Chapter

Machine Health Monitoring and Fault Diagnosis Techniques Review in Industrial Power-Line Network

Saud Altaf and Shafiq Ahmad

Abstract

The machinery arrangements in industrial environment normally consist of motors of diverse sizes and specifications that are provided power and connected with common power-bus. The power-line could be act as a good source for travelling the signal through power-line network and this can be leave a faulty symptom while inspection of motors. This influence on other neighbouring motors with noisy signal that may present some type of fault condition in healthy motors. Further intricacy arises when this type of signal is propagated on power-line network by motors at different slip speeds, power rating and many faulty motors within the network. This sort of convolution and diversification of signals from multiple motors makes it challenging to measure and accurately relate to a certain motor or specific fault. This chapter presents a critical literature review analysis on machine-fault diagnosis and its related topics. The review covers a wide range of recent literature in this problem domain. A significant related research development and contribution of different areas regarding fault diagnosis and traceability within power-line networks will be discussed in detail throughout this chapter.

Keywords: fault diagnosis, machine health monitoring, signal processing, industrial power-line network, artificial intelligence, wireless sensor network

1. Introduction

This chapter presents a critical literature review analysis on machine-fault diagnosis and related topics. Most of the contents are extracted from doctoral thesis of the first author of this chapter [1]. The review covers a wide range of recent literature in the problem domain and is classified into the following groups:

- Existing signal processing techniques
- Feature extraction methods
- Existing fault diagnosis methods
- Propagation of fault signals in industrial power-line network

- Fault type diagnosis using wireless sensor networks (WSNs) within industrial machinery networks
- Identified shortcomings in electric current fault diagnosis research

A significant related contribution, and development of these areas, namely fault diagnosis and traceability within power-line networks will be discussed in detail throughout this chapter.

2. Signal processing techniques

In order to collect useful data from targeted physical assets, various fault diagnosis techniques are used in real environments. Machine condition monitoring data include vibration, electric current, temperature and pressure or environmental data.

There are more studies on isolated machine fault diagnosis [1–5] than multiple motors' signal fault diagnosis [6, 7]. Raw data acquired from sensors were preprocessed before being used for further analysis. Errors caused by background noise, human factors and sensor faults need to be eliminated and appropriate features need to be calculated, selected and/or extracted for further fault diagnosis. Once a number of features are obtained, feature-selection methods need to be employed to identify the most effective features to facilitate the fault diagnosis process [7].

2.1 Feature extraction techniques

For accurate fault diagnosis, data must be turned into information before knowledge can be acquired. To turn waveform data into information, fault condition indicators (features) are extracted and/or selected from the acquired signals. Reliable features generally have the following characteristics [8, 9]:

- Inexpensive computational measurement
- Understandable in physical terms
- Mathematically properly definable
- Insensitive to unnecessary variables
- Uncorrelated with other domain features

After acquiring the spectrum data, different types of signal processing methods have been utilised to extract useful feature information and interpret signal waveform data for further fault diagnosis purposes in motors. Most feature extraction techniques can be divided into three groups, as shown in **Figure 1**:

2.1.1 Time-domain feature

Time-domain methods are based on the statistically characteristic behaviours of the waveform signal in time. The most prominent and simplest features in time-domain analysis are root mean square (RMS) and crest factor (CF) of the signal [10]. Other most frequently used features are variance, kurtosis, standard deviation

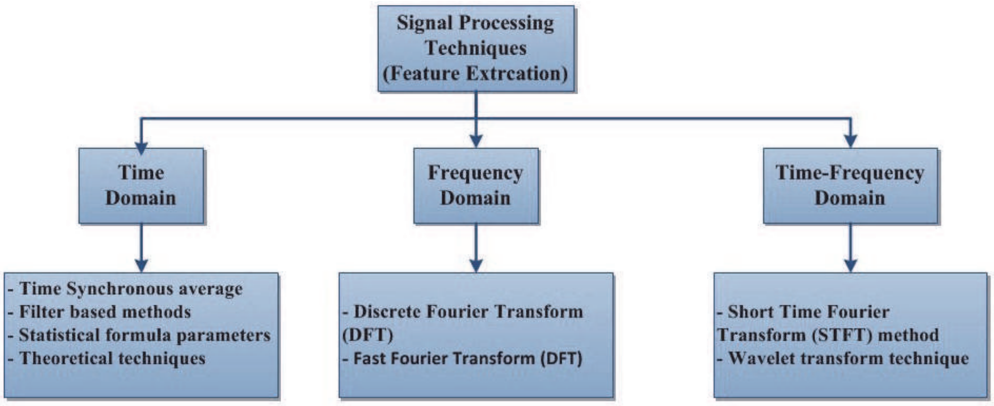

Figure 1.
Overview of common feature extraction techniques.

and skewness. These features are based on the distribution of signal samples with time series random variables also called moments or cumulate. In most constituent moments, the probability density function (PDF) can be broken down into parts, because any change in the signal could alter the behaviour of the PDF and would change the cumulate. Therefore, observing this circumstance can provide useful diagnostic information.

