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A Review on Fault Detection, Diagnosis and Prognosis, in Vibration Measurement through Wavelets on Machine Elements

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Abstract

For the past few years research on machine fault detection, diagnosis and prognosis have been developed rapidly. Fault detection intends to determine the faults present in the monitored process, while fault diagnosis seeks to identify the causes of the faults Electrical machines elements are used in many industrial applications. The important aspect to monitor the device to assess their safety and reliability. Fault detection is used to detect malfunctions in real time, as soon and as surely as possible. Diagnosis can be regarded as a posterior event analysis, which deals with the fault symptoms in the machine and their classification.Vibration measurement is a well-established technique for condition monitoring of rotating machines as the vibration patterns differ depending on the fault or machine condition. This paper summarizes the recent techniques of fault detection and diagnosis in vibration measurement through wavelets on machine elements.

Keywords: Fault detection, Fault Diagnosis and Prognosis, Wavelets.

1. INTRODUCTION

Nowadays, fault detection and diagnosis, the prognosis of modern industrial systems represents a major task and an active field of research. [1] Fault means The partial or total failure of a device and the Detection is The ability to recognize the functional ability of a device. Fault Detection is important in many industries to provide safe operation of a process. To determine the kind, size, location and time. Fault detection is used to capturing the fault and estimating the time of fault occurrence.Fault is an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable condition. It causes like design errors, implementation errors, human errors, use, wears, deterioration, damages, aging. Consequences of the fault are worse performances, energy waste, waste of raw materials, economic losses, lower quality, lower production, environmental damages, human damages. Machine fault and prevention are the concerns with personal safety, reliability, failure cost.

[2]In the past, fault detection of electrical machines was based on simple techniques such as over current and overvoltage detection. After detection, the machine needed to be offline to clear the fault.[2] In continuous operations, however, a shutdown of the motor may not be acceptable; hence, it is necessary to detect the fault quickly and find out accurately its location and rigorousness. An early detection of an initial fault avoids difficult consequences and reduces financial loss, bringing about only short downtime for the working process.[3]In fact, both correct diagnosis and early detection of incipient faults lead to fast unscheduled maintenance and short downtime for the process under consideration. They also prevent the harmful and sometimes devastating consequences of faults and failures.[4] Generally, failure prevention can be identified as the process of fault detection, diagnosis, and prognosis. If a fault is detected, repairs are made fast and to restore full protective functionality. In cases where repairs cannot be readily accomplished, alternate protection is placed in service or operations are taken to a stable, safe state until the repairs can be made.[5]The two methods of fault diagnosis are classification method and inference method. Classification methods are used when structural knowledge is available between the symptom and fault. inference method is used for fault diagnosis.

[6]Vibration is the back and forth or repetitive motion of an object from its point of rest. The rotating machines produce vibrations that are function of the machine dynamics, such as the alignment and balance of the rotating parts. Vibration measurement is an effective, non-intrusive method to monitor machine condition during startups, shutdowns and normal operation. Vibration analysis is used primarily on rotating equipment such as steam and gas turbines, pumps, motors, compressors, paper machines, rolling mills, machine tools, and gearboxes. Vibration analysis is used to determine the operating and mechanical condition of equipment. A major advantage is that vibration analysis can identify developing problems before they become too serious and cause unscheduled downtime. This can be achieved by conducting regular monitoring of machine vibrations either on a continuous basis or at scheduled intervals. Regular vibration monitoring can detect deteriorating or defective bearings, mechanical looseness, and worn or broken gears. Vibration analysis can also detect misalignment and unbalance before these conditions result in bearing or shaft deterioration. [7] Vibration is a widely measured parameter in many industrial applications. [8] Vibrations response measurements give valuable information on common faults. The wavelet contains both the analyzing shape and the window. However, wavelets have been applied in many other areas including nonlinear regression and compression. Wavelet decomposes a signal in both time and frequency in terms of a wavelet, called mother wavelet. Wavelets are a powerful statistical tool which can be

used for a wide range of applications, namely Signal processing, Data compression, Industrial supervision of gear-wheel etc[7].[9]Wavelets provide a time-scale information of a signal, enabling the extraction of features that vary in time. This property makes wavelets an ideal tool for analyzing signals of a transient or non-stationary nature.

