Acoustic Emission and Artificial Intelligent Methods in Condition Monitoring of Rotating Machine – A Review

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Abstract—Machinery condition monitoring has become one of the essential components in the industry due to the ability of providing insight to the machine condition during operation as well as enhancing productivity and increasing machine reliability. This paper provides a review on using acoustic emission (AE) technique combined with artificial intelligence (AI) methods in the field of machinery condition monitoring and fault diagnosis. Even though many papers have been published in the area of machinery condition monitoring, this paper puts emphasis on gears and bearing only. Furthermore, the paper attempts to summarize and evaluate the recent condition monitoring research that utilizing AI includes fuzzy logic, artificial neural network (ANN), support vector machine (SVM), and genetic algorithms (GA) in fault diagnosis, fault classification, fault localization and fault size estimation in gear and bearing based on features extraction from AE signal. Machine condition monitoring philosophy and techniques have evolved based on intellectual systems. However, the acquired AE signal was found to be complicated in the application of gear and bearing monitoring, therefore it is required more attention. In addition, the use of AI methods in gear and bearing fault diagnosis still in the growing stage that requires lots of encouragement as it has a promising future in the field of machinery condition monitoring.

Keywords— rotating machine; artificial intelligence; acoustic emission; condition monitoring; fault diagnosis.

1. INTRODUCTION

Fault diagnosis for transmission tool and rolling element bearing gas gained lots of attention as an important module of mechanical equipment. The utilization rate of any machine can be enhanced using latest sensor and signal processing method-based process monitoring system. It can also be combined with existing knowledge based on information technology system to permit automatic conversion of a specific data evaluation schedule to several processes.

The aim of condition monitoring (CM) is to discover failures in rotating machines before a serious damage occurs [1]. Acoustic Emission technique is a precise method in machinery condition monitoring and fault diagnosis due to its high sensitivity in locating micro cracks in high frequency domain. The principle of acoustic emission technique is the elastic waves sent from the acoustic emission source. These waves are transferred to the material surface by transmission media and subsequently converted into electric signals by sensors before amplification, processing and recording. The analysis and processing of the obtained signals helps in detecting any defect within the material [2]. The quest to prevent machinery performance degradation, malfunction, or even catastrophic failures, has resulted in the development of reliable bearing health condition monitoring and failure prognostic techniques which has been the focus of various undertakings in a wide array of industries[3].

Figure 1 shows several methods which have been designed for CM to reduce and avoid the unpredictable outage . Even if these techniques are potentially to be more efficient in the area of CM and fault detection, there are still lots of complications when comes to the real industrial application. This is particularly true, if the machines are in operation due to the requirement of monitoring sensors to be installed inside the running gearbox.

The CM system was primarily executed by utilizing an integrated method dealing with numerous commercial equipment contractors. The requirement for integrated procedures is due to the absence of a single method that can offer comprehensive and trustworthy solutions desired by the industry [4].

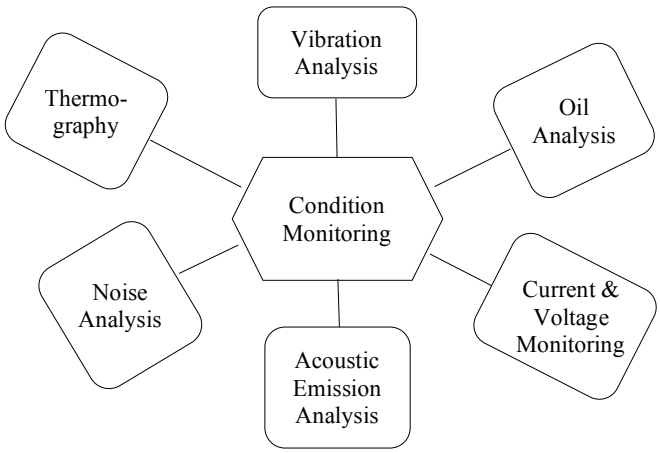

Figure 1: Common Condition Monitoring Methods

Recently, AI technique has been used for fault detection of machine tool. Moreover, AI can also predict the remaining life of machine tools. In this paper, a survey on the use Artificial Intelligence (AI) for CM and diagnosis of machine tools is presented. However, there is a need to make the classification process quicker and accurate using the least number of features. Primarily, it illustrates the system conditions with optimized structure or parameters of Artificial Neural Network (ANN) and Genetic algorithms (GAs) which were used for automatic feature selection in machine condition monitoring [4].

