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Fault Identification based on Condition Monitoring for Motor using MATLAB

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Abstract

Rotating machines are commonly employed in a wide range of industrial applications. To minimise failures, boost dependability, and reduce maintenance costs, condition-based maintenance must be implemented for spinning machinery. It is very critical to identify the fault and predict the life of any machines. Henceforth, present study is focused on reliability of machines using neural network by the aid of statistical tool named MATLAB which ensures the proper validation which has 99% accuracy for the obtained data.

Keywords: Condition monitoring; FFT Analyzer; Neural Network; ISO severity chart

Introduction

In the modern era, industries have well equipped facilities to maintain the machines in stable condition. Machines operating at higher speeds starts to fail, if it's not maintained regularly that in turn affects the health of machines leading to major disaster in industries. Henceforth it is necessary to suggest the optimum solution by framework predictive maintenance approach to enhance the life of rotating machines [1-6](1). Nowadays industrial maintenance is focused only on alarm indications and expertise reviews. The hazards of motor rotating at higher rpm leads to failure of machines if properly not maintained regularly also leading to major economic losses (2).

Problem Identification

In a steel manufacturing industry, products of various cross sections are to be produced. One of the issues with fault classification is the high dimensionality of rotating equipment. Many factors, including as load, saturation, unexpected operating conditions, electrical noise, and temperature, may all impact the fault identification process. So, its much essential for maintaining the accuracy level for validation using the statistical tool.

Standard measurements for Critical Rotating Machine

The predictive maintenance or condition monitoring is among the planning maintenance part of other maintenances such as a preventive and production maintenances and it involves the trending and analysis of the machinery performance parameters to detect and identify developing problems before a catastrophic failure can occur. The motor drive end of the machine was found to be in critical condition which are above 7.1mm/s at 60Hz and 1550rpm and to be followed according to vibration severity chart. The vibration program for maintenance of rotating machines is based on factors like plant survey, machine condition, measurement points and instrumentation selections, time period, tolerance etc.,

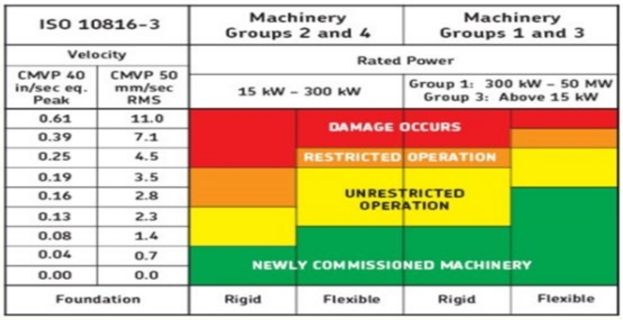

Figure 1: ISO 10816-3 Industrial machines with nominal power and speeds between 120 r/min and 15000 r/min.

The ISO 10816-3 Vibration Severity Chart as shown in above figure.1 is divided into three zones, the zone A (green) for vibration values from new machines, zone B (yellow) for machines without restriction and zone C (red)for machines in which the damage could occur any time.

MOTOR – DRIVE END (DE)					
SL NO	***Frequency***		***Velocity***		
	X in Hz	***RPM***	***V-H***	***V-V***	***V-A***
1	20	1450	0.02	0.01	0.01
2	40	1500	0.02	0.01	0.02
3	60	1550	7.91	8.15	7.78
4	80	1600	0.06	0.05	0.03
5	100	1650	0.35	0.16	0.19
6	120	1700	0.01	0.03	0.03
7	140	1750	0.01	0.04	0.05
8	160	1800	0.02	0.05	0.03
9	180	1850	0.01	0.09	0.04
10	200	1900	0.01	0.04	0.02
11	220	1950	0.02	0.01	0.02
12	240	2000	0.01	0.01	0.01
13	260	2050	0.01	0.01	0.01
14	280	2100	0.02	0.01	0.04
15	300	2150	0.02	0.02	0.04
16	320	2200	0.01	0.01	0.03
17	340	2250	0.01	0.01	0.08
18	360	2300	0.02	0.01	0.01
19	380	2350	0.01	0.01	0.01
20	400	2400	0.01	0.01	0.01

Table 1: Motor Drive End representing Frequency and speed versus different Velocities such as V-H (Horizontal), V-V(vertical), V-A(Axial).

