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Fault Diagnosis of Shaft Misalignment for Rotating Machinery using Artificial Neural Network

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Abstract

Experimental investigations utilized a rotor dynamic testing system to anticipate the vibration spectrum caused by shaft misalignment. These studies used a custom-designed, simple three-pin flexible coupling. A dual-channel vibration analyzer was used to evaluate rotor shaft accelerations in the presence of misalignment circumstances. Nevertheless, the 2X misalignment does not adequately align with any of the system's natural frequencies to notably excite the system. If the 2X shaft operating speed coincides with or approaches one of the system's natural frequencies, the impact of misalignment may be exacerbated and observable in the frequency spectrum. This study employs a Neural Network model for classification to facilitate fault detection and diagnosis in bearings using vibration data. To build features and train models, the machine learning toolbox in MATLAB is used, as is the diagnostic feature. The results of the confusion matrix also indicate that the model has a relatively high overall accuracy of 0.93 and a good balance of performance for different classes.

Major Findings: *The faulty machine vibration data is collected using a vibrometer instrument for the span of one month and it is diagnosed using Mat lab for better accuracy to increase the life of the motor is suggested in the present work.*

Keywords:*Maintenance, MATLAB, Misalignment, Prediction, Vibration Analysis*

1.0 Introduction to Maintenance

The increasing necessity to effectively display equipment containers, which serve as critical components in various domestic and commercial applications, particularly in energy transmission systems, has stimulated research focused on the design and implementation of rapid and accurate assessments of non-negative techniques[1]. This aims to prevent performance degradation and potential catastrophic failures of machinery. It is a well-documented observation that faults in a machine can be effectively identified by the type of noise it produces, as

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well as through its vibrations[2]. The ability to monitor the operational condition of machines represents a significant advancement in the field known as predictive maintenance. This approach can enhance the efficiency of continuously operating plants, such as those in the power generation and chemical sectors, and can also be significantly beneficial in the development of various machines[3,4].

Maintenance comprises a series of structured activities aimed at preserving an item in optimal operational condition while minimizing associated costs. Predictive Maintenance (PdM) is a maintenance program that makes maintenance recommendations based on data collected through condition monitoring techniques, statistical process control, or equipment performance. Its goal is to help with the early detection and eradication of equipment flaws that could cause unplanned machinery downtime or excessive costs[5]. Especially Gears and rolling element bearings are critical components of spinning machinery. Thus, predictive maintenance is frequently implemented for these elements. Fault signals in gearboxes and rolling-element bearings exhibit nonstationary characteristics[6].

2.0 Vibration Analysis

The obtained vibrational signals must first be translated into an electrical signal by an appropriate transducer. Transducers are categorized into three categories that measure velocity, relative displacement, and acceleration, respectively. Acceleration transducers, particularly accelerometers, are preferred because of their wide frequency and dynamic range[7]. The system's robust structure and lack of moving components contribute to its great physical stability. High-impedance accelerometers can be reduced by using transistorized preamplifiers that convert high impedance to low impedance while also providing signal processing, such as amplification and integration. Frequency analysis is the act of breaking down vibration warnings into distinct frequency components. The time domain is distinguished by amplitude variations across time, whereas the frequency domain is defined by value variations in relation to frequency[8].

Misalignment is the main cause of system vibration. Understanding and addressing the foundations of rotating shaft parameters is critical to avoiding unwanted vibration, lowering maintenance costs, and increasing equipment uptime. In industry, equipment misalignment accounts for 30% of device downtime. Rotor shaft misalignment is a common problem in the operation of rotating equipment and is critical to any business, but it remains poorly understood[9]. Despite significant advances in rotor dynamics technology, there remains a scarcity of thorough analysis that explains the variety of observable occurrences. Given the significance of shaft misalignment, detecting and diagnosing this issue remains difficult. Vibration in rotating machinery is typically caused by unbalance, misalignment, mechanical looseness, shaft cracks, and other defects[10-13].

2.1 Fault Diagnosis

In the present world scenario in industries, major issuesdeal with plant efficiency, maintenance and reliability. Fault detection is identified by generating an alarm signal when the machine has reached faulty condition and focusing on the source and severity fault to isolate. Reduction in the efficiency of machines which are operating in faulty conditions can lead the system to fail and by the aid of fault diagnosis, critical systems can be controlled and monitored frequently in order to improve the quality of the products[14].

