Identification of Unbalance and Looseness in Rotor Bearing Systems using Neural Networks

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Abstract

In diagnosing mechanical faults of rotating machinery, it is very important to know the vibration feature of the machine with various forms of fault. A rotor system with fault is generally a complicated non-linear vibrating system. Its vibration is in a very complex form. Rotating machinery is very popular in industrial applications. Most of the mechanical failures are due to vibrations. It is more so in case of rotating machinery. Main cause of vibrations is faults in the rotating systems like unbalance, looseness, etc.. In this paper Artificial Neural Networks (ANN) are used to identify unbalance and looseness in rotor bearing system. Here it is considered as two class classification problem. Experiments are conducted to collect the vibration data in both horizontal and vertical directions, from the rotating system. Statistical features are extracted from the vibration data and fed to neural networks for classifying the unbalance and looseness. These results are useful for making maintenance decision.

Keywords: Unbalance, Looseness, Rotor, and Neural Networks

1 Introduction

An unexpected failure of rotating machinery may result in significant economic losses in terms of maintenance cost as well as huge production losses in continuous process industry. Pedestal looseness is one of the common faults that occur in rotating machinery. It is usually caused by the poor quality of installation or long period of vibration of the machine. under the action of the imbalance force, the rotor system with pedestal looseness will have a periodic beating. This will generally lead to a change in stiffness of the system and the impact effect. Therefore, the system will often show very complicated vibration phenomenon. In this paper artificial neural networks are used to identify the unbalance versus looseness fault.

There are many vibration-based diagnosis techniques available for rotating machinery [1]. Lei et al. [2] proposed a new approach to intelligent fault diagnosis of rotating machinery based on statistics analysis, and adaptive neuro-fuzzy interface system (ANFIS). Some faults that usually occur in rotor-bearing systems are: unbalance in rotors, shaft-to-shaft misalignment, shaft cracks, mechanical looseness, bearing defects, etc. Each fault has different characteristic behaviour on the system and thus the vibration response. Unbalance is one of the important faults needs to be monitored to maintain the designed efficiency of the system. In addition looseness is also an important fault to be monitored. In practice, rotors can never be perfectly

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balanced because of manufacturing errors such as porosity in castings, non-uniform density of material, manufacturing tolerances, and gain or loss of material during operation [3]. In literature, different techniques are used for modeling the unbalance response of the system. Genta and Bona [4] obtained unbalance response of the system using a modal approach. Goldman and Muszynska [5] performed experimental, analytical and numerical investigations on the unbalance response of a rotating machine with one loose pedestal. There have been several methods for determining the periodic response of the non-linear rotor systems, including the series expansion[6] and the harmonic balance method as used in references [7,8]. Sekhar [9] proposed a model-based method for the on-line identification of unbalance and crack in a rotor and simulated identification process when both unbalance and crack are acting simultaneously on the rotor. Zio and Gola [10] proposed neuro-fuzzy approach for fault diagnosis of rotating machinery. A new technique based on auto-associative neural networks and wavelet transforms is presented by Sanz et al. [11] for fault diagnosis of rotating machinery. It is very important to distinguish between unbalance and looseness, which is the objective of the present study Based on the literature survey it motivated me to take up the problem of rotating machine faults by using statistical features and ANN.

2 Experimental Study

2.1 Experimental setup

Experiments are conducted on the machine fault simulator shown in Fig.1, at a rotor speed of 2400 rpm, by simulating unbalance and looseness. An 8 gm unbalance is placed at 7.04 cm radius. Looseness is created by loosening the pedestal bolt, in the rotor system as shown in Fig.1. In each case 20 sets of data are taken. The pre processing is performed on the whole signal to extract the required statistical features like mean (μ), root mean square (rms) and variance (σ^2), standard deviation, skewness and kurtosis using MATLAB. Training and testing of the neural network is done with the experimental data and confusion matrix is obtained in two cases: one is with statistical features in horizontal direction, second is with statistical features in vertical direction. Unbalance and looseness of the rotor bearing system is classified based on the above mentioned two methods and using ANNs.

2.2 Instrumentation

Following instruments are used for obtaining and processing the vibration signals.

