National High School of Technology
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Application of artificial intelligence methods in automatic diagnosis of rotating machines

Master's thesis in
industrial maintenance management and engineering

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Abstract: Nowadays, the rapid technological advance gave birth to Industry 4.0 concept, in which interconnectivity, automation, machine learning, and real-time data processing are considered as the key elements. As an important part of industry, maintenance was also evolved under this revolution. In this context, i.e., innovation in preventive maintenance, a literature review is made about rotating machinery automatic diagnostic techniques that combine between AI and vibration analysis. It was concluded that Deep learning methods are more efficient in fault detection and automatic fault diagnosis that classic AI methods. So, a theoretical background of some recent methods, such as Convolutional neural network, Recurrent neural network and Deep neural network are introduced. Furthermore, the paper includes the advantages and disadvantages of time-domain and frequency-domain vibration analysis techniques.

Key-words: Fault Diagnosis Rotating machinery Artificial Intelligence Deep Learning Convolutional Neural Network Industry 4.0

Contents

1 Introduction 2
2 Theoretical Background 4
3 Conclusion 8

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1. Introduction

In the industry 4.0, Artificial Intelligence (AI) has attracted increasing interest for various research applications. In recent years in predictive maintenance, AI and deep learning models have been extensively implemented in machinery fault detection and diagnosis (FDD) systems. Machine fault diagnosis and condition monitoring are key elements in the maintenance system, this is because rotating machinery is a vital component in many industries, and it is prone to failure due to harsh working conditions and long operational times.

The valuable industrial equipment like rotating machinery needs continuous monitoring to enchase the safety, reliability and availability and to decrease the cost of maintenance. Rolling bearings are considered to be the main component of rotating machinery and any failure of this component can lead to a serious problem and a breakdown of the whole industrial system. So, several experimental investigations have been conducted in the frame of condition monitoring and fault detection and diagnostic of rotating machinery, especially for rolling elements bearing based on artificial intelligence methods (ANN, Neuro-fuzzy, Deep Neural Network, Support Vector Machine...) [1].

According to research conducted by Ruonan Liu et al, Artificial Intelligence (AI) techniques are effective solutions for the diagnosis of rotating machine defects. The authors presented a comparative assessment of some AI algorithms, namely, k-nearest neighbour, naive Bayes, support vector machine, artificial neural network and deep learning, in the diagnosis of rotating machine defects, both from the point of view of theory and industrial applications. this article concludes with the advantages, the limitations and practical implications of the different algorithms of AI and a comparison of performance between these AI algorithms [2].

Algorithms	Advantages	Disadvantages
k-NN	Mature theory and easy to implement. Can be used for both classification and regression.	Large computation. Needs lots of storage space. The selection of k influence rightarrow too much.
Naive Bayes	to missing values. Requires little storage space. Good physical explanation ability	Strong prior assumptions. Combinatorial explosion and computation problem. Need of prior probability.
SVM	High classification accuracy. Can deal with high-dimensional features.	Low efficiency for big data. No physical meaning.
ANN	High classification accuracy. Good approximation of complex nonlinear function.	Many parameters and easy to over-fitting. physical meaning. Training procedure cannot be seen.
Deep Learning	Learning features and recognizing fault automatically. Learning more complex structure from data due to the deep architecture. Do not need the feature extractor	Needs of large samples. No physical meaning. Training for long time.

Table 1: List of AI algorithms and their advantages and limitations [2].

K Kudelina et al, studied different diagnostic techniques (Decision Trees, Support Vector Machines, Principal Component Analysis, Genetic Algorithm, Artificial Neural Networks and Fuzzy Logic) that can be used for training algorithms and performing preventive maintenance. The advantages and disadvantages of intelligent diagnostic techniques are highlighted. The most common defects in electrical machines are discussed and parameter monitoring techniques are introduced [3].

Proceedings of M. F. E. G. I. M. - 2021/2022

Table 2: Benefits and drawbacks of intelligent diagnostic techniques [3].

