A Data-Driven Approach Based Bearing Faults Detection and Diagnosis: A Review

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Abstract. Monitoring the condition of rotating machines is essential for system safety, reducing costs, and increasing reliability. This paper tries to present a comprehensive review of the previously conducted research concerning bearing faults detection and diagnosis based on what is known as model-free or data-driven approaches. Mainly, two data-driven approaches are discussed, which are statistical-based approaches and artificial intelligence-based approaches. The employed condition monitoring techniques in diagnosing faults in different machinery are also deliberated. These include vibration, motor current signature, and acoustic emission signals analysis as they are widely utilized in condition monitoring based data-driven approaches. The advantages, limitations, and practical implications of each approach and technique are presented. However, it has been concluded that very few studies have adopted the statistical-based approach for bearings health monitoring. Thus, it is advised that more investigations have to be conducted in this regard, and hence it will be our next aim.

Keywords. Data-driven, fault detection, Artificial intelligence, Condition monitoring, Statistical control charts.

1. Introduction
Rotating machinery is a crucial manufacturing component of the modern world. For example, in the United States, motors are currently equipping over 50% of the mechanical energy supply to manufacturing applications [1]. Rolling element bearings are the most accurately made devices; yet, they could fail prematurely if worrying forces are applied [2]. Faults in bearings can damage the level of production and tools and are also probably unsafe. Therefore, condition monitoring and fault diagnosis of these bearings have become an essential research theme for improvement and industrial applications [3]. As a base, faults, which predominately happen in rolling elements like the balls and internal and external races, are generated and increased during bearing running. It is essential to diagnose the faults at an early stage before getting expanded [4]. In the implementation of various condition control systems, different physical magnitudes such as vibration, stator currents, and acoustic emission signals can be considered. Stator current signature analysis has been widely adopted by several researchers for condition monitoring in electrical rotating machines because of its features of being non-invasive and easy to apply. While vibration analysis is best suited for the automated identification of faults, current analysis may also identify the influences of mechanical defects since the consumption of the induction motor current varies...
with the mechanical efforts and vibration patterns in the rotating system. Sound analysis, however, addresses the use of emitted acoustic signals for fault detection [5]. This article is generally organized as follows: the second subsection discusses the commonly used data-driven approaches, specifically the statistical and artificial-based approaches. The statistical approaches include the statistical control charts, while the artificial intelligence approaches comprise the artificial neural network, fuzzy logic, genetic algorithm, and support vector machines. After that, the widely used condition monitoring techniques, such as vibration, current, and acoustic emission, are discussed. The article is wrapped up with a conclusion containing the observed remarks.

2. Model-Free (data-driven) approaches

The data-driven methods are focused on the calculated data being highlighted in order to construct a process model. These approaches may be categorized into artificial intelligence (AI)-based and statistical approaches. A discussion of these techniques and their implementations is introduced in the following paragraphs [6].

2.1. Statistical-based approaches

Control charts are an exemplary method for statistical process control. Various control charts have been established to discover process variations, e.g., mean shift and/or variation shift. Due to its ease of running, the Shewhart X chart is popular for mean shift detection. The exponentially weighted moving average (EWMA) and cumulative sum (CUSUM) graphs are usually used to detect relatively small shifts. The standard deviation (S) and range (R) charts are suitable for identifying divergence changes. For differential shift detection, the S and R charts are suitable. The combined use of X and S (or R) charts will simultaneously detect mean and differential changes. The CUSUM control chart of the weighted loss function (WLC) can spot both mean and distinct changes and provide a practical approach to the control border design. It was used effectively for health state observation, with the state analysis being shaft misalignment. A sufficient statistic for WLC charts was the residuals between the fitted vibration signals using autoregressive models and the examined vibration signals. It shows that the chart can differentiate between healthy and deficient states and specify the fault harshness. The control charts are known as an unsupervised tool for defining health states because their design requires only healthy state information in cases where there is a lack of incorrect state information [7]. A technique for the state observation of a gearbox to distinguish the defect at a first stage by employing the control chart as a tool and utilizing time-domain acceleration signals analysis was applied in [8]. To derive the properties of the characteristics of defects, the time series model is used. To observe the deviations of the function values, the exponentially weighted moving average (EWMA) control charts are used. The distinction between these features is observed using EWMA control charts. A gear defect in the gearbox can be simulated by different techniques. The most frequently found defect in the gearbox is gear tooth loss because of wear, scoring, pitting, and tooth fracture, which can be mimicked by partial tooth removal throughout the test. In the experimental work, defects with growing severity are simulated via the spur gear tooth filling phase. Practical information for health gear and gear with three gear tooth removal stages, i.e., 37.5, 75, and 100%, is obtained, as shown in Figure 1. EWMA charts were charted utilizing the information obtained for the above types of faults, and the result showed that a control chart is a useful tool to define the divergence from the standard (healthy) state. Jaber and Bicker [9] have suggested a procedure for designing and implementing a robot fault detection approach relying on Shewhart statistical control charts for averaging, usually called the X-bar chart with R-chart or S-chart. One of the robot joints was chosen to mimics various defects in the robot. A comprehensive explanation of the chosen joint mechanical construction and the various faults associated with the power transmission system in the robot were discussed. The data acquisition system is designed using National Instrument (NI) software and hardware.
An appropriate accelerometer was chosen. For three axes vibration signal capturing, an aluminum adapter was designed to carry three accelerometers in an orthogonal arrangement. Vibration signals were acquired from the robot while performing a handling job simulates one of its real jobs several times and with seeded backlash faults of various intensity levels. After analyzing these signals using a signal processing technique, some statistical properties were extracted from them. To recognize between the healthy and defective robot states, the standard deviations (STDs) features were employed as they proved to be the best fault-sensitive function. Minitab software was utilized to create the chart, as shown in Figure 2, and subsequently, test its ability to detect robot health differences. The results showed that the statistical control chart (SCC) could detect the robot health condition variations. The primary benefit of control charts is that their construction needs only knowledge about the machine stable circumstances, which is appropriate in states where information about the faulty states are unavailable. Their major drawback is that they can only detect the damage without identifying where it is exactly, rather than its quantification and location.
2.2. Artificial intelligence-based approaches