]The required degree of fault prevention depends strongly on the complexity of the system and the application.[4] The rotating machinery used in the industry to perform fault detection, diagnosis with different means as well as prognosis to predict the time of failure of the critical components. Bearings are among the most critical mechanical components that have wide applications in many industries and have proven to be reliable and long-lived when properly applied. As a result of improvements in bearing materials, design, lubrication technology and service life, they have been gradually employed under more severe application requirements such as higher load, higher speed, and restricted lubrication. These requirements have made condition monitoring and fault diagnosis of bearings very important to ensure safe operation of rotary machines[4].[10] Detection can often be as simple as determining that a serious change has occurred in the mechanical condition of the machine. Diagnosis in effect determines the location and type of the fault and the prognosis involves estimation of the remaining life of the damaged bearing.[11] There are a lot of different causes for failures in electrical machines such as eccentricity, load torque oscillations, and stator turns short circuit. So, monitoring has become an important industrial research area in order to assess their safety and reliability. Bearing faults are part of mechanical defaults

The paper is organizing as follows. Section 2 briefly presents the machine fault detection, diagnosis, and prognosis of the rolling bearing. Section 3 describes the liberation measurement of the wavelet through the machine elements. Sections 4 present the most important technologies or methodology of fault detection, diagnosis and prognosis respectively. Finally, Section 5 gives some conclusions and states new challenges.

2. MACHINE FAULT DETECTION, DIAGNOSIS AND PROGNOSIS

Fault detection is the process of observing the measured system data and system status information and comparing them with a normal range of observed attributes to determine whether some measurements fall outside the range representing the healthy condition of the system[4]. Fault detection can be classified based on either detection by a signal model-based approach and model-based approach[5]. Model-based methods of fault detection use the relationship between several measured variables to extract information on possible changes caused by faults. The signal models which allow the main frequencies and their amplitudes to be directly estimated and which are especially sensitive to small frequency changes can also be used.[12] Fault detection is highly desired to increase the product quality, expedite the progress of unscheduled maintenance and short the machine downtime. fault detection and diagnosis methods are widely used in real-time monitoring and diagnosis for motors, buildings, power converters, and other mechanical systems. [13]Any type of fault that occurs in a system that leads to automatically to unexpected safety hazards, reduced efficiency, power availability, systems reliability and safety[8]. A typical fault detection method consists of the following stages: Data Acquisition, Parameter Extraction, Fault Analysis, and Decision Making.[14]

Fault detection methods have a rich history in the control community[15]. These techniques are generally classified as model-based approaches and data-driven approach Frequency domain. Fault detection techniques provide early warning to the system operators and prevent the system causing failures.[12]Fault detection algorithm involves two processes, Residual generation, and Residual evaluation. The Residual generator generates a residual and the Residual evaluator compares the residual with a threshold to determine the occurrence of a fault.

Model-based approach is widely used because it is the most economical. Data-driven methods produce accurate results than a model based on fault detection purpose.

Diagnosis is the process of determining the state of failing components and identifying the cause of the failure[4]. Prognosis is the process of predicting impending component failures or abnormal system states before they actually occur and estimates their remaining useful life. Prognosis, on the other hand, has been defined as “estimation of the time to failure and the risk for one or more existing and future failure modes.[5] The two methods of fault diagnosis are classification method and inference method. Classification methods are used when structural knowledge is available between the symptom and fault.[3]The most commonly employed solution approaches for fault diagnosis system include (i) model-based, (ii) knowledge-based, and (iii) pattern recognition-based approaches.[16]The the literature on machine fault diagnosis and prognosis is huge and diverse primarily due to a wide variety of systems, components, and parts.

a. Model-Based Approaches

Model-based methods can be designed in order to minimize the effect of unknown disturbance and perform the consistent sensitivity analysis. [3] The model-based methods perform fault diagnosis relied on analytical redundancy in which the consistency between the measurements and expected behavior of the process is checked by analytical models. These analytical models could be physical specific or explicit mathematical model of the monitored machine. model-based methods have been successfully applied for diagnosing the faults of components of the mechanical system such as gearboxes, rotors, and bearings.This approach can be more effective if a correct and accurate model is built. . This process is illustrated in Fig. 1

