

# Comparative Analysis an Early Fault Diagnosis Approaches in Rotating Machinery by Convolution Neural Network

P. Karuppusamy,

Professor, Department of EEE,  
Shree Venkateshwara Hi-Tech Engineering College,  
Erode, India.  
Email id: [pkarrupusamyphd@gmail.com](mailto:pkarrupusamyphd@gmail.com)

**Abstract-** In several industrial applications, rotating machinery is widely utilized in various forms. A growing amount of study, in the academic and industrial fields, as a potential sector for the confidentiality of modern industrial labor systems, has been drawing early fault diagnosis (EFD) techniques. However, EFD plays an essential role in providing sufficient information for performing maintenance activities, preventing and reducing financial loss and disastrous defaults. Many of the existing techniques for identifying rotations were ineffective. For the identification of spinning machine faults, many in-depth learning methods have recently been developed. This research report has included and analysed a number of research publications that have higher precision than standard algorithms for detecting early failures in rotating machinery. In addition to the artificial intelligence monitoring (AIM) model, detecting the defects in rotating machine was also realized through the simulation output. AIM framework model is also testing the rotating machinery in three different stages, which is based on the vibration signal obtained from the bearing system and further it has been trained with the neural network preceding. Compared to other traditional algorithms, the AIM model has achieved greater precision and also the other performance measures are tabulated in the result and discussion section.

**Keywords:** *Deep learning, early fault detection*

## 1. INTRODUCTION

The demand for accurate detection, preventive predictions, and the human use of complex and expensive technologies has been constant for a long time. Efforts to develop and employ various measuring and predictive skills have a long history. Rotating equipment is one of the most difficult things to maintain and repair. Supervision, forecast, and weakness diagnosis mechanisms play a significant role in intelligent oil, oil, gas, petroleum, transport, aviation, military vessels, and commercial vessels, and other related sectors. One of the most important challenges faced by health management systems is the defect diagnosis and anticipation [1]. Figure 1 shows bearing faults due to vibration factor.



**Figure 1** Faults based on vibration problems

Different methods should be proposed to reduce support, operating expenses and overall ownership over the life cycle of many types of machinery and sophisticated systems, and improve the safety levels. The rise in diagnostic failures on rotating devices and other difficult devices helps to comprehend the possibility of identifying and technically desired anticipated mistakes. The greatest difficulty is solving the signal for roller bearings. Luggage failures as blows caused by passing roll components on the surface of the failure [2, 3]. Figure 2 shows torsional failure in rotating machine.



**Figure 2** torsional failure in rotating machinery

These faults can hardly be identified and monitored, especially in its early stages, a very small failure and easily obscured by others. To adapt better to the peculiarities of non-linear systems, all defect prediction techniques must be enhanced for its usage in real-time contexts. Large-scale rotating machinery is used in different sectors including steam turbines, wind turbines, and mills. Through technological progress, the technological level and complexity of these systems are also improved [4].

Failure of these systems results in unanticipated downtime, which results in large running and maintenance expenses. The ability to detect, isolate, and diagnose a problem before a breakdown occurs is critical for ensuring the safety and dependability of these systems. The most often used rotating machinery includes civil and military applications, such as compressors, steam turbines, automobiles, industrial fans, and aircraft engines. Due to high service load, difficult working circumstances, or inevitable fatigue, faults might occur in the case of rotary machinery [5, 6].

If the problem cannot be immediately recognized, the whole system might be disrupted and possibly disturbed. It is therefore important to avoid catastrophic events by identifying the equipment's safe operation and assessing the severity of the defect as soon as possible [7]. But

current wavelets with these capabilities have many limitations. The first was to convert wavelet coefficients into a single-dimensional vector, which was insufficient to transform the two-dimensional time-frequency domain and resulted in information loss [8, 9]. The other is specialization, which is inflexible and difficult to reach an overall solution by significantly depending on the choice and extraction of characteristics [10, 11].

## **2. ORGANIZATION OF THE RESEARCH**

This research article is constructed as follows: Section 3 provides relevant work on difficulties with rotating equipment. The methodology for early identification of failures is discussed in section 4. Section 5 describes the findings of different early failure detection tests. Finally, the proposed study article is concluded in Section 6.

