-based technique deals with signals in the high-frequency range, and thus it requires much higher sampling rates than vibration-based techniques. A comparative study for gearbox tooth damage level diagnostics using AE and vibration measurements based on the same sampling rate has been conducted recently (Qu et al. 2014). Partial tooth cut faults are seeded in a gearbox test rig and experimentally tested in a laboratory. It was concluded that the AE signals show more stable performance in fault detection, and reported that the AE-based approach has the capability to differentiate gear tooth damage levels in comparison with the vibration-based approach, since the vibration signals are easily affected by mechanical resonance.

2.2.3 Motor Current Signature Analysis

Motor current signal analysis (MCSA) offers a non-intrusive and alternative method to detect mechanical faults through investigating electrical signatures. Provided there is access to the current-carrying conductor to the motor, the drawn current by the stator of the motor can be measured at distant locations from the motor; this represents one of the advantageous of MCSA techniques, since there is no need to mount any transducers or measuring equipment on or near the monitored machine. The MCSA technique was limited to monitoring different faults on induction motors (Kar and Mohanty 2006), including bearings faults.

Schoen et al. (1995) addressed the application of motor current spectral analysis for rolling-element bearing damage detection in induction machines. The study, first, reviewed and found the bearing characteristic frequencies and the modes of failure associated with the construction of the bearings. Then, the relationship between motor current and induced vibration, due to incipient bearing faults, was considered and investigated. This was done by deriving the effects of different bearing faults on the stator current spectrum. The experimental results verified the predicted relationship between the vibration and current frequencies, and confirmed that the stator current signature can be applied to detect the presence of a bearing fault. Another study by Stack et al. (2004) developed a method for detecting progressive motor bearing faults via stator current analysis. The method starts by removing the significant frequency content that are irrelevant to bearing faults by filtering the stator current. The filtered healthy current signal is then used to train an autoregressive model to produce a baseline or reference model. When bearing health is degraded, the deviation in spectral content from its baseline measurement is increased. This increase in spectral deviation was then used as the fault index. A CM technique based on statistical and numerical tools was suggested for detecting the onset of faults in induction motors (García-Escudero et al. 2011). The FFT was used to find the spectrum of the motor current, and a multi-resolution technique using wavelet function was implemented on this spectrum in order to detect the significant peaks. The researchers carried out an experimental study to prove the effectiveness of this approach, concluding that it is very reliable and convenient in detecting failures at their early stages, and it can also take into account the presence of serious anomalous feature measurements.

Nowadays, however, many studies have concentrated on using MCSA for power transmission systems condition monitoring as a replacement for typical monitoring techniques. The MCSA was used as the basis for CM of a multi-stage gearbox by using discrete wavelet transform (DWT) (Kar and Mohanty 2006). By observing the FFT analysis of the captured signals it was concluded that the low frequencies of vibration signatures have sidebands across line frequency of the motor current whereas high frequencies of vibration signature were difficult to detect. A suggestion of applying the discrete wavelet (DWT) to decompose the current signal was made, followed by FFT analysis on some of the DWT results to trace the sidebands of the high frequencies of vibration. In the experimental test rig the faults

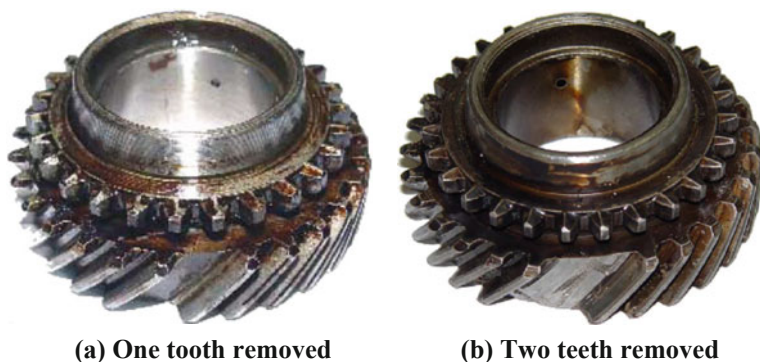


Fig. 2.10 Simulated faults in the gears (Kar and Mohanty 2006)

was artificially simulated on one of the gears by removing one tooth and then two teeth, Fig. 2.10.

The electromagnetic motor torque estimation can give significant information about the efficiency and health condition of an electromechanical system, and this technique has recently been used for fault diagnosis of gears. The loss of lubrication in a gearbox is considered as a gear failure due to its influences on the vibration and on the electromagnetic estimated torque signatures. By using the electromagnetic torque estimation technique this and other fault types, such as tooth breakage fault in a high-ratio gear in cement kiln drives, have been identified (Kia et al. 2010; Bogiatzidis et al. 2013). Initially, a theoretical validation through a modelling approach to investigate how periodic impulse torque excitation affects the motor current spectrum and how it is expected to be demonstrated at the motor electromagnetic torque has been fulfilled. The effectiveness of this technique has successfully been demonstrated via experimental verification, and validated using vibration signal measurement and analysis simultaneously with the electromagnetic torque analysis.

Apart from aforementioned techniques, several non-destructive and contactless condition monitoring methods have been developed for monitoring machine health and compared with the traditional ones. For instance, a research group applied an infrared thermo-graphic technique to monitor deep-grooved ball bearing with circular weights mounted on them and different lubrication states (Seo et al. 2011). They compared the results from this method with those of the traditional vibration spectrum analysis to evaluate the efficiency of the suggested method. Figure 2.11 shows the test rig, and the infrared camera (Silver 450 M from Cedip Corp). The vibration analyzer shown in Fig. 2.11 was used for spectrum analysis, and the data acquired using this technique was reported to be clearer than that derived using vibration analysis technique.