Some other time-domain feature extraction techniques discussed in [10–13] include demodulation and adaptive noise cancelling, filter-based and stochastic techniques. One of the shortcomings of the time-domain feature extraction technique is a lack of visible symptoms of faults particularly when a fault is at an early phase. The technique may be useful when short-duration features are extracted from the signal [12].

RMS is one of the most significant time-domain features and is very efficient in distinguishing any imbalance, related fault in industrial rotating equipment. However, it cannot normally identify explicit failing components. It is also not sensitive enough to detect incipient machinery fault [12]. RMS is the measure of the power content of a waveform and can be expressed as follows:

$$RMS = X_{rms} = \sqrt{\frac{\sum_{n=1}^{N} f^2 S(n)}{\sum_{n=1}^{N} S(n)}} \quad (1)$$

where, f =frequency value; and $S(n)$=spectrum for n^{th}sample of waveform from failing components, that is $n = 1, 2, 3, \ldots, n$.

Crest factor (CF) is expressed as a percentage of the peak level of an input signal to RMS level. However, signal peaks in the time domain lead to change in the CF value dynamically [14]. CF can be useful for the detection of impulse vibration changes. CF is defined as:

$$CrestFactor = CF = \frac{Amp_{\max}}{X_{rms}} \quad (2)$$

where, $Amp_{\max}$ is the maximum value of amplitude in signal.

Other significant time-domain features can be calculated by the following equations:

$$Kurtosis = kur = \frac{\frac{1}{n}(X_{rms})^4}{X_{rms}} \quad (3)$$

$$Variance = \sigma^2 = \frac{1}{2}P(X_{rms})^2 \tag{4}$$

$$Skewness = ske = \frac{P(X_{rms})^3}{X_{rms}} \tag{5}$$

where P indicates the expected value of the function.

An approach using NN has been developed and considers signal vibrations to be input features [15]. They use genetic algorithm [15] to extract the most considerable input features for fault diagnosis contexts. When doing this, six input features are selected from a large set of possible available features. Pineda et al. [16] discussed the major disadvantage of cost for vibration monitoring that require access to the machine.

2.1.2 Frequency-domain feature

Frequency-domain features are capable of overcoming the weaknesses of time-domain analysis. Frequency-domain methods are based on the information that a localised fault is produced by a periodic waveform signal, along with distinctive frequency points and features.

When frequency-domain features are used for fault symptom detection, some changes in frequency-domain parameters may indicate the existence of faults, because diverse faults have different spectrums in the frequency domain. Frequency-domain parameters can be also used for early detection of machine faults and failures [17]. Therefore, such indices can be used to perform fault diagnostics processes.

Fast Fourier transform (FFT) is one of the most commonly used techniques in the frequency domain [35]. The FFT, which is a fast algorithm for discrete Fourier transform (DFT), can easily transform a signal into the frequency domain. If it is difficult to analyse a signal in the time domain, it is easier to transform and analyse it in the frequency domain [17].

To enhance the results of spectrum analysis, several types of frequency filter, side-band structure analysis, demodulation and descriptive representation methods are often used [18]. Different types of frequency spectra, such as power spectrum and high-order spectrum, have been developed. The most traditional way of producing a power spectrum is by using a DFT, but some additional methods can also be used, such as the maximum entropy technique. The following parameters in the frequency domain are commonly used as fault indicators for diagnostics [19].