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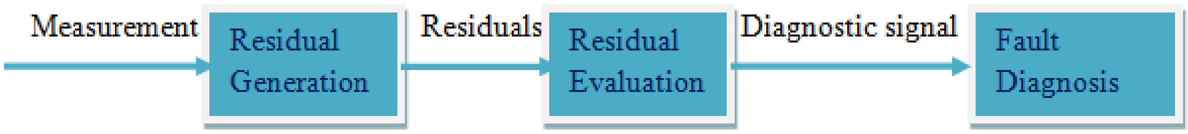

Fig 1: General Flowchart of Model-Based Approach

[38] The ability to diagnose component faults in their infancy is currently limited, due in part to sufficiently large sensitivity to signal noise, dependence on environmental and operating conditions, lack of fault detection and uncertainties in maintenance schedules. Diagnostic challenges exist due to problems with verification and validation.

Now model-based techniques for diagnosis have been examined in the artificial intelligence (AI) community under the title of model-based reasoning [3]. The use of AI techniques or the combination of conventional techniques and AI techniques has greatly enhanced the efficiency of model-based approaches in fault diagnosis. [17]] Model-based fault diagnosis methods are broadly classified as qualitative or quantitative.

1. Quantitative and Qualitative Methods

Quantitative model-based fault diagnosis methods utilize a model where the input-output relationship of the plant is expressed in terms of mathematical functions.[18] Quantitative models are sets of quantitative mathematical relationships based on the underlying physics of the processes. Quantitative model-based methods include those based on detailed physical models as well as those based on simplified models of the physical processes. These models can be steady-state, linear dynamic, or nonlinear dynamic. Quantitative models also have an advantage in modeling the transient behavior of the systems more precisely than any other modeling technique. They provide the most accurate estimators of output when they are well formulated.

The transients in a dynamic system can only be modeled with detailed physical models. They can be complex and computationally intensive. The effort required to develop a model is significant. These models generally require many inputs to describe the system, some for which values may not be readily available. Extensive user input creates opportunities for poor judgment or input errors that can have significant impacts on results.

Qualitative model-based fault diagnosis methods utilize a model where the input-output relationship of the plant is expressed in terms of qualitative functions cantered around different units in the process. [18] Qualitative models are models consisting of qualitative relationships derived from knowledge of the underlying physics. Qualitative model-based approaches include rule-based systems and models based on qualitative physics. qualitative modeling techniques employ causal knowledge of the process or system to diagnose faults. Other qualitative causal models include bond graphs and case-based reasoning. Some qualitative methods accept quantitative inputs directly, but others require qualitative inputs so that preprocessing is required before quantitative data are used. They are well suited for data-rich environments and noncritical processes. These methods are simple to develop and apply. Their reasoning is transparent, and they provide the ability to reason even under uncertainty. [11]They possess the ability to provide explanations for the suggested diagnoses because the method relies on cause-effect relationships.

The methods are specific to a system or a process. Although these methods are easy to develop, it is difficult to ensure that all rules are always applicable and to find a complete set of rules, especially when the system is complex. As new rules are added to extend the existing rules or accommodate special circumstances, the simplicity is lost. Quantitative model-based Fault detection methods are most accurate and reliable, they are generally more complex and\ computationally intensive compared to models based on other approaches

b. Knowledge-Based Approaches

Knowledge-based methods are used when there is a lot of experience but not enough details to develop accurate quantitative models. Knowledge-based system fault diagnosis is performed based upon the evaluation of on-line monitored data according to a rule set which is determined by expert knowledge[3]. This knowledge includes the locations of input and output process variables, patterns of abnormal process conditions, fault symptom, operational constraints, and performance criteria. The operators and engineers' intelligence related to the specific process systems can be implemented into this approach. Their knowledge can help to recognize the potential faults based on previous experiences[17]. This approach can reduce the difficulties on exact numeric information and automates the human intelligence for process supervision.

c. Pattern Recognition-Based Approaches

Pattern recognition methods are applicable to a wide variety of systems and exhibit real-time characteristics. Pattern recognition is a process of mapping the information obtained from the measurement space and/or features from the feature space to machine faults in the fault space[13]. Traditionally, pattern recognition is manually done by auxiliary graphical tools such as the power spectrum graph, phase spectrum graph, autoregressive spectrum, spectrogram, wavelet phase graph, etc. However, manual pattern recognition requires expertise in the specific area of diagnosis application. Thus, highly trained and skilled personnel are necessary. Therefore, automatic pattern recognition is exceedingly desirable. This can be achieved by classification of signals based on the information and feature extracted from the signals.

