Chapter 14

Artificial Intelligence Application in Machine Condition Monitoring and Fault Diagnosis

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Abstract

The subject of machine condition monitoring and fault diagnosis as a part of system maintenance has gained a lot of interest due to the potential benefits to be learned from reduced maintenance budgets, enhanced productivity and improved machine availability. Artificial intelligence (AI) is a successful method of machine condition monitoring and fault diagnosis since these techniques are used as tools for routine maintenance. This chapter attempts to summarize and review the recent research and developments in the field of signal analysis through artificial intelligence in machine condition monitoring and fault diagnosis. Intelligent systems such as artificial neural network (ANN), fuzzy logic system (FLS), genetic algorithms (GA) and support vector machine (SVM) have previously developed many different methods. However, the use of acoustic emission (AE) signal analysis and AI techniques for machine condition monitoring and fault diagnosis is still rare. In the future, the applications of AI in machine condition monitoring and fault diagnosis still need more encouragement and attention due to the gap in the literature.

Keywords: artificial intelligence, machine condition monitoring, fault diagnosis

1. Introduction

In the current commercial production industries, there is an increasing trend towards the need for higher availability equipment that can work nonstop 24/7. Thus, any type of failure, even minor, cannot be accepted as it can significantly affect the cost and the production. Hence, a very accurate monitoring of the machine condition and a proper fault diagnosis of the machine failure is necessary. The machine fault diagnosis had seen a vast improvement since the maintenance was provided after the machine had developed a fault and affected the production. After that, it developed into preventive maintenance in the past few years before all the industries started using the condition-based maintenance. Preventive maintenance can be defined as providing maintenance before the machinery faces any fault.

On the other hand, condition-based maintenance can be defined as providing maintenance depending on the data obtained from target measurements. The efficiency of this technique is measured depending on the accurate diagnostic tactics, which are fulfilled. For surviving in the current competitive market, the industries need to improve their product reliability and also reduce their production costs. The product reliability is more important for specific productions like for the aviation, nuclear and the petrochemical industries where any failure can lead to severe environmental disasters.

Currently, industries have shifted from using the condition-based (predictive) approach to the maintenance-based approach depending on the trending and the data analysis from one or more parameters that indicate the development or the presence of known failures or faults. The effective machine condition monitoring technique must be able to determine the onset of any fault in its early stages and also provide an accurate diagnosis regarding the type of the fault and its location. Ideally, the condition monitoring technique must give an overall and a detailed accurate health assessment of the equipment.

However, conventionally, it would include the aural and the visual inspection (applying all the human senses), temperature monitoring, oil analysis (known as the wear debris analysis), measurement of the vibrations and its analysis, motor current signature analysis, airborne sounds and the acoustic emission (AE) analysis. In acoustic emission analysis, the waves are sent from an emission source and transferred to the surface by the transmission medium. The low-displacement or high-frequency mechanical waves can be picked up as electronic signals. The signal strength can be increased by using a preamplifier before the data are interpreted by the AE equipment [1, 2].

Furthermore, there is a growing interest in developing new technologies to overcome the problems in condition monitoring and diagnostics of complex industrial machinery applications, which were not resolved till now. This provides excellent opportunities for the AI technology to grow continuously, with the rapid increase in the growth of intelligent information, sensor and data acquisition capabilities, combined with the rapid advances in intelligent signal processing techniques [3]. AI techniques that have been extensively used in the field of engineering include genetic algorithms (GA), support vector machine (SVM), fuzzy logic system (FLS) and artificial neural network (ANN). As compared to the common fault diagnostic approaches, the AI techniques are instrumental if they can be improved [4]. Apart from improving performance, these techniques can be easily extended and modified. These can be made adaptive by the integrating new data or information [5].

In this chapter, an attempt has been made to review the recent developments in the field of acoustic emission signal analysis for fault diagnostics of the machine based on the aforementioned AI techniques. These systems can be mutually integrated with each other and also with other traditional techniques.

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2. Artificial intelligence

The AI is the system that thinks and acts like a human being. It can also imitate human behaviour. It is majorly concerned with the development of a computer's ability to engage in human-like thought processes like learning, reasoning and self-correction [6]. In the last decade, there has been a growing need in AI to solve the problems of engineering. Earlier, these problems were considered hard to be solved analytically or by using mathematical modelling and needed human intelligence [7].