Another study by Onsy et al. (2012) applied an image registration (IR) technique for online health monitoring of gears system. The main aim of this study was

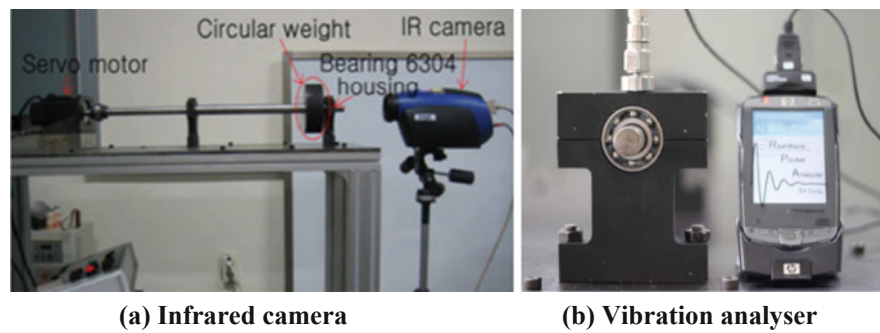
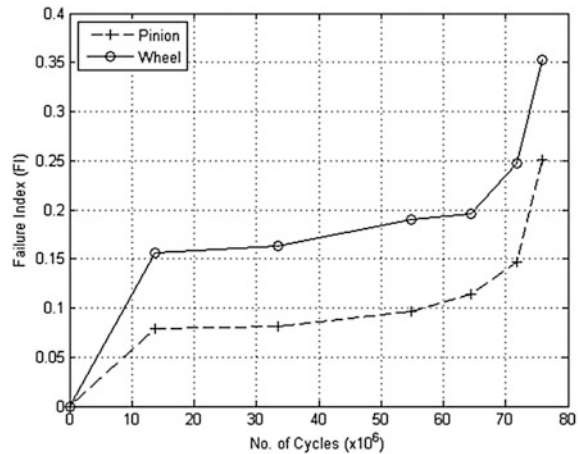


Fig. 2.11 Test rig for comparison between the thermo-graphic and vibration analysis techniques for bearing health monitoring (Seo et al. 2011)

Fig. 2.12 Failure index (FI) values of geared system (Onsy et al. 2012)



monitoring the progression of micro-pitting and surface scuffing failures. A back-to-back gearbox was designed, and a variable speed electric motor used to drive the system. To evaluate the state of health of this system, the failure index (FI) was found by comparing captured images at different time intervals with reference images taken before running the test. Figure 2.12 shows the values of failure index for pinion and wheel gears versus number of cycles and it can be concluded that the micro-pitting progressed gradually during testing. To check the capability of this technique, the FI results computed using the IR technique were correlated with vibration and oil debris analysis indicators measured for the same test rig and the findings were considered promising.

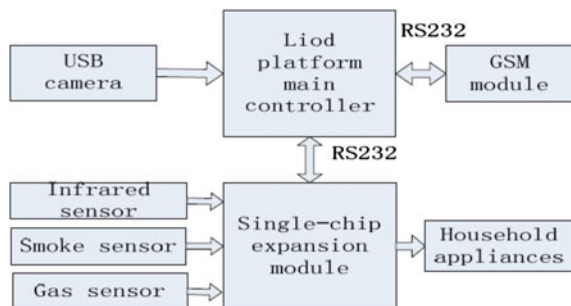
2.3 Embedded Systems for Condition Monitoring Applications

An embedded system consists of computer hardware with software embedded in it, and has a set of specific functions to be performed, often in real-time. Embedded devices can be used to control, monitor or assist in the operation of equipment, machinery or plant. They differ from general purpose computers such as a personal computer (PC) which are to be flexible enough to perform many different tasks and to meet a wide range of user requirements. The prime differences between embedded systems and PC computers are that the former often do not have displays or keyboards, usually come within larger systems or machines, and have constraints such as small memory, slow CPU or real-time response (Collins 2000).

Embedded systems are found in many applications, including modern cars, airplanes, and mobile robots. Their main merits are low-cost, flexible structure, steady performance, small size, low power consumption, high reliability and integration, and the ability to work in constricted spaces and tough environments (Wang 2009; Sarrafzadeh et al. 2006). Basically, all embedded systems contain a processor and software to execute instructions, and incorporate a memory to store the executable code, as well as input and output devices. Sensors and probe devices can be used to provide inputs, and outputs generally display the changes in the physical world via wire or wireless communications links (M 2002).

Embedded systems are one of the most widely used types of device in many current applications. One research study has described the applications of embedded systems for diagnostic and treatment planning in health care applications for patients with chronic diseases (Srovnal and Penhaker 2007), where the systems have to be portable, non-intrusive, and low in weight and cost in order to be suitable for use. This research also suggests that embedded home care systems could be used as predictive diagnostic systems. Interestingly, proposed applications have expanded to include home safety and environment (Zhai and Cheng 2011). In this study an embedded system was designed to monitor smog percentage and gas parameters, and to collect video information from within a house. Figure 2.13 shows the architecture of the proposed system, which basically contains two

Fig. 2.13 Embedded system for household appliance monitoring (Zhai and Cheng 2011)



controllers (a main controller and an expansion module), and a number of different sensors connected to them. In addition, this system has the ability to communicate remotely with household appliances using a global mobile communications (GSM).

Recent years have witnessed a trend in using the embedded systems for machine fault detection and diagnosis. Generally speaking, there are two categories of embedded systems that can be used for industrial machinery condition monitoring; these are discussed as follows.