Prognosis is to use the given current and past machine condition to predict how much time is left before a failure occurs. [3]The fault prognosis process is usually tracked by a trending or forecasting model for certain condition variables. The approaches to prognosis fall into three main categories: statistical approaches, model-based approaches, and data-driven based approaches

a. Statistical Approaches

Statistical approaches can be trained to recognize the types of faults. Do not require condition monitoring in this approach. Statistical approaches, which are the simplest forms of prognosis techniques, collect statistical information from a large number of component samples to indicate the survival duration of the component before failure occurs[3]. Its Only provide general, overall estimates for the entire population of identical units

b. Model-based Prognostic Approaches

Model-based prognostic approaches are applicable to where accurate mathematical models can be constructed from a physical system[3]. Its require less data then data-driven approaches. Simplifying assumptions need to be examined and various physics parameters need to be determined. Model-based approach is highly accurate.

c. Data-Driven Techniques

Data-driven techniques are also known as data mining techniques or machine learning techniques. They utilize and require a large amount of historical failure data to build a prognostic model that learns the system behavior[3]. Among these techniques, artificial intelligence was regularly used because of its flexibility in generating an appropriate model. This approach does not require assumption or empirical estimation of physics parameters and prior knowledge

3. VIBRATION MEASUREMENT THROUGH THE WAVELETS IN MACHINE ELEMENTS

Vibration measurement is an effective, non-intrusive method to monitor machine condition during start-ups, shutdowns, and normal operation. Vibration analysis is used to determine the operating and mechanical condition of equipment[6]. There are three main parameters are measured to evaluate the vibration characteristics of any dynamic system as displacement, velocity, and acceleration.[19]Vibration analysis is performed to detect the fault in bearings. The bearings are the most important components in rotary machines. The life of a rolling element bearing is determined by exposing temperature, carrying loads, maintenance frequency, proper lubrication, handling, installation etc. The overall performance is affected by its carrying capacity and reliability. Vibration analysis is a suitable method for fault diagnosis. The obtained signal was a time-domain signal. This time-domain signal was converted into time-frequency domain data by using Discrete Wavelet Transform (DWT). Using Discrete Wavelet Transform (DWT), the features from the time-domain signal were extracted.

Vibration measurement in the frequency domain has the advantage that it can detect the location of the defect[20]. Vibration measurement in both time and frequency domains along with signal processing techniques such as the high-frequency resonance technique have been covered.[21]Vibrations generated by large structural components contain measurement noises which mask fault-related vibration signals generated by the smaller gears, making it difficult to identify the fault-related features. All rotating machines produce vibrations that are a function of the machine dynamics, such as the alignment and balance of the rotating parts.[6] Vibration measurement is an effective, non-intrusive method to monitor machine condition during start-ups, shutdowns and normal operation

Wavelets, on the other hand, have gained ground as a competent tool for machine condition monitoring and fault diagnosis in general and bearing fault detection in particular due to their flexibility and efficient computational implementation[22]. main aspects of wavelets for machine fault diagnosis which includes time-frequency analysis of signals, fault feature extraction, singularity detection for signals, denoising and extraction of the weak signals, compression of vibration signals and the system identification. Vibrations generated by large structural components contain measurement noises which mask fault-related vibration signals generated by the smaller gears, making it difficult to identify the fault-related features.

4. TECHNIQUES OF FAULT DETECTION, DIAGNOSIS AND PROGNOSIS

In this section, we have discussed the various methods used in the literature for fault detection and diagnosis in vibration measurement through wavelets on machine elements. Fault detection and diagnosis, prognosis in bearings have been widely studied for several years by using signal processing approaches and more recently by using machine learning methods [23].