The motor was positioned to ensure that the weight was evenly distributed across both sides. The mounting facilitated even distribution of load on the bearings, preventing one-sided or excessive wear. The support intentionally created an imbalanced motor to simulate industrial applications. The testbed motor was located in a home garage, free from vibratory interference. The garage exhibited vulnerability to elevated temperature and humidity; however, neither factor interfered with the vibration data. The sensors are affixed to the motor using the most robust, commercially available, nonpermanent adhesives. A temporary adhesive should be utilized since the motor is scheduled for return to the motor shop. The sensors must be detached, and the motor should be preserved intact. Figure 1 illustrates the motor setup[15].

2.2 The Shaft

A cracked shaft indicates a significant failure in rotating machinery and should consistently be regarded as a critical event. A crack in a shaft can lead to significant catastrophic failure. A shaft crack results in two main effects: a reduction in stiffness leading to rotor anisotropy and a displacement of the pliancy axis, causing the rotor to bow and affecting the balance state. To obtain a simplified version of a rotor with a fractured shaft. In order to install



Figure 1. Testbed motor configuration.

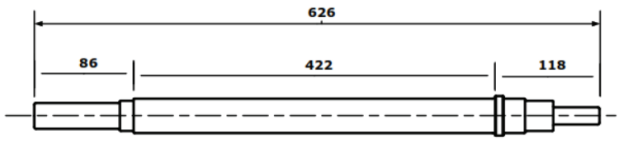


Figure 2. The cracked shaftbowof rotating machinery (front view).

or remove the components, the shaft was built with different diameters. E295 is the shaft's material (St50-2, Germany standard)[16]. The below Figure 2 represents the shaft bow of rotating machines.

2.3 Collecting Data for Shaft Misalignment

To simulate shaft misalignment as shown in Table 1, the shaft and the bearings should be slightly misaligned during the data collection process while collecting the vibration signals. This will result in an increased axial vibration signal with a characteristic frequency equal to the running speed of the motor. The vibration signals collected during this condition can be used to train the ANN model to identify shaft misalignment faults in the future[17].

For this research work, the machine imbalance was studied and corrected for a motor used in the manufacturing industry. An Artificial Neural Network Model was also generated using the available data for future prediction. The features extracted from the dataset are Max, Min, Mean, and Std. Dev, RMS, Skewness, Crest Factor, Form Factor. These factors are used to teach the Neural network model to identify the different conditions under observation[17-20]. The Table 2 display the data collected for motor drive end before and after.

2.4 Graphs Spectrum

The frequency data collected was analysed using an FFT analyser and the results are as given in the below Figure 3 and 4.

Table 1. Shaft misalignment sample statistical features from the shaft setup

Max	Min	Mean	Std	RMS	Skewness	Kurtosis	Crest Factor	Form Factor
0.427	-0.957	-0.1143	0.1130	0.1607	0.0022	0.7488	2.6556	-1.4056
0.63	-0.854	-0.1142	0.1121	0.1601	-0.0171	0.8112	3.9336	-1.4012
0.645	-0.718	-0.1141	0.1115	0.1595	0.0487	0.5291	4.0414	-1.3985
0.815	-0.728	-0.1150	0.1104	0.1594	0.0608	0.9638	5.1116	-1.386
0.474	-0.71	-0.1153	0.1132	0.1616	-0.0189	0.6504	2.9323	-1.4013
0.5	-0.747	-0.1141	0.1148	0.1619	-0.0051	0.6192	3.0875	-1.4185
0.637	-0.964	-0.1145	0.1143	0.1618	-0.0215	0.9641	3.9357	-1.41343
0.664	-0.701	-0.1139	0.1153	0.1622	0.0056	0.6838	4.0936	-1.4225
0.491	-0.828	-0.1143	0.1157	0.1627	0.0170	0.8490	3.0177	-1.4224
0.486	-0.82	-0.1146	0.1121	0.1603	-0.0314	0.6587	3.0299	-1.3993