Results and discussions

An Artificial Neural Network (ANN) is a data processing model inspired by how the human brain analyses data. There is a wealth of material outlining the fundamental architecture and parallels to organic neurons. The material here is restricted to a general overview of the various components involved in the ANN implementation. The network design or topology, which includes the number of nodes in hidden layers, network connections, initial weight assignments, and activation functions, is particularly crucial in ANN performance and largely relies on the situation at hand.

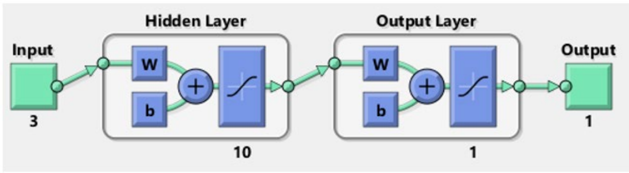

Figure 2: Neural network topology having 3 inputs and 1 output.

Figure 2 shows the neural network for the motor drive end having three input and 10 hidden layers and one output was established. Purelin and transig functions are used for further obtaining of results as a transfer functions.

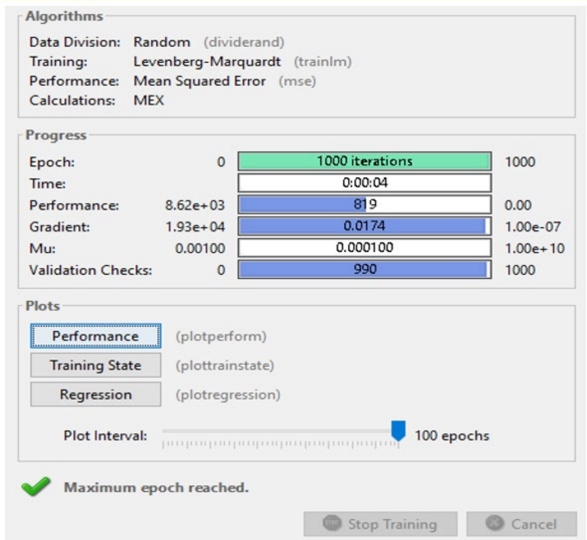

Figure 3: Algorithm and Regression window showing 1000 iterations of Epoch.

The Figure 3 shows the possible regression results established upon changing the values. The epoch of 1000 iterations was trained in the network having the performance value of 8.62e+03 and gradient is 1.93e+04 with the maximum epoch readings. The values are consistent as per the literature survey examined. Hence this type of approach can be adopted for failure estimation of machines [1, 7-17].

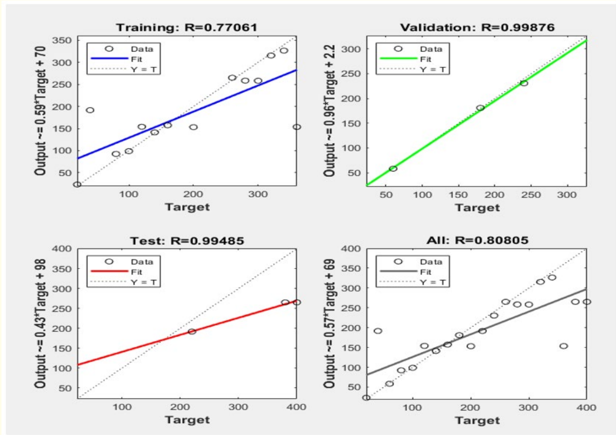

Figure 4: Regression validation output.

Figure 4 shows the validation of the results using Levenberg algorithm for obtaining regression values which has higher accuracy rate of 99%.