Nowadays, there is an increased demand for advanced AE analysis tools. This chapter shows that many scholars have studied the detection and diagnostic of several faults by using the AE methods in AET and signal analysis. The AI techniques as mentioned earlier have also been extensively used in the field of engineering.

2.1. Artificial neural network-based fault diagnosis

Artificial neural network (ANN) is an information-processing approach. It works like the biological nervous systems like how the brain processes the information in the human body. The discussion was limited to an introduction of many components, which were involved in the ANN implementation. The network architecture or topology (including number of nodes in hidden layers, network connections, initial weight assignments and activation functions) played a key role in the ANN performance and depended on the problem at hand. **Figure 1** shows a simple ANN and its constituents. In most cases, setting the correct topology was based on a heuristic model. On the other hand, the dimensions of the input and the output spaces generally suggested the number of input and output layer nodes. Selecting the network complexity or regularization was very important [8]. When designing a neural network, there are a number of different parameters that must be decided. Some of these parameters are the number of

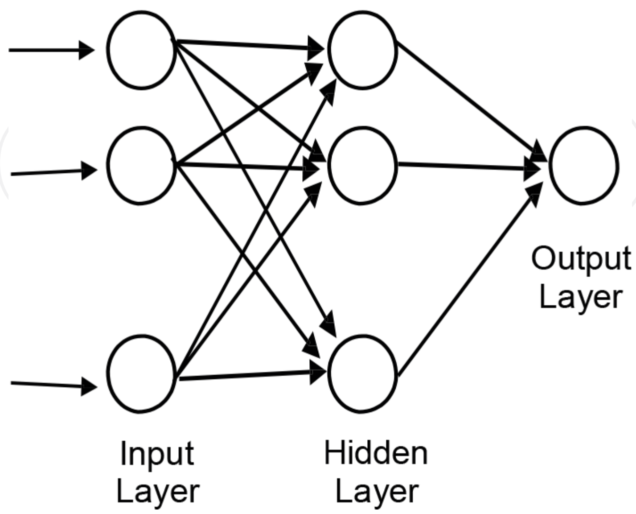

Figure 1. Architecture of a neural network.

training iterations, the number of layers, the learning rate, the number of neurons per layer and the transfer functions, and so on.

The benefit of ANN was that it had the ability to respond to an input pattern in a desirable manner after the learning phase. Previous studies have proved that the efficiency of ANN can predict the faults of machining processes. This technique was found to be very useful as it can be used in industrial automation in a more flexible manner [9]. ANN has been extensively used in health diagnosis of mechanical gear, bearing and rotating machines by using features more from vibration signals and less from the acoustic signals.

There has been an increasing demand for advanced AE analysis tools, which have the capacity to distinguish different sources of AE data. This has resulted in developing modern and more flexible pattern recognition software, combining traditional, graphical AE analysis and advanced unsupervised pattern recognition (UPR) and supervised pattern recognition (SPR) analysis. Application of the UPR techniques on AE data during various test cases has also increased the understanding of the damage evolution and the capacity of noise discrimination [10].

The problem of a roller with health monitoring has illustrated the effectiveness of GA for fault classification by using ANNs [8]. In this regard, Al–Balushi and Samanta have suggested a procedure to diagnose the fault of gears by wavelet transformation and ANN for AE signals. These features were taken from wavelet transformation and were used as an input to an ANN based on diagnosing approach [11]. In the fault prognosis systems, the acoustic emission and vibration signal were utilised as an input signal. Additionally, ANN was utilised as a prognosis system for rotating machinery failure [12]. In this way, a multiple-layer neural network was successfully used to detect the fault in the gearbox, and classification was used to utilise the supervised learning with an experimentally obtained data. The data were presented as processed vibration and acoustic emission signals [13]. The utilisation of acoustic emission for early detection of the helicopter rotor head dynamic component faults was previously studied. They analysed the stress wave of the flight-test data set by using the wavelet-based techniques for assessing the background operational noise as compared to machinery failure results. The feed-forward neural network was used as a classifier to determine the correct fight regime [14].