Artificial intelligence (AI) is considered a robust pattern recognition tool, and it has attracted significant attention of many researchers. A popular fault diagnosis system often consists of two key steps: data processing (feature extraction) and fault identification [10]. However, artificial intelligence is a promising technique for identifying faults, and thus it is widely utilized.

2.2.1. Artificial neural network (ANN). It is a data processing paradigm stimulated by how the human brain processes data. Each ANN consists of at least one hidden layer plus input and output layers [11]. The structural unit of ANN, as seen in Figure 3, is the neuron, consisting of summer and an activation mechanism. The inputs to the neuron with the corresponding weights $W_1$, $W_2$, $W_3$, $W_n$ are $X_1$, $X_2$, $X_3$, and $X_n$, which models the synaptic neuronal linking in biological networks and operates in such a manner that the input signals to the neuron, are enhanced or decreased. A threshold term ($b$) might sometimes be applied to the inputs. In general, a real value or binary or bipolar value may be inputs, weights, thresholds, and neuron output. Both inputs are compounded by the respective weights and summed to form the net input of the neuron [12].

![Figure 3. Structure of the artificial neural network [12].](image)

Dhomad and Jaber [12] have developed bearings fault diagnosis system considering motor current signature analysis (MCSA), and the extracted features were then classified utilizing the artificial neural network. The result showed that utilizing the ANN for features classification represents a perfect technique to diagnose various kinds of bearings faults by training it with the extracted features from current signals. Based on the backpropagation artificial neural network (ANN), a health monitoring approach for a pulley-belt rotating system was proposed. A pulley-belt test rig composed of steel structure, flat belt, and DC motor was designed and manufactured. By employing two MEMS type accelerometers, Arduino microcontroller (MEGA 2560), and LabVIEW software, a low-cost data acquisition system was constructed. The obtained features have a pivotal turning in any health monitoring system and specifically in high-performance ANN training. So, feature extraction based time-domain signal analysis was accomplished. Different characteristics, like kurtosis and skewness, were calculated. A comprehensive empirical examination was executed on the pulley-belt test rig. Vibration signatures were obtained, and then the features were extrapolated from the system when it is healthy. More signals and other features were obtained when five various faults were inserted. The mimicked defects were unbalanced in the driving pulley, a driving pulley fault, chipped side, and pulleys misalignment. It was noticed that vibration signal analysis based on the time-domain approach guarantees decent discrimination among the healthy and fault states [13].

2.2.2. Fuzzy logic (FL). The Fuzzy Logic approach has shown a very suitable growth and solves problems related to uncertainty, utilizing formal methods to express comprehensible ideas. This technique utilizes ambiguous concepts to decrease the intuitive complication of performing the control process, either almost or heuristically, on non-linear processes or differences over time [14]. A fuzzy inference system was
proposed to indicate the motor health state based on vibration signal analysis to show whether it is in a good state or not [15]. The vibration values of less than 1.2 indicate the output motor state is good, between 0.8 and less than 3.4, the motor state is good enough, between 2.4 and 7.2, the motor state is observing closely, and bigger than 6, designates the output motor state of inadmissible. The result showed that detecting machines fault the motor state early and doing predictive maintenance. Fu, et al [16] conducted fault diagnosis work based on time-domain analysis and adaptive fuzzy -means clustering. Nine standard time-domain parameters are extracted from the gathered vibration signals. Based on the utilized adaptive fuzzy -means clustering, the optimal clustering number can be obtained to distinguish various fault types. Furthermore, five parameters, including variance, root mean square (RMS), kurtosis, skewness, and crest factor, of the nine features, are chosen as the new eigenvector matrix to be clustered for more optimal gathering performance. The experiment showed the validity and robustness of the method in applying defect detection of micro size, potentially diagnosing defects at the first stage of their growth.

