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Performance Analysis of Motor Vibration Based Condition Monitoring Using R-curve

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Abstract

Traditional techniques of manually extracting characteristics from monitoring data need skill in signal processing and previous knowledge in failure detection, which is seldom possible on a machinery big data platform. As a result, a unique approach for automatically extracting adaptive fault characteristics from monitoring data and intelligently diagnosing fault patterns is projected to accomplish rotating equipment problem identification on a machinery big data platform. This study is focused on knowledge acquired from vibration analysis and applying towards condition monitoring techniques. Results showed 99.87% accuracy level of vibration that improves the performance of motor.

Keywords: *Condition monitoring, FFT Analyzer, Maintenance, Neural Network, Vibration*

1.0 Introduction

As we are approaching towards Industry 4.0 scenario becomes more challenging for the maintenance of machines having high precision[1]. Manufacturing facilities are the core of industrial firms worldwide. Implementing proactive predictive maintenance techniques goes beyond effective plant management; it is a sound business strategy. Currently, a mere 3 to 5 % of the vast amount of data that is accessible is utilised for making crucial operational decisions. Digitization is crucial for accessing the large quantities of unexplored data integrated inside your organisation. Integrate data, analysis, and adaptive models throughout your entire business to enhance the effectiveness of your investments and profitability, reduce expenses, and optimise the allocation of key resources[2,3]. If maintenance of a particular machine is monitored regularly such type of maintenance known as predictive maintenance. It also involves the use of technologies of hybrid advanced tools like Python, Artificial Intelligence, MATLAB and Machine Learning, etc. These ways to leverage predictive analytics are just the tip of the iceberg.

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There is an enormous potential that data analytics offers to improve the way industries operate and ensure optimal utilization of resources. Condition monitoring technique is the one that monitors the life and health efficiently of machines[4,5]. Unlike traditional interval-based preventive maintenance, real-time data which is based on condition monitoring indicates more warning levels to show the system failure or deforming[6]. But still, preventive maintenance does not give a full diagnostic on the best time to perform maintenance.

2.0 Literature Survey with Gap Identified

Jamdhar *et al.,*[7] evolved neural networks based on fault detection. The approach of neural network is examined only from data obtained from the bearing itself. Bearing fault detection are feature engineering and characteristic getting to know to apply the CNN in this data, the network is trying to learn alterations on the data that result in betterr epresentation of data for eventual classification task.

Lokesha li *et al*.,[8] looked into using a fuzzy approach to fault detection in non-homogeneous Markovian systems design clearance. The intended fuzzy version, which is mostly based on fault detection, can undoubtedly ensure robustness and sensitivity of the residual sign to defects.

Chunzi et al.,[9] deals studies show with real time fault identification with Takagi-Sugeno (T-S) fuzzy structures.

Pankaj *et al.,*[10] showed various diagnosis technique that has success demonstration on the application to rotating machines and briefing fault identification and detection techniques mainly based upon vibration analysis. This paper concludes new techniques of approach for the diagnosis by many other fault diagnosis techniques.

Ana Muniz *et al*.,[11] paper presents method detection of failure initially which is developed and combining the energy balance together which is based on Kalman filter to be estimated for model parameter to the purpose of cooling and heating systems. The parameters of model which directly relates to change in temperature inturn gives the sign of degradation during transient phase of the pump station. From the inspection of pump, it is found that vibration has higher level of temperature to validate the real data.

James[12] , This paper authors attempted to approach on online monitoring technique for the goal to obtain innovation on low speed machines which mainly concentrates on the roller bearings based on condition monitoring. The high speed machinery bearings lead to higher velocity and responses only to higher rate of impact. The rotating components of machines which needs online condition monitoring with mandatory for gears and bearings. Paper found a drawback of interest limited survey was carried out on low speed machines.

There is enormous research work carried in the area of condition monitoring. The research work is to investigate the fault and diagnose the severity level of machines in industry.

3.0 Fault Identification of Critical Component

At present world scenario in industries major issue deals with plant efficiency, maintenance and reliability. Reduction in the efficiency of machines that are operating

Figure 1. Vibrometer instrument along with measurement cables.