$$Sideband\_peakvalue = Pv = \max|i(j)| \tag{6}$$

$$Frequency\_Centre = FC = \frac{\sum_{n=1}^{N} f.S(n)}{\sum_{n=1}^{N} S(n)} \tag{7}$$

$$Mean\ Square\ Frequency = \mathrm{MSF} = \frac{\int_0^{+\infty} f^2 p(f)\partial f}{\int^{+\infty} p(f)} \tag{8}$$

$$Root\ Mean\ Square\ Frequency = R\mathrm{MSF} = \sqrt{\frac{\int_0^{+\infty} f^2 p(f)\partial f}{\int^{+\infty} p(f)}} \tag{9}$$

$$\text{Standard deviation Frequency} = SDF = \sqrt{\frac{\sum_{n=1}^{n} (f - f_c)^2 S(n)}{\sum_{n=1}^{n} S(n)}} \tag{10}$$

where, f represents frequency value in cycles per second (Hz); P = number of poles; n_s = synchronous speed in revolutions per minute (RPM); n_r = motor speed in RPM; n = total number of samples; $Amp_{\max}$ = maximum value of amplitude in signal; $i(j)$ = series of signals for $j = 1,2,3, \dots ,N$ and N is the number of data points in the signal; and $S(n)$ = spectrum for nth sample value, i.e. $n = 1,2,3, \dots ,n$.

Camps et al. [19] present the measurement of the instantaneous supply frequency for the diagnosis of two electric machines with rotor asymmetries [20]. The technique of instantaneous frequency is used based on the extraction of fault components (RMS, crest factor, etc.) associated with the frequency side bands and the assessment of the instantaneous supply frequency. Furthermore, in case of failure of this technique, the neural network is described in [21] to solve the rotor asymmetries-related faults.

Furthermore, authors [21] suggest further improvements in their previously introduced methodology for the detection of rotor asymmetries and eccentricities for the detection of double-faults rotor asymmetry and eccentricity. They used slip and speed as frequency-domain features on a single isolated motor for fault diagnosis. But in this research, other features are not considered that shows some side bands related to other faults.

Moreover, another relevant study is introduced in [22] that is quite similar with the work discussed in [21]. A critical analysis of temporal lateral side fault component for physically pattern evaluation is presented, with amplitude and frequency values to ends with the proposition method.

The technique proposed in [23] is structured on the extraction of the sideband fault component, and its comparison with the simulated pattern computed in the previous study. It also introduces a method for the quantification of the fault, dividing the spectrum of the fault component of the start-up signal. Mróz et al. [24] introduced a systematised methodology and extended it theoretically to any type of induction machine fault, in which its fault components are a function of the slip, providing a practical guide for the application of the methodology.

2.1.3 Time-frequency domain

Time-frequency methods have the ability to describe machinery fault signatures in both time and frequency domains when the signal is non-stationary [4]. The traditional time-frequency technique uses the time and frequency distributions that signify the energy of the signal in two dimensions.

Short-time Fourier transform (STFT) is the most commonly used distribution technique when the signal is in a non-stationary state [5]. STFT is an enhanced form of Fourier transform (FT). In this technique, the target signal is converted into small windows. After choosing the width of the window function, this is multiplied and shifted with the signal segment to produce concise non-stationary signals. Based on the same procedure, FT is then applied at each segment to obtain the STFT of the signal. This shows the changing behaviour of the frequency spectrum with time value. STFT gives a constant resolution at all necessary frequency points.

Another new time-frequency domain technique is wavelet transform, which overcomes the shortcomings of STFT. This technique is also used to analyse the signal in a non-stationary state with time values. Wavelet transform provides multiresolution at different frequency levels.

A comparison of FFT, STFT and continuous wavelet transform (CWT) methods [9–11] is summarised in **Table 1**.

2.2 Fault diagnostic methods

Different fault diagnosis techniques have been applied for single and multiple fault diagnosis in industrial machinery systems. The four main types are signal-based, model-based, knowledge-based and hybrid methods [8]. Further classifications of these methods are presented in **Figure 2**.

2.2.1 Signal-based methods

Signal-based methods are largely dependent on signal processing methods for fault diagnosis. Usually, these techniques require pre-identified circumferences. Signals are dependent on features. Once the signal or features pass outside their boundaries, an abnormal situation may be happening [22]. There are many methods available that are based on signal analysis, such as vibration analysis, MCSA, axial flow (AF), torque analysis, noise monitoring and impedance of inverse sequences.

Techniques	Faults diagnosed	Advantages	Disadvantages
FFT [6]	• Broken rotor bar fault • Short winding fault • Air gap eccentricity • Bearing faults	• Suitable for high load conditions • Easy to implement • Good for visualisation fault symptoms	• Lost time information • Not effective in light load condition
STFT [7]	• Broken rotor bar fault • Bearing faults	• Fast speed • Suitable for varying load conditions	• Analyse signal with fixed sized window • Poor frequency resolution
Wavelet transform [8, 9]	• Broken rotor bar fault • Short winding fault • Bearing faults • Load fault	• Fast speed • Suitable for varying load and light load conditions • Excellent low time and frequency resolution for low-frequency side-band components	• Absence of phase information for a complex-value signal • Poor directionality • Shift sensitive for input-signal, causes an unpredictable change in transform coefficients in time.