For solving the issues of velocity and the time differences, a new approach to AE source localization was described. This new approach to AE source location was documented on the wing spar cut-out of L-39 aircraft, as this method was used to estimate the AE source coordination by using the ANN process which extracted signal parameters [15]. Fog et al. studied the detection of the exhaust valve burn—through a four-cylinder, 500 mm bore and two-stroke marine diesel engine. This investigation comprised of monitoring three different valve conditions (normal, leak and large leak). Vibration and structure-born stress waves (AE) were monitored. The acoustic emission (AE) signal features were extracted by using principal component analysis (PCA). A feed-forward neural classifier was also used for discriminating between the three valve conditions [16].

The AE data collected during a static test of a 12-m FRP wind turbine blade was analysed and classified by using different unsupervised pattern recognition (UPR) techniques, and using the UPR results, a supervised pattern recognition (SPR) method was trained based on the back-propagation neural network. This was applied to the AE data collection and a subsequent biaxial fatigue loading of the same blade [17].

The neural network gained attention in grinding research due to its functions of learning, interpolation and pattern recognition and classification. Different other examples of the application in the engineering field were also reported [18–22]. Aguiar et al. attempted to attain the classification of burn degrees of the surface-grinding machine, which was utilised for grinding tests with an aluminium oxide-grinding wheel and the utilisation of neural networks. The AE and power signal along with the statistics from the digital signal processing of these signals were used as inputs of the neural networks [9].

Furthermore, the ANN approach was proposed for the detection of work-piece "burn", the unwanted change in metallurgical properties of the material produced by overly aggressive or otherwise inappropriate grinding [19]. The grinding AE signals for 52100 bearing steel were collected and digested to extract feature vectors. These appeared to be more useful for ANN processing. Aguiar et al.'s work was different as it used grinding parameters as an input to the neural networks that were not tested yet in surface roughness prediction by neural networks. In addition, a higher sampling rate data acquisition system was used to get the acoustic emission and cutting power [23].

Goebel and Wright developed hybrid architecture, featuring fuzzy logic and neural networks to cope with weaknesses of traditional methods for monitoring and diagnosing an unattended milling machine. Force, spindle current and acoustic emission data were used as inputs to the neural network after they underwent some signal processing for calculating the membership functions of fuzzy relations. Additionally, fuzzy logic principles were utilised for diagnosing the system's status concerning tool wear and chatter [24]. The findings of it was encouraging to use neural network in detection and classification of work piece "burn" and surface roughness prediction revealed that AE signal from grinding machine [9, 19, 23, 24].

Impact damage is a problem that damages the composite industry. This damage may seem superficial, but it may often have negative effects on the performance of the composite structure. The conventional NDE techniques can detect the locations or the shapes of the impact damage and cannot quantify its effects on the structure. Conversely, AE records the active flaw growth when the structure gets loaded. It also measures the reduction in the structural performance produced by an impact load. AE signal analysis was used to measure the effect of impact damage on burst pressure in 5.75 inch diameter, inert propellant-filled and filament-wound pressure vessels. The AE data were collected from 15 graphite/epoxy pressure vessels featuring 5 damage states and 3 resin systems. A burst pressure prediction model was developed by correlating the AE amplitude (frequency) distribution, generated during the first pressure ramp, to 800 psig to known burst pressures using a four-layered back-propagation neural network [25].

The ANN pattern recognition technique was used for analysing the AE source signals of the pressure vessel in the site. For this purpose, a new quantitative analysis concept for AE sources of pressure vessel was introduced by using artificial neural network classification along with raising a new method to evaluate the severity of the AE sources [26].

Macías conducted an analysis of the relationship between AE signals and the main parameters of friction stir welding (FSW) process on the basis of ANN. The AE signals were acquired by data acquisition, applied in the welding process, carrying out plates 3 mm thick of aluminium alloy. Wavelet transform (WT) was also used for the statistical and temporal parameters of the decomposition of EA signals as input for the multilayer feed-forward ANN [27].

The partial discharge (PD) detection, signal analysis and pattern identification, using AE measurements and the back-propagation (BP) ANN, were also studied. In this way, the measured signals were processed with three-dimensional patterns and short duration Fourier transforms (SDFT). The findings showed that utilisation of BP ANN with the SDFT components for the classification of the different PD patterns provided excellent results [28].