## **3. PRELIMINARIES**

Zhang et al used eight different types of wavelets in the computation of first-order WGMs. WGM fault lines that match eight wavelets are presented. It shows that, three waves, namely Dmeyer, Meyer, and Morlet, differ from the faults present in equipment [12, 13]. Yan and Gao have used the energy-to-Shannon entropy measure to choose the optimum vibration signal wavelet. The test signal for the Morlet wavelet is higher than the wavelets mentioned in the article by underlying the energy-to-Shannon entropy ratio. The Morlet is the best wavelet for signal analysis. [14, 15].

To pick IMFs, Wang et al used an adjustable Q-factor wavelet for early fault detection. To detect early weak faults in rolling rooms, demodulation of the envelope was then used [16, 17]. Žvokelj et al used ICA for IMF choices and early rolling. The envelope analysis has identified and tracked the sliding configuration failures of rolling bearings [18, 19]. Chen et al put the IMFs in an early planetary equipment removal stochastic adaptive isometric system. Several improved EEMD methods have been presented to improve the performance of EEMD in spinning EFD equipment [20].

Guo et al suggested an improved EEMD to create a mono-component for reliable rolling bearing problem diagnosis using the similarity criterion [21]. The adaptive technique for the

selection of the optimum amplitude and EEMD testing ensemble for roller bearing damage detection was proposed by Tabrizi and co-authors [22]. Jiang et al used multi-wavelet packets to locate spinning machinery using multi-fault diagnostics in the prefilters to enhance the results of EEMD decomposition. [23].

A technique to identify distinct vibrational signals that contain failures has been presented by Vakharia et al [24]. Characteristics, including elongation, squaring and mean, and mean root square or more advanced features such as the entropy of the time domain, frequency dominance, and discrete wavelet transformation are also calculated. The top features include feature rating techniques like Qi square and the Assist-F method. Soft and logical wavelet translation methods are used by Singh and their team. Their technique may be adapted for frequency segmentation in order to produce several filters with different bandwidths. The maximum level of shock detection by the self-assembling extension of the intermediate energy feature makes the optimal selection of a filter. It completely coincides with the faults present in the stimulated area [25].

## **4. METHODOLOGIES**

### **4.1 Manual Continuous Monitoring (MCM) Procedure**

Conditional control for life refers to the plant and equipment's manual continuous examination. The operating parameters of an engine are checked during online operation. The main benefit of online monitoring is that it may detect a potential device problem earlier, before it causes significant deterioration or disintegration. This has prompted more study into systems for monitoring online mechanical equipment, particularly electrical equipment, such as induction engines, power generators, and transformers. The specialist can prepare and organize the necessary preventative maintenance repair elements. In maintenance procedure, this type of optimization technique is used to reduce any rotary machinery inactiveness and further it increases the reliability through visual inspection. This is considered as the limitation of this procedure.

