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Acoustic Emission Signal Analysis and Artificial Intelligence Techniques in Machine Condition Monitoring and Fault Diagnosis: A Review

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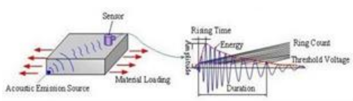
Graphical abstract



Abstract

Acoustic Emission technique is a successful method in machinery condition monitoring and fault diagnosis due to its high sensitivity on locating micro cracks in high frequency domain. A recently developed method is by using artificial intelligence techniques as tools for routine maintenance. This paper presents a review of recent literature in the field of acoustic emission signal analysis through artificial intelligence in machine conditioning monitoring and fault diagnosis. Many different methods have been previously developed on the basis of intelligent systems such as artificial neural network, fuzzy logic system, Genetic Algorithms, and Support Vector Machine. However, the use of Acoustic Emission signal analysis and artificial intelligence techniques for machine condition monitoring and fault diagnosis is still rare. Although many papers have been written in area of artificial intelligence methods, this paper puts emphasis on Acoustic Emission signal analysis and limits the scope to artificial intelligence methods. In the future, the applications of artificial intelligence in machine condition monitoring and fault diagnosis still need more encouragement and attention due to the gap in the literature.

Keywords: Artificial intelligence method; acoustic emission; condition monitoring; fault diagnosis

1.0 INTRODUCTION

Machine condition monitoring and fault diagnosis are key elements in the maintenance system. These are receiving global attention in the present day. These have been found useful in maintenance cost reduction, better productivity and increased machine availability. Acoustic Emission Technique (AET) is considered to be a very useful tool in various fields of non-destructive evaluation [1-3].

There is a growing interest for developing new AE technologies to overcome the problems in condition monitoring and diagnostics of complex industrial machinery applications which were not resolved till now. This provides good opportunities for the AE 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 [1].

Artificial Intelligence (AI) techniques that have been extensively used in the field of engineering include Genetic Algorithms (GA), Support Vector Machine (SVM), Fuzzy Logic Systems (FLS) and Artificial Neural Networks (ANN). As compared to the conventional fault diagnostic approaches, the AI techniques are very useful 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 study, 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 into each other and also with other traditional techniques.

A number of previous studies were reviewed and classified into categories depending on the method used in fault diagnoses. However, some publications belong to more than one category and have been classified based on their dominant contribution.

This paper consists of the following four parts: an introduction, AE Theory, classification of the various AI techniques and the concluding remarks.

2.0 ACOUSTIC EMISSION THEORY

According to ASTM, acoustic emission refers to generation of transient elastic waves produced by fast energy release from a localized source within the material [6]. There are different causes for the occurrence of acoustic emission as compared to the natural events like earthquakes or rocks cracks during the slip and disruption movements. It also has fracture, fatigue, crack transmission, melting and material phase conversion. The acoustic emission testing principle where the elastic waves sent from acoustic emission source is shown in Figure 1.

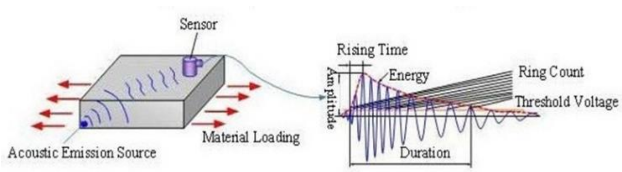


Figure 1 Principle of acoustic emission testing [7]

These waves are transmitted to the material surface by transmission media. Then they are converted into electric signals by sensors before magnification, processing and recording. The analysis and processing of the acquired signals helps in detecting any defect within the material [7].

In the last few years, the use of AET has become very popular methods in machinery condition monitoring and fault diagnosis. Keeping in view the special and identical features of AE, particularly, the diagnostic processes or variation in materials, AE is believed to provide more accurate information about the actual source of energy within the machinery. Many other analysis techniques can also be used for analyzing the AE signals in the frequency domain as well as in time domain. Some of the signal processing methods used in AE sensor monitoring system within the machinery technologies are: continuous Fourier transform, discrete Fourier transform, Gaber wavelet transform and amplitude distribution method (statistical analysis method) [8]. Some of Artificial Intelligence methods used now in machine condition monitoring and fault diagnoses after with AE signal like GA, SVM, FLS and ANN.

In another study, P. Nivesrangsan *et al*. explained about the transmission of AE signals in diesel engine. They discovered that the real cause of AE signals had mechanical impact and fluid flow excitation for valve events [9]. In addition to this, many other studies have been done on designing more accurate source location techniques and the supervising mechanical detection events procedures by using AE [10-13]. These researchers finally reported that high spatial and temporal resolution of the AE signals is responsible for focusing the supervising techniques on each and every events and procedures individually. Application of the acoustic emission as a diagnostic method, structural integrity assessment tool is used when a qualitative or quantitative relationship between detected acoustic emission and material condition is established for a specific material and structure [14].