To determine the quality of feature extraction and for the ANN classifier, performances were also conducted through a series of experimentations. This helped in input data acquisition during AE experiments on the chemical process plant. These input data consisted of a set of AE power spectra. Each source input data file was subjected to preprocessing consisting of additional linear averaging in each input vector and individual amplitude normalisation by removing the mean value and division by the standard deviation of the feature. Three-layer networks using the back-propagation updating scheme were used for assessing their combined feature extraction and classification capabilities, while solving the problem of process stage recognition [29].

Until 2015, there is no study in the literature related to the estimation of oil film thickness through acoustic emission signals, so to predict and monitor oil film thickness of spur gear, a test rig was built and the gearbox was run at different speeds and load conditions. Artificial neural network (ANN) and regression models used to predict the lubricant regime depended on oil temperature, acoustic emission signals and specific film thickness (λ). Both FFBP and Elman network models were used to predict specific oil film thickness with input as AE and temperature data. The results showed that FFBP and Elman models were effective in predicting oil film thickness from acoustic emission signal and temperature, and this suggested technique attained 99.9% success in prediction and classification at high speed during training. The FFBP was better than Elman during testing and gave excellent results in prediction and classification. Thus, the architecture and topology of the network through specific systems can be used for online monitoring of oil film thickness and to predict any causes of failure of spur gear operation [30, 31].

2.2. Spiking neural network

Recently, spiking neural network (SNN) is the third-generation neural network (**Figure 2**) and has gained a lot of interest in the scientific community [32]. The SNNs became famous before the introduction of the sigmoidal or the perceptron neuron [32]. It was observed that the SNNs were very suitable for the parallel implementation in the digital hardware [32] and in the analogue hardware [33, 34].

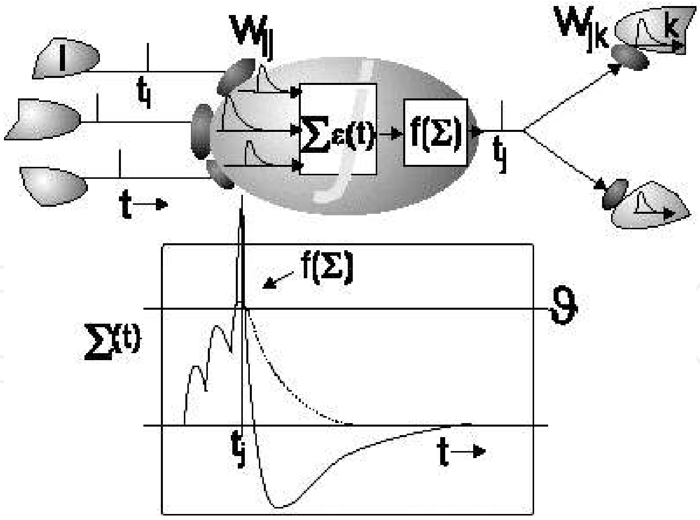

Figure 2. Spiking neural network [32].

The earlier generations of the neural networks used the analogue signals for conveying the data from one neuron to the next. This communication between the neurons in the SNNs used spikes, which was similar to the system used in the actual human neurons. The spikes could be recognized only at those instances when they had occurred. With the help of the weighted sum of the analogue input value, the earlier neuron estimated the value using the sum-specific non-linear function. The value helped in determining the delay in the spike output, which was aimed for the succeeding neuron. Generally, the spiking neuron was viewed as the leaky integrator because the target neuron integrated the spikes for a period of time and accepted the resultant integrated values used as the membrane potential. When the membrane potential value approached a specific threshold value, then, the neuron was seen to send a spike; thereafter, the membrane potential value was reset.

An increased knowledge in the information processing of the biological neurons helped in explaining many additional parameters (like the gene and the protein expression) that needed to be taken into consideration for the neurons to spike [33–35]. The additional parameters included the different physical properties of the connections [32], the likelihood of the spikes being accepted at the synapse and the emitted neurotransmitters or the open-ion channels [36, 37]. Several of the properties were modelled mathematically and were used for studying the biological neuronal system [38, 39]. The SNNs were made of the artificial neurons that communicated using the trains that were considered as the pulse-coded data [40]. The SNN was biologically acceptable, and it was seen to offer a means for the representation of the frequency, time, phase and such other features for the information processing. Moreover, the SNN possessed the ability for training the neurons for converting their spatial-temporal data to spikes (their properties include the spiking rates and spiking time). When one was selecting the neuronal model for an SNN, one needed to consider the computational efficacy and the biological credibility [40]. If it was seen that the computational efficacy was better than the biological plausibility, then the leaky integrate-and-fire (LIF) model needed to be adopted due to its cost effectiveness.