- DEWE 43 Data acquisition card (16 bit, 8 channel, ± 10 V)
- Dewesoft 7.02 software
- Power supply
- Signal conditioner
- ICP type Accelerometers
- 1024Hz is the sampling frequency with 500 Hz Frequency range

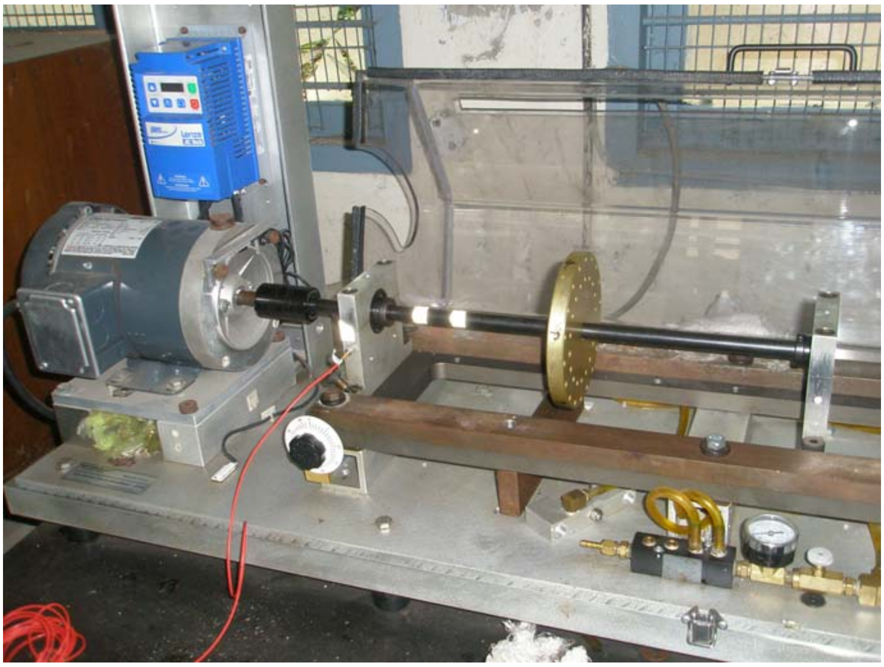

Fig.1 MFS Rotor

3 Application of Neural Networks

Artificial neural networks are inspired by biological findings relating to the behaviour of the brain as a network of units called neurons and have been found to be an effective tool for pattern recognition in many situations where data are fuzzy or incomplete. Artificial neural networks offer advantages for automatic detection and diagnostics of rotating machines. However they require a large number of training examples. The basic building block for an artificial neural network is the neuron. Each neuron consists of many inputs and outputs. A typical neuron model is shown in Fig. 2. In the model the activation value (x) is given by the weighted sum of its M

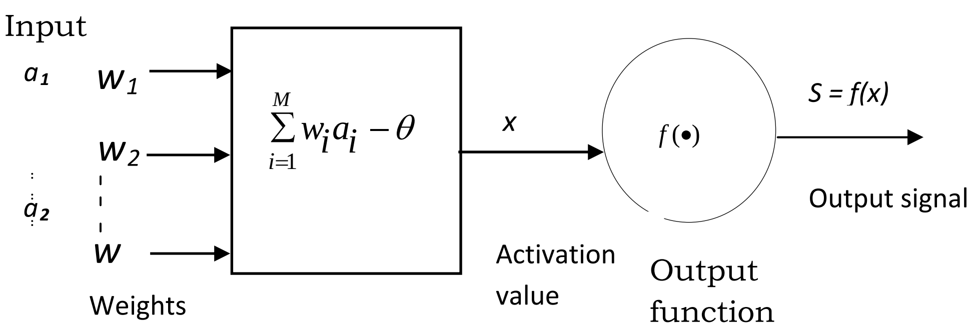

Fig.2 A typical neuron model

input values (a_i) and a bias term (θ_N). The output signal (S) is typically a nonlinear function $f(x)$ of the activation value. A two layered feed forward neural network consists of two layers:

(i) The hidden layer which processes the data
(ii) The output layer that provides the result of the analysis.

4 Results and Discussion

Experiments are conducted with unbalance and looseness and time domain vibration acceleration amplitudes were acquired. Fig. 3 shows typical unbalance time domain vibration acceleration plot. Each case is considered as a separate class, like class 1 and class 2. From the experimental data various statistical features are extracted. Neural network is modeled as a classification problem. Data is fed to the neural network and confusion matrices are obtained as shown in Fig. 4 and Fig. 5 in horizontal and vertical directions respectively. It shows that 95 % of the data is classified accurately in horizontal direction and 97.5% of the data is classified accurately in the vertical direction. It shows how classification is done between target class (actual class) and output class. Once the neural network is stabilized, that can be used to take the new values and it tells which class it belong to. From this we can make decision by knowing the fault to which it belongs to, whether unbalance or looseness depending on the class to which it belongs to.