2. GEAR

Transmission system is the main element for controlling and influencing the worldwide dynamic performance of a machine. A powerful command over a machine, in fact can be obtained by appropriately controlling the torque transmitted to it [5].The failures noted in gearboxes are classically a combination of the following five failure mechanisms: (1) Lubrication loss; (2) Initiation and Propagation Crack; (3) Surface Wear; (4) Surface Fatigue; and (5) Structural Fatigue. It was also observed that the aforementioned failure mechanisms are intimately related in practice and they have the ability to accelerate each other [6].

3. BEARING

The common cause of failure in modern rotating machinery is a damaged rolling element bearing. It is compulsory that maintenance engineers should apply suitable techniques and equipment to observe and detect faults so that corrective maintenance can be taken [7]. The accurate diagnosis of a bearing failure is imperative to prevent repeated failures and their additional expenses. The following are some common failure types: (1) Failure of a rolling-element bearing caused by a static load; (2) Premature fatigue failure; (3) Surface fatigue in either the balls/rollers or the raceways; (4) Wear – Foreign Material; and (5) Inadequate Lubrication.

4. ACOUSTIC EMISSION APPLICATION

Acoustic emission signals are outside human hearing and occur on the surface or from within materials when elastic waves at 20 kHz–1MHz are released [8].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 [9,10] .The main application of Acoustic Emission (AE) to gear fault detection and monitoring, is to ascertain the AE behavior and its response to the typical failures, which includes surface damage, and tooth fracture through either natural or seeded defects or both. The awareness of using AE technology to monitor gearboxes has increased in the last few decades. Until now, most studies involving the application of AE in gearbox diagnosis have been carried out on spur gears and slow speed rolling element bearings [11].

By using AE methods, it is possible to predict the crack initiation feasibility for hardened gear but difficult for normalized gear [12-13]. Many gear tooth bending fatigue tests was conducted for validating the efficiency of AE in supervising the crack initiation and transmission [14]. The AE method extensively utilized the vibration and debris monitoring technique for detecting the growth of gear tooth crack, proving that AE could identify the initial indications of failures in very early stage [15].

Many techniques used to analyze AE for correlating the possible failure modes of a gearbox during its useful duration have been discovered [16]. Another study used vibration and AE for monitoring normal wind turbine gearbox [17]. The findings by several researchers revealed that AE technique is having better capability in detecting bending fatigue breakdown and fault detection in advance as compared to the vibration monitoring technique [12-17].

Two experimental studies [18] applied AE to detect gear pitting. The study concluded that the AE sensor should be very close to the monitored part in order to maximize the detection capability of pits. The AE technique is able to identify tooth surface failure attributed to the repeated gear revolution [19]. More so, a study used a seeded defect tests on spur gears for observing the fault detection capability of the AE technique and to compare with vibration technique [20]. Most researchers agreed that AE technique is most importantly useful to identify the gear or gearboxes problems at the earlier stages [18-20].

The application of the AE monitoring technique for gear fault detection by using the industrial gear rig, and the application of AE and vibration monitoring techniques for condition monitoring of a typical driveline was reported [21-22]. An energy-based feature extracted has been used to extract from AE signatures for diagnosing and monitoring gear faults [23]. In addition, some interesting investigation of AE activity due to misalignment and natural pitting on spur gear was made [24]. The experimental explanation for evaluating the efficiency of AE was carried out to observe the seeded faults on helical gears [25]. The current improvement on the AE technique has also showed the ability of AE to be gear or gearboxes diagnosis tool [26-30].

Signal processing method has been used to identify gear fault using AE signals. A new AE sensor based gear fault detection approach the frequency reduction technique and a modified time synchronous average (TSA) was introduced [31-32]. Other studies [33-34] was carried out to analyze the two gearboxes, made by the same manufacturer, to identify the difference between the vibro-acoustic emission of two gearboxes, due to the phenomenon of gear whine.