Diagnostic Technique	Advantages	Disadvantages
Decision Trees	Small computational power is required. Simple structure. No need for data pre-processing.	High possibility of overtraining. Not suitable for regression tasks. Increased training time.
Support Vector Machines	Operation in high dimensionality. Work with nonlinear processes. Small computational power is required. No need for data specification.	No ability to filter unnecessary information. Complicated managing of kernel machine. Overlapping risk.
Principal Component Analysis	No overlapping. Reduced training time. Good visualization.	Possible loss of information. Reduced accuracy.
Genetic Algorithm	Adaptive algorithm. Rapid processing.	Overlapping risk.
Artificial Neural Networks	any ML algorithm. Fast learning. Not sensitive to data noise.	Must be balance between under- and overfitted data. "Black box" phenomenon. Overtraining risk.
Fuzzy Logic	Simple structure. Flexible algorithm. No need for specific hardware. Easy reprogramming.	A lot of data is needed. Inaccurate data lead to poor results.

Yasir Hassan Ali et al, presented a review of recent literature in the field of acoustic emission signal analysis using artificial intelligence in machine conditioning monitoring and fault diagnosis. most of the researchers established that the acoustic emission technique is an effective method of monitoring the state of the machine and diagnosing faults due to its high sensitivity to the location of micro-cracks in the high frequency domain. The recent developed method is based on artificial intelligence techniques such as artificial neural network, fuzzy logic system, genetic algorithms and the vector support machine [4].

Lucas C et al, revealed that the monitoring of rotating machinery is an essential task in today's production processes. They proposed a new approach for fault detection and diagnosis in rotating machinery. The methodology consists of three parts: feature extraction, fault detection and fault diagnosis. In the first part, the vibration features in the time and frequency domains are extracted. Secondly, in the fault detection, the presence of fault is verified in an unsupervised manner based on anomaly detection algorithms. The modularity of the methodology allows different algorithms to be implemented. Finally, in fault diagnosis, Shapley Additive Explanations (SHAP), a technique to interpret black-box models, is used. The study also presented a comparison between models used in machine learning explainability [5].

According to research by Shengnan Tang et al, fault diagnosis of rotating machinery plays a significant role in the industrial production and engineering field. Due to the disadvantages of traditional fault detection methods, intelligent fault diagnosis based on deep learning (DL) has aroused the interest of researchers. Therefore, in this review, DL and DL-based intelligent fault diagnosis techniques are overviewed. DL-based fault diagnosis approaches for rotating machinery are summarized and discussed, including bearing, gear/gearbox and pumps [6].

Jong-Myon Kim et al also revealed that bearings are critical components in rotating machinery, and it is crucial to diagnose their faults at an early stage. Since the existing methods of fault diagnosis are mostly limited to traditional AI learning schemes such as neural networks, support vector machines, they proposed an adaptive deep convolutional neural network (ADCNN) that utilizes cyclic spectrum maps (CSM) of raw vibration signal as bearing health states to automate feature extraction and classification process. The efficiency of the proposed algorithm (CSM+ADCNN) was is validated using a set of baseline data obtained from bearing tests. Experimental results indicate that the proposed methodology surpasses state-of-the-art algorithms, resulting in an improvement in classification performance from 8.25% to 13.75% [7].

Long Wen et al proposed a new Convolutional neural network (CNN) based on LeNet-5 for diagnosis and early detections of manufacturing system fault. It was established that Deep learning (DL) method provides an effective way to extract the features of raw data automatically. Through a conversion method converting signals to 2-D images, the proposed method which is tested on three famous datasets, including motor bearing dataset, self-priming centrifugal pump dataset,

Proceedings of M.E.C.I.M. - 2021/2022

axial piston hydraulic pump dataset, has achieved prediction accuracy of 99.79%, 99.481% and 100% respectively. The results have been compared with other DL and traditional methods, the comparisons show that the proposed CNN based data-driven fault diagnosis method has achieved significant improvements [8].

According to the literature review we conclude that CNN method plays a very important role in maintenance system, especially in predictive maintenance, and it's considered as the best methods because of its simplicity and accuracy in machinery condition monitoring and fault diagnosis.

2. Theoretical Background

2.1. Artificial Intelligence

2.1.1 Introduction

Artificial intelligence refers to systems that act and think like humans. It is also capable of mimicking human behavior. It focuses on improving computers' ability to engage in human-like cognitive processes such as learning, reasoning, and self-correction [4]. AI, as a novel and multidisciplinary discipline, aims to use a computer tool to simulate aspects of human thinking processes and intelligent behavior [6].
Because of their robustness and adaptability, AI algorithms for fault diagnosis of rotating machinery have grown widespread. They also don't need much prior physical knowledge, which might be difficult to acquire in practice. The most prevalent AI algorithms used in fault diagnosis are k-Nearest Neighbor (k-NN), Fuzzy Logic, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) [2].