Table 1: Statistical features at unbalance in horizontal direction

S.No.	*Mean*	*rms*	*Variance*	*Skewness*	*Kurtosis*
1	-4.4756E-04	1.6830E-01	2.8300E-02	3.7000E-03	3.1142E+00
2	1.2000E-03	1.8540E-01	3.4400E-02	6.0500E-02	3.0909E+00
3	-1.0383E-05	1.9490E-01	3.8000E-02	1.4110E-01	3.1139E+00
4	-3.1618E-04	1.9040E-01	3.6300E-02	-1.3300E-02	2.8330E+00
5	1.4000E-03	1.8630E-01	3.4700E-02	1.6830E-01	3.1412E+00
6	8.6324E-05	1.8670E-01	3.4900E-02	1.6580E-01	3.2086E+00
7	1.7000E-03	1.9260E-01	3.7100E-02	2.0910E-01	3.3952E+00
8	-1.3000E-03	1.9120E-01	3.6600E-02	9.8700E-02	3.0654E+00
9	-2.3000E-03	2.0710E-01	4.2900E-02	-1.2800E-02	3.0164E+00
10	2.3000E-03	2.2240E-01	4.9500E-02	9.5000E-02	2.9640E+00
11	-1.1000E-03	2.1840E-01	4.7700E-02	-1.2430E-01	3.4513E+00
12	1.2000E-03	2.0120E-01	4.0500E-02	6.1100E-02	3.2419E+00
13	9.9312E-04	2.1950E-01	4.8200E-02	9.5600E-02	3.2700E+00
14	2.9024E-04	2.1840E-01	4.7800E-02	1.0370E-01	3.3024E+00
15	2.8000E-03	2.0980E-01	4.4000E-02	1.7970E-01	3.6898E+00
16	1.2347E-04	2.1080E-01	4.4500E-02	8.6900E-02	3.6086E+00
17	3.2000E-03	2.0990E-01	4.4100E-02	8.4100E-02	3.3407E+00
18	1.2000E-03	2.1660E-01	4.7000E-02	2.1400E-01	3.1966E+00
19	1.8000E-03	2.1390E-01	4.5800E-02	2.0310E-01	3.1013E+00
20	-1.5000E-03	2.0870E-01	4.3600E-02	6.9700E-02	3.5538E+00

Statistical features at unbalance and looseness in both horizontal and vertical directions are given in the tables 1-3.

Table 2: Statistical features at looseness in horizontal direction

S.No.	*Mean*	*Rms*	*Variance*	*Skewness*	*Kurtosis*
1	1.7000E-03	1.8000E-03	2.1523E-07	1.4070E-01	2.8473E+00
2	9.9964E-04	3.8200E-02	1.5000E-03	-4.8568E+00	5.2958E+01
3	3.5000E-03	2.9700E-02	8.6903E-04	-8.2786E+00	1.4503E+02
4	4.0432E-04	4.1700E-02	1.7000E-03	-8.2010E+00	1.0768E+02
5	3.7000E-03	2.1800E-02	4.6326E-04	-8.2897E+00	1.3317E+02
6	9.5731E-04	3.3200E-02	1.1000E-03	-4.5557E+00	3.8565E+01
7	1.5000E-03	5.3600E-02	2.9000E-03	-2.6439E+00	1.9537E+01
8	4.7000E-03	1.7900E-02	2.9789E-04	3.4390E-01	2.3444E+01
9	1.9452E-04	5.1400E-02	2.6000E-03	-4.4565E+00	4.0078E+01
10	4.2000E-03	3.9800E-02	1.6000E-03	-2.3579E+00	2.0889E+01
11	4.0000E-03	2.0400E-02	4.0148E-04	-2.4576E+00	3.1546E+01
12	-8.4541E-04	4.2800E-02	1.8000E-03	-4.9093E+00	4.2589E+01
13	3.6000E-03	2.2900E-02	5.1435E-04	-4.7413E+00	5.8538E+01
14	2.4000E-03	2.1100E-02	4.4042E-04	-6.2605E+00	6.5345E+01
15	2.1000E-03	2.9100E-02	8.4589E-04	-4.2134E+00	4.4072E+01
16	2.6000E-03	2.9500E-02	8.6272E-04	-2.2432E+00	2.3251E+01
17	1.3000E-03	2.7300E-02	7.4657E-04	-3.1921E+00	2.7171E+01
18	1.4000E-03	2.6900E-02	7.2322E-04	-3.1662E+00	2.0602E+01
19	2.6000E-03	3.1400E-02	9.7849E-04	-3.1545E+00	3.0446E+01
20	2.8000E-03	1.8600E-02	3.3954E-04	-3.8884E+00	3.3269E+01