A remarkable amount of work has been undertaken over the last 20-years in developing the application of AE technology for bearing health monitoring. Salah et al [32] have been reviewing in various literatures on the significant research on the use of AE in rolling elements for condition monitoring and faults diagnosis. However, the studies carried out by Al-Dossary *et al.* [36-37] on the capability of AE technology for describing the defect sizes on a radially loaded bearing showed a direct relationship between the AE burst period and the defect length for bearing faults, thus creating a way for the user to observe the rate of degradation on the bearing was created; which is not visibly obtainable with vibration analysis [38].

Some research shows that AE measurements are superior to vibration measurements which can offer earlier fault detection and enhanced identification capabilities [35]. The important scope of study by Sayed [39] is to understand the effectiveness of AE signal parameters to distinguish between lubricated and dry bearings under similar operating conditions. Some researchers also have studied in-depth the defect classifications of roller bearings relating to the peak, root mean square (RMS), kurtosis, and duration of the acoustic emission signals [40].

The application of spectral kurtosis (SK) as a denoising tool has been able to improve the bearing fault features from an AE signal [41]. An observation into the applicability of stress wave analysis for detecting early stages of bearing damage was carried out [42]. The use of AE in very slow rotating machinery has proved successful in monitoring faults in rolling bearing [43-44]. The result showed that the use of AE parameters such as ring-down counts and peak amplitudes could identify bearing defects [45].

Another study clearly showed that scuffing wear and pitting was measurable with AE [46]. Salah [47] states that there is a significant difference in the variance of AE parameters when speed level is changed.

5. ARTIFICIAL INTELLIGENCE (AI)

Artificial intelligence (AI) is a system that thinks and acts like humans. AI is concerned with the development of computers capability to involve in human-like thought processes such as learning, reasoning, and self-correction [48].

The desire to develop new technologies and to beat many unsettled problems in CM and diagnostics of the complex industrial machinery applications have provided huge opportunities for the continuous growing of the AE technology. This can be seen in the significant growth in the current global claimant for AE sensors. With the increasing speed in the development of intelligent information, sensor and data acquisition technologies are joined with the fast development in intelligent signal processing techniques [49]. Currently, the improvement of maintenance strategy is assisted by computer technology both in hardware and software. A recently developed method for CM and diagnostics is using AI techniques as tools for maintenance routine (refer Figure 2).

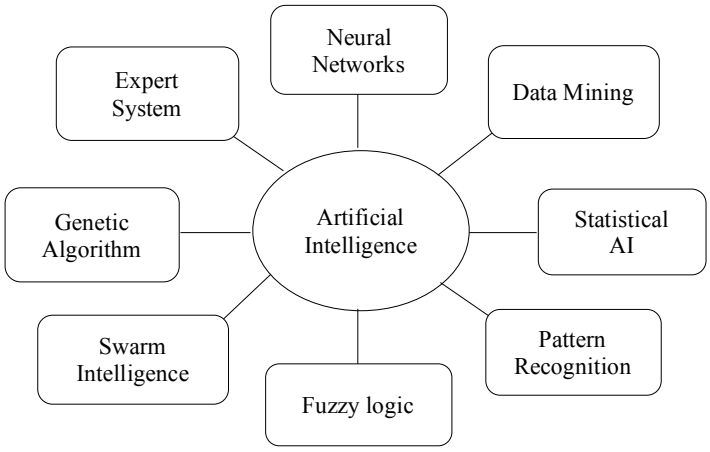

Figure 2: Branches of Artificial Intelligence (AI)

A. Artificial Neural Networks

The Artificial Neural Network (ANN) is an information-processing model, which is related to the biological nervous systems such as brain processes the information received. Its effectiveness is revealed by its ability in responding to an input pattern in a desirable way after the learning phase [50-50].

ANNs have been extensively used for health diagnosis of mechanical gear and bearing using features extracted from vibration signal and fewer from acoustic emission signals. ANN has also been used to show Genetic algorithm's (GA) effectiveness in monitoring roller bearing health in terms of feature selection for fault classification [50]. ANN uses vibration signals and acoustic emissions as input signals for predicting system faults. In addition, ANN was utilized as prognosis system for rotating machinery failure [52].