Fault detection is limited by the result of knowing whether the device is in a different condition from the normal or nominal state[[23]. After fault detection, assessment of the damage is needed. Usually, the diagnosis is limited by the result of knowing the fault mode in which the device is working, but the magnitude of the fault is not analyzed. The vibration signal coming from a ball bearing system can reveal the location of a fault. [24]The detection of those faults in the incipient stage avoids unexpected breakdowns, increases reliability, operator safety, availability of the drive, and reduces maintenance costs. Fault detection in rolling bearings is performed by processing and analyzing vibration signals caused by alterations in the induction motor dynamics due to a fault.

Olivier Janssens et al [25] developed convolutional neural networks based fault detection. This approach is to autonomously learn useful features for bearing fault detection from the data itself. Two methods for bearing fault detection are feature engineering and feature learning to apply the CNN on this rawdata,the network learns transformations onthedatathatresultinbetterrepresentationofthedatafortheevent ual classification task in the output layer. To automatically detect faulty components, machine learning algorithms can be used. Machine learning algorithms use data to construct a model that can detect different conditions. The major advantage of an end-to-end machine learning system which uses feature learning is that less domain expertise is required to achieve very good results, as has been shown for computer vision research in the past. This method increases the classification accuracy without relying on extensive domain knowledge for detecting faults.

Jonas Guedes Borges et al[26] proposed bearing fault detection of a three-phase induction motor is performed by analyzing squared envelope spectrum of the stator current. Spectral Kurtosis based algorithms, fast kurtogram, and the wavelet kurtogram are also applied to improve the envelope analysis. One of the most important elements of the induction motor is the rolling bearing. This method allows the detection of localized faults without the need for any modeling or analysis based on the stator current of the machine in a healthy condition, as well as any prior knowledge of other information besides the shaft speed and bearing dimensions. The squared envelope analysis of the current produced promising results if an appropriate demodulation frequency band was selected. In this sense, fast kurtogram algorithm proved to be more efficient to identify frequency bands where the fault impulses are concentrated. Its indicate that the proposed method was reliable for detecting faults in the bearing outer race using fast kurtogram, properly indicating the characteristic frequency of the fault in both tested damaged bearings.

Picot et al[27] have considered an original method for bearing fault detection in high-speed synchronous machines. The principle of the method is to statistically compare the current spectrum to a healthy reference so as to quantify the changes over time. A statistic-based indicator is then constructed by monitoring specific harmonic family. The method was evaluated using a rigorous performance evaluation metric. A threshold evaluation was performed and shows that the proposed method is very tolerant to the machine speed. It shows a better robustness of the proposed method since good performance can be obtained with the same detection threshold whatever the speed or the measuring campaign whereas it needs to be redefined for each case with the classical indicator. The experimental protocol is separated into two measurement parts. The first part is performed with a healthy bearing and the second one with a faulty bearing. that the statistic-based indicator achieves a more accurate bearing fault detection as it is more stable and more reproducible. The present work shows that bearing faults were hardly reproducible from one machine to another. It highlights the need to develop normalized indicators whose performance is reproducible. Further work should explore adjustment of the proposed method to induction machines

Amarnath et al [28] implemented of empirical mode decomposition (EMD) method for monitoring simulated faults using vibration and acoustic signals in a two-stage helical gearbox. To demonstrate the effectiveness of EMD based statistical parameters to diagnose the severity of local faults on helical gear tooth EMD method was used to detect faults in ball bearing and helically geared system. Kurtosis values of unprocessed signals failed to reveal reliable fault propagation information whereas EMD based kurtosis values provided much better fault diagnostic information in bearing and geared system. EMD based statistical parameters of sound and vibration signals are used to diagnose the severity of faults in the geared system. EMD based kurtosis values extracted from vibration and sound signals provide good diagnostic information due to its ability to decompose the signals into higher and low-frequency modes. Higher-order statistical parameters sound and vibration signals have failed reliable diagnostic information. Local fault detection in a helical geared system using EMD based statistical parameter analysis improves the diagnostic capability thereby minimizing the possibility of catastrophic consequences or unexpected shutdowns in the geared systems

Fanbiao Li et al.[29] investigates fault detection filter design for nonhomogeneous Markovian jump systems by a Takagi-Sugeno fuzzy approach. The designed fuzzy model-based fault detection filter can guarantee the sensitivity of the residual signal to faults and the robustness of the external disturbances. MJS has been demonstrated by a great number of successful applications in industrial processes and automatic control systems. A fuzzy model-based fault detection filtering problem has been solved such that the fault detection dynamics are stochastically stability with a disturbance attenuation level. nonhomogeneous Markovian jump systems are characterized by a time-dependent transition probabilities matrix.In this work consider sojourn time-dependent jump systems. The desired full- and reduced-order fault detection filters have been designed.