■3.0 ARTIFICIAL INTELLIGENCE

The artificial intelligence is the Systems that thinks and acts like human beings. It can also imitate human behavior. It is majorly concerned with the development of computers' ability to engage in human like thought processes like learning, reasoning and self-correction [15]. In the last decade, there has been a growing need in artificial intelligence to solve the problems of engineering. Earlier, these problems were considered hard to be solved analytically or by using mathematical modeling and needs human intelligence [16].

Nowadays, there is an increased demand for advanced AE analysis tools. This review will show 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 which have also been extensively used in the field of engineering include the following: expert systems, Genetic Algorithms, Support Vector Machine, fuzzy logic and Neural Networks.

3.1 Artificial Neural Networks Based Fault Diagnosis

The Artificial Neural Network (ANN) is an information-processing approach. It works like the biological nervous systems like how the brain processes the information in human body. Here the discussion is limited to introduction of many components which are involved in the ANN implementation. The network architecture or topology (including: number of nodes in hidden layers, network connections, initial weight assignments, activation functions) play a key role in the ANN performance and depends on the problem at hand. Figure 2 shows a simple ANN and its constituents. In most cases, setting the correct topology is based on a heuristic model. On the other hand, the number of input and output layer nodes is generally suggested by the dimensions of the input and the output spaces. Selecting the network complexity or regularization is again very important [17].

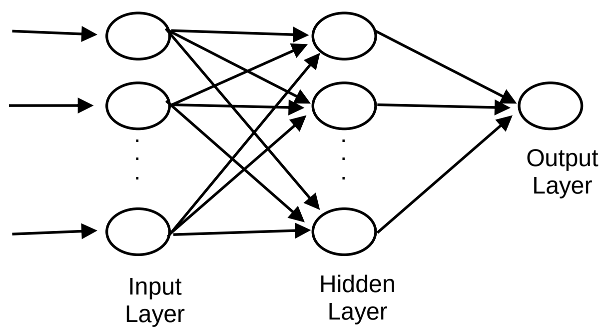


Figure 2 Architecture of a neural network

The benefit of ANN is that it has the ability to respond an input pattern in a desirable manner after the learning phase. Previous studies have proved the efficiency of the artificial neural network to predict the faults of machining processes. This technique has also been found very useful. This can be used in industrial automation in a more flexible manner [18]. ANN have been extensively used in health diagnosis of mechanical Gear, bearing and rotating machine by using features more from vibration signals and less from the acoustic signals.

There is an increasing demand for advanced AE analysis tools having 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 as 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 [19].

The problem of a roller with health monitoring has illustrated the effectiveness of GA for fault classification by using ANNs [17]. In this regard, Al-Balushi and Samanta have suggested a procedure to diagnose fault of gears by wavelet transformation and ANN for AE signals. These features taken from wavelet transformation were used as an input to an ANN based on diagnosing approach [20]. In the fault prognosis systems, the acoustic emission and vibration signal was utilized as an input signal. Additionally, ANN was utilized as prognosis system for rotating machinery failure [21]. In this way, a multiple layer neural network was successfully used to detect the fault in gearbox and classification and to utilize the supervised learning with an experimentally obtained data. The data were presented as processed vibration and acoustic emission signals [22]. Utilization of acoustic emission for early detection of the helicopter rotor head dynamic component faults has been previously studied. Analyzed the stress wave of flight-test dataset by using the wavelet-based techniques for assessing the background operational noise as compared to machinery failure results. Feed forward neural network was used classifier determines the correct fight regime [23].

For solving the issues of velocity and the time differences, a new approach to AE source localization has been described. This new approach to AE source location has been documented on the wing spar cutout of L-39 aircraft this method is used to estimate the AE source coordination by using the artificial neural network (ANN) processing extracted signal parameters [24]. Fog *et al*. studied detection of exhaust valve burn-through on a 4-cylinder, 500mm bore and 2-stroke marine diesel engine. This investigation comprised of monitoring 3 different valve conditions (normal, leak & large leak). Vibration & structure-born stress waves (AE) were monitored. The AE signals features were extracted by using principal component analysis (PCA). A feed-forward neural classifier was used also for discriminating between the 3 valve conditions [25].

Acoustic emission (AE) data collected during a static test of a 12-m FRP wind turbine blade was analyzed and classified into classes by using different unsupervised pattern recognition (UPR) techniques and using the UPR results, a supervised pattern recognition (SPR) method was trained based on back propagation neural network. This was applied to AE data collection and a subsequent biaxial fatigue loading of the same blade [26].