In their study, Silva et al. [41, 42] depicted the applications of the prototype decision support system for monitoring the tool wear depending on the SNN technique. This system consisted of six different components, that is, collection of data, feature extraction, multi-sensor integration, pattern recognition, tool wear estimation and the outlier detection. Their proposed architecture consisted of one built-in self-organizing neural architecture part that was based on the SNN. Their study showed that the modelling process was very efficient for classifying the tool wear level of the tool inserts with the help of the apparent weak features. Their method showed the effectiveness of using the SNN model for the tool condition monitoring, thus implying that the approach was feasible for many industrial applications, wherein a lot of noisy data are obtained. This researcher was the only one who used SNN in condition monitoring; the result showed the capability of spiking neuron networks for tool condition monitoring.

2.3. Genetic algorithm-based fault diagnosis

GA created by John Holland in the 1970s is an evolutionary algorithm which is part of the field of artificial intelligence. A genetic algorithm (GA) is a method for solving both constrained and unconstrained optimization problems based on a natural selection process that mimics biological evolution. The algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects individuals from the current population and uses them as parents to produce the children for the next generation. Over successive generations, the population "evolves" towards an optimal solution.

As originally proposed, a simple GA mainly consists of three processes: selection, genetic operation and replacement. Description of a typical GA cycle and its high-level description are provided in **Figure 3**. The population composed of a group of chromosomes, which were the candidates for the solution. The fitness values of all chromosomes were evaluated by an

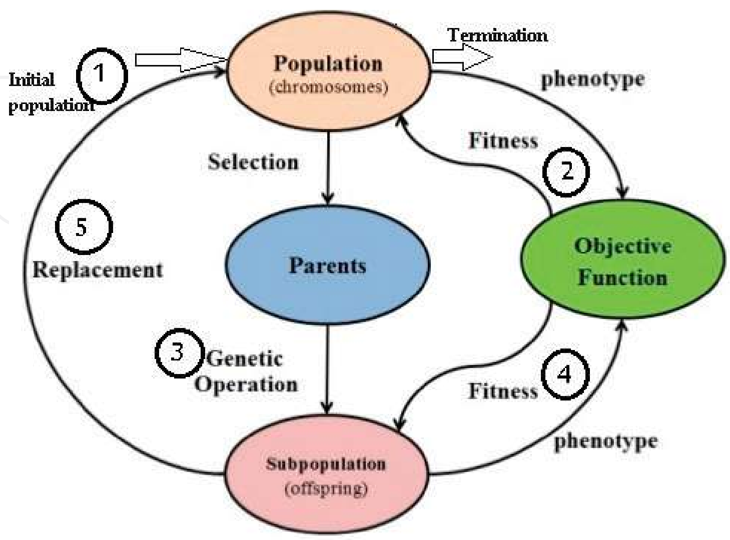

Figure 3. Genetic algorithm cycle.

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objective function (performance criteria or a system's behaviour) in a decoded form (phenotype). A particular group of parents was selected from the population for generating offspring on the basis of the defined genetic operations of crossover and mutation.

The fitness of all offsprings was then evaluated using the same criterion. The chromosomes in the current population were then replaced by their offspring on the basis of a certain replacement strategy. Such a GA cycle was repeated until the termination criterion was reached [8]. Using ANNs utilised a simple problem of a roller with health monitoring to illustrate the effectiveness of GA in AE feature selection for fault classification. It revealed that utilising GAs to select an optimal feature set for a classification application of ANNs was a very powerful technique [8]. Ming applies the AE technique for bearing condition monitoring and fault diagnosis. Scales for continuous wavelet transform, wavelet-based waveform parameter selection and optimisation on the basis of genetic algorithm were the proposed selection methods [43].

The AE was monitored by utilising a data acquisition system during the process of conducting the mechanical tests on several materials. Two of the sensors were positioned directly on the specimen. AE signals were thought to be pattern vectors described by a number of writers. In this chapter, "model" data sets were generated to become closer to AE signals that were recorded during the tests. This chapter presented and validated a genetic algorithm-based approach to cluster the AE signals. Its superiority over the k-means algorithm was highlighted by the study of different "model" data sets. The genetic strategy can be characterised by a high stability and a high performance especially to cluster data sets consisting of a minority class, a cluster with signals of extreme features or a set of clusters with very different sizes [44].