Table 3: Statistical features at unbalance in vertical direction

S.No.	*Mean*	*Rms*	*Variance*	*Skewness*	*Kurtosis*
1	9.7445E-04	1.6380E-01	2.6800E-02	-2.2910E-01	2.9114E+00
2	8.3182E-04	1.6610E-01	2.7600E-02	-2.8630E-01	3.0759E+00
3	1.6000E-03	1.6980E-01	2.8800E-02	-3.4350E-01	4.2981E+00
4	3.0100E-04	1.6420E-01	2.7000E-02	-3.0760E-01	3.0767E+00
5	-4.0813E-04	1.6920E-01	2.8700E-02	-4.7090E-01	3.3780E+00
6	1.6553E-04	1.6020E-01	2.5700E-02	-2.4240E-01	3.0979E+00
7	-1.2049E-04	1.6820E-01	2.8300E-02	-3.1570E-01	3.1428E+00
8	8.1940E-04	1.6420E-01	2.7000E-02	-3.9090E-01	3.0753E+00
9	3.7000E-03	1.7900E-01	3.2100E-02	-4.5300E-02	3.3744E+00
10	1.2000E-03	1.8280E-01	3.3400E-02	-3.3060E-01	3.3696E+00
11	3.0000E-03	1.7780E-01	3.1700E-02	-1.7800E-01	3.1747E+00
12	4.9554E-04	1.7720E-01	3.1400E-02	-2.9300E-01	3.5729E+00
13	-2.1000E-03	1.7330E-01	3.0000E-02	-1.6490E-01	2.9917E+00
14	-1.2000E-03	1.7460E-01	3.0500E-02	-1.3360E-01	2.8150E+00
15	3.1000E-03	1.6370E-01	2.6800E-02	-2.7400E-01	3.3236E+00
16	-3.7000E-03	1.8680E-01	3.4900E-02	-4.5770E-01	3.4101E+00
17	2.8000E-03	1.8100E-01	3.2800E-02	-2.3510E-01	3.5659E+00
18	4.4000E-03	1.7860E-01	3.1900E-02	-1.8030E-01	3.3612E+00
19	-8.2905E-04	1.8900E-01	3.5800E-02	-2.7170E-01	3.2822E+00
20	1.7000E-03	1.8260E-01	3.3400E-02	-2.2890E-01	3.6167E+00