The neural network has gained much attention in grinding research due to its functions of learning, interpolation and pattern recognition and classification. Different other examples of the application in engineering field are also reported [27-31]. Aguiar *et al*. attempts to attain the classification of burn degrees of the surface grinding machine that is utilized for grinding tests with an aluminum oxide grinding wheel and the utilization of neural networks. The acoustic emission and power signal along with the statistics from the digital signal processing of these signals are used as inputs of the neural networks [18].

ANN approach has been 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 [28]. The grinding acoustic emission (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.* work is different as it uses grinding parameters as an input to the neural networks that have not been 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 [32].

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 are used as input to the neural network after they undergo some signal processing for calculating the membership functions of fuzzy relations. Additionally, fuzzy logic principles are utilized for diagnosing the system's status concerning tool wear and chatter [33]. 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 [18, 28, 32, 33].

Impact damage is a problem that damages the composite industry. This damage may seem superficial, but it may often have very negative effect 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, acoustic emission records the active flaw growth when the structure gets loaded. It also measures the reduction in the structural performance produced by an impact load. Acoustic emission (AE) signal analysis has been used to measure the effect of impact damage on burst pressure in 5.75-inch diameter, inert propellant filled, filament wound pressure vessels. The AE data were collected from fifteen graphite/epoxy pressure vessels featuring five damage states and three 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 [34].

The artificial neural network pattern recognition technique was used for analyzing the AE sources signals of 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 [35].

Conduct an analysis of the relationship between acoustic emissions (AE) signals and the main parameters of friction stir welding (FSW) process on the basis of ANN. The AE signals are acquired by data acquisition, applied in the welding process carrying out plates of 3 mm thick of aluminum alloy. The statistical and temporal parameters of the decomposition of EA signals by using Wavelet Transform (WT) have also been used as input for the multilayer feed-forward ANN [36].

The partial discharge (PD) detection, signal analysis and pattern identification, using acoustic emission measurements and the back-propagation (BP) artificial neural network (ANN) are also studied. In this way, the measured signals were processed with three-dimensional patterns and short duration Fourier transforms (SDFT). The findings showed that utilization of BP ANN with the SDFT components for the classification of the different PD patterns provides excellent overall results [37].

To determine the quality of features 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. This 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 normalization 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 [38].

3.2 Genetic Algorithms Based Fault Diagnosis

GA is a searching process and works on the laws of natural selection and genetics. 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 are the candidates for the solution. The fitness values of all chromosomes are evaluated by of an objective function (performance criteria or a system’s behavior) in a decoded form (phenotype). A particular group of parents is selected from the population for generating offspring on the basis of the defined genetic operations of crossover and mutation.

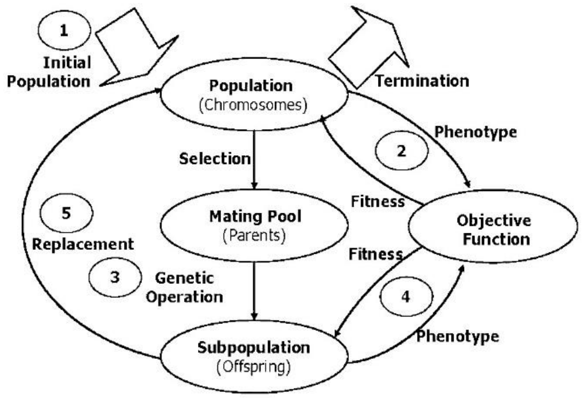


Figure 3 Genetic algorithm cycle [17]

The fitness of all offspring is then evaluated using the same criterion. The chromosomes in the current population are then replaced by their offspring on the basis of a certain replacement strategy. Such a GA cycle is repeated till the termination criterion is reached [17]. A simple problem of a roller with health monitoring was utilized to illustrate the effectiveness of GA in AE feature selection for fault classification by using ANNs. It has been shown that utilizing GAs to select an optimal feature set for a classification application of ANNs is a very powerful technique [17]. Ming applies acoustic emission technique for bearing condition monitoring and fault diagnosis. Scales for continuous wavelet transform and wavelet-based waveform parameter selection and optimization on the basis of genetic algorithm proposed selection method [39].

The acoustic emission was monitored by utilizing 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 are thought to be a pattern vectors described by a number of writers. In the present work, "model" data sets were generated for becoming closer to AE signals were recorded during the tests. This paper 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 characterized 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 [40].

3.3 Fuzzy logic Based Fault Diagnosis

Zadeh introduced the fuzzy logic in 1965[41-43]. Fuzzy Logic (FL) is a multi-valued logic that actually allows the intermediate values between conventional evaluations like true/false, yes/no, high/low and so on. The Fuzzy Logic helps in providing a various way 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 [44].