2.4. Fuzzy logic-based fault diagnosis

Zadeh introduced the fuzzy logic (FL) in 1965 [45–47]. FL is a multi-valued logic that allows the intermediate values between conventional evaluations like true/false, yes/no, high/low, and so on. The FL helps in providing a variety of ways to solve a control or classification problem. Thus, this method focuses on what the system should do rather than trying to model how it works [48].

Aguiar et al. work is mentioned twice in this chapter because it contains two parts: first part used ANN for the classification of burn degrees of the surface grinding machine; in this part, a methodology was used to predict the surface roughness of advanced ceramics by using an adaptive neuro-fuzzy inference system (ANFIS). For this study, alumina work pieces were pressed and sintered into rectangular bars. The statistical data processed from the AE signal and the cutting power were also used as input data for ANFIS [9]. Cusido et al. provided approaches for a one-board fault detecting system and test program set (TPS) fault detecting system for electromechanical actuators (EMA) ball bearings by analysing the different vibration and AE signals and by using FL inference techniques [49].

Omkar et al. presented the results of fuzzy modelling to discover the problem in grinding through digital processing of the acoustic emission signals produced during the process. Fuzzy C-means (FCM) clustering was utilised in classification of the AE signal to different sources of signals. FCM was potentially helpful in discovering the cluster among the data, when the boundaries between the subgroups overlap. AE test was conducted by using pulse, pencil and spark signal source on the surface of solid steel block. Four parameters such as event duration, peak amplitude, rise time and ring down count were measured with the help of AET 5000 system. These data were then used in training and validation of the FCM-based classification [50].

Aguiar et al. investigated the burning in the grinding process on the basis of a fuzzy model. The inputs of the models were received from the digital processing of the raw AE and cutting power signals. The parameters obtained and used in this study consisted of the mean-value deviance, grinding power and root mean square (RMS) of the acoustic emission signal [51]. Ren et al. also attempted to introduce the most successful AE model during the continuous cutting periods by using fuzzy modelling. The fuzzy identification method provided a simple way to arrive at a more definite conclusion on the basis of the information collected with the difficulty in understanding the exact physics of the machining process [52].

Recent studies used type-2 fuzzy logic in their research [53–56] because of the need to have extremely fuzzy situations to use type-2 fuzzy. If we were extending the use of FL to a higher order, then it is called type-2 FL. Hence, Ren et al. explained how type-2 TSK [Takagi–Sugeno–Kang (TSK)] fuzzy uncertainty estimation method was implemented to filter the raw AE signal directly from the AE sensor during turning process. This paper specifically focuses on filtering and capturing the uncertainty by type-2 TSK fuzzy approach on the interval of AE signal during one 10 mm cutting length [53].

Ren et al. attempted to find out the relationship between AE and tool wear. They presented an application of type-2 FL on AE signal modelling in precision manufacturing. Type-2 fuzzy modelling was used for distinguishing the AE signal in precision machining. It provided a simple way for arriving at a definite conclusion without understanding the exact physics of the machining process [54].

The knowledge about uncertainty prediction of tool life was highly essential for tool condition investigation. It was also important for taking decisions about how to maintain the machine quality. Ren et al. presented a type-2 fuzzy tool condition monitoring (TCM) system based on AE in micro-milling. In the system, type-2 FLSs were utilised for analysing the AE signal feature (SF) and choosing the most reliable ones for integration to effectively estimate the cutting tool condition through its life. The acquired results show that the type-2 fuzzy tool life estimation is in accordance with the cutting tool wear state during the micro-milling process [55].

A type-2 fuzzy analysis method was utilised to analyse the AE SFs in TCM in micro-milling process. The interval output of type-2 approach provided an interval of uncertainty associated with SFs of AE signal. The SFs with less RMSE and variation were selected to estimate the cutting tool life in the future [56]. The new philosophy for AE source localisation under high background noise was also designed. The algorithm was based on probabilistic and fuzzy-neuro principles, so AE events can be put to classification according to their energy and location probability. AE signals recorded during the stamping processes of a thin metal sheet were used for new algorithm testing [57].