## 4.2 Current Monitoring (CM)

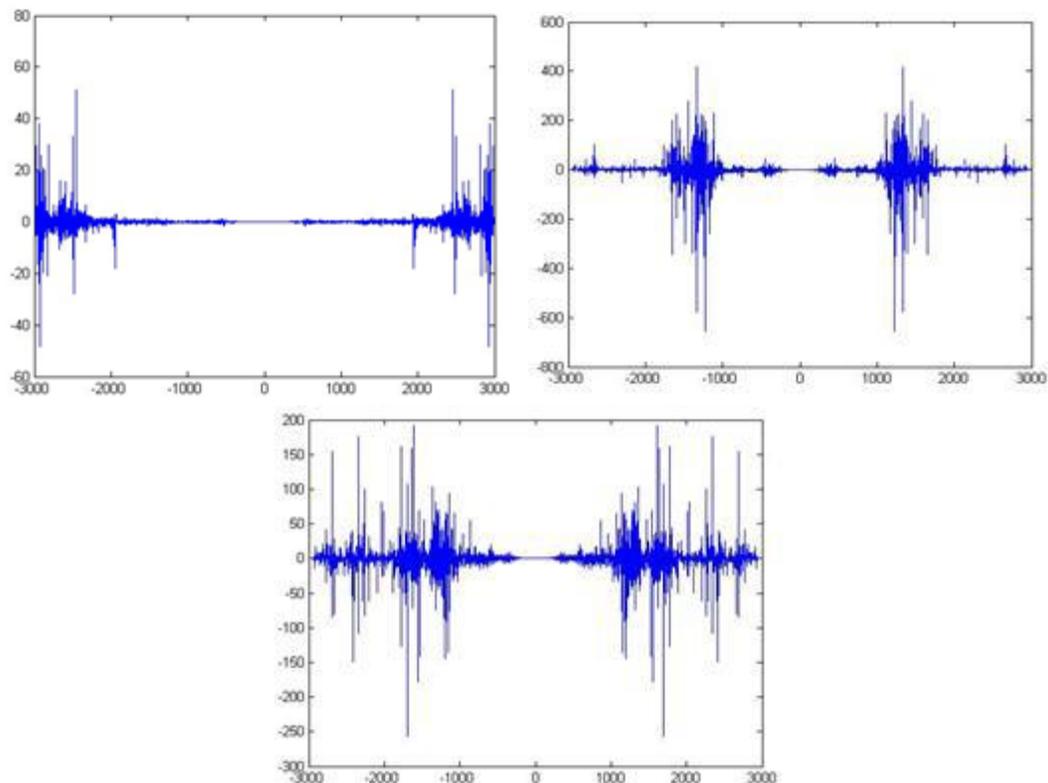
The current vector and sequence of zero parks are one of the categories of electric monitoring, and the negative current sequence monitoring and existing signature analysis. These techniques use current stators to recognize different types of machines and faults. In most of the applications, the stator current of an induction engine is accessible as it is used to protect the equipment against damaging overflows, land currents, and so on. Recently, this monitoring is performed in the least feasible sensor fault detection based on the current phenomenon variations. The early fault diagnosis is lagging through this monitoring approach.

## 4.3 Vibration Monitoring (VM)

For information on the motor conditions for all-electric motors, an analysis on the produced noise and vibration may be used. The frame of the machine even has a little vibration amplitude that might cause substantial noise. Magnetic, mechanical, and aerodynamic forces in electrical equipment create noise and vibration. One of the drawbacks and advantages of this vibration monitoring system is that it is not a simple solution to monitor stationary signal vibration, but it is generally best utilized in non-stationary MCSA [26].

## 4.4 Artificial Intelligence monitoring (AIM) for early detection

Recently, the CNN is including more filtering operations and a classification procedure to detect the faults in any rotary machinery at early stage. These three stages are monitored and finally the features are extracted from the input images for performing classification through various filters. Based on joint training, feature extraction is used for stage-wise classification [27].

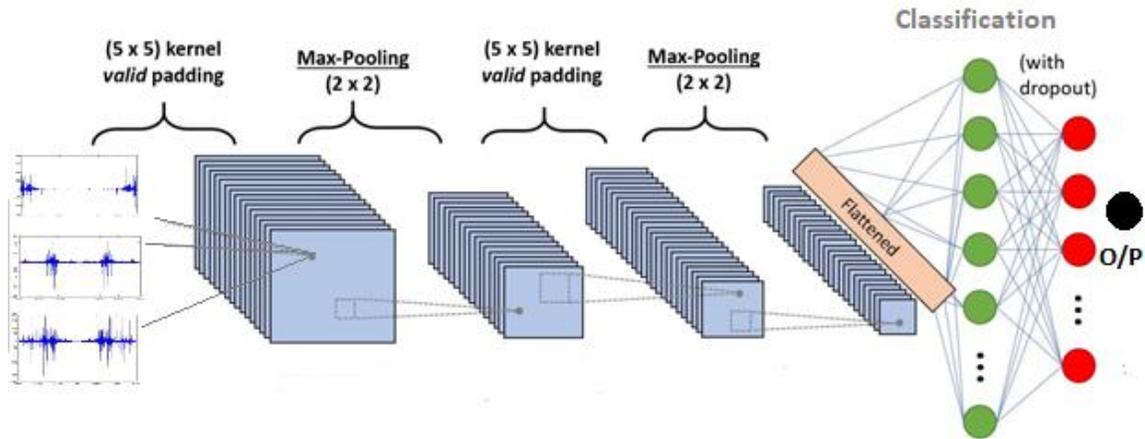


**Figure 3** various stages of rotary machinery faults in signal representation

Mostly, deep learning methods are used to classify serious faults and provide high accuracy detection. This method provides the attention mechanism that is used to stimulate attention control in the system. This method is comparing the features at several time constraints that are utilized in the continuous monitoring procedure. The information loss is very less due to the several filters stages available in the neural networks [28].