2.3.1 *Wired Systems*

Health monitoring systems are typically fulfilled using wired embedded systems by connecting communication cables directly between the processing and the input/output units. Different varieties of such systems are available nowadays; ranging from simple sensing devices that detect peak-acceleration or peak-strain and inform the user when a certain threshold is exceeded to a more complex system such as a piezoelectric accelerometer with a built-in charge amplifier connected directly to a hand-held, single-channel fast Fourier transform (FFT) analyser. For instance, a microcontroller-based data acquisition system integrated with an accelerometer was used for a milling machine vibration monitoring (Zhang and Chen 2008). The acquired data was sent to and analysed on a PC in real-time manner utilizing software developed in Visual Basic. Time-domain and FFT signal analyses methods were applied for feature extraction and visual interpretation was relied for tool health assessment. Furthermore, a vibration faults simulation system, which involves data acquisition and analysis using LabVIEW-based virtual instrument technology, was proposed to serve as teaching equipment for mechatronics students in the area of CM (Gani and Salami 2004). A test rig was developed to simulate and study most common vibration fault signatures encountered in rotating machines.

An embedded system which implements self-organizing maps using a neural network has been applied to the online detection and classification of faults in electromechanical valves used for flow control (Gonçalves et al. 2009). The aim was to build a proactive maintenance scheme for these valves. A mathematical model of the valve was used to train the map for the fault detection process, and fault classification training was carried out by fault injection based on parameter deviations using the same model. Throughout the online monitoring, the embedded system works to find the best match between the current torque and position, and their values which were calculated using the trained map. The embedded system was prototyped using a Xilinx FPGA (Field programmable gate array) development board. It was found that the embedded system is a hopeful solution for predictive maintenance in these actuators. Cabal-Yepez et al. (2013) has presented a design and implementation of an embedded system that utilizes reconfigurable hardware based on FPGA. This system performs time-frequency signal analysis techniques, such as short time Fourier transform (STFT) and discrete wavelet transform (DWT),

on vibration signals captured from an industrial robot for the purpose of early abnormalities diagnosis. To the best of the author knowledge, this paper is considered the only one which focuses in the area of industrial robotics CM based on embedded system. However, there are several shortcomings in the paper, such as: only backlash fault has been considered, lack of intelligence capability since it cannot notify the operator if a fault has developed, and it relies on a wired communication.

A smart sensor network based on Texas Instrument digital signal processor (DSP) type TMS320F2812, AD7656 analogue-to-digital converter (ADC), accelerometer and temperature sensor was used to establish an embedded system for vehicle fault diagnosis (Lijun et al. 2010). The wavelet transform (WT) signal analysis technique for feature extraction was implemented on the system. The communication between the DSP and the other hardware peripherals was enabled using a controller area network (CAN) bus, which is a communication standard designed to permit microcontrollers and devices to communicate with each other in applications without a host computer. Other successful utilizations of DSPs as an embedded system are for medical diagnosis and gearbox vibration signals analysis (Chen et al. 2009b; Lijun et al. 2010). WT was also applied in these two papers, but on this occasion using a TMS320C6713 DSP.

It is clear that the digital signal processing and artificial intelligence algorithms are very powerful and becoming more commonly employed as tools for solving different monitoring problems. Traditionally, these algorithms are implemented using PCs, dedicated DSP chips or FPGAs. These solutions are very efficient in this matter but, on the other hand, they are expensive and large, as in the case of implementing them on PCs. Thus, low cost microcontrollers, such as Arduino and PIC microcontrollers, represent an alternative solution to implement these algorithms. An example is the implementation of ANN on an inexpensive 8-bit PIC microcontroller (Cotton et al. 2008; Tripathy et al. 2014; Rai and Rai 2013). Marandu (2014) has designed an intelligent mechatronic system based on modern version of PIC Microcontrollers, called dsPIC digital signal controller. It has been used for online dental material testing and surface wear monitoring with vibration signal capturing and analysis. LabVIEW software was used to design the graphical user interface (GUI) to send and receive the data from the system. Limitations of these controllers, however, are low memory and central processing unit (CPU) performance.

2.3.2 Wireless Systems

Based on the concept of wireless sensor networks (WSNs), which comprise of a number of battery-powered (or take advantage of nearby power supply if available) sensor nodes, each of which contains different (or the same) sensors types to monitor different variables and transmit the data wirelessly, embedded systems have been extensively used for building different wireless condition monitoring systems.

The typical sensor node should be small size, low power consumption and low cost. WSN solutions are being increasingly employed in CM applications, for example in vehicle fault diagnosis (Shukla et al. 2009). The system comprises a large number of sensors able to communicate with each other through a wireless network, able to get live data from the vehicle, such as oil temperature, wheel balance, and fuel level. The embedded microprocessors gather the data and send them to an external monitoring entity. Another paper has suggested an intelligent diagnosis system combining WSN with a multi-agent system (MAS) (Wu et al. 2011); to satisfy the needs for high sampling rates, high precision, high speed and large amounts of data transmitted from mechanical equipment. The efficiency of the system for a coal preparation plant was investigated, and its practicability was demonstrated.