Mariela Cerrada et al [30] introduce Fault diagnosis in spur gears based on genetic algorithm and random forest. The main aim was to build a robust system for multi-class fault diagnosis in spur gears by selecting the best set of condition parameters on time, frequency and time-frequency domains which are extracted from vibration signals. The diagnosis system is performed by using a genetic algorithm and classifier based on the random forest in a supervised environment. This work combines different methods for proposing best features an accurate model for spur gear fault diagnosis.The problem of features selection is an address by using GA and the selected features are used as input attributes forth RF based fault classifier. In this work, two approaches was designed the fault diagnosis system for the spur gear . First step is a genetic algorithm for attributes selection is used in a supervised environment with random forest based diagnose in the second step the fault diagnosis is trained again by using selected attributes. This approach aims discover which is the adequate subset of features regarding the classical time and frequency parameters, and the energy from wavelet coefficients that leads to a better performance for fault diagnosis .

Linlin Li, et al.[31] deals with a real-time weighted observer-based fault detection (FD) scheme for Takagi-Sugeno (T-S) fuzzy systems. To develop a weighted diagnostic observer-based FD system to optimize the worst-case robustness and fault sensitivity simultaneously by using the information provided by each local system. Takagi Sugeno (T-S) fuzzy dynamic model has been recognized as a powerful tool to describe the global behaviors of nonlinear systems. To be specific, the Fault Detection system is designed such that the residual signal is robust against known and unknown inputs, and meanwhile sensitive to fault variables. The weighting matrices are implemented here for further improving the fault delectability by taking into account the local dynamics of each local system. The fuzzy Lyapunov functions, sufficient conditions for guaranteeing the robustness and fault sensitivity simultaneously are studied for the fuzzy systems with un measurable premise variable case.

Mohamed Elforjani et al.[32] developed Acoustic Emission machine learning technique. This technique utilized for condition monitoring of various machining and industrial processes. The feasibility of Acoustic Emission (AE) to detect very small energy release rates. To keep machines function at optimal levels, fault prognosis model to predict the Remaining Useful Life (RUL) of machine components is required. To estimating the RUL for slow speed naturally degrading bearings using AE technology. The prognostic models have successfully been applied to specifically designed test rig, instrumentations, and particular AE tests, it is a fundamental principle to undertake further investigations and analysis to assess the feasibility of these models in real-world applications where other factors such as structural noise and other operating conditions are present. Using new and more appropriate regression functions to improve the fitting of the extracted features from the AE signals.

Amir Hossein et al.[33] implemented the anomaly detection algorithm for fault diagnosis. This method employs classification techniques to discriminate between defect examples. The performance of the developed algorithms was examined through real data from a test to failure bearing. In this research is to propose a fault diagnosis method that is able to overcome all the above-mentioned drawbacks, provide the system with higher sensitivity in fault detection and the most important point is it does not need huge historical data with fault samples. The algorithm may not recognize future failures and will assume they are normal if the training data set includes the effects of the intrusions. anomaly detection is applied to diagnose early defects in wind turbine bearings. This method employs a learning algorithm to categorize the anomalies from normal data. anomaly detection learning techniques can achieve higher accuracy with better efficiency for bearing fault diagnosis compared to the previously applied method using the SVM classifier approach and anomaly detection converges to an optimum value with high accuracy and fewer required data samples.

B. Samanta et al. [34] are presented for fault diagnosis of rolling element bearings through the artificial neural network (ANN). The ANN is trained using back propagation algorithm with a subset of the experimental data for known machine conditions. The ANN is tested using the remaining set of data. The effects of some preprocessing techniques like high-pass, band-pass filtration, demodulation and wavelet transform of the vibration signals. Its requires only a few features extracted from the measured vibration data either directly or with simple preprocessing. The reduced number of inputs leads to faster training requiring far fewer iterations making the procedure suitable for on-line condition monitoring and diagnostics of machines. Artificial neural networks (ANNs) have potential applications in automated detection and diagnosis of machine conditions. The most significant group of vibration signals and the characteristic features were identified. The accelerometers should be so placed that the bearing defects have an effective contribution to the accelerometer outputs. The features are effective in the ANN-based diagnosis of bearing failures using both original signals and the high-frequency components of the signals. The present approach also shows the importance of using multiple signals in the diagnostic process.