Table 2. Data collected for Motor drive end (Before and After)

Motor – Drive End (DE)–Before (09-06-24)					
S. No.	Frequency		Velocity		
	Hz	RPM	V-H	V-V	V-A
1	50	1450	0.03	0.03	0.02
2	100	1450	0.41	0.5	0.27
3	150	1450	0.04	0.12	0.03
4	200	1450	0.01	0	0.01
5	250	1450	0.01	0.01	0.02
6	300	1450	0.01	0.02	0.01
7	350	1450	0	0	0.01
8	400	1450	0.02	0.02	0.01
9	450	1450	0.01	0.01	0.01
10	500	1450	0.01	0.01	0.01
11	550	1450	0	0.01	0.01
12	600	1450	0.01	0.01	0.02
13	650	1450	0.02	0.01	0.01
14	700	1450	0	0.02	0.01
15	750	1450	0.01	0	0.02
16	800	1450	0	0.02	0.01

Motor – Drive End (DE)–After (09-07-24)					
S. No.	Frequency		Velocity		
	Hz	RPM	V-H	V-V	V-A
1	50	1450	0.03	0.05	0.05
2	100	1450	0.1	0.37	0.15
3	150	1450	0.02	0.05	0.03
4	200	1450	0.02	0.02	0.02
5	250	1450	0.02	0.02	0.02
6	300	1450	0.01	0	0.01
7	350	1450	0.01	0.01	0.01
8	400	1450	0.02	0.02	0.01
9	450	1450	0.01	0.01	0
10	500	1450	0.01	0.01	0
11	550	1450	0	0.01	0.01
12	600	1450	0.01	0.01	0.01
13	650	1450	0.02	0.01	0.01
14	700	1450	0	0.02	0.01
15	750	1450	0.01	0.01	0.01
16	800	1450	0	0.02	0.01

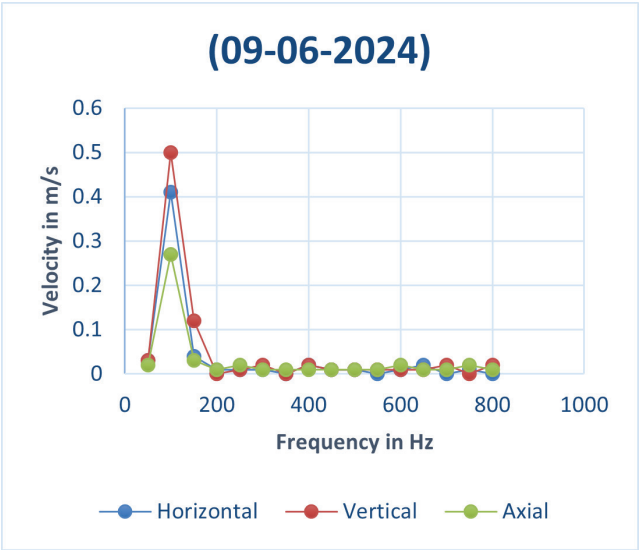


Figure 3. Drive end before data collection.

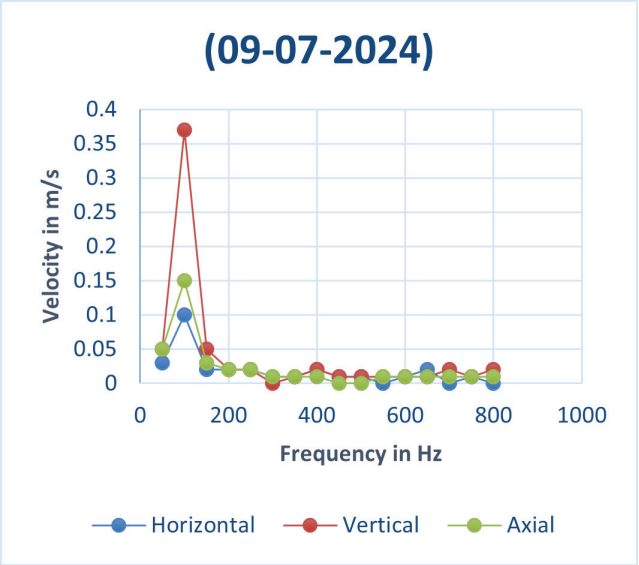


Figure 4. Drive end after data collection.