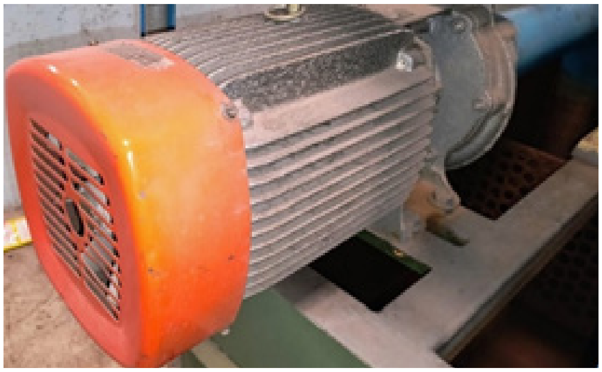

Figure 2. Critical component: Motor of turbine.

in faulty condition can lead the system to fail and with the aid of fault diagnosis technique critical failure can be controlled and monitored frequently to enhance quality of the products[13,14]. As the fault diagnosis is focused to extend the machine life which is classified as a signal-based, model-based, network-based diagnosis. Fault detection and diagnostic methods can be used to create a vibration condition monitoring system. The detection of abnormal circumstances in rotating machines is the major focus of fault detection. Fault diagnosis is the process of analysing data in order to pinpoint the kind, severity, and location of a fault. The below Figure 1 and Figure 2 shows