Table 1.
Comparison between FFT, STFT and CWT.

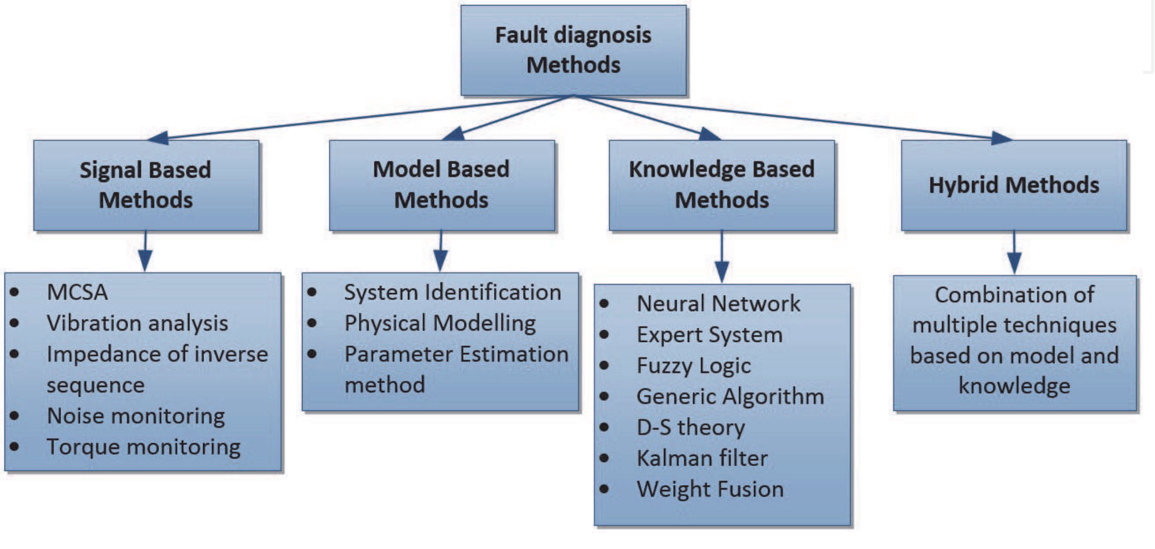

Figure 2.
Classification of different fault diagnosis methods [1].

Most mechanical faults in high-speed rotating machines lead to increase in vibration levels. The largest sources of vibration and noise in electric machines are the radial forces due to the air-gap field. Vibration monitoring is an effective and efficient approach to providing condition indicators for machine health management [23]. Vibration-based diagnostics is the best method for fault diagnosis, but needs expensive accelerometers and associated wiring. This limits its use in several applications, especially in small machines where cost plays a major factor in deciding the condition monitoring method. And this limitation becomes more complex when the diagnosis is based on multiple motors that are running in parallel with much noise.

Some studies [21–24] discussed the multi-motor faults detection methods using vibration analysis when motors are running in isolation from the system. Different signal processing techniques were used for feature extraction. These studies compared different features in time and frequency domain using ANN, but they never observed the different behavioral conditions of multiple motors that simultaneously running within same power-line.

In recent years, the stator current monitoring, well recognised as MCSA, has become the focus for many researchers in both academia and the industry. It can provide an indication of motor condition similar to the indication provided by other monitoring methods (e.g., vibration), without any need to access the motor [14]. In most electrical machine applications, the stator current is usually measured for motor protection. When the motor is being controlled by drive, measuring the current becomes integral to the drive apparatus, which makes it available at no cost. There are three main methods through which captured current data can be analysed for fault detection using current signature analysis. These are: frequency spectral analysis; negative-positive and zero-sequence current components; and Park's vector representation of the three-phase electric current [15].

Different authors [22–25] in recent years have discussed multiple-motor faults detection using MCSA method, but they isolated motors from the system. Author [25] introduced, in a concise manner, MCSA for the diagnosis of abnormal mechanical and electrical conditions that specify, or may cause, a failure of multiple induction motors, but analyse through separation of the system. The MCSA utilises the results of signal analysis of the stator electric current for the detection of broken rotor bars, air-gap eccentricity and other component damage. Another research [26] discussed fault diagnosis using MCSA on multiple motors simultaneously, but they diagnose a single fault and noise level in each motor. However, in this research, the authors did not focus much on uncertainty management due to the complexity of different faulty signals.