The features that are extracted from AE signal were used as an input to ANN for diagnosis the fault in ball bearing and use the same data as an input for another ANN for predicting the remaining useful life for the bearing [53]. The AE technique acquires data from bearing in decibel (dB), and distress level and then used the collected data to develop the ANN model for bearing failure prognosis. Based on the results, Levenberg-Marquardt Back-propagation and Elman network training algorithms, were shown to be suitable functions for hidden node and the output node was losig/purelin [54].

A new study [55] used artificial neural network (ANN) computational modeling to correlate spur gear data from acoustic emissions, lubricant temperature, and specific film thickness (λ). The approach is using an algorithm to monitor the oil film thickness and to detect which lubrication regime the gearbox is running either hydrodynamic, elastohydrodynamic, or boundary. This monitoring can aid identification of fault development. The methods used in this paper shows accurate predictions from ANN model.

Another study [56], for spur gear condition monitoring a new approach based on mathematical model was presented for oil film regimes detection. This study focused on the ability of regression model to find whether the gearbox is running in elastohydrodynamic, mixed wear or severe wear lubrication regime. Then, prediction the accuracy of the model is measured by examining the error that been produced by using Mean Squared Error and Mean Absolute Error. In this paper a mathematical model for time-series prediction was considered and the results shows the ability of the regression model to predict oil film regime. this study is consider to be the only one in the literature related to the estimation of oil film thickness through Acoustic emission signals.

In another work the neural network classifier determines the correct flight regime, by usinge stress wave data analysis of the flight-test dataset [57]. A wavelet-based techniques was used for measuring the background operational noise vs machinery failure. Al-Balushi and Samanta [58] offered a procedure for fault diagnosis of gears through wavelet transforms and ANN, for AE signals where the extracted features from the wavelet transform used as inputs to an ANN based diagnostic approach.

A multiple layer neural network has been used in a successful way to detect a gearbox fault and classification through supervised learning with experimental vibration and acoustic emission data. The network correctly classifies over 92% of the defects through the testing phase. The results showed that after properly training the neural network, its power and reliability as a tool increases in solving classification and pattern recognition problems such as gearbox health monitoring [59].

B. Genetic Algorithms, fuzzy, Support Vector Machine

Genetic algorithms (GAs) are software programs that provide evolutionary systems solutions through modelling or by imitating the biological evolution processes through a three-stage process of Selection, Genetic Operation and Replacement [50, 60-61]. GA is used in artificial intelligence to classify faults and monitor the conditions of various applications. Abhinav and Ashraf [50] applied ANN technique to classify and monitor a selected set of optimal features by GA in roller bearing health and the result shows that the application of ANNs with GA is a powerful technique. In a related study, acoustic emission technique was used by Zhang [62] to diagnose faults and monitor bearing conditions. Continuous wavelet transform and wavelet-based waveform parameter selection were used to measure and optimize genetic algorithm selection. Zadeh, in 1965[63], proposed a multivalued logic which enabled the definition of intermediate values between traditional evaluations such as yes/no, true/false, which he termed as Fuzzy Logic [64-66].

The approaches presented by Jordi [67] for Test Program Set (TPS) fault detection system for electro mechanical actuators (EMA) and a one-board fault detection system by analysis of various vibration and acoustic emissions signals applying fuzzy logic inference techniques. Subsequently, the approach of support vector machine (SVM) is carried out as classification technique with emphasis on statistical learning theory (SLT) relying on the concept of hyper plane classifier or linearly separability. The major reason of SVM is to initiate a linear optimal hyper plane which shortened the margin of distance between the two classes [68]. Mic showed that a fault diagnosis of low speed bearings with emphasis on AE technique and vibration signal. The analysis of fault is conducted using classification techniques involving relevance vector machine (RVM) and support vector machine (SVM). A comparative study between RVM and SVM in fault diagnosis of low speed bearing was made from the classification process [69-70].

4. CONCLUSION

According to previous studies, acoustic emission (AE) signals contain valuable information that can be used for gear and bearing condition monitoring and fault detection. Thus the result is enough to encourage and motivate the AE technique to be the new CM tool. Moreover, to make sure that this method is efficient, the fault detection ability on the other modes of gear breakdown, surface damage and fatigue need to be further investigated.

On the other hand, 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 need additional attention because of the absence of existed paper. Lastly, the future works will be to find a new novel idea for machine condition monitoring and diagnosis using AE signal analysis and AI.

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