M.S. Safizadeh st al [35] presents a method for bearing fault diagnosis using the fusion of two primary sensors: an accelerometer and a load cell. To obtain acceleration and load signals, a work bench has been used. the load cell is powerful to detect the healthy ball bearings from the defected ones, and the accelerometer is useful to detect the location of the fault. An accelerometer is usually used to measure the vibration signal of the defective bearing. The bearing is a key element in rotating machinery and any defect can cause malfunctioning of the machine. To combine load and vibration based fault detection techniques using decision fusion in order to obtain a bearing monitoring system with greater efficiency in detection and decision-making capabilities than the individual diagnostic tools. This method was applied to three cases of bearing fault detection and its results were compared with the results of conventional methods using individual sensors. In conclusion, the experimental results show the benefits of the proposed method for improving fault detection and diagnosis accuracy.

Ye Tian et al. [36] Fault diagnosis for rolling bearings under variable conditions using local mean decomposition (LMD) singular value decomposition (SVD) and extreme learning machine is proposed. LMD, a new self-adaptive time-frequency analysis method, was applied to decompose the nonlinear and non-stationary vibration signals into a series of product functions from which instantaneous frequencies with physical significance can be obtained. singular value decomposition (SVD) was introduced in this study to compress the scale of the fault feature vectors and obtain more stable feature vectors.ELM was introduced for identification and classification of bearing faults. ELM as an intelligent technology has shown its good performance in regression applications as well as in large dataset and multi-label classification applications vibration monitoring has been proven to be an effective method of enhancing the reliability and safety of rotating machinery. LMD-SVD and ELM method is suitable and efficient for fault diagnosis of rolling bearings under variable conditions and shows promise for applications in other rotating machinery. This method can accurately diagnose and identify different fault types of rolling bearings under variable conditions in a relatively shorter time.

Matej Žvokelj et al [37] have considered EEMD-based multi-scale ICA method for slewing bearing fault detection and diagnosis. Ensemble Empirical Mode Decomposition, which adaptively decomposes signals into different time scales and can thus cope with multi-scale system dynamics. This method was tested on simulated as well as real vibration and Acoustic Emission (AE) signals obtained through conducting an accelerated run-to-failure lifetime experiment on a purpose-built laboratory slewing bearing test stand. EEMD-based multi-scale ICA does not determine the bearing health status based on the comparison of new observations against the reference data, set but it detects a potential fault based only on current operation condition. The method efficiency was evaluated on simulated as well as on real AE and vibration signals collected during accelerated run-to-failure testing of a slewing bearing conducted on a purpose-built laboratory test stand. The developed method combines the ICA-based multivariate monitoring method, which enables extraction and structuring of useful information from a high-dimensional, noisy, and possibly highly correlated data, with EEMD which adaptively decomposes signals into different time scales and can thus cope with multi-scale system dynamics. This method is highly changeable operating and environment conditions.

Yi Wang et al[38] illustrated waveform feature manifold (WFM) method for rolling element bearing fault diagnosis. The proposed method is applied to analyze the noise-contaminated simulation signal In this method signal in each time-frequency sub space is considered as wave form feature(WF). WF space is a fusion of different frequency band signals. Aiming at the shortcomings of the optimal filter band selection methods, the WFM technique intends to mine the nonlinear WF structure by manifold learning to obtain transient signal feature for bearing fault diagnosis. The experimental results verified the effectiveness of the WFM method in bearing incipient defect detection and providing potential proof to the maintenance personnel for diagnosis decision-making. The results validate the proposed method is able to extract fault signatures from weak signals and can be regarded as an effective and reliable method for rolling element bearing faults diagnosis at an early stage. This method has better waveform characteristics.