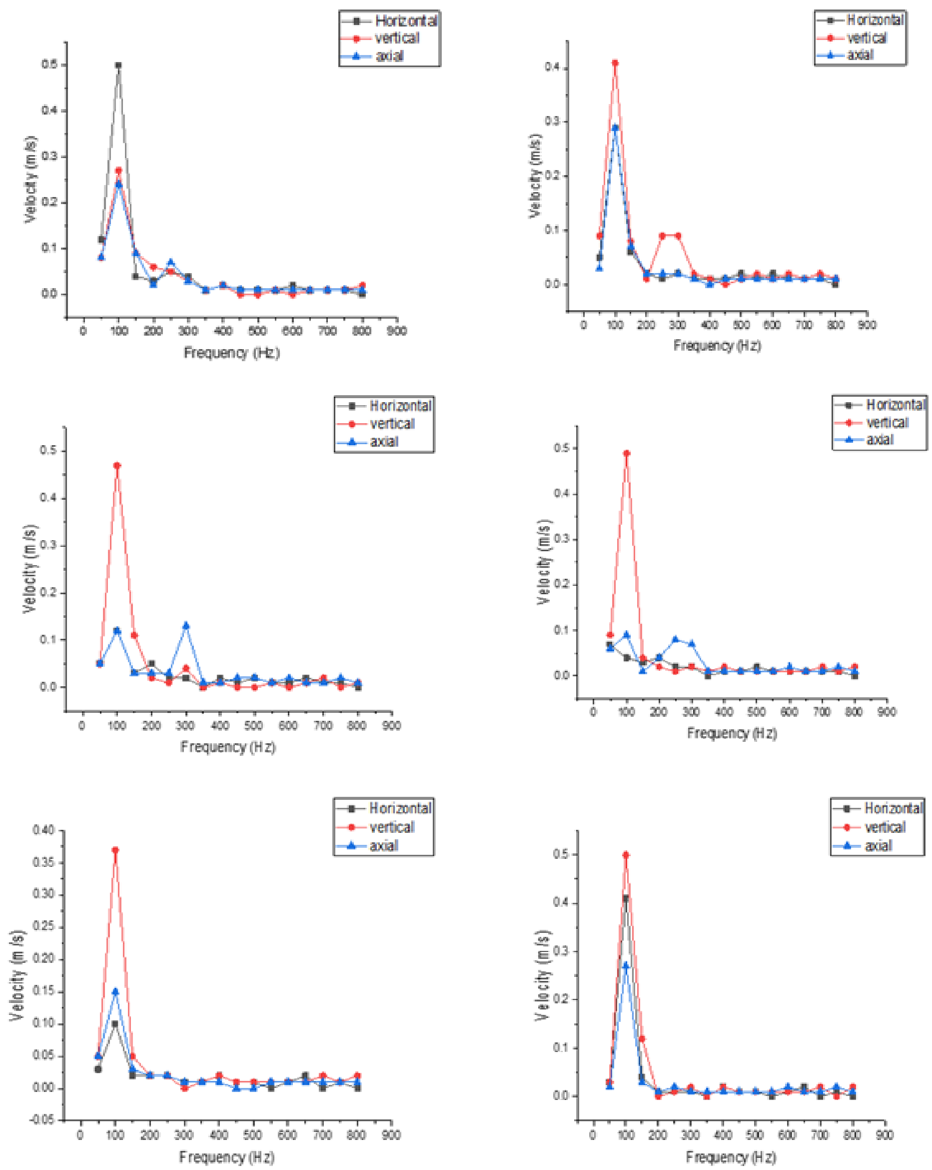

Figure 3. Velocity frequency spectrum operating at different periods.

Vibrometer instrument is used for data acquisition from machines with respect to Horizontal, Vertical and Axial positions respectively.

Data is acquisitioned using Vibrometer for the critical machine and represented in the below spectrums in Figure 3.

Frequency-domain analysis demonstrates the maximum peaks is found at 2x level with three different positions as shown in Figure 3.

4.0 Neural Network

A neural network generally consists of 3 different types of layers namely input, hidden, output which has a data driven diagnosis of fault such that input data needs to be standardized before processing to the desired output. The information from the input data is effectively transferred to hidden layer by selecting number of neurons for the achievement of higher accuracy levels. Flow diagram network as shown below in Figure 4, Levenberg algorithm is selected for data training.

The algorithm applied in the present work is Levenberg Marquardt which has less time with more memory. The training data stops automatically as and when improvement in generalization stops in turn shows an increase relative to mean square error and R value.

Performance evaluation is done using mean square error and peak SN ratio which are computationally fast in histogram[15]. The effectiveness of data is analyzed and drawn as shown below. The graph is computed by instances and error having 20bins but zero error can be found at 8629 instance.

The Figure 5 and Figure 6 shows the plot of gradient value 193e+04 at epoch 1000 iterations having 6 validation checks at epoch 9 is obtained for the machine. The results represent that minimum number of epochs is be obtained

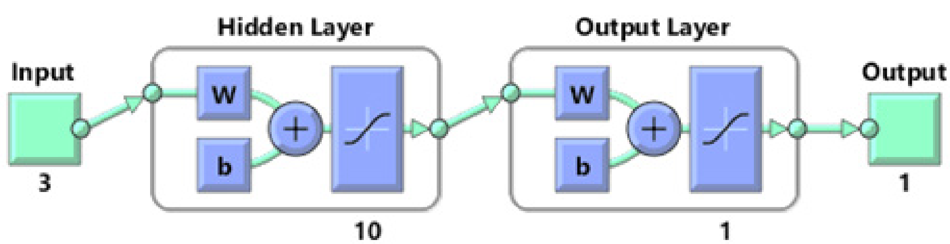

Figure 4. Neural Network Layers.

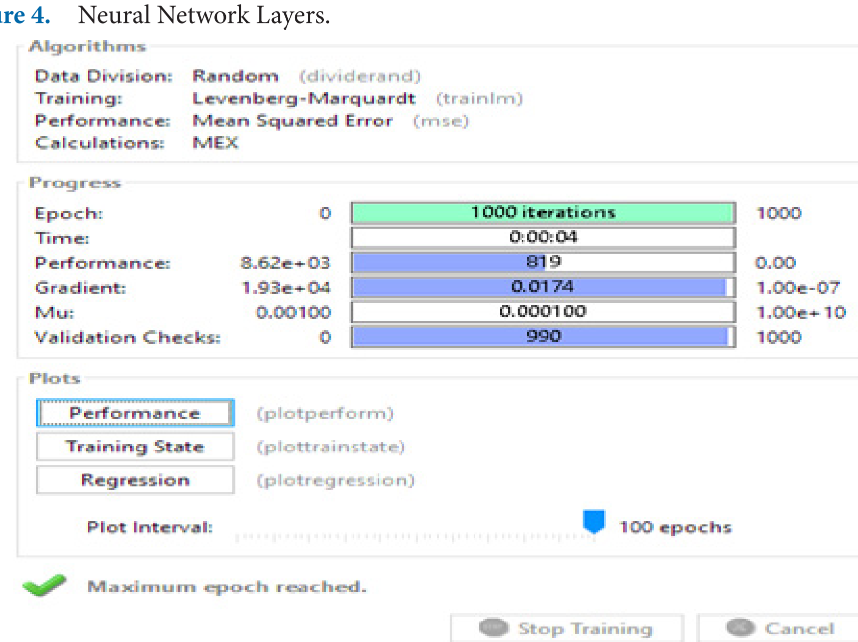

Figure 5. Algorithms with gradient and performance display.