2.2.3. Genetic algorithm (GA). It was first presented by J. Holland to solve a massive number of complicated optimization issues. Each solution displays an individual coded in one or more chromosomes. These chromosomes embody the difficulty variables. First, an initial group composed of a fixed number of individuals is created; subsequently, an operator of reproduction is applied to some individuals chosen in accordance with their suitability consequence. This procedure is reiterated until the maximum number of iterations has arrived. GA has been utilized in many optimization problems in many applications, telecommunication, routing, and scheduling, and it confirms its efficiency in getting the right solution [17]. Unal et al. [18] introduced a fault diagnosis approach for rolling-element bearing based on the envelope and FFT analysis using the backpropagation ANN algorithm for classification. By performing several experiments and implementing a set of signal processing techniques, various vibrational signals were tested. The classification efficiency was successfully improved by the production of GA. Sixteen attributes, offering 98% success, were used as inputs to an ANN model. The study revealed that the multilayer feed-forward network focused on envelope analysis, FFT, and GA proved to be a valuable computational approach for defect detection and diagnosis of roller bearings. For defective bearing conditions, which are normal-faulty, fault location, defect duration, and defect position, three categories were realized. For the defect-free, fault position situations, 98% of all fault states, the accuracy of GA configured by ANN was 100 percent. The proposed combined GA-ANN strategy could help experts develop an effective, easy, and accurate ANN framework for a given diagnostic problem. In the development of an ANN structure, the joint GA-ANN architecture achieves greater outcomes than any techniques that rely on trial and error approaches. Hocene and Ahmed [17] explain ANN's utilization in automating the fault diagnosis process in the electric motor bearing, depending on vibration signal analysis. At first, the vibration signals were acquired from a test rig and processed to obtain the most suitable observation parameters for the experimental device health monitoring. After that, a database was built and utilized to train and test the multilayer perceptron (MLP). Different possible types of faults have been taken. Also, the ANN performance was based on the training information collection size, the size of the ANN (the number of the hidden layer and the neurons per hidden layer). The GA was employed, as shown in Figure 4, in order to find out the optimal value of the number of hidden neurons. Thus, the value that allows getting the best performance of ANN was obtained. The result showed the competence of the optimization in choosing the GA factors.

![Figure 4. ANN optimization using GA [17].](image-url)
2.2.4. Support vector machines (SVM). These are a general synthetic intelligence approach generally employed for organization and regression information. Vapnik first presented the SVMs technique in the late 1990s; it was based on supervised learning methods derived from statistical learning theory. Supervised learning methods are referred to as machine learning techniques that attempt to create an apparent map between the training information inputs and outputs. SVMs are appropriate for two-class classification, but many extensions have allowed this method to be utilized for different-classes sorting problems [6]. Semil and Jaiswal [19] have studied the roller element bearings (REB) defect diagnosis utilizing the support vector machine (SVM) algorithm. For optimizing and cross-validation purposes, GA was employed. In most states, the precision of the cross-validation (CV) approach was much better than the GA based approach. Also, and the complexity of GA is higher than the CV based approach. Both techniques indicated the best result for SVM, but the cross-validation method was utilized with SVM as it is simple and can be stabilized easily. The input characteristic was obtained from time-domain vibration signal analysis, low pass and high pass filtering, etc. The significance of dissimilar signal processing and vibration signal analysis has been confirmed. More investigation is utilizing the best parameter development technique to optimize the parameters of SVM. Wang and Liu [20] established that the Lempel-Ziv complexity and Tsallis entropy are dependent as two indicators to describe the properties of the acoustic emission signal of a bearing in the initial defect stage. The comparison with skewness, kurtosis, and crest factor display that these two indicators are more sensitive for distinguishing various fault conditions. However, there is no fond impulse phenomenon in the waveform of an acoustic emission signal. Based on these two complexity measures, a ν support vector machine is further showed to realize precise defect classification. The main feature of the method is that the variable model parameters and ρ can be developed according to the training samples. So it can be dependent on a real manufacturing environment easily. The classification of three types of initial bearing defect state displays that the combination of complexity measures and a ν support vector machine classifier can build the discriminative boundary between various categories carefully in the state of a small sample size. For the detection of defects in bearings, a low-cost, non-contact vibration sensor was used. To investigate the integrated sensor efficacy, the support vector machine (SVM) was used. To strengthen a method for diagnosing machine health monitoring defects, realistic vibration information obtained for different bearing faults under different loading and operating states was analyzed. Using the discrete wavelet transform to denoise the signal, fault diagnosis was achieved. Mahalanobis distance parameters were used to pick the powerful function of the related characteristics extracted. To define and classify the various bearing faults, the chosen characteristics were transferred to the SVM classifier. The findings show that the vibration signatures acquired from advancing non-contact sensors are compared with the accelerometer information of the same states. An advanced sensor is a promising method for identifying the damage to the bearing and determining its classification. SVM findings have shown that the established non-contact sensor efficacy as a vibration measuring instrument is a cost-effective instrument for state observation of rotating machines [21].

3. Condition monitoring techniques
Condition monitoring is a repeatedly implemented condition-based maintenance approach to observe the component health condition, where vibration, temperature, and sound pressure monitoring are considered the most used techniques. Any significant difference signifies the growth of a fault. Vibration, lubricating oil, and acoustic signal analysis are being utilized broadly in rotating machinery defect diagnosis. Previous researchers performed vibration analysis and debriefed statistical features to recognize the defect present in the bearings undergoing constant operating speeds [22]. In this part, a summarized depiction of the initial three strategies with a review of formerly and newly accomplished work dependent on them will be given [6].
3.1. Vibration-based condition monitoring