A comparison of MCSA, vibration and other methods [13–17] is summarised in **Table 2** as follows.

2.2.2 Model-based methods

Model-based fault diagnosis techniques are normally dependant on the dynamic system model. The model-based methods of an industrial system benefit from the actual system and model output. A comparison can be made between the simulation and actual data outputs and, therefore, through visualisation, the condition of a motor can be ascertained. Dynamic models can be developed using physical modelling, system identification and parameter estimation methods. The most significant problem with the model-based methods is that the accuracy of the developed model describes the behaviour of the diagnosis system [27]. Modelling uncertainty happens from the unfeasibility of obtaining knowledge from monitoring process when the system is running in a noisy environment.

Normally, model-based methods have also been used to collect the dynamic response of systems under normal and fault conditions, by different authors [24–27], but on motors isolated from systems. A general architecture of the model-based method is shown in **Figure 3** as follows.

Typically, model-based methods can be divided into two parts: residual generation and decision-making. A fault diagnostics structure is presented in **Figure 3**. In the first portion of the diagram, process models in healthy and faulty conditions are compared with actual process measurements to produce continuation that describes the present condition of the development. In the second portion, the decision-making process is done based on the residual results. In both parts of fault diagnosis, it applies separate models that can be based on data, knowledge-based or a combination of both analytical models. The residual generation in the fault diagnostics system is normally based on model and pre-defined process outputs, but residuals can be generated through different methods where model parameter features are estimated from process measurements.

2.2.3 Knowledge-based methods

Knowledge-based model strategies usually implement human brain-like knowledge of the process for machine fault diagnosis. In real-time fault diagnostic practices, the human professional expert could be an engineer who applies and operates the diagnosis process, having good knowledge about the strategies and methods of diagnosing multiple motor faults. The knowledge-based methods also work on expertise, like engineers, to diagnose the fault in a motor system when the signal is

Methods	Required measurement	Faults diagnosis	Advantages	Disadvantages
MCSA	Stator electric current	• BRB • Air-gap eccentricity • Stator electric current fault	• Non-sensitive • Low cost	• Limited to some fault conditions at no-load • Frequency levels vary with motor size
Vibration analysis	Accelerometers and associated wiring	• Bearing fault • Other mechanical faults	• Available in many configurations • Integrate to velocity output	• Sensitive to mounting techniques and surface conditions • One accelerometer does not fit all applications
Torque harmonics analysis	Two stator electric current and voltage	• BRB • Mechanical faults in small load • Stator winding fault	• Non-sensitive • Good for mechanical faults detection	Not accurate in short circuit-related faults diagnosis
Axial flow	Axial flow	• Air-gap eccentricity • BRB • Stator current fault	• Cheap solution	• Non-invasive • Not good for dynamic condition
Impedances of inverse sequence	Two stator voltage and electric current values	• Stator winding fault	• Initial faults detection • Non-intrusive	• Needs high measurement accuracy

Table 2.
Summary comparison of MCSA, vibration and other methods.

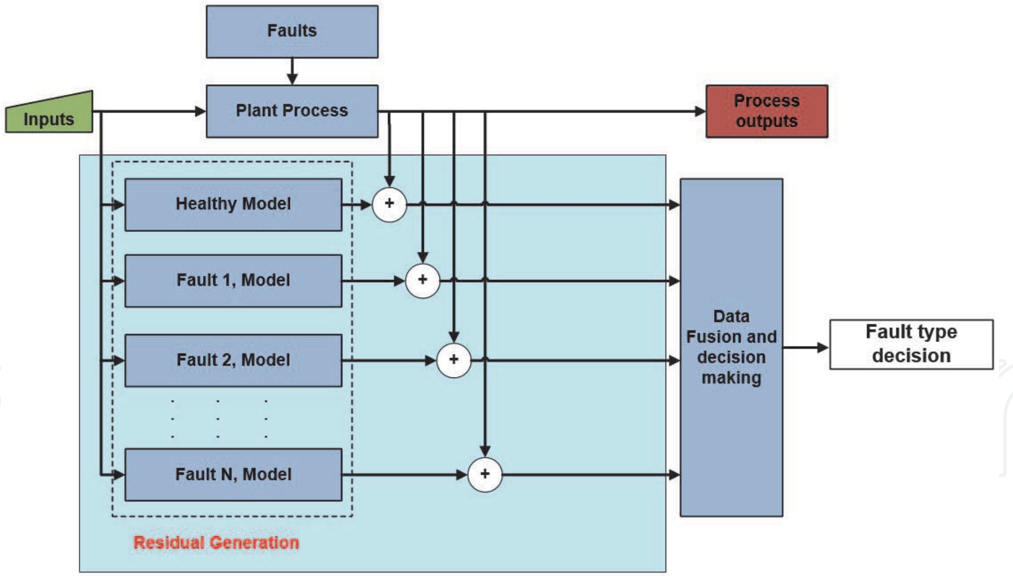

Figure 3.
Architecture of model-based methods.