3.0 Artificial Neural Network (ANN)

To define a pattern recognition problem, organize a collection of input vectors (predictors) into columns of a matrix. Subsequently, organize an additional set of response vectors that denote the classes assigned to the observations. In a binary classification problem, each response consists of two elements, 0 and 1, which denote the class to which the corresponding observation belongs, Figure 5 shows the neural network pattern recognition

The network has a two-layer feedforward design, with a sigmoid transfer function in the hidden layer and a Softmaxtransfer function in the output layer. The hidden layer's size is governed by the number of hidden neurons. The standard layer size is ten. The network architecture is displayed in the Network pane. The output neurons are set to 2, which corresponds to the number of classes defined by the response data[15,21].

To train the network, click Train.

The Training pane displays the progress of the training. Training persists until a stopping criterion is satisfied. In this instance, training persists until the validation error rises consecutively for six iterations[22-26]. Figure 6 shows the training data set.

Divide the dataset into training, validation, and test subsets. Maintain the default configurations. The dataset is divided as follows.

- 70% allocated for training.

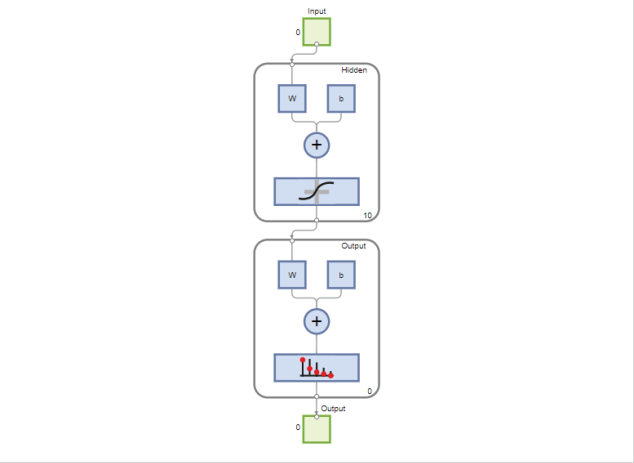


Figure 5. Neural network pattern recognition[1].

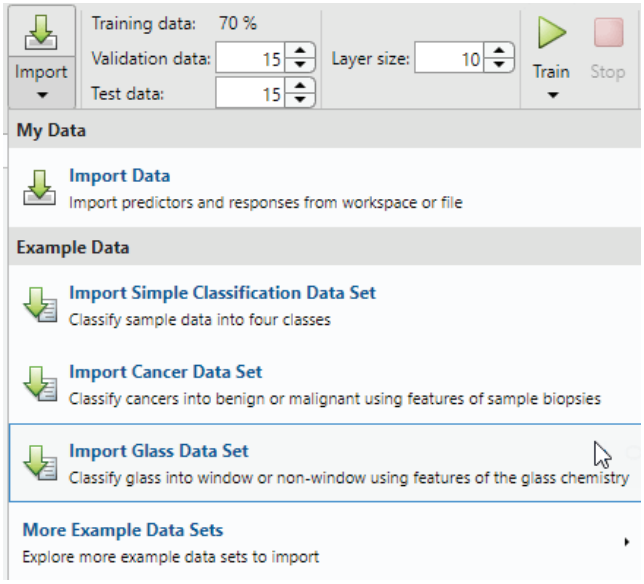


Figure 6. Training data set[2].

- 15% is set aside to test the network's generalization and to halt training prior to overfitting.
- 15% allocated for independent testing of network generalization[27].

Refer to the section on data division for optimal neural network training for further details in Figure 7.

4.0 Confusion Matrix

Further analysis of the results can be conducted through the generation of plots figure8. To generate the confusion matrices, navigate to the plots section and select Confusion Matrix. The network outputs demonstrate high accuracy, evidenced by the substantial number of correct classifications in the green squares (diagonal) and the minimal number of incorrect classifications in the red squares (off-diagonal)[28-32].