Significant power is created when the flaw in the bearing rolling elements touches another external component, leading to producing an impact force in the bearing [23]. This force, which is created at any component of the bearing, is transported to another component, for example, internal race, external race, ball, and enclosure of the rolling element bearing. Serious cataclysmic outcomes will happen in the machines if the flaw in any of the rolling component is not dealt with correctly, which brings about the expensive interruption. Thus, for carefully revealing the deformity in the rolling element bearing, the vibration analysis technique is broadly utilized. Subsequently, the various vibration information obtained is used to locate the imperfections, such as inward race flaw, external race flaw, ball flaw, and the mix of various bearing element flaws. The kurtosis value of a vibration signal was calculated and used to recognize the bearing condition [24]. The Fast Fourier Transform (FFT) was then employed to distinguish the fault type in a deep groove ball bearing. The test was executed at three various speeds with no load situation. Labview software was utilized for time and frequency-domains signals analysis. It was observed that the value of kurtosis was less than the theoretical value with all velocity values, which means that the endurance condition is good. Thus, it was concluded that the kurtosis value is not positively affected by the velocity increase, which indicates that it does not differ with velocity. The time-domain analysis is a powerful approach in monitoring bearing condition. The extracted experimental bearing frequencies at all three speeds were less than the fundamental frequencies calculated theoretically, which refers to that the bearing has not got inner race, outer race, or ball faults. It was noticed that the time-domain signal analysis is useful for health conditions observing reason, and frequency domain analysis is beneficial for both condition and fault identification. In another research, for fault finding and diagnosis of rolling bearings, the extracted features of vibration signals and the adaptive neuro-fuzzy interface system (ANFIS) network were utilized [25]. Single point defects with defect diameters of 0.007 and 0.021 inches and depth of 0.011 inches were inset to the experiment bearings utilizing electro-discharge machining, as shown in Figure 5. Time-domain and frequency-domain statistical characteristics have been used to extract fault features from vibration signals. Besides, the extracted experimental information sets were employed to design the ANFIS network. The designed monitoring system efficiency reached 98%. The conclusion was that the proposed method could reduce the detection errors in bearings and can be used to concurrently identify the riskiness and class of defects with high accuracy.

![Figure 5](image-url). The simulated faults in the bearings by Helmi and Forouzan tabar [25].
Saruhan et al. [26] utilized the vibration spectrum analysis method to investigate the health state condition and deliberately faulty bearings under two load levels with various shaft operation frequencies (17, 25, 33, and 41) Hz. The information collected was monitored, analyzed, and showed in detail during the experiments, and satisfying results were obtained. However, identifying the influence of localized faults such as spall on the amplitude of vibration using root mean square analysis was conducted by [27]. The author has analyzed the vibration responses of a horizontal rotor backing on taper roller bearings. An experimental study based on a rotor-bearing system was carried out to take out the vibration response due to localized fault on the outer race, inner race, and rolling elements. The results showed that each fault influences the system with its unique frequency. It has also been observed that the intensive vibrations (the maximum vibration peak) happen in the case of the bearing with an outer race fault. Also, presenting the inner and outer faults result in intensive vibrations. Kunli and Yunxin [28] described the utilization of vibration measurements for a periodic health monitoring system of the rolling element bearings of a centrifugal machine. Vibration information was collected utilizing accelerometers fixed on a position at both the drive end and the centrifugal machine's driven end. A 16-channel data recorder was used to collect vibration signals, and the signal was processed using an analysis program based on a personal computer. Simple diagnosis approach depends on analysis of low and high frequency bands in synchronism with the time domain waveform. Defective vibration signals are typically defined as a mixture of effects on the source and propagation direction. For example, in the vehicle gearbox, internal forces that are the source of vibration act on a device whose characteristics may be a frequency response function between the point of force execution and the measurement point [29]. In the case of a car, a traditional frequency analysis of a continuum can have propagation path effects influencing the proper source signature and will not correctly distinguish the faults where the problem is correlated with more than one sideband and harmonic. The propagation path effects are additive and distinguished in autocorrelation and cepstrum studies and provide reliable detection of periodic structure in a spectrum connected to several harmonics sidebands as a single component for each sideband family. A test rig has two dynamometers; the input dynamometer acts as the internal combustion engine, and the other dynamometer mimics the internal combustion engine and payload on the output joint shaft flange. An artificial flaw is presented in automobile gearbox bearings: an orthogonally located groove on the inner race with an initial width of approximately 0.6 mm. The findings illustrated the utility of the suggested analyses in diagnosing and identifying the rolling bearing health status. Another paper discussed a new method of diagnosing bearing failures based on frequency response analysis [30]. The frequency response was determined for non-rigid multi-mass structures with dominant mechanical resonance frequencies during plant commissioning for safety and control purposes. This objective was accomplished by calculating two drive control variables, both influenced by the bearing fault. It was indicated that calculating frequency response is an appropriate technique for detecting incipient faults. A two-channel method for bearing damage diagnosis without external sensors is established. Deviations from stable state frequency response act as a fault indicator. As the two signals can be evaluated during daily plant activity, an online bearing fault diagnosis approach was accomplished. Morsy and Achtenova [31] used an optimal Morlet wavelet filter in conjunction with an autocorrelation enhancement algorithm based on time waveform analysis for bearing fault recognition. The optimal Morlet wavelet filter was utilized to remove the meddlesome vibration signal created from other sources and adequately extract the fault element critical characteristic. The results have been measured based on the test rig shown in figure 6. The vibration signal was filtered with a band-pass filter utilizing the optimal Morlet wavelet whose parameters are optimized based on maximum kurtosis to minimize the in-band residual noise further. An autocorrelation enhancement algorithm is adopted. The proposed technique could be conducted nearly automatically, with the least degree of user interference, and valid at various running conditions. The method used does not require much experience in the signal processing method. The optimal Morlet function is utilized as a filter with a band-pass filter to minimize the residual in-band noise and highlight
the periodic impulsive feature. The characteristic features can be identified based on autocorrelation analysis (finding repetitive patterns) of defect bearing at various running speeds.