Other applications of embedded system are found in structural health monitoring. Rad and Shafai (2009) utilized wireless embedded sensors as a successful alternative to fiber optics sensors to assess the state of the infrastructure of bridges in North America. Wireless sensor networks have also shown sufficient potential in data collection when they have been applied to monitor wind turbine blades (Taylor et al. 2011). Here piezotronic accelerometers were used to pick up the signals from blades in both healthy and damaged states, and the sensors were fixed at different locations on the blades and wireless data acquisition utilized. Micro-electro-mechanical-sensors (MEMS) have also been used for condition monitoring. For example, a tiny and very light weight MEMS accelerometer has been mounted on a rotor shaft to monitor its dynamic behavior (Elnady et al. 2011). The accelerometer was connected to a wireless sensor node for the wireless transmission of vibration signals, as shown in Fig. 2.14. Without any added imbalance and at different rotating speeds, vibration measurements such as acceleration values were taken with acceptable performance. It was reported that this technique assisted in reducing the number of sensors needed to monitor the rotating parts.

An embedded system has been applied to helicopter gearbox monitoring (Qin and Hu 2012), with the aim of designing a wireless sensor node fixed to the planetary gears' carrier in order to gather vibration signals to an external receiver through the antenna which extends into the gearbox. The acquired signal was

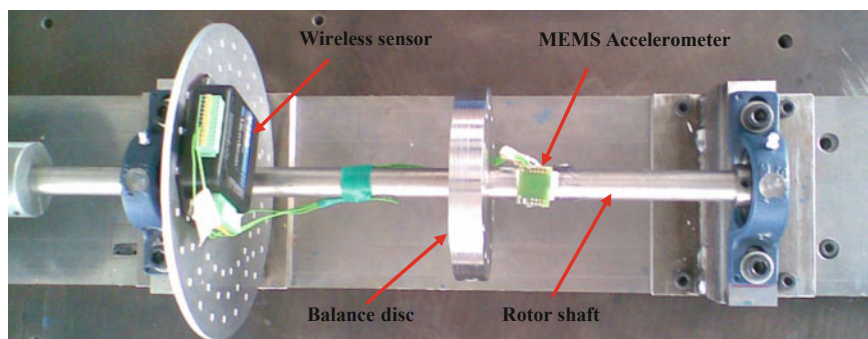


Fig. 2.14 Vibration measurement using MEMS accelerometer (Elnady et al. 2011)

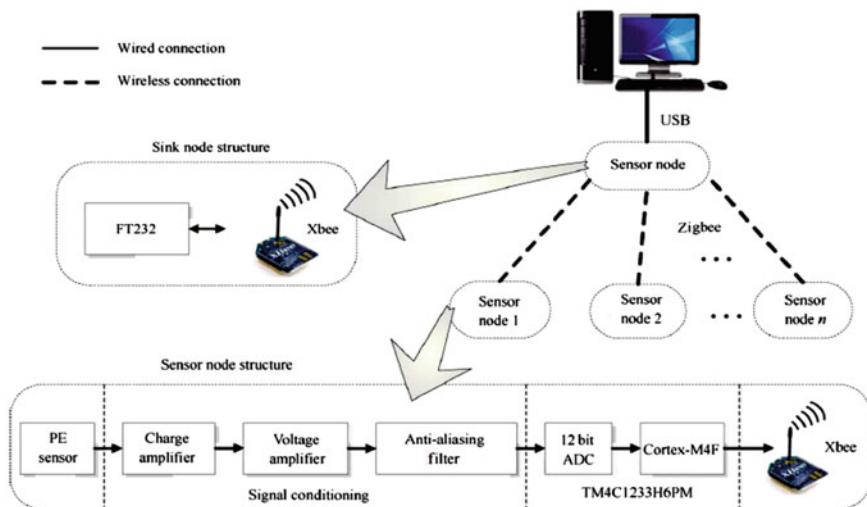


Fig. 2.15 Structure of the wireless bearing CM system (Feng et al. 2015)

analyzed using signal processing methods. An experimental system consisting of a set of planetary gears built using one sun gear and four planetary gears was constructed, and four wireless sensor nodes were installed in the space between each two neighboring gears.

Zigbee is a wireless protocol widely adopted in WSN because of its low cost, low power consumption and applicability to create large scale networks. A research study has implemented the envelope analysis algorithm for wireless bearing CM based on vibration signals measurement (Feng et al. 2015), however, to overcome the limitations of memory size and restricted computational capabilities in the commercially available wireless nodes, the authors have used a 32-bit microcontroller type TM4C1233H6PM from Texas Instruments along with Zigbee wireless module. The power consumption on the wireless node, which represents a considerable problem in the WSN systems, has been reduced by processing the acquired vibration signal on-board at the sensor node with the result communicated to the recipient node. The hardware architecture of the proposed wireless monitoring systems is shown in Fig. 2.15.

Interestingly, the rapid developments in smartphones and portable devices have changed the traditional way of using them. Researchers have developed a scalable android application based on a smartphone to diagnose some types of fault in an industrial air compressor (Verma et al. 2013). They mentioned that the developed system is very reliable. Another paper has presented a remote monitoring system for a rotating machine which can be run based on smartphone or PDA (personal digital assistant) (Wanbin and Tse 2006). In this paper the developers put the capability of informing the concerned user if a fault appears in the remotely monitored machine. Similarly, a paper proposes a real-time method to perform the monitoring of