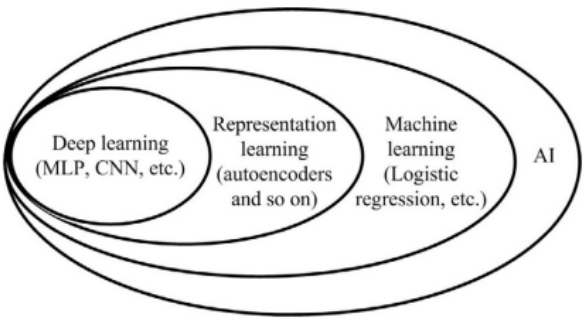


Figure 1: Relationship between different AI disciplines [2]

2.1.2 Deep Learning

Deep learning (DL) is one kind of machine learning and reveals the profound development of AI. DL stands for feature learning or representation learning, and it is characterized by various and high-level data representations. Specifically, low-level characteristics from simple and nonlinear modules were composed to generate more abstract high-level representations in terms of categories or features. When compared to traditional machine learning, the major benefit of DL is that layers of features are automatically learnt from raw data using a general-purpose learning technique, rather than relying on engineering skills and domain experience. DL methods can be used for rotating machinery faults diagnosis. Very Deep Neural Networks are a type of deep learning model. Deep models, such as Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN), rely heavily on DNN [6].

Convolutional Neural Network (CNN)

Convolutional neural network (CNN), one of the most classical models in deep learning, is a feedforward neural network [9]. CNN has achieved remarkable success in many research and industry, and it has excellent performance in the field of image recognition, natural language processing and target detection [10]. As seen in Fig 2, CNN composed of convolution layers, pooling layers, fully connected layers, input and output layers [11]. It has three structural characteristics: local connection (sparse connectivity), weight sharing, and time or space sampling (pooling or dowen-samling of pooling layer). These characteristics make the convolutional neural network advantageous in feature extraction [12].

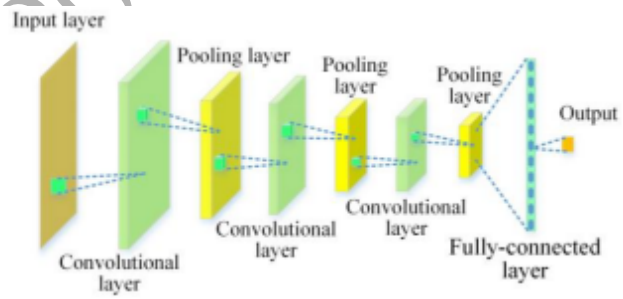


Figure 2: Typical network structure of CNN [10].

Convolution layer: The main function of the convolutional layer is to get the functionality maps through a series of convolutional filter operations on the input. The convolutional layer is usually composed of a set of learnable kernels and bias [13], whose results are inputted into an activation function [9]. The convolution operation can be expressed as follows [9]:

$$X_j^l = f(\sum_{i \in Mj} x_i^{l-1}.\omega_{ij}^l + b_j^l) \quad (1)$$

where X_j^l is the jth element in the lth layer, Mj is the jth convolution region in the $(l-1)th$ layer, x_i^{l-1} is the element, ω_{ij}^l is the weight matrix, b_j^l is the bias and f is generally a nonlinear ReLU activation function, and it can be written as follows: [9]

$$f(x) = MAX(0, lg(1+e^x)) \quad (2)$$

Proceedings of M-E-C-E-D-C-2021 2022

Pooling layer: Pooling layer is often connected behind convolution layer [9]. Generally, the main task of the pooling layer is to reduce the dimensions of the output of the previous layer, so the essence of the pooling layer is to compress the data volume, thus reducing the required computing resources and time. Besides, another advantage of the pooling operation in the pooling layer is that can enable the earned convolutional features to be shift-invariant [13]. Pooling layer has a common methods, Max Pooling, Mean Pooling and Stochastic Pooling [9].

fully-connected layer: After the input image is propagated alternately through several convolution layers and pooling layers, the extracted features are classified and used as the input of fully-connected layer. The input is obtained by weighted summation of one-dimensional feature vectors expanded by all feature graphs [9]. Main function of fully-connected layer is to further extract the features and to connect the output stage with the softmax classifier [13], and its mathematical expression can be written as [9]:

$$y^i = (w^i x^{i-1} + b^i) \tag{3}$$

where i is the sequence number of network layer, y^i is the output of fully connected layer, x^{i-1} is one-dimensional feature vectors, w^i is the weight coefficient and b^i is bias, the activation function f of the final layer in the FC-layer is the Softmax function for classification tasks. Moreover, a dropout operation, which known as a regularization technique, can be added after each C-layer or FC-layer to enhance the generalization ability of the designed CNN model and avoid overfitting during the model training [10].