in a dynamic condition. These methods can be very useful to reduce the percentage of uncertainty when signals are in complex form.

Many studies have been presented in the research area of fault diagnosis using isolated induction motors based on different techniques [27]. The artificial neural network (ANN) has been perhaps the most commonly used artificial intelligence technique in motor condition monitoring and fault diagnosis, due to its excellent pattern recognition ability and ability to recognise fuzzy and indefinite signals. ANN has the following special characteristics, enabling many applications in information fusion and fault diagnosis [28]:

- The neural network has the ability to gain new knowledge, similar to the way human beings acquire their knowledge. The learning process is implemented by continuous adjusting of the weight values among the neurons
- A neural network can be a multi-input and multi-output system (MIMO). This structure demonstrates that neural networks can handle complicated multiple object problems, like multiple faults in a machine
- The neural network processes the information in a parallel way, similar to the way humans process complicated information. This special feature indicates that neural networks can fuse information from different sources simultaneously and naturally
- The knowledge in a trained neural network is stored in a distributed way, by means of a set of weights. This also resembles the way the knowledge is stored in human memory
- A neural network has good fault tolerance performance. This property mainly originates from its parallel structure and distributed information storage system

ANN is reported in the literature as being a knowledge-based technique for single/multiple motor fault diagnosis. These studies perform the diagnoses by mapping different fault symptoms in an isolated motor to produce a diagnosis decision.

Authors [29] presented a diagnosis system based on ANN on machines isolated from system, which applies the RMS measurements of electric current, voltage and speed to train the ANN in diagnosis of motor rotor faults. Voltage faults are only identified in a steady-state condition, not in a dynamic-load condition.

Another study was presented by Shoba [29], based on the influence of the rotor fault on electric current in the frequency domain, using ANN in a steady-motor operating condition. This study demonstrated the possible symptoms of significant frequency components on the frequency spectrum related to a broken rotor bar fault. These symptoms are used as an input matrix using the supervised ANN architecture. The proposed technique concluded that the process of rotor fault diagnosis and discrimination between each fault occurred with reasonable accuracy.

Another author [30] presented a rotor fault model using fast Fourier transform (FFT) and the supervised ANN learning method. Significant features (RMS, crest factor, highest magnitude, etc.) were extracted from the electric current spectrum and all possible high peak side-band values were observed using neural network (NN). The back propagation neural network (BPNN) algorithm is applied for training to detect a rotor fault on a single motor. To introduce complexity to the model, they injected some noisy signals into the healthy spectrum to obtain a reliable and intelligent NN.

Zhou et al. [31] carried out the work on fault diagnosis using four layers of feed forward neural network (FFNN) for identification of broken rotor bar and eccentricity faults. They noted that the accuracy in fault detection was 86–92 %, depending on NN architecture, classification method and number of classified samples. The best NN structure [$11 \times 13 \times 11 \times 2$] was proposed from different architectures, using the Levenberg Marquardt (LM) algorithm with 92.11 % accuracy in classification.

Most fault diagnosis studies based on ANN using isolated motors have been successful. But in the case of a distributed network, this may create confusion through multiple similar motor faults in a network, due to non-linear manipulation of the signal. This sort of complexity and mixture of signals from multiple sources make it difficult to measure and precisely correlate the fault to a given machine or fault type. To overcome this confusion, a distributed ANN approach is used in this research to identify the fault type and location within a motor network on the basis of significant motor features.

2.2.4 Hybrid methods

As each method for fault diagnosis has its own limitations, a combination of several approaches may become a good option. Several different authors have proposed combined techniques such as neuro-fuzzy [26], neural network and Bayesian interface [27] and DS theory with expert system [28]. A hybrid system called generic integrated intelligent system architecture was proposed for equipment monitoring, fault diagnosis and maintenance [29]. The system integrated different AI techniques such as fuzzy logic and neural network.