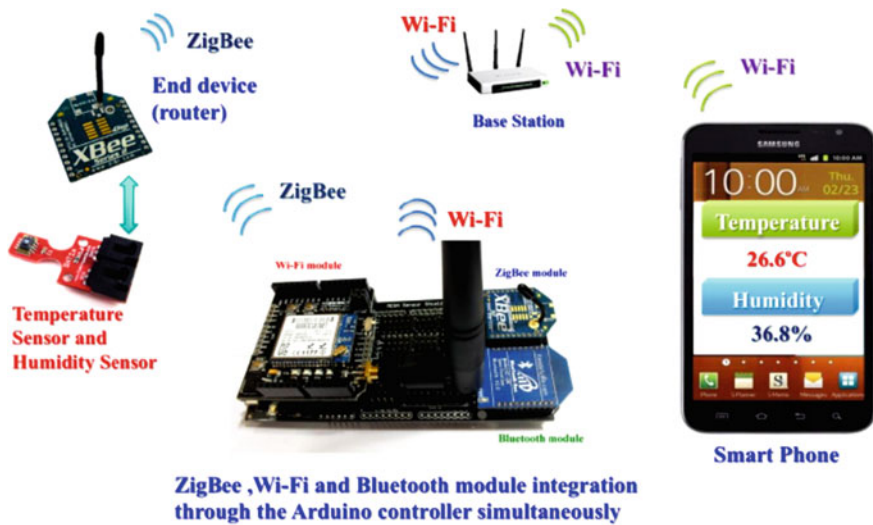


Fig. 2.16 Intelligent embedded system for a factory monitoring

temperature, humidity, air quality and vibrations of operating machinery in a factory zone using smart phones (Lian et al. 2013). The integration of ZigBee and Wi-Fi communication protocol were utilized to build the intelligent monitoring system, Fig. 2.16. By using the ZigBee protocol, the sensors on the factory site transport the real-time sensed data to an integrated embedded controller. The embedded controller was constructed based on an open-source, 32-bit ARM core Arduino Due module. This controller is able to instantly provide numerical results, depending on the received and analysed data, to the smart phones of the factory manager. However, this aspect of CM is lacking of exploration and needs to be further investigated in order to be applied to different machines.

2.4 Applications of Condition Monitoring Techniques in Industrial Robots

After reviewing the previously applied condition monitoring approaches and techniques for a range of machinery, this section explores how these approaches and techniques are applied to industrial robots health monitoring; and to survey the state of the art research with a view to making existing gaps in this area clearer to the readers and researchers. Unfortunately, there is very little (or no) published information regarding the distribution of the robot fault types. Even if available, the most recent one was published in 2000 and it is mainly related to the robot actuator faults (Arvallo and Tesar 2000), and it does not include gearbox faults, which could be a large proportion since robotic gearboxes are frequently overloaded and

experience direct effects of shocks. The author has contacted several robot manufacturers regarding this matter, but regrettably no one of these companies has provided information, not surprisingly, since this might be something connected with their reputation in the competitive market.

Industrial robots are extremely complex mechanism and hence the application of condition monitoring for them differs from that of ‘simple’ rotating machinery. This is basically due to the instantaneous change of geometrical configuration of the robot arm. Previously in this chapter, it has mentioned that there are two approaches to condition monitoring, which are model-based and model-free. Either of these approaches or a combination of both has been adapted in industrial robot condition monitoring. Filaretov et al. (1999) used a nonlinear model to address problems of fault detection and isolation in complex systems, such as in robot manipulators. Algebraic functions were implemented to design the nonlinear diagnostic observer, which was able to dispense with the linearization in nonlinear models to avoid model errors. The robot modeling was conducted using Matlab in discrete time. It was shown that, despite the fact that the use of this model dispenses with linearization, it does not allow some faults to be isolated. In another paper, a model-based fault detection and isolation (FDI) scheme for rigid manipulators was designed which depends on a suboptimal second-order sliding-mode (SOSM) algorithm (Brambilla et al. 2008). In order to make the procedure of FDI possible, an input signal estimator and output observers were adopted and SOSM was used to design the input laws for the observers. Experimental work and theoretical simulations were accomplished with a COMAU SMART3-S2 robot manipulator, and the results showed that the scheme has a good ability to detect and identify faults. On the other hand, the proposed scheme was not able to deal with multiple faults in more than one actuator or sensor, and is also neglected elastic effects in the robot.

Another technique proposed for fault detection and isolation in robot manipulators was based on a new simplified Euler-Lagrange (EL) equation capable of reducing the complexity of the approach (Mohseni and Namvar 2009). The use of this equation allowed the uncertainty in the manipulator’s gravity term to be handled. Moreover, the effects of noise and an uncalibrated joint torque sensor could be taken into account. Simulation was conducted using Matlab-Simulink environment to illustrate the performance of this method. A study by Caccavale et al. (2009) presented an approach based on support vector machines (SVM) to detect and isolate fault in a robot’s actuators, using an available dynamic model of the manipulator, and trained SVMs offline to compensate for unknown dynamics, uncertainties and disturbances. Furthermore, a radial basis function network was implemented to interpolate unknown actuator faults. Finally, an investigation was performed experimentally using Comau SMART-3S industrial robot to check the effectiveness of the approach.

A model-based fault diagnosis to detect actuator faults in a robot manipulator was introduced by Capisani et al. (2010). Analytical redundancy was achieved using higher order sliding mode unknown input observers (UIO). In addition, the design of the input laws for the observers was based on the super-twisting second order sliding mode control (SOSMC) approach. Simulation and experimental work