This work mention two time in this review because it contain from two parts first part use ANN for classification of burn degrees of the surface grinding machine, in this part, a methodology has been used to predict the surface roughness of advanced ceramics by using an Adaptive Neuro-Fuzzy Inference System (ANFIS). For this work, 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 [18]. Cusido *et al*. provides approaches for a one board fault detecting system and Test Program Set (TPS) fault detecting system for electro mechanical actuators (EMA) ball bearings by analyzing the different vibration and acoustic emission signals and by using fuzzy logic inference techniques [45]. Omkar *et al*. presented the results of fuzzy modeling to discover the problem in grinding, through digital processing of the acoustic emission signals produced during the process. Fuzzy C-means (FCM) clustering is utilized in classification of the Acoustic Emission (AE) signal to different sources of signals. FCM is potentially helpful to discover the cluster among the data, when the boundaries between the sub-group overlap. AE test is conducted by using pulse, pencil and spark signal source on the surface of solid steel block. Four parameters-Event duration, Peak amplitude, Rise time and Ring down count are measured with the help of AET 5000 system. These-data's are then used in training and validation of the FCM based classification [46].

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 acoustic emission and cutting power signals. The parameters obtained and used in this work consist of the mean-value deviance, grinding power, and root mean square (RMS) of the acoustic emission signal [47]. Ren, *et al*. also attempts to come by the most successfully AE model during the continuous cutting periods by using fuzzy modeling. The fuzzy identification method provides 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 [48].

Recent studies use type-2 fuzzy logic in their research [49-52]. Because the need to have extremely fuzzy situations to use type-2 fuzzy. Type-2 fuzzy logic if we are extending the use of fuzzy logic to a higher order, then it called type-2 fuzzy logic.
Hence, Ren, *et al*. explains about how type-2 TSK (Takagi-Sugeno-Kang (TSK)) fuzzy uncertainty estimation method is implemented to filter the raw AE signal directly from the AE sensor during turning process. This paper specifically focuses the filtering and capturing the uncertainty by type-2 TSK fuzzy approach on the interval of AE signal during one 10mm cutting length [49].

Ren, *et al*. attempted to find out the relationship between AE and tool wear. He presents an application of type-2 fuzzy logic on acoustic emission (AE) signal modeling in precision manufacturing.Type-2 fuzzy modeling is used for distinguishing the AE signal in precision machining. It provides a simple way for arriving at a definite conclusion without understanding the exact physics of the machining process [50].

The knowledge about uncertainty prediction of tool life is highly essential for tool condition investigation. It is also important for taking decisions about how to maintain the machining 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 utilized for analyzing 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 [51].

A type-2 fuzzy analysis method was utilized to analyze the AE SFs in TCM in micro milling process. The interval output of type-2 approach provides 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 [52]. The new philosophy for AE source localization under high background noise was also designed. The algorithm is 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 [53].

Khalifa and Komarizadeh developed an efficient walnut recognition system through putting together the acoustic emissions 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 classification phase, selected statistical features were used as the input of the ANFIS classifier [54].

3.4 Support Vector Machine

The support vector machine (SVM) approach was utilized in the form of a classification technique on the basis of the Statistical Learning Theory (SLT). It is basically based on the principle of hyper plane classifier or linearly separability. The main purpose of SVM is to explore a linear optimal hyper plane for maximizing the margin of separation between the two classes [55, 56].

The support vector machine (SVM) was utilized in fault diagnosis of spur bevel gear box. This is considered to be a popular machine learning application due to its higher accuracy and for its generalization capabilities [57]. 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 support vector machine (SVM). The classification process provides a comparative study between RVM and SVM in fault diagnosis of low speed bearing [58, 59].

Yu and Zhou shows the method to classify the AE signals in composite laminates by utilizing SVM. The classifier had built to achieve the identification and classification of acoustic emission signals. The results of simulation showed that support vector machine has the potential to effectively distinguish different acoustic emission signal and noise signal. The classification accuracy rate of grid search parameters is higher than the GA algorithm by this method [60]. Chu-Shu also informs about the method how to classify the AE signals in composite laminates by using the Support Vector Machine [61].

On the basis of thorough review of literature this study informs about the new approaches on the basis of a 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 [62]. Thus the paper proposes a novel grinding wheel wear monitoring system based on discrete wavelet decomposition and support vector machine. The grinding signals are collected by an acoustic emission (AE) sensor [63].

■4.0 CONCLUSION

This paper 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 a keyword index machine condition monitoring and machine fault diagnosis using AE signal analysis and AI.

We can conclude that the classification of acoustic emission signals carries a high importance in machine condition monitoring and fault diagnosis. ANN based on AE have been successfully applied to a many of relevant problems 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 existed paper. The experimental results prove that the use of fuzzy logic method is efficient and feasible.

The efforts to find a new 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 new novel idea for machine condition monitoring and diagnosis using AE signal analysis and AI will be future works.

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