A hybrid method [30] was developed that used neural networks to estimate an engine's internal health, and generic algorithms to detect and estimate sensor bias. The method had the advantage of a non-linear approximation facility provided by neural networks, and advances the system robustness in measuring uncertainty through the combination of generic algorithms within the application.

2.3 Propagation of fault signal in industrial power-line network

In an industrial power-line network, when a faulty wave signal propagates within the main power-line, it shows a strong relationship between the electric current and voltage waves with certain impedance characteristics [31]. The given input impedance of the multiple connected electric motors has been an interesting parameter, mainly in the closeness of the grid frequency (50/60 Hz) [32]. The importance of input impedance at a higher signal frequency level has gained attention due to the universal usage of available motor variable speed drives. The fast switching between the different phases of power semiconductors of the inverter injects different signals with high energy contents and a large frequency spectrum into the motor feeder cable. Due to the injection of the spectrum into the power-line network, it can generate electromagnetic emission, invertor problems and damage the insulation winding of induction motors. The presence of these complications is related to the impedance discrepancy between the motor and industrial feeder cable. As discussed earlier, the induction motor acts as a termination impedance when transmitting signals into an industrial low-voltage distribution network between the power-line and motor network. The high-frequency signal characteristics of the induction motor may affect the influence of the high-frequency characteristics of the main power-line path.

Induction motors within power-line network depend on several factors based on input impedance. In supplying the grid, different frequencies propagate close to the supply frequency and change the behaviour of different motor characteristics due to the injection of electric current signals into the induction motor terminals through stator winding. In this case, the input impedance may rely on the leakage induction, magnetisation inductance of the stator coils resistance and mechanical torque load of the induction motor [32]. At high levels of frequency, the input impedance of induction motors may be affected due to capacitance and leakage inductance. Furthermore, due to the skin effect, all resistances of induction motors increase, depending on frequency points.

There are a number of approaches that describe the propagation of fault signals throughout the power-line network. But power-line communication (PLC) is a widely used strategy in the industrial power system to transfer transmission control messages through the power line network. PLC technology uses the power lines for signal propagation. Frequencies in the range of 30–500 kHz have been utilised in the industry for PLC communication [33]. These ranges of frequency are considered sufficient to be isolated from the normal operation of the power system. The available impedance characteristics of a power transmission-line are presented as the ratio between the electric current and voltage of the travelling waves with an infinite spectrum length.

The fault signal may manifest within the electric current of different motors through the main power-line. It can be suffered from attenuation factor due to power-line characteristics and show faulty impedance pattern at the junction points of motors connections. The propagation delay between the multiple paths of the signal can result in disturbance of the signal. Therefore, attenuation is a very significant factor because it decides the signal strength as a function of distance; therefore, it plays an important role in validating the locations of faulty motors with in the power-line network. Continuous propagation of signal impedance in power-line becomes a combination of the inductance, resistance and parallel capacitance of the transmission line [34].

Several studies have been presented [31–34] about implementation of the PLC concept in power-lines for fault diagnosis. The propagating frequency of PLC channels is higher than the fault signature frequency and is useful in estimating the attenuation level over transmission lines. However, the calculation method combines with some technical approaches to develop a fault and attenuation pattern. For the authenticity of the fault signal within power-line network, different measuring points would be a better approach to diagnosing the origin of a fault generator.

2.4 Industrial fault diagnosis using wireless sensor networks

Several WSN solutions for industrial machinery have been developed and reported on from commercial organisations [31, 32] or individual researchers [33, 34]. Most of these solutions only use the WSN for data acquisition and transmitting signals. Feature extraction and data fusion tasks are then performed on a central computer. Upon sensor data acquisition, feature extraction and fault diagnosis is another tactic capable of diffusing raw data that can scale down the number of features and save node power. But most of these solutions are based on isolated motors. Industrial wireless sensor network (IWSN) for motor fault diagnosis and condition monitoring needs to consider the high-power system requirements of industrial processes and the distinctive available characteristics of motors [33]. Some industrial processes are very important, such as high sampling rate, quick data transmission rate and reliability of data. However, there are constraints in IWSN, such as computational ability, limited radio bandwidth and battery energy. Thus, limitations exist between the high system requirements of electrical machine fault diagnosis and the resource constraints feature characteristics of IWSN.