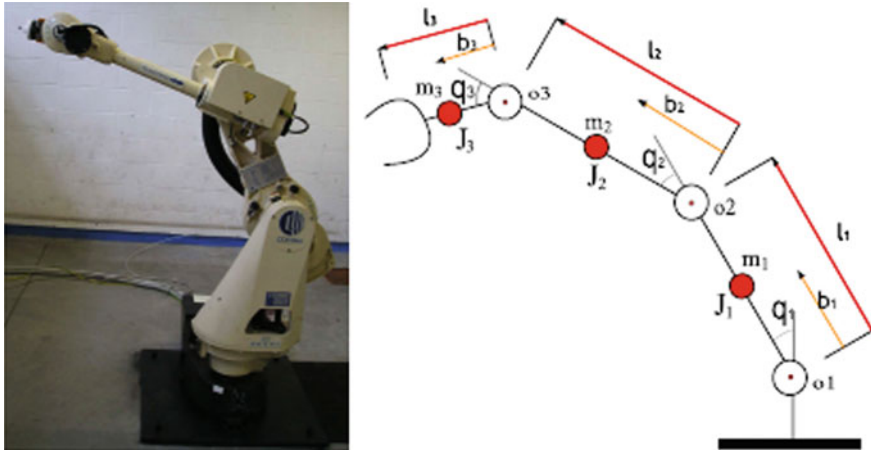


Fig. 2.17 The SMART3-S2 robot (Capisani et al. 2010)

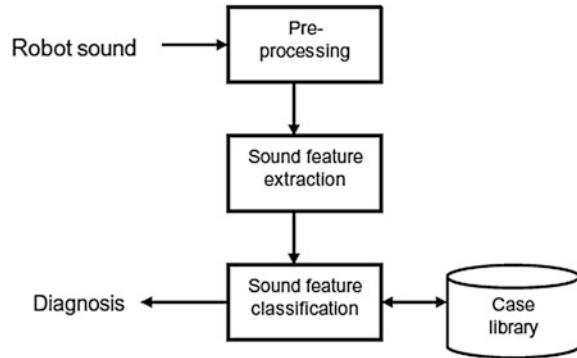
was conducted on a COMAU SMART3-S2 with three links and three joints as illustrated in Fig. 2.17. The results were compared with those of previously proposed approach which depends on sub-optimal second order sliding mode control (SOSMC). It was concluded that the super-twisting approach did not always provide good performance in terms of avoiding false alarms.

Because of the wear process in robot's joints, the friction level will increase, and a study has been conducted to consider the problem of wear estimation in standard industrial robot joints (Bittencourt et al. 2011). A static friction model was used to find the wear level and then this model was extended to take account of the effects of wear. The resulting model illustrates the relationship between friction in the joints and changes in speed, load, temperature and wear. As a result of the experimental and theoretical work, a wear estimator was proposed which was able to distinguish between wear effects under large temperature variations.

Because precise mathematical models for complex systems like a robot are difficult to obtain, model-free methods based on AI or statistical approaches have become prevalent choices for robot health monitoring. The backlash and looseness in the power transmission system of a robot may cause torque variations. However, the electric motor itself generates what is known as a back electromotive force (EMF) when subjected to mechanical load making them acting as a torque transducer (Yuan et al. 2011). The torque variations measurements via current fluctuations on robotic actuators have been applied for robot monitoring (Abdul and Liu 2008; Yuan et al. 2011). The advantage of this technique, as early mentioned, to the robots health monitoring is that the motor current can remotely be measured along the power cables utilizing standard current sensors without supplementary instrumentation on the robot.

Some reported robot fault diagnostic systems are based on acoustic signals analysis. Such systems would have to be able to distinguish the correct information

Fig. 2.18 Fault diagnosis steps (Olsson et al. 2004)



from the ambient noise. Case-based reasoning and signal processing were adopted to build an approach to diagnosis the faults in an industrial robot (Olsson et al. 2004). Wavelet analysis was applied to remove noise from the acoustic signals and to extract the most relevant features, which were then sent to the classification component, which uses case-based reasoning to identify the class of faults according to the characteristic of the previous fault cases. Experimental work on an industrial robot was used to assess the performance of this approach, and Fig. 2.18 shows a schematic diagram of the set-up.

A microphone was used to gather sound signals from the robot, and unwanted noise was filtered out in a pre-processing step, after which the important sound features were extracted, and their classification was performed based on previously classified sound descriptions in the case library. The authors reported that “this system is able to successfully diagnose faults in an industrial robot based on a low number of previous examples”. The same principle was applied to an industrial robot, but on this occasion the ANN was used for noise analysis and classification (Yildirim and Eski 2010). Noise sensors with data acquisition hardware and feature extraction software were used to prepare the training data for designing the ANN-based noise fault detection of robot manipulator’s joints.

Different types of faults in robot transmission systems, such as bearing and gear faults, can cause system degradations and thus lead to development of lost motion (looseness). Vibration analysis algorithms, which rely on measured vibration signal by an accelerometer, are often used and represent the vast majority of utilized techniques for industrial robot health monitoring. Modal analysis, which can give information concerning the dynamic characteristics of machines, involves machine vibration measurement has previously been applied to assess the dynamic characteristics or for fault detection of industrial robots or rotating machinery (Ma et al. 2007; Liguó et al. 2009). Experimental modal analysis was utilized to find the dynamic characteristics of a PUMA 560 robot and use them to detect robots joint faults (Bicker et al. 1989). An experimental programme was accomplished to investigate the changes in the vibration spectra resulting from induced faults in the transmission of the elbow joint on the robot. From the obtained results, the