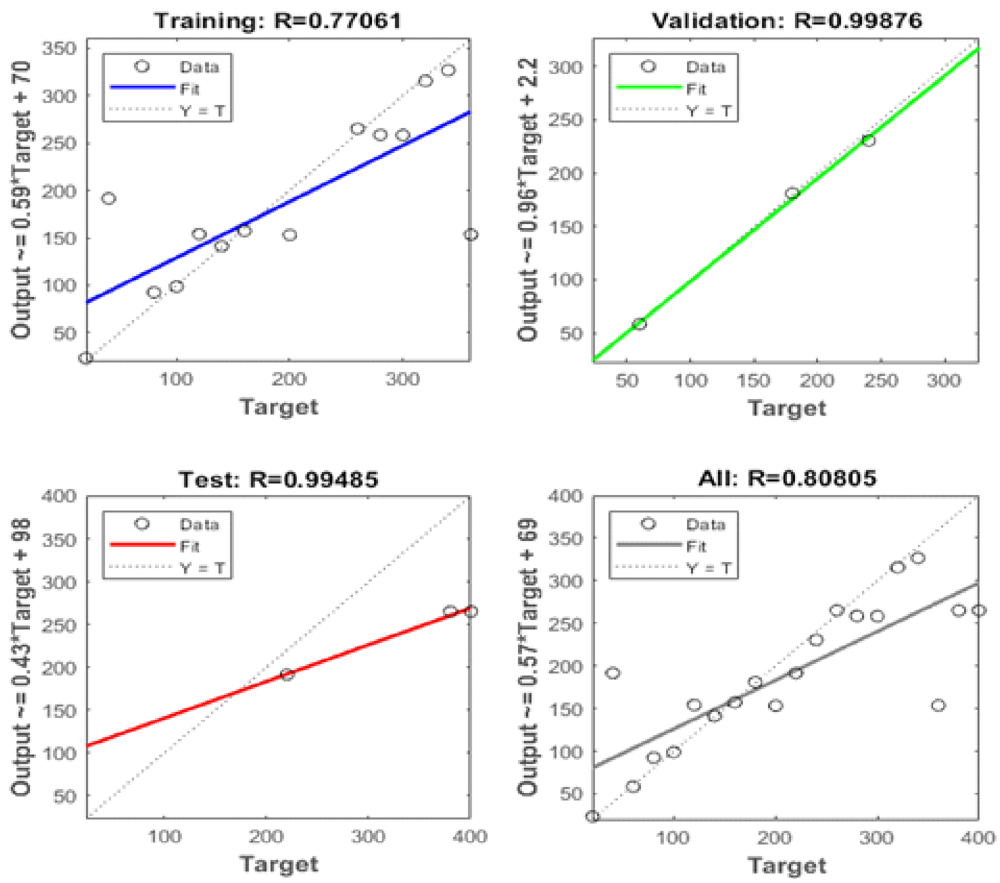

Figure 6. R-Curve has training, test and validation data.

from the training data. A gradient plot is a first order optimization in algorithm that takes into account while performing many parameters. the validation output 15% is considered and obtained from training data is 99.87% accurate.

5.0 Conclusion

It is valuable to diminish stoppages and lift the effectiveness of the hardware by taking on dynamic strides during activity and support to forestall impromptu breakdowns, lessen recurrence of upkeep, and for proactive condition-based upkeep. The main strategy to stay away from disastrous disappointment and save upkeep costs for turning machines is to utilize condition checking. The results and validation in this paper demonstrate the procedure of neural network importance for evaluating the fault in the machine. The results are with accuracy of 99.87% upon network performance.

6.0 References

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