Wu and Chen [32] used the continuous wavelet transform technique for defect diagnosis. The proposed continuous wavelet algorithm was utilized for defect signal diagnosis in an internal combustion engine and its cooling system. The experimental results demonstrated that the proposed continuous wavelet transform technique successfully diagnosed the defect signal. The Hilbert-Huang transform (HHT) offers an effective instrument for evaluating transient vibration signal as a time-frequency signal decomposition technique. Numerical and experimental studies were conducted on a specifically fabricated bearing test rig, as illustrated in figure 7. The results indicated that the tested bearing deterioration could be successfully revealed via the time-dependent amplitudes and instant frequencies produced from the HHT.

Another study offered an automated methodology for bearings fault diagnosis, relying on 2D vibration investigation under changing speed conditions [34]. Another research provided an automated approach under changing speed conditions for fault diagnosis in bearings based on 2D vibration analysis. Specific textures for each defect were found for extracting images from the vibration signals showing minimum difference at shaft speed. The analysis of these pictures by microtexture is used to establish single fault signatures at different velocities for each fault type. A neighbor classifier that is closest to the other will detect errors at different speeds by utilizing fault signatures that are generated for one speed. The method
is tested using Case Western Reserve University bearing defect dataset, and the result is contrasted with that of a spectral imaging approach. By testing the designed classifier with the default images at three running speeds, the classification output was calculated. The classification offers an average accuracy of 99.74%, which indicates that the methodology proposed to shaft shift is invariant. Yan and Gao [35] utilize cross-correlation measures to search for the best wavelet basis for bearing vibration analysis. The empirical results have shown that the cross-correlation coefficient between the extracted data utilizing Morlet wavelet and the defect-related transient data inherent in the signal is the more prominent among five frequently utilized complex-valued wavelets, and its ability efficiently identifies characteristic fault frequency when connected with the multiscale enveloping analysis method. The cross-correlation analysis, therefore, offers a quantitative test for directing the selection of the wavelet basis. An improved Hilbert time–time (IHTT) transform method was suggested to enhance extraction of the weak defect-related features of malfunctioned bearings by utilizing the principal component analysis (PCA) with a Hilbert time–time (HTT) transform [36]. Practically, the defect impact signal produced by the faulty bearing was easily suppressed by noise and harmonic obstructions. Benefited by the features of HTT transforms, the HTT transform method prevents harmonic interference by extracting the diagonal information of the HTT transform matrix; however, its ability is influenced by noise. With PCA implementation to de-noise the HTT transform matrix, the noise is significantly inhibited, and the IHTT transform spectrum is obtained. The diagonal information of the IHTT transform spectrum afford more noticeable shock features and refined results. Both the simulated and experimental investigations were utilized to investigate the suggested method. The results showed that the IHTT transform ameliorated the HTT transform analysis when analyzing noise signals. In another study, a real-time wavelet analysis system was considered [37]. Hybrid programming based on LabVIEW graphical programming and Matlab textural programming was adopted and proven to be an active tool to construct an intelligent signal monitoring and features extraction system. Furthermore, this system can be utilized for many applications, like noise elimination, biomedical signal analysis, and defect detection, or it could be adapted for utilization in many control purposes. Then, synthetic intelligence techniques are applied, like fuzzy logic or neural networks, for feature grouping and making decision. Moreover, by utilizing wavelet analysis, signal noise can be eliminated, and the original signal can be reconstructed; subsequently, the signal-to-noise ratio is enhanced [38]. By employing the wavelet decomposition approach, the signal can be separated based on its sub-band frequencies. Thus, a real-time wavelet analysis system was designed. The Arduino-UNO board was efficiently interfaced to LabVIEW after installing LabVIEW Interface for Arduino toolkit to obtain a cost-effective data acquisition system. Hybrid programming, combining LabVIEW graphical programming with Matlab textural programming, has proven to be a successful way for building an automated signal processing and feature extraction system. This system displayed reasonable outcomes when it was applied to artificial robot defect identification.