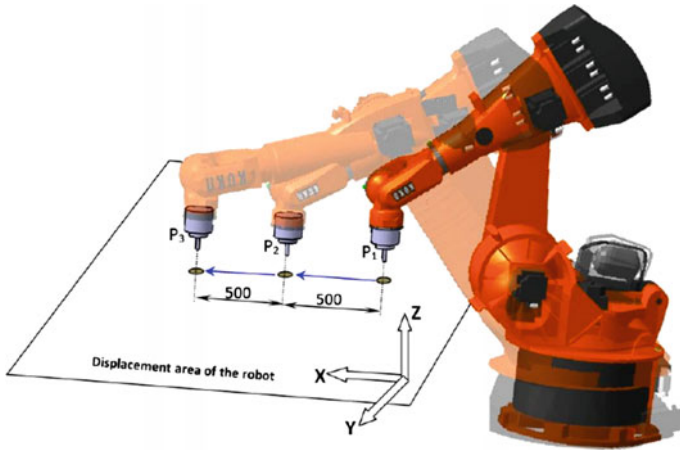


Fig. 2.19 The experimental configuration for impact test (Claudiu et al. 2012)

researchers concluded that backlash can influence the vibration response of the robot elements during normal operations. But, the slight change of peak amplitude at some frequency bands for various backlash conditions was not reliable enough to be used as a criterion for fault diagnosis. Also, at the reversal of motion, the characteristics of backlash can be averaged out over the whole cycle if a conventional spectrum analysis is used to process the vibration signatures. Consequently, the distinct differences between the signatures for different fault conditions cannot be identified accurately.

Recently, modal analysis of KUKA type milling robot has been carried out by Claudiu et al. (2012). The researchers tried to evaluate the robot stiffness at three different and most commonly applied working configurations, as in Fig. 2.19. The first step in this research was to identify the robot self-excited frequencies using impact testing (modal analysis). Then, vibration analysis was conducted first when the robot moving, and after that whilst performing milling process. The result showed that the robot configuration has a significant effect on its stiffness, and therefore on its natural frequencies.

In another study of fault diagnosis in rigid link manipulators, an online learning architecture with a neural network was used for fault detection and isolation by monitoring the behavior of the system (Vemuri et al. 1998). A two-link robotic system was used to show the capability of the neural network in fault diagnosis. Results showed that the learning methodology which was used can provide a model of a fault via analysis of input/output properties as well as detecting its occurrence. A large backlash level in the robot's joints represents a very serious problem. Pan et al. (1998) used vibration signals during normal operation to diagnose joint-backlash on a PUMA 762 industrial robot. Time-domain and frequency-domain analyses were employed to identify features such as probability and density. Artificial neural networks were then used for pattern recognition. The experimental work was performed as shown in Fig. 2.20. One accelerometer was fixed

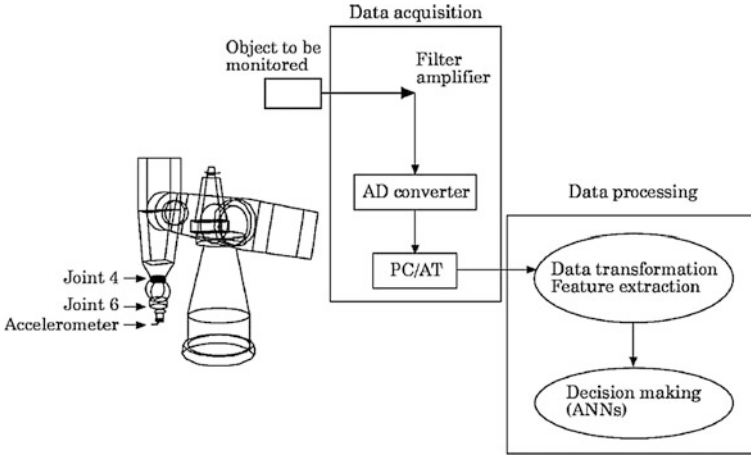


Fig. 2.20 Schematic diagram of the experimental set-up (Pan et al. 1998)

on the robot end effector to measure vibration responses. Additionally, different levels of backlash were artificially contrived in joints 4 and 6 to validate this method. It was pointed out that this technique could be applied in real working environments, and moreover it was inexpensive as only one sensor was used to detect the robot's faults.

Artificial neural networks (ANNs) were used for residual generation and analyzing them in robotic manipulators (Terra and Tinós 2001). For residual analysis, three types of ANN architectures were employed. The first is the radial basis function network (RBFN), which uses position and velocity residuals to identify faults. The second architecture also uses a RBFN, but it utilizes only the velocity residual, and the third is a multilayer perceptron (MLP). A comprehensive simulation study of the PUMA 560 yielded results collected from three joints. It was concluded that the post-failure control of the mechanical manipulator in a hybrid system framework could be included in this work.

Similarly, a technique using only one accelerometer mounted at the robot tip has been applied for the online fault diagnosis in the 4 Degree of Freedom (DOF) SCARA robot (Liu et al. 2009). The tip acceleration was calculated using a dynamic model of the robot, and was used as a reference. By comparing the experimental tip acceleration with the reference, the condition of the robot could be identified. In contrast, another study used more than one sensor for robot joint condition monitoring (Trendafilova and Van Brussel 2003). The objectives were to extract the vital features directly from the measured acceleration signals, and to try to specify defects by finding properties dependent on fault size. Signals were analyzed from the robot joints without error, and subsequently from joints having backlash, using nonlinear dynamics and statistical tools. The proposed system was validated using three robot types: spherical robot arm; SCARA robot arm; revolute robot arm, and on different joints. In order to simulate robot damage conditions,

three levels of backlash (small, medium, and large) were generated in the joints by implementing a variety of loads and adjusting the backlash screws. The authors used the pattern recognition principle with nonlinear autoregressive (NAR) analysis for the detection of defect from the data, and acceptable performance was demonstrated. The same technique applied for fault quantification was less effective, however.