Khalifa and Komarizadeh developed an efficient walnut recognition system through putting together the AE analysis, principle component analysis (PCA) and adaptive neuro-fuzzy inference system (ANFIS) classifier. This new system was tested later and classified walnuts into two classes. In the classification phase, selected statistical features were used as the input for the ANFIS classifier [58].

2.5. Support vector machine-based fault diagnosis

The support vector machine (SVM) approach was utilised in the form of a classification technique on the basis of the statistical learning theory (SLT). It was basically based on the principle of hyperplane classifier or linear separability. The main purpose of SVM was to explore a linear optimal hyperplane for maximizing the margin of separation between the two classes [59, 60].

The SVM was utilised for fault diagnosis of spur bevel gear box. This was considered to be a popular machine learning application due to its higher accuracy and for its generalization capabilities [61]. These studies also examined the fault diagnosis of low-speed bearings based on AE technique and vibration signal. Fault diagnosis was conducted by using the classification technique with the help of relevance vector machine (RVM) and SVM. The classification process provided a comparative study between RVM and SVM for fault diagnosis of low-speed bearing [62, 63].

Yu and Zhou exposed the method to classify the AE signals in composite laminates by utilising SVM. The classifier had built to achieve the identification and classification of AE signals. The results of simulation showed that SVM had the potential to effectively distinguish different acoustic emission signals and noise signals. The classification accuracy rate of grid search parameters was higher than the GA algorithm by this method [64]. Chu-Shu also revealed the method on how to classify the AE signals in composite laminates by using the SVM [65].

On the basis of a thorough review of literature, this study informs about the new approaches on the basis of hierarchical clustering and support vector machines (SVM) and are introduced to cluster AE signals and to detect P-waves for micro-crack location in the presence of noise through inducing the cracks in rock specimens during a surface instability test [66]. Thus, this chapter proposes a novel grinding wheel wear monitoring system based on discrete wavelet decomposition and SVM. The grinding signals were collected by an AE sensor [67].

Elforjani used a model to analyse the output signals of a machine while in operation and accordingly helps to set an early alarm tool that reduces the untimely replacement of components and the wasteful machine downtime. In this work, Elforjani uses three supervised machine learning techniques such as Gaussian process regression (GPR), support vector machine regression (SVMR) and multi-layer artificial neural network (ANN) model to correlate AE features with corresponding natural wear of slow-speed bearings throughout the series of laboratory experiments. Analysis of signal parameters such as root mean square (RMS) and signal intensity estimator (SIE) was done to discriminate the individual types of early damage. It was concluded that neural network models with back-propagation learning algorithm have an advantage over the other models in estimating the remaining useful life (RUL) for slow-speed bearings if the proper network structure is chosen and sufficient data are provided [68].

The development of AI technique shows a promising potential in machine condition monitoring and diagnosis, although only few articles were found in this area. However, ANN based on AE has been successfully applied to many relevant problems. It can be considered that ANN is the most new popular method in condition monitoring with AE signal. The use of fuzzy, GA and SVM in condition monitoring and fault diagnosis based on AE signal analysis still needs additional attention because of the absence of available papers. Finally, the future works will be able to find a novel idea for machine condition monitoring and fault diagnosis using AE signal analysis and AI [69].

3. Conclusion

This chapter presents a survey based on a literature review using AE signal analysis and AI techniques in machine condition monitoring and fault diagnosis. It surveys the articles with a keyword index machine condition monitoring and machine fault diagnosis using AE signal analysis and AI.

We can conclude that the classification of AE signals carries high importance in machine condition monitoring and fault diagnosis. AI has several advantages when compared to the traditional mathematical modelling and statistical analysis. This includes dispensing of the necessity for detailed system behaviour knowledge, which can be replaced by relatively simple computational methods. ANN based on AE has been successfully applied to numerous relevant problems. Therefore, we can consider that ANN is the most new popular method in AE signal analysis.

GA applications with AE signal analysis in machine condition monitoring and fault diagnosis still need more support and attention because of the lack of existing evidence. The experimental results prove that the use of fuzzy logic method is efficient and feasible. The efforts to find a novel idea must be encouraged to give more contributions in robust machine condition monitoring and fault diagnosis.

Finally, the ability to continually change and obtain a novel idea for machine condition monitoring and diagnosis using AE signal analysis and AI will be in future works.

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Conflict of interest

The author declares that there is no conflict of interest regarding the publication of this chapter.

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