### 3.2. Motor current signature analysis (MCSA)

The spectrum produced by the motor current can be examined to observe the machine healthy running status. With the difference in the machines various mechanical parts, the variations happen in the electric background noise; so, motor current signal analysis methods can be utilized to detect defect signatures [23]. Based on the MCSA technique, a fault diagnosis system for bearings was developed [12]. A test rig was built, as shown in figure 8, and subsequently, various bearing defects were simulated and investigated. Three SCT013 current sensors were interfaced with and used jointly for data collection by Arduino MEGA 2560 microcontroller. The time-domain signal analysis technique was used to obtain some of the characteristics of the simulated defect. It has been shown that the artificial bearing defects have contributed to the generation of vibrations in the induction motors, which in turn cause variation in their magnetic field. The artificial neural network (ANN) was used to classify the extracted features. An ANN model was created using the Matlab ANN toolbox to detect simulated faults and to show the state of the system.
The possibility of using MCSA for online recognition of oil whirl instability in journal bearing and amplified clearance was assessed in [39]. An experimental configuration based on a small-scale journal bearing has been reported to enable testing of bearing problems under controlled fault conditions in a laboratory setting. On sealless siphon engines in the field with oil spin unsteadiness and on the specially manufactured engine with controllable journal bearing clearance, the vibration analysis, and MCSA were accomplished. The experimental results showed that MCSA could also detect journal bearing instabilities, such as oil whirls, and increased clearance resulting from mechanical wear that can only be detected in the field with vibration analysis. For large motors without mechanical sensors and minimum voltage, the results are predictable to assist in providing a minimum cost approach for wireless monitoring of log bearing problems in the field. It is anticipated that the journal bearing design for depressed voltage motors would facilitate the detection of journal bearing defects under-regulated defect conditions in a laboratory setting. Rabbi and Rahman [40] accomplished research based on stator current signatures to detect torsional oscillations in LSIPM motors. Rotor speed changes associated with torsional oscillations in the LSIPM engine influence electrical equipment and incorporate the lower and upper sidebands changing amplitude into the stator's current. They used frequency domain analysis of non-stationary current signals to detect the sideband frequency components superimposed on the essentials. The proposed method is confirmed by practicing finite element analysis (FEA) of a 3-phase 4-pole 1HP LSIPM motor drive. In order to verify the proposed method output under the operating conditions, experimental investigations were conducted for the same motor drive. Based on FEA and experimental data, the suggested technique can effectively identify the start of torsional oscillations in the drive system without using a vibration sensory system. Another analysis was performed by integrating Clarke's transform pattern, discrete wavelet decomposition, and K-means clustering to detect multiple fault detection using MCSA to extract bearing and gear fault characteristics [41]. The results are optimistic, but due to the long calculation time needed to perform the wavelet transformation, there is an important constraint. Despite this limitation, this functionality of approach is distinguished by its success in detecting and assorting multiple faults. The methods used make it possible to capture rapid transitions in a non-stationary mode and filter time and frequency domains simultaneously. Imaouchen et al. [42] have utilized the wavelet packet transform as a robust diagnostic method for finding primary faults in the bearing based on stator current analysis. The envelope of the motor current signal, which comprises bearings fault-concerning frequency data, was first concentrated by the Hilbert transform. As an effective replacement for vibration signals to detect bearing defects, a current signal processing procedure applied to electric current signals is suggested. In Figure 9, the research test rig used is shown. As the stator current signal is non-stationary, this approach shows some advantages over the Fourier analysis; so under different loading conditions, the wavelet packet transformation can offer better analysis. Because of the slippage that happens inside the bearing, the frequency ranges in fault detection are more tolerant since the real bearing-fault-induced vibration frequency can differ marginally from the expected standards. This spectrum of frequency bands can be protected by the wavelet packet transform.
Nordin and Singh [43] utilized MCSA and MLP neural networks to detect and classify the induction motor faults. MCSA method has been used to get an informed combination of the three-phase stator current. The three-phase stator current was transformed to power spectral density by utilizing the PSD method. Power spectral consisted of odd numbers of harmonics ranging from the fundamental frequencies until the 19th frequency in 1000 Hz. The frequencies were fed into the MLP neural network for defect categorization purposes. The accuracy, mean square error, the number of iteration, and the neural network required training time are discussed. The Levenberg-Marquardt training approach was employed to obtain the results from the MLP neural network, which indicated the best classification precision (97.2%), less required time (1.87 seconds), fewer iterations number (58 iterations), and quicker MSE convergence of (0.0059) in comparison with the other training techniques.

3.3. Acoustic emission (AE) based condition monitoring

The AE is considered as one of the primary strategies for machinery condition monitoring. The structural change that happens in a solid material under thermal or mechanical stresses leads to produce very fast strain energy, which generates transient elastic waves. This concept is named acoustic emission (AE). Plastic deformation, arising from generation and crack propagation, is the key cause of AE. [23]. American Society for Testing and Materials standard (ASTM) defined acoustic emission as the obstetrics of transient elastic waves, which happens during the release of energy from localized sources inside a material. Acoustic emission sources in metals are due to the initiation and stretching of cracks in a structure under test and loading, dislocation movement that accompanies plastic deformation. Phase transformation, thermal stresses, and melting are also sources that could lead to acoustic emission. Acoustic Emission systems work in a range of 100 kHz to 2MHz. This lower frequency determination is due to surroundings noises like friction, process results, signals, or outside impacts. The upper-frequency border is due to debility, and the range of detection of acoustic emission signals is border by this factor [44]. In this regard, Albarbar et al. [45] investigated how to extract fast data about the internal combustion running states of engine through their induced acoustic signals in an ordinary, acoustically untreated laboratory environment, without any sound measurement provisions. Essential features extracted from the time domain, frequency domain, and other statistical analysis techniques were studied, and also, a brief outline of the engine acoustic sources was presented. For generating typical baseline engine characteristics, acoustic signals were extracted considering various values of loads and speeds. Then, the measured parameters from the engine test rig were evaluated for the purpose of detection, diagnosis, and assessment of the severity level of the defects. These defects include compression ratio reduction, the injection pressure variation, and changing the exhaust and intake valve clearances. Defects related to the exhaust valve clearance were also spotted and identified by observing the spikiness intensity utilizing the RMS and kurtosis indicators for each of the engine cylinders' acoustic signals. The introduced approaches
proved to be suitable for small variations detection in the default settings, making it useful online state observation tools. Vicuña [46] carried out experimental tests on a health planetary gearbox. The consideration of planetary gearbox was due to its typical uses in machines exposed to changing running speed. The influence of the applied load, the temperature of the lubricant, and rotational speed were studied. However, the temperature influences the lubricant film thickness, limiting the amount of asperity contact between the meshing teeth. The film thickness reduction has two antithesis influences on the AE. The relationship between them is dynamic, and it controls the global RMS attitude of the AE. The experimental results with variable loads and rotational speeds presented that rotational speed is the essential parameter affecting the generated acoustic emission signals on the planetary gearbox. At lower rotational speeds, the effect of the load in the resulting AE can be significant. However, at high rotational speeds, the load effect is covered by the effect of the rotational speed. These results agree with the acoustic emissions behavior measured on the bucket wheel excavator planetary gearbox. Besides, Ogbonnah [44] studied the directions in a gear tooth pitting progression over time, utilizing wavelet analysis. The results showed that the mean absolute deviation and standard deviation wavelet statistical methods present quite a pretty prognosis for detecting the pitting progression. The wavelet compression method was very beneficial in limiting the rate at which the pitting process progressed. A linear relationship between acoustic emission, gearbox operation time, and pitting progression was presented by utilizing the wavelet analysis because the perfect correlation coefficient result was based on the wavelet statistical methods utilized. Moreover, there is typically a third particle abrasion due to the detached wear particles that are trapped between mating gears.