Recurrent Neural Network (RNN)

A Recurrent neural network (RNN) is a type of Artificial Neural Networks (ANN) which utilizes connections of units to form a directed graph along with a sequence input. This enables the display of dynamic temporal behavior. Because all RNN inputs are connected, the previous hidden state value is given as an input to the current state [14], RNN adds self-connected neurons in the hidden layer to form internal memory and uses backpropagation to realize the memory of historical information and network state feedback. The special network structure of RNN can retain the state information of the hidden layer, and it has a powerful advantage in the field of complex dynamic system modeling [15]. As a result, RNN is capable of managing variable length sequential data, making it very useful for DL. It's commonly utilized in fields like machine translation and language processing [14].

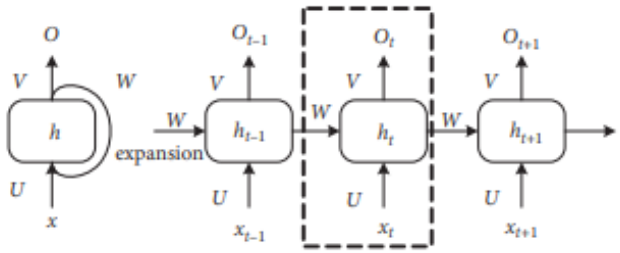


Figure 3: The structure of Recurrent Neural Network (RNN) [15]

Generative Adversarial Network (GAN)

Generative adversarial network (GAN) is a feature learning algorithm based on game scenarios. Feature learning is performed through adversarial learning, which can be used to solve the data imbalance problem [15]. GAN consists of two parts which are the generator F_G and the discriminator F_D which compete with each other whereby F_G tries to confuse F_D while the latter tries to distinguish samples generated by the former. They are competing with each other to gain increased capability for imitating the original data samples and then to discriminate iteratively [16].

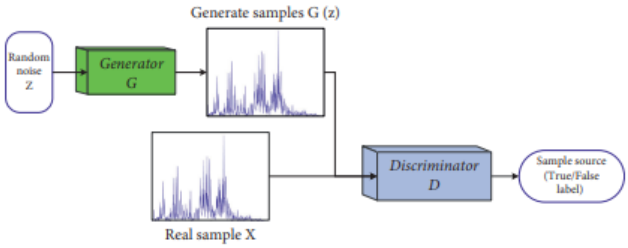


Figure 4: The structure of GAN [15].

Autoencoder (AE)

Autoencoder (AE) is an unsupervised learning algorithm that uses back-propagation (BP) to extract a feature from input data [14]. it is a feed-forward neural network with input layer, hidden layer, and output layer. the input layer and the hidden layer form a coding network, and the hidden layer and the output layer form a decoding network [15]. The fundamental concept of AE is to transform the input high-dimensional data into a low-dimensional encode vector through nonlinear mapping through the coding network, then reconstruct the code vector through the decoding network, and then learn new data representation [15].

Proceedings of W.E.C.E. G.I.M. - 2021/2022

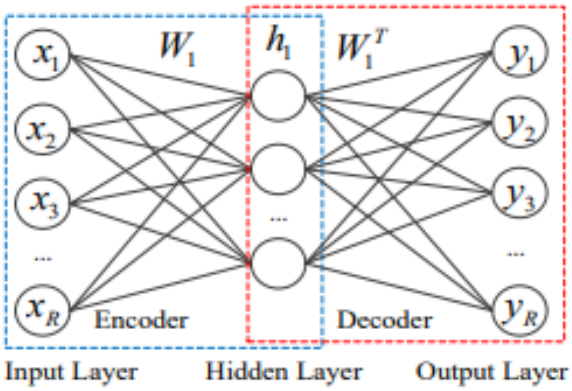


Figure 5: The structure of AE [17]