Halme (2006) studied the condition monitoring of servomotors and gears in an industrial robot using performance criteria monitoring, which is a model-free method. This study was implemented with a 6 DOF robot (type Fanuc R-J2 M-6i) utilized for material handling. This robot has a weight of 290 kg, and is capable of moving 6 kg with a repeatability of ± 0.1 mm in space. Acceleration, acoustic emission, and sound sensors were used in order to monitor the accuracy of the robot's path. By comparing different vibration signatures with signals measured over time, deviations in the performance of the robot could be found. However, this method cannot represent an eclectic technique since it always needs to compare signals with references measured at different times and from the same production process.

Another research study used wavelet multi-resolution analysis (WMRA) coupled with a neural network-based approach in order to diagnosis faults in an industrial robot manipulator (Datta et al. 2007). A Matlab-Simulink environment was used to monitor the neural network classifier for a robot used in semi-conductor fabrication. It was concluded that the WMRA is excellent for data reduction and capturing the important properties of signals, although it did not show good performance in distinguishing some of the signals. On the other hand, two neural networks have been used to propose an algorithm for the online monitoring of two-link manipulators (Van et al. 2011). This approach focuses on identifying changes in robot dynamics due to faults. It was noted that this technique was able to provide estimates of fault characteristics.

2.5 Summary

The foregoing literature review has covered a variety of topics, approaches, and techniques applied in the field of CM. The review has shown that two main categories of CM approaches are available: model-based and model-free approaches. In model-based CM, a model of the system (or of how it is presumed to behave) is created. Then, the predicted behaviour from this model is compared to the actual behaviour of the machine and any detected significant deviations can be interpreted as indications of faults. Accurate analytical models of industrial robots are often not practicable and difficult to be constructed due to dynamic complexity of the robot and unavoidable uncertainties (Verdonck et al. 2001). Accordingly, model-free approaches based on statistical and artificial intelligence tools are going to be considered for establishing the condition monitoring system of the robot.

It has also been established that many different techniques of machine condition monitoring, such as the analysis of vibration, acoustic emission, wear and thermal measurements, are frequently used. Vibration and acoustic emission analysis represent the most important techniques that have commonly been applied to monitor the status of industrial machines, and such methods have been widely studied by researchers. Because of the high frequency range of the acoustic signals, CM systems based on AE techniques require highly specialized, expensive sensors and extremely high sampling rates, which means a considerable amount of data has to be acquired in order to detect the exceptional events (Ogbonnah 2007; Randall 2011). Also, due to the acoustic signal attenuation during propagation, the AE sensors need to be as close to the source as possible. In contrast, vibration signal respond immediately to manifest itself if any change has appeared in the monitored machine. Consequently, it provides an easy and cost-effective sensing technique to detect faults in machines and for this reason it will be applied for CM of the robot.

Generally speaking, the vast majority of the literature focuses on finding a monitoring system able to take minimum and precise measurements necessary from machines, which can give clear indications of incipient fault modes in a minimum time. Moreover, the issue of feature extraction from data gathered has been a point of debate among many researchers. In short, to design a reliable condition monitoring system, sensors have to be chosen correctly in order to get accurate signals from faulty parts, and appropriate signal analysis techniques have to be employed since these have a significant impact on the sensitivity of the features extracted from the signals captured.

Recently, the field of the condition monitoring of machines has moved from the use of conventional to AI techniques. A wide variety of AI techniques have been applied extensively in monitoring very complex and non-linear systems such as industrial robots, where it is difficult to build accurate mathematical models of the system. However, each of the AI techniques has strengths and weaknesses, and many studies have concluded that combining multiple methods can give better performance in many condition monitoring applications. Nevertheless, despite the large amount of research conducted in the area of AI in condition monitoring, it is still inadequate and requires significant investigation to be performed. Artificial neural networks (ANNs) have broadly been applied in a number of real-world problems of considerable importance and complexity and will be utilized in this research, not only because of their ability to handle the highly non-linear relationships that exist between industrial robot parameters but also because they can deal with large numbers of variables and provide general solutions with significant predictive accuracy (Ogaji 2003).

In the majority of CM systems, with a special focus on industrial robots, it has been noted that for signal acquisition, processing, storage and decision making, data acquisition (DAQ) cards connected to PCs, as their main processing core, were extensively used, which adds considerably to the cost of CM system. Recent developments in electronics and computing have opened new horizons in the area of condition monitoring, and embedded devices offer promising solutions, and have shown their practicality in fault detection and diagnosis processes in many of

areas. The main aim of using embedded systems is to allow data analysis, which includes feature extraction and diagnostics, to be carried out locally at field level and transmitting the results wirelessly to the base station, which as a result will help to overcome the need for wiring. Furthermore, it seems that there is a serious shortage of studies applying the embedded devices in the industrial monitoring field, and thus they need to be investigated thoroughly, both by researchers, as in this thesis, and by interested companies.

The use of industrial robots has been rapidly increased in a wide range of industrial applications. Therefore, the need for reliable fault detection and diagnosis methods for industrial robots has been increased recently. Most faults in industrial robots occur in their joints, since they have many mechanical and electromechanical parts, such as gears and motors. However, in the above reviewed work in the area of industrial robot CM it is noted that much of the work has been aimed directly at detection of only backlash fault in the gear transmission system. This means that other types of gear and bearing faults have not yet been fully investigated. In this work, an effort to fill part of the gap in the subject of industrial robot CM by not only detection the backlash fault but also other faults, such as gear tooth wear and inner and outer race bearing faults, will be assessed using vibration signal analysis.

In summary, the endeavour of the work in this thesis is to build a wireless and intelligent condition monitoring system for an industrial robot based on an embedded system capable of performing signal capturing, analysis, feature extraction, and then fault detection and diagnosis in real-time operation. The adoption of this route is to try to contribute to the concept of factories-of-future in the 21st century.

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