Conclusion

In this study, a generic methodology for detecting machinery faults using a pattern regression technique is proposed. This entails gathering data, extracting features, reducing high-dimensional data, and classifying it using MPL and closest neighbour. Although we utilized bearing fault diagnostics as illustrative examples, the suggested technique may be used to different applications by simply altering the sensory signal properties. The approaches described are appropriate for rotating equipment defect identification and diagnosis and found to be 99% accuracy when validated using neural network. Finally, maintenance strategy is implemented such that, it will be performed prior to the scheduled date.

References

1. I Vishwas., et al. "Fault Identification of Vibration - Based Condition Monitoring of Motor Using Minitab and Matlab: A Case Study on Francis Turbine". 11.1 (2025): 222-226.
2. BKP Kumar., et al. "Fault Diagnosis of Shaft Misalignment for Rotating Machinery using Artificial Neural Network". 73.6 (2025): 1527-1534.
3. BK Pavan Kumar., et al. "Optimization of Vibration-Based Condition Monitoring of Motor Drive End Using Taguchi Technique: A Case Study on Milling Machine". 2022): 187-193.
4. BK Pavan Kumar., et al. "Optimization of process parameters for turning machine using Taguchi super ranking method: A case study in valve industry". Mater. Today Proc 47 (2021): 2505-2508.
5. BK Pavan Kumar., et al. "Optimization of process parameters for turning machine using Taguchi super ranking method: A case study in valve industry". Mater. Today Proc 47 (2021): 2505-2508.
6. BK Pavan Kumar, Y Basavaraj and MJ Sandeep. "Effect on Bearings in Rotating Components by Vibration Analysis: A Case Study in Steel Plant". Lect. Notes Mech. Eng (2020): 275-282.
7. S Ma., et al. "High-Voltage Circuit Breaker Fault Diagnosis Using a Hybrid Feature Transformation Approach Based on Random Forest and Stacked Autoencoder". IEEE Trans. Ind. Electron 66.12 (2019): 9777-9788.
8. W Qian., et al. "A novel transfer learning method for robust fault diagnosis of rotating machines under variable working condi-

tions". Meas. J. Int. Meas. Confed 138 (2019): 514-525.

9. S Boral, SK Chaturvedi and VNA Naikan. "A case-based reasoning system for fault detection and isolation: a case study on complex gearboxes". J. Qual. Maint. Eng 25.2 (2019): 213-235.
10. A Kausar. "Interpenetrating polymer network and nanocomposite IPN of polyurethane/epoxy: a review on fundamentals and advancements". Polym. Technol. Mater 58.7 (2019): 691-706.
11. YG Thyavihalli Girijappa., et al. "Natural Fibers as Sustainable and Renewable Resource for Development of Eco-Friendly Composites: A Comprehensive Review". Front. Mater 6 (2019): 1-14.
12. C Wu., et al. "Intelligent fault diagnosis of rotating machinery based on one-dimensional convolutional neural network". Comput. Ind 108 (2019): 53-61.
13. P Liang., et al. "Compound Fault Diagnosis of Gearboxes via Multi-label Convolutional Neural Network and Wavelet Transform". Comput. Ind 113 (2019): 103132.
14. S Liu., et al. "Intelligent fault diagnosis of rotating machine via Expansive dual-attention fusion Transformer enhanced by semi-supervised learning". Expert Syst. Appl 260 (2025): 125398.
15. M Furbino., et al. "Corrosion behavior of steel parts repaired using additive manufacturing: Overview and research perspective". Mater. Des 252 (2025).
16. VY Kenchannavar., et al. "Synthesis and Characterization of ZrO_2 Reinforced Al7075 MMC's: A Study on Mechanical Property Enhancement". J. Mines, Met. Fuels 73.5 (2025): 1225-1236.
17. S Arena., et al. "A conceptual framework for machine learning algorithm selection for predictive maintenance". Eng. Appl. Artif. Intell 133 (2024).

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