4. Conclusion

Condition monitoring plays a significant role in maintaining the machine to proceed correctly and away from additional costs. Therefore, there is great interest and development in this field. Data-driven approaches can be divided into statistical methods and artificial intelligence (AI) techniques. Control charts are a powerful tool in monitoring and controlling industrial processes. Shewhart control chart is widespread as it is easy to design and operate. The S- and R-charts are appropriate for divergence shift detection. The combined utilization of them can detect mean and difference shifts concurrently. It was then developed to the EWMA, and CUSUM charts which are ordinarily utilized for comparatively tiny shift discovery. However, control charts can only detect the onset of the fault but cannot tell its type. Thus for fault classification in the data-driven fault diagnosis systems, the artificial intelligence approaches were successfully employed. The commonly used classification methods are artificial neural networks (ANN), fuzzy logic (FL), genetic algorithm (GA), and support vector machines (SVM). It can be deduced that these techniques were very suitable for the fault diagnosis step. Thus, main conclusion of this review is that combining the statistical control chart with artificial intelligence techniques could produce a robust machinery health monitoring system that can be applied to detect and diagnose different fault types simultaneously.

5. Reference

[1] X Jin, M Zhao, T W Chow and M Pecht 2013 Motor Bearing Fault Diagnosis using Trace Ratio Linear Discriminant Analysis (IEEE Transactions on Industrial Electronics) vol 61 pp 2441-2451

[2] D S Chandra and Y S Rao 2019 Fault Diagnosis of a Double-Row Spherical Roller Bearing for Induction Motor Using Vibration Monitoring Technique (Journal of Failure Analysis and Prevention) vol 19 pp 1144-1152

[3] A Boudiaf, A Moussaoui, A Dahane and I Atoui 2016 A Comparative Study of Various Methods of Bearing Faults Diagnosis using the Case Western Reserve University Data (Journal of Failure Analysis and Prevention) vol 16 pp 271-284

[4] S Fu, K Liu, Y Xu and Y Liu 2016 Rolling Bearing Diagnosing Method Based on Time Domain
Analysis and Adaptive Fuzzy-Means Clustering (Shock and Vibration) vol 2016

[5] J J Saucedo-Dorantes, M Delgado-Prieto, J A Ortega-Redondo, R A Osorio-Rios and R d J Romero-Troncoso 2016 Multiple-Fault Detection Methodology Based on Vibration and Current Analysis Applied to Bearings in Induction Motors and Gearboxes on the Kinematic Chain (Shock and Vibration) vol 2016

[6] A A Jaber 2016 Design of an Intelligent Embedded System for Condition Monitoring of an Industrial Robot (Phd, Newcastle University)

[7] S Zhang, J Mathew, L Ma, Y Sun and A Mathew 2004 Statistical Condition Monitoring Based On Vibration Signals (QUT Digital Repository)

[8] H Lal and P V Kane 2019 Gearbox Fault Detection using ExponentiallyWeighted Moving Average Control Charts (Springer Nature Singapore) 2019

[9] A A Jaber and R Bicker 2016 Industrial Robot Fault Detection Based on Statistical Control Chart (American Journal of Engineering and Applied Sciences)

[10] R Liu, B Yang, E Zio and X Chen 2018 Artificial Intelligence for Fault Diagnosis of Rotating Machinery: A Review (Mechanical Systems and Signal Processing)

[11] B K N Rao, P S Pai and T N Nagabhushana 2012 Failure Diagnosis and Prognosis of Rolling – Element Bearings using Artificial Neural Networks: A Critical Overview (Journal of Physics: Conference Series)

[12] T A Dhomad and A A Jaber 2020 Bearing Fault Diagnosis using Motor Current Signature Analysis and the Artificial Neural Network (International Journal on advanced science Engineering Information Technology) vol 10

[13] A A Jaber and K M Ali 2019 Artificial Neural Network Based Fault Diagnosis of a Pulley-Belt Rotating System (International Journal on Advanced Scince Engineering Information Technology) vol 2

[14] E R Valencia-Nuñez, A M Wilches-Medina and V A Correa-Barrera 2018 Analysis of Transport Logistics Costs in Supply Chain Management by Applying Fuzzy Logic (Technology Trends) vol 8 p 145

[15] J B Janier and M F Z Zaharia 2011 Artificial Neural Network Based Fault Diagnosis of a Pulley-Belt Rotating System (IEEE)

[16] S Fu, K Liu, Y Xu and Y Liu 2016 Rolling Bearing Diagnosing Method Based on Time Domain Analysis and Adaptive Fuzzy (Shock and Vibration)

[17] F Hocine and F Ahmed 2014 Electric Motor Bearing Diagnosis Based on Vibration Signal Analysis and Artificial Neural Networks Optimized by the Genetic Algorithm (International Conference on Condition Monitoring of Machinery in Non-Stationary Operation) pp 277-289