Jinde Zheng et al.[39] illustrated composite multiscale fuzzy entropy (CMFE) and ensemble support vector machines (ESVM) for rolling bearing fault detection diagnosis. CMFE is employed to measure the complexity of vibration signals of rolling bearings and is applied to extract the nonlinear features hidden in the vibration signals and it obtains much more stable and consistent values for a short-term time series. CMFE is used to extract the hidden nonlinear features from vibration signals of the rolling bearing. After obtaining the features for representing main fault information of vibration signals, an intelligent pattern classification method is needed to fulfill the fault diagnosis automatically. SVM learning is time-consuming on a large scale. CMFE is an effective complexity analysis method of time series. It can reflect the complexity characteristic of time series from multiple scales and also has an anti-noise calculation and a stable entropy for short-term data. In ESVM, each individual SVM is trained independently from the randomly chosen training samples and the correctly-classified area in the space of data samples of each SVM becomes limited to a certain area. The classification performance will be improved by using the ensemble SVM. to rolling bearing experiment data and the analysis results had verified the efficiency of the method as the superiority of ESVMs.

Aleksandra Ziaja et al[40] presented wavelet-based variance analysis and novelty detection for rolling element bearing in fault detection. To explore the self-similarity of bearing vibration data for novelty detection based on artificial neural networks. It is commonly known that the wavelet transform can be treated as an extension of the traditional Fourier transform with an adjustable window location and size. Wavelet variance characteristics were used to form the novelty indicator. The wavelet-based variance – originally developed for self-similarity analysis and neural networks are used for fault detection. The wavelet variance results show that long vibration measurements from bearings can be characterized by a short set of numbers which are able to represent the frequency content of the analyzed signal, being sensitive to modulations, impulsivity, and intensity. The work demonstrates that wavelet variances can be used directly as inputs to the network. It is also important to note that the novelty detection approach used does not require training with data representing various fault conditions.

Haoting Wang et al [41] carried out the Deep Learning and Dynamic Identification for early Fault Detection of Machine Tools. machine tools play an important role in modern digital manufacturing. They are used for shaping or machining metal or other rigid materials, usually by cutting, boring, grinding, shearing or other forms of deformation deep learning model is constructed to automatically select the impulse responses from the vibration signals in long-term running of days. Early fault detection means mining sensitive fault features from large-scale vibration data in long-term running. First, a deep learning model is used to automatically select the impulse responses from the long-term vibrations. It can be expected that any possible potential improvements in traditional methods would cost a large amount of labor and time.. First, the dynamic properties were used for early fault detection in machine tools for the first time. Second, a deep learning model was used to identify the dynamic properties. Third, the health status of machine tool under time-varying operation condition was diagnosed and monitored for the first time Fourth, this method is validated by actual industrial machining data collected continuously days. This method was not affected by time-varying conditions and showed considerable potential for early fault.

M.S. Patil et al.[42] postulated an analytical model for predicting the effect of a localized defect on the ball bearing vibrations. The localized defects include cracks, pits, and spalls caused by fatigue on rolling surfaces. Different methods are used for detection and diagnosis of the bearing defects.

They may be classified as vibration measurement, acoustic measurement, temperature measurement and wear analysis. The model makes it possible to detect the frequency spectrum having peaks at the bearing defect frequencies. The model predicts the frequency spectrum having peaks at characteristic defect frequencies and the amplitudes at these frequencies emanating from the bearings. authors believe that the moment load effects are not large enough and therefore, may not lead to large error in the results. However, this model will be upgraded at a future time to incorporate the effect of ball skidding to predict the spectral components of bearing with defects. It helps to predict the effect of the defect size and its position.

5. CONCLUSION

In this paper, an overview of fault detection and diagnosis methods vibration measurement through wavelets on machine elements. As shown in this paper many methods for fault detection and diagnosis have been investigated in order to solve this issue. fault detection and diagnosis techniques, which should be characterized by their efficiency, simplicity in terms of implementation, fast fault detection and diagnosis algorithms, capability generalization ability to identify multiple faults and ability to detect new faults. The effectiveness of a monitoring /faults detection system is related to the precision of measurement. The critical challenges are real-time diagnostic and prognostic method was integrated for much industrial application. This paper is to make a review to categorize, describe and compare the various Fault detection diagnosis and prognosis in vibration measurement techniques for machine elements.

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