The early fault detection procedure can be improved through vibration, current and electrical equipment signal processing with the existing operating conditions. The operating frequency condition specification is used as a dataset to train the neural network. Continuous frequency monitoring of the rotary machinery system provides good results in performing early fault detection by using the CNN method. The failure comprehensive reproduction test has been done for early fault detection. This test contains various rotors, vibration sensors, and the rolling

bearing of the machine. The figure shows the internal architecture of early fault detection by the CNN approach [29].



**Figure 4** early fault detection by CNN approach

It gives different categories named as normal state or early faulty state, faulty state and broken failure state. During the inspection, the motor rotates at a constant speed. With the aid of the training dataset, the problem may be discovered earlier. Other classifiers such as SVM, decision tree and random forest are providing good classification results [30].

## 5. RESULTS & DISCUSSION

Only the artificial intelligence approach of the CNN technique was investigated in this study work. It verifies the accuracy of the classification model. Table 1 shows the standard fault occurrence possibilities of the motor.

**Table 1** Fault occurrence possibility on induction motor [31]

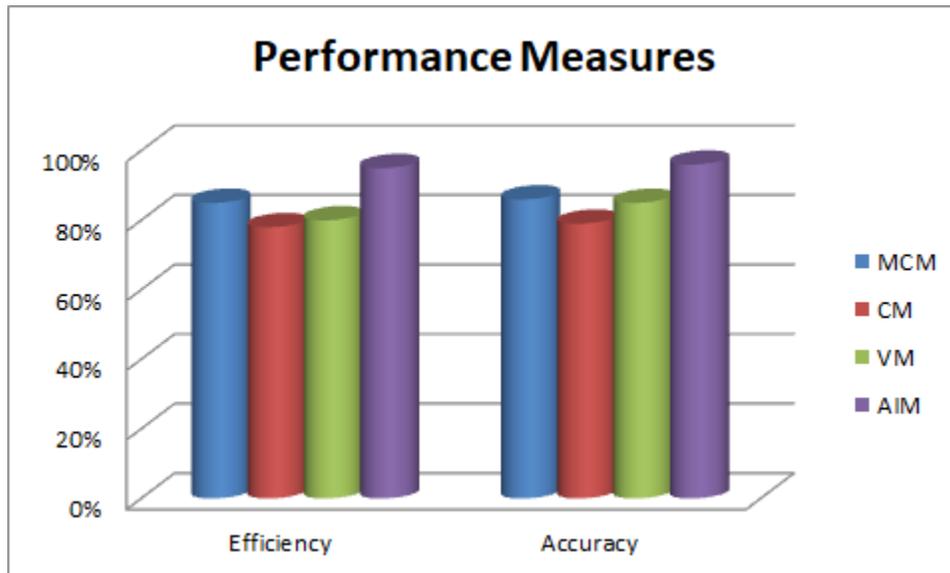
Research Studied by	Bearing Fault	Stator Faults	Rotor fault	Others
IEEE	42%	28%	8%	22%
EPRI	41%	36%	9%	14%

It uses vibration sensors on the rolling bearings to test rotary machinery at a constant speed. The various categories are named as normal state or early faulty state, faulty state, and broken failure state. Table 2 shows the overall performance measures of various methodologies for fault identification.

**Table 2** overall performance of various methodology of fault identification

S.NO	Method	Fault State				Performance analysis		Identification	
		<i>NS</i>	<i>EFS</i>	<i>FS</i>	<i>BFS</i>	<i>Efficiency</i>	<i>Accuracy</i>	<i>All type problem</i>	<i>Automatic</i>
1	MCM	Y	N	Y	Y	85%	86%	Yes	No
2	CM	Y	N	N	Y	78%	79%	No	Partial
3	VM	Y	N	N	Y	80%	85%	No	Partial
4	AIM	Y	Y	Y	Y	95%	96%	Yes	Yes

Besides, the same faults at different speeds of the machine are tabulated here. The dataset is used to identify the fault at early stages with the highest accuracy in achieving the AIM based CNN method [32]. Figure 5 shows the overall performance measure graphs after the calculation.