[18] M Unal, M Onat, M Demetgul and H Kucuk 2014 Fault Diagnosis of Rolling Bearings Using A Genetic Algorithm Optimized Neural Network (Measurement) vol 58 pp 187-196

[19] R Semil and P Jaiswal 2019 Bearing Fault Diagnosis using Support Vector Machine with Genetic Algorithms Based Optimization and K Fold Cross-Validation Method (International Journal of Recent Technology and Engineering (IJRTE) vol 8

[20] G Wang and C Liu 2013 Fault Diagnosis of Rolling Element Bearings Based on Complexity Measure and N Support Vector Machine (BEARINGS CM) vol 55

[21] D Goyal, A Choudhary, B S Pabla and S S Dhami 2019 Support Vector Machines Based Non-Contact Fault Diagnosis System for Bearings (Journal of Intelligent Manufacturing)

[22] V Inturi, G Sabareesh, K Supradeepan and P Penumakala 2019 Integrated Condition Monitoring Scheme for Bearing Fault Diagnosis of A Wind Turbine Gearbox (Vibration and Control)

[23] C Malla and I Panigrahi 2019 Review of Condition Monitoring of Rolling Element Bearing Using Vibration Analysis and Other Techniques (Journal of Vibration Engineering & Technologies)

[24] P R Manve and R S 2017 Condition Monitoring and Fault Identification of New Deep Groove Ball Bearing using Labview (Journal of Emerging Technologies and Innovative Research (JETIR))
[25] H Helmi and A Forouzantabar 2018 Rolling Bearing Fault Detection of Electric Motor using Time Domain and Frequency Domain Features Extraction and ANFIS (IET Electric Power Applications)

[26] H Saruhan, S Saridemir, A Çiçek and i Uygur 2014 Vibration Analysis of Rolling Element Bearings Defects (Journal of Applied Research and Technology) vol 12

[27] S Sharma 2011 Fault Identification In Roller Bearing using Vibration Signature Analysis (Msc, Thapar University)

[28] M Kunli and W Yunxin 2011 Fault Diagnosis of Rolling Element Bearing Based on Vibration Frequency Analysis (Measuring Technology and Mechatronics Automation)

[29] M E Morsy and G Achtenová 2015 Rolling Bearing Fault Diagnosis Techniques - Autocorrelation and Cepstrum Analyses (Mediterranean Conference on Control and Automation (MED))

[30] H Zoubek, S Villwock and M Pacas 2008 Frequency Response Analysis for Rolling-Bearing Damage Diagnosis (IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS) vol 55

[31] M E Morsy and G Achtenova 2015 Fault Diagnosis of Rolling Bearing Based on Time Waveform Analysis (SAE International)

[32] J-D Wu and J-C Chen 2005 Continuous Wavelet Transform Technique for Fault Signal Diagnosis of Internal Combustion Engines (Elsevier)

[33] R Yan and R X Gao 2006 Hilbert–Huang Transform-Based Vibration Signal Analysis for Machine Health Monitoring (IEEE TRANSACTIONS ON INSTRUMENTATION AND MEASUREMENT) vol 55

[34] S A Khan and J-M Kim 2011 Automated Bearing Fault Diagnosis Using 2D Analysis of Vibration Acceleration Signals under Variable Speed Conditions (Shock and Vibration)

[35] R Yan and R X Gao 2011 Impact of Wavelet Basis on Vibration Analysis for Rolling Bearing Defect Diagnosis (IEEE)

[36] B Pang, G Tang, T Tian and C Zhou 2018 Rolling Bearing Fault Diagnosis Based on an Improved HTT Transform (journal sensors)

[37] A A Jaber and R Bicke 2014 A Simulation of Non-stationary Signal Analysis Using Wavelet Transform Based on LabVIEW and Matlab (IEEE computer society)

[38] A A Jaber and R Bicker 2015 Real-Time Wavelet Analysis of a Vibration Signal Based on Arduino-UNO and LabVIEW (International Journal of Materials Science and Engineering) vol 3

[39] J Jung, Y Park, C Cho, K Kim, E Wiedenbrug and M Teska 2015 Monitoring of Journal Bearing Faults based on Motor Current Signature Analysis for Induction Motors (IEEE)

[40] S F Rabbi and M A Rahman 2016 Detection of Torsional Oscillations in Line-Start IPM Motor Drives Using Motor Current Signature Analysis (IEEE)

[41] N G Lo, A Soualhi, M Frini and H Razik 2018 Gear and Bearings Fault Detection using Motor Current Signature Analysis (IEEE)

[42] Y Imaouchen, R Alkama and M Thomas 2015 Bearing Fault Detection using Motor Current Signal Analysis Based on Wavelet Packet Decomposition and Hilbert Envelope (EDP Sciences)

[43] N Nordin and H Singh 2014 Detection and classification of induction motor faults using Motor Current Signature Analysis and Multilayer Perceptron (Power Engineering and Optimization Conference (PEOCO)) pp 35-40

[44] V Ogbonnah 2007 Condition Monitoring of Gear Failure with Acoustic Emission (ed, 2007)

[45] A Albarbar, A Ball and A Starr 2008 on Acoustic Measurement-Based Condition Monitoring of Internal Combustion Engines: Condition Monitoring (Insight (Northampton)) vol 50 pp 30-34

[46] C M Viciña 2014 Effects of Operating Conditions on the Acoustic Emissions (AE) From Planetary Gearboxes (Elsevier)