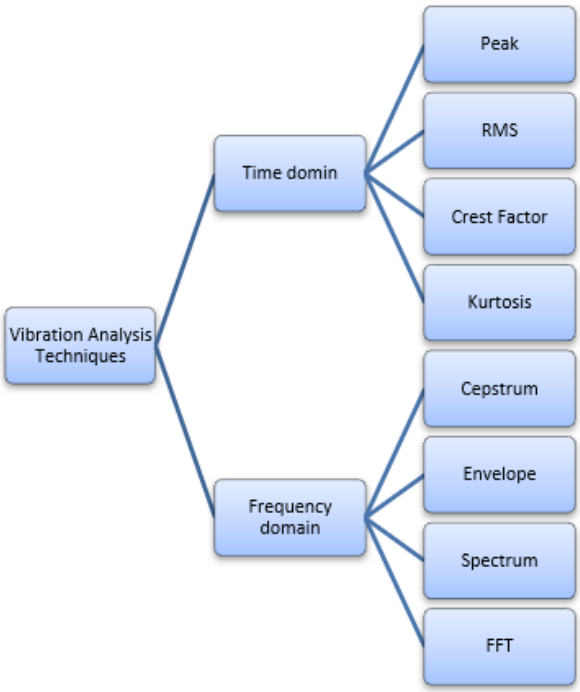


Figure 6: The vibration Analysis Techniques.

2.2. Vibration analysis techniques

Vibration is considered the most commonly measured parameter in condition monitoring (CM) of rotating machinery, and it is widely employed in numerous industrial applications [16]. since vibration analysis has the ability to detect, locate and distinguish different types of faults since its inception before they become critical and dangerous, and that by measuring a vibration signal on the machine and using vibration analysis techniques on it [18].

Vibration analysis techniques can be divided into two main different processing groups. These two main processing groups are: Time-domain techniques and Frequency-domain techniques.

2.2.1 Time-Domain Techniques

Time-domain techniques is one of the traditional methods used in rotating machinery failure detection and condition monitoring. Time-domain techniques use vibration data as a function of time, simply where time is plotted against the amplitude of the vibration signal. Using the time-domain techniques, a defect can be detected and its magnitude assessed using statistics indicators such as (Root Mean Square – RMS), Peak value, crest factor (CF) and kurtosis (KU) [16]. The mathematical expression of this statistics indicators, advantages and disadvantages of each one can be seen in Table 3 [19].

Table 3: Mathematical expression, Advantages and Disadvantages of Time-Domain Techniques [19].

Proceedings of M
G. I. M. - 2021 / 2

Time-Domain Techniques	mathematical expression	Advantages	Disadvantages
Peak value	$Peak = MAX(\|v(t)\|)$	Simple and easy technique.	Sensitive to noise.
RMS	$RMS = \sqrt{\frac{1}{N_e}\sum_{n=1}^{N_e}\left[s(t)\right]^2}$	Simple and easy technique, directly related to the energy content of the vibration profile.	Changes in RMS vibrations are only sensitive to high-amplitude components.
CF	$F_C = \frac{Peak}{RMS}$	Easily available and affordable crest factor meter.	Only reliable in the presence of significant impulsiveness.
KU	$\frac{\frac{1}{N_e}\sum_{n=1}^{N_e}[s(t)-s]^4}{\left[\frac{1}{N_e}\sum_{n=1}^{N_e}[s(t)-s]^2\right]^2}$	High performance in detecting periodic impulse force, highly sensitive to shock, can be assimilated with a shape factor, independent of the signal amplitude.	Costly kurtosis meter can be erroneous.

2.2.2 Frequency-Domain Techniques

The majority of real-world signals can be broken down into a combination of unique sine waves, every sine wave separated from the signal appears as a vertical line in the frequency domain. Its height represents its amplitude and its position represents the frequency. In frequency domain analysis, the amplitude is plotted against frequency and compared to the time domain, and the detection of the resonant frequency component is easier. this is one of the reasons why frequency domain methods are favorable in detecting faults in the machine [19]. Frequency domain analysis not only detects the faults in rotating machinery but also indicates the cause of the defect [20]. The advantages and disadvantages of each frequency domain method can be seen in Table 4 [19].

Cepstrum Analysis

Cepstrum analysis can be defined as the power spectrum of the logarithm of the power spectrum [19], it is a very useful tool for fault diagnosis in rotating machinery, particular in gears and bearings [18]. There are four types of cepstrum which are real cepstrum, complex cepstrum, power spectrum, and phase spectrum, but power cepstrum is the most widely used cepstrum in machine diagnosis and monitoring [18].