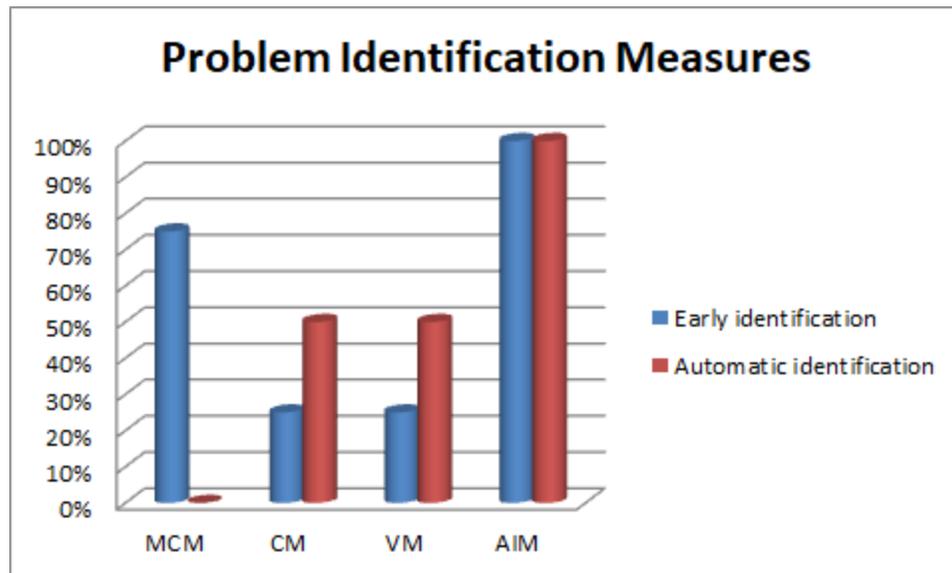


**Figure 5** overall performance measure

The operating characteristics are analysed to detect different faults in the rolling bearing of rotary machinery throughout its life cycle. The examination can be clarified by the labourers after their testing. All of the following problems are occurred with the rotary machinery.

1. Rotor imbalance
2. Rotor misalignment
3. Bearing block looseness
4. Contact rubbing

Figure 6 shows the problem identification measure after computation. The AIM procedure shows its superior properties in all computation functions, such as overall performance analysis and problem identification in all sectors. The performance analysis considers the efficiency and accuracy with which the system's performance is computed. Problem identification includes the identification of all types of problems, such as rotor imbalance and misalignment and bearing control through the contact knob. The AIM method has achieved good results in all sectors when compared to all other traditional methods.



**Figure 6** overall problem identification measures

## 6. CONCLUSION

Based on an existing survey from numerous research papers, this research article has effectively evaluated and given a comprehensive evaluation of early defect detection of rotating equipment. Mainly, the continuous monitoring system has failed and AI-based early detection has succeeded in many environments by considering various types of chemical and rotating machinery-based industries and further it is compared to the traditional procedure. Early diagnosis of rotating equipment faults is critical to avoiding large-scale industry losses, which can lead to major economic downturns. The signal processing technique should be incorporated to the early defect detection algorithm to implement highest level of accuracy. Vibration-based frequency collection data is more sensitive to early detection of a defect in any rotating machinery. The multi-acquired information is used to detect faults at an early stage with high accuracy.

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### **Author's Biography**

P. Karuppusamy, is working as a Professor and Head in the Department of Electrical and Electronics Engineering at Shree Venkateshwara Hi-Tech Engineering College, Erode, India. In 2017, he completed doctorate in Anna University, Chennai, and in 2007, he completed his postgraduate Power Electronics and Drives in Government College of Technology, Coimbatore, India. He has more than 12 years of teaching experience. He has published more than 60 papers in national and international journals and conferences. He has acted as Conference Chair in IEEE and Springer international conferences and Guest Editor in reputed journals. His research area includes modeling of PV arrays and adaptive neuro-fuzzy model for grid connected photovoltaic systems with multilevel inverter.