Some recent literature focuses on the application of IWSN in machine condition monitoring and fault diagnosis, pumping fault diagnosis, manufacturing machines, smart grids, power plants and structural health monitoring. Ref. [33] presents electric current and vibration-based data acquisition for monitoring rotating machinery in power plants. They present a sensor-level data fusion algorithm to diagnose the condition of isolated machines. A comparison result has been performed between available fused and healthy data by using wireless nodes. A time-series data judgement and task-level fusion algorithm was introduced to reduce power and bandwidth needs.

The authors, in [34], introduced a diagnosis solution using electric current and vibration signature data acquisition system for observing rotating machinery at power plants. The diagnosis system monitors the motor vibration and stator electric current signatures from two different motors. Node-level feature extraction techniques were implemented and a neural network classification method used for training and uncertainty management. Decision-level fusion was implemented at the node coordinator. The training was executed in offline mode in an efficient manner, and the BRB and eccentricity fault states have to be detected manually at two experimental motors by applying different load levels.

2.5 Shortcomings in existing fault diagnosis research

The current harmonics present in the motor electric current are mainly created by machine asymmetries and vibrations from machine faults. The reliability of signal-processing techniques depends upon a good understanding of the electric and mechanical characteristics of the machine in both a healthy and faulted state under different loading conditions. The following shortcomings were identified on the basis of information discussed in the literature review:

- Most of research has been effectively tested on isolate motors to diagnose its current condition and performance by comparing healthy and faulty motors characteristics. Limited research has been done on distributed multi-motor signature analysis where all motors are part of the system and propagate a faulty signal over the network.

- Some limitations have been perceived in implementing diagnosis in a distributed motor network, with confusion between different similar machine fault symptoms in the power-line network, and lack of accuracy in the analysis system due to the existence of non-linear interference from industrial noise signals.

- There has been only limited research on the effect of load variations on the amplitudes of fault frequency components under healthy and faulty conditions. The majority of the studies only consider a full-load case, with limited research considering partial-load cases. To detect faults and estimate fault severity in machines, using characteristic fault frequencies, it is important to examine the variability in their amplitudes with other effects than load and fault severity. This area has had limited research on machine condition monitoring.

- Few studies have focused on the detection of multiple faults, that is, the combination of broken rotor bars and eccentricity faults under varying loading conditions.

- The majority of studies considered only the stator electric current as a diagnostic medium to detect different faults in induction motors. Only a few researchers have proposed using an instantaneous network power signal as a diagnostic medium to detect rotor-related faults under different load conditions. The use of instantaneous power to detect other major faults in the machines (eccentricity, shorted turn and misalignment) and multiple faults (combinations of different faults) under varying loading condition has not been reported in previous research.

- Insensitivity to and independence of operating conditions in the power-line network system.

- Utilisation of the neural network technique on distributed industrial motor networks has not been reported in previous research where the signal propagation process could change the pattern behaviour of each neighbouring motor and create a confusion in identifying the actual source of fault indices.

- To date, distributed signature analysis using WSN with sensor-level data fusion, based on multiple motors that are propagating signals into the power-line network, is a relatively unexplored topic where all motors send their respective features, data to central computer for fault diagnosis.

Based on the above-identified shortcomings, the focus of this research was to diagnose multiple faults when all motors operating are part of system and propagating a faulty signal over the network can create confusion between different similar motor faults symptoms in the power-line network. To overcome this confusion, ANN was utilised in identification of fault indices within a network when faulty signals manifest into healthy signals from other motors. Finally, wireless sensor-level data fusion was implemented using an Arduino development kit to improve efficiency and accuracy in decision-making when all motors are operating in parallel.

3. Conclusions

This chapter has covered a variety of different topics, as well as several particular techniques, algorithms, approaches and methods. The literature was mainly categorised into three major themes: fault propagation and diagnosis in power-line network; data fusion and wireless sensor networks. The following conclusions were drawn from the literature review:

- Machinery fault diagnosis has been too reliant on single information sources of data, especially electric current or vibration data. The use of multiple information sources for fault diagnosis from multiple connected motors within the same power-line has not been well addressed and is an unexplored area.

- Correct feature extraction and selection increase the performance of a network and reduce the network input dimensions and training time.

- Consideration of multi-parameter data-fusion techniques can play a vital role in improving system performance, such as in accuracy, reliability and robustness.

- Deployment of the WSN in industrial-machinery fault diagnosis can improve its efficiency and reliability, and reduce the chances of uncertainty in management of complex data.

Based on the above concluding points, the scope for this research was limited to the significant utilisation of available advanced techniques and approaches for feature extraction and motor fault diagnosis using WSN.

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Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this book chapter.

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