Envelope Analysis

The Envelope Analysis is one of the most important and effective techniques of signal processing [18]. this technique separates the low-frequency signal from background noise. The Envelope Analysis is widely used in rolling element bearing and low-speed machine diagnosis and has the advantage of early detection of bearing problems [19]. Signal filtering, envelope extraction of the filtered signal using the Hilbert transform (HT), and spectrum determination of the envelope using the FFT are the three procedures that make up EA's work methodology [18].

Hilbert transform of the signal $x(t)$ is given by:

$$\hat{x} = \frac{1}{\Pi}\int_{\infty}^{+\infty}\frac{x(t)}{t-\tau}dt \tag{4}$$

The analytical signal $x_+(t)$ of signal $x(t)$ is defined as:

$$x_+(t) = x(t) + j\hat{x}(t) \tag{5}$$

The envelope $v(t)$ of the signal is defined as the magnitude of the analytical

$$v(t) = \sqrt{\hat{x}(t)^2 - x(t)^2} \tag{6}$$

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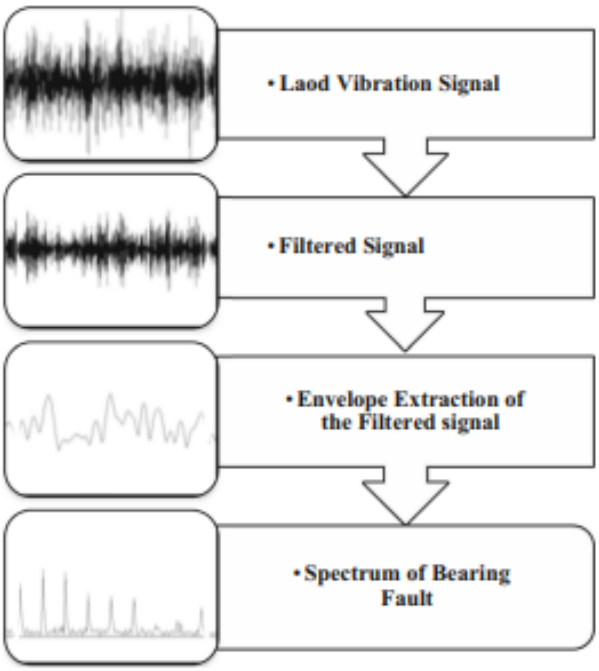


Figure 7: Procedure of envelope analysis [18].

Spectral Analysis
spectral analysis is the most traditional method which can be employed for analyzing the vibration signals [21]. It is the most commonly used vibration analysis technique for condition monitoring in geared transmission systems and has proved a valuable tool for detection and basic diagnosis of faults in simple rotating machinery. The simple spectral analysis is generally unable to detect gear failures at an early stage because of the spectral analysis presents some limitations in the analysis of non-stationary signals, for this reason, many researchers have proposed the application of other vibration analysis techniques for the early detection of fault symptoms [20].

Fast Fourier Transform
Fast Fourier Transform (FFT) is a commonly used signal processing and analysis method. It can transform a time domain signal to a frequency domain signal so that some features which are not clear in time domain can be found easily [9]. and its mathematical expression can be written as:

$$F(\omega) = \int f(t)e^{-i\omega t}dt \qquad (7)$$

where $F(\Omega)$ is the image function of $f(t)$ and $f(t)$ is the primitive function of $F(\Omega)$ [9].

Table 4: The advantages and disadvantages of frequency domain methods [19]

Frequency domain methods	Advantages	Disadvantages
Cepstrum Analysis	Easy to implement, useful in side band analysis.	Can only be applied to the well separated harmonics, the fluctuations of the curve of the spectrum are averaged-out due to the filtering.
Envelope analysis	Excellent application in bearing system, works well even in the presence of a small random fluctuation.	Can lead to a gross diagnosis error, not suitable to be applied in the gear system.
Spectrum analysis	Useful in detecting signal that changes significantly over a short period of time.	Require experts' skills due to its complexity.
FFT	Easy to implement, fast technique.	Cannot efficiently analyze transient features in time.

3. Conclusion

Rotating machinery are a principal part of industry, reliability and efficiency of those machines are one of the most important purposes that industry wants to achieve, fault diagnostics of rotating machinery Plays a significant role of the reliability and efficiency. one of the traditional methods used in fault diagnosis and condition monitoring detection is vibration analysis techniques in addition to modern methods as AI. Among all the methods there is an emerging method in industrial applications field named CNN, this method has achieved impressive results and great success in diagnosing faults in rotating machines, so it is considered to be one of the most important and best methods in the maintenance system because of its simplicity and accuracy in monitoring and diagnosis.

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