5.0 Conclusion

The objectives of the study as described in the text are to design and develop a Data Acquisition System for capturing vibration signals from rotating machines and design and develop an Artificial Neural Network (ANN) based fault diagnosis system that incorporates the Taguchi technique for improved efficiency, accuracy, and reliability. The study also aims to validate the accuracy of the ANN-based fault diagnosis system through

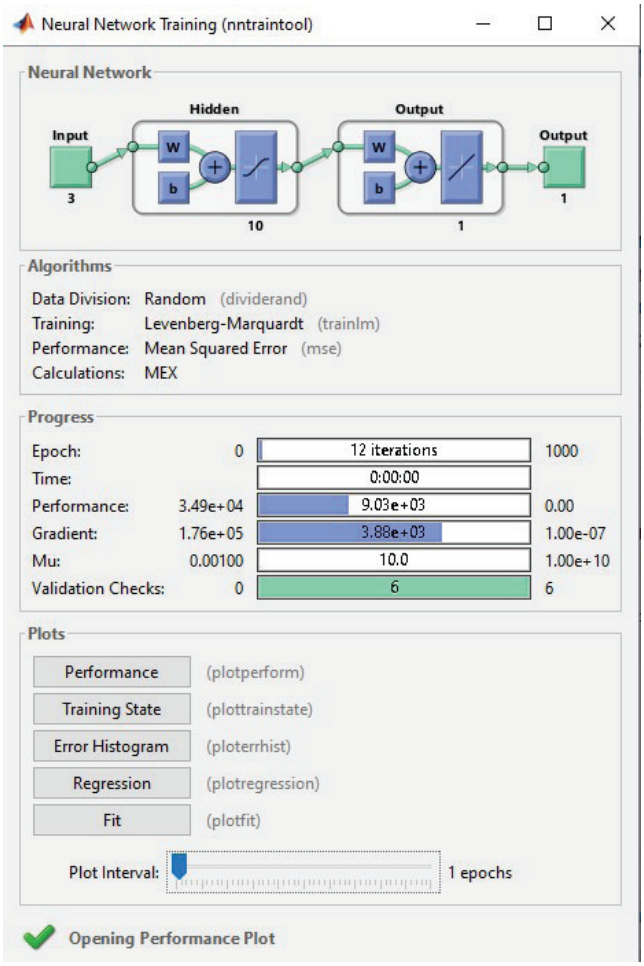


Figure 7. Training algorithm[3].

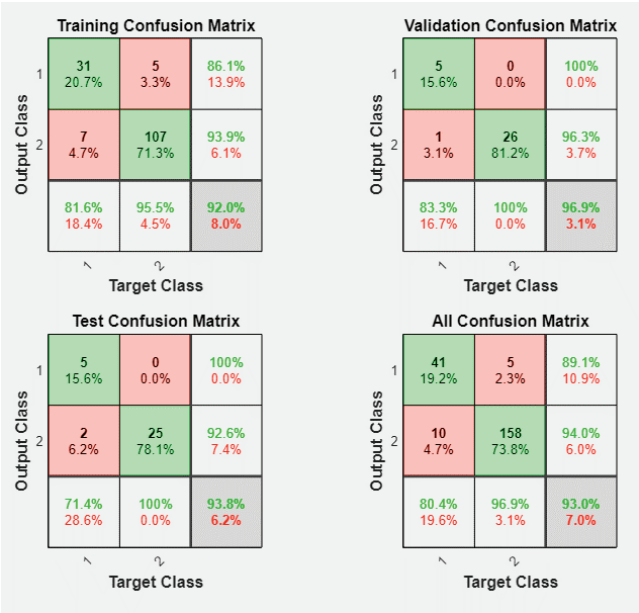


Figure 8. Confusion matrix[4].

comparison with test results and continuous improvement through iterative analysis and refinement.

The results of the confusion matrix also indicate that the model has a relatively high overall accuracy of 0.93 and a good balance of performance for different classes. The model has a high precision for different fault classes and the normal condition, meaning that it is good at identifying positive instances of each fault class and the normal condition. The recall values for different fault classes and the normal condition are also relatively high, meaning that the model is able to correctly identify most of the instances of each fault class and the normal condition[1]. Based on these results, it can be concluded that the ANN-based fault diagnosis system developed in this study is effective in accurately diagnosing faults in rotating machines.

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