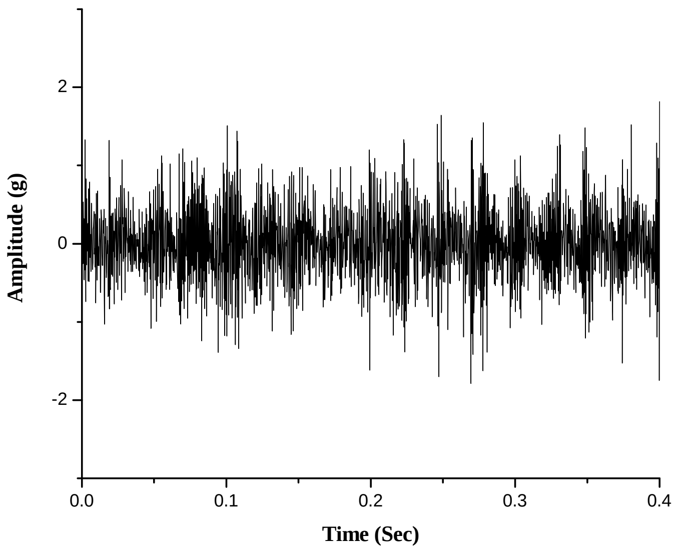

Fig. 3. Typical unbalance time domain vibration acceleration plot

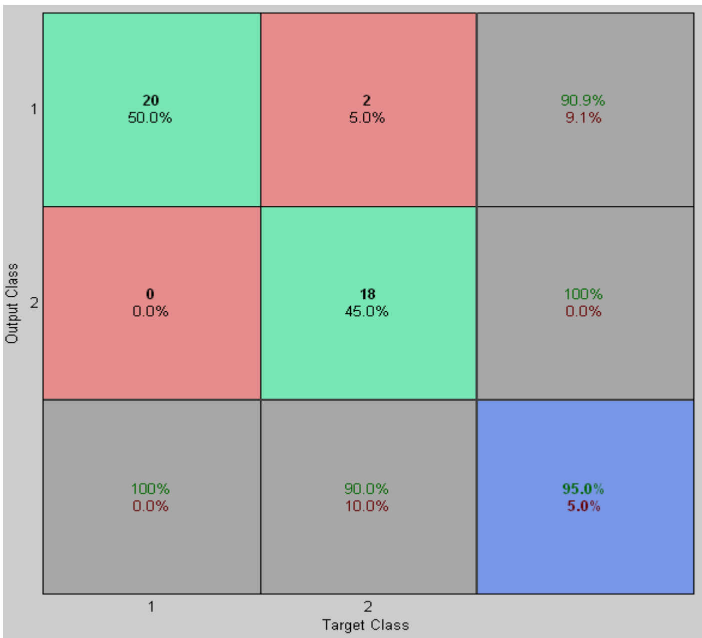

Fig. 4. Confusion matrix (Statistical features in horizontal direction)

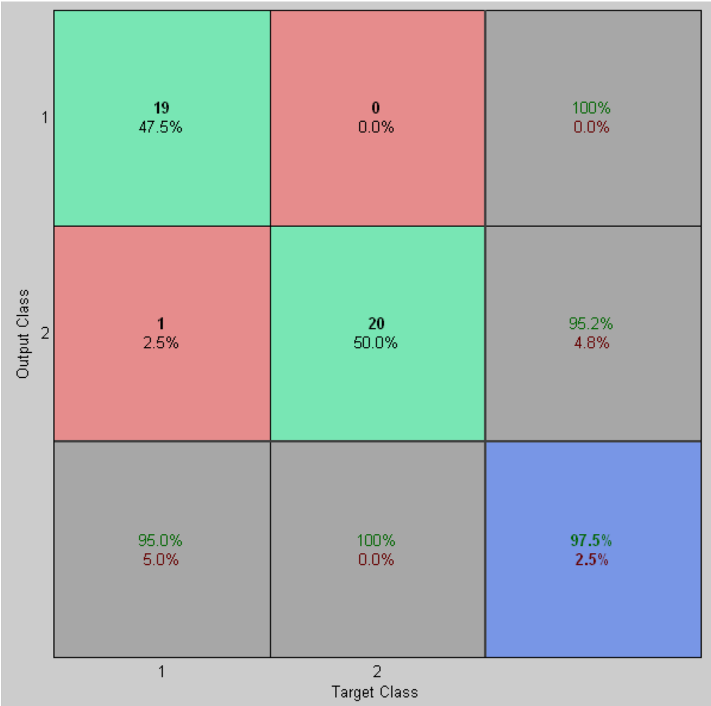

Fig. 5. Confusion matrix (Statistical features in vertical direction)

Data sets used for training and testing were different. 70% of the data points were used for training and 30% of the data points were used for testing. There are 20data points were there in each set. Data is acquired with only one fault at a time. The network is modelled as a two class problem and trained and tested accordingly. Here unbalance and looseness faults are separately simulated. It is a two class problem, it just tells whether the fault is unbalance or looseness. From time domain vibration signals FFT plots are obtained and clear peaks are seen in vertical direction than in horizontal direction readings. Because of clear peaks in the vertical data, may be vertical data classification is better than horizontal. Here we will not get the severity of the problem, we get only type of problem i.e., unbalance or looseness. Based on the input (statistical features) given to the ANN and the ANN tool box of matlab program will form the confusion matrix. Here it is formulated as a two class problem, and it gives whether the fault is unbalance or looseness.

5 Conclusions

This study presents a procedure for identification of unbalance and looseness using ANNs. Experiments are conducted by simulating unbalance and looseness in the rotor bearing system. From the vibration signals obtained in horizontal and vertical directions, various statistical features are extracted and fed to the neural network and used to train and test the ANN. In both the cases ANNs are trained and tested by both horizontal and vertical readings. By modeling the neural network as a classification problem the data is classified into two classes. ANNs are used to classify the unbalance and looseness. It is observed that vertical direction readings are giving good results over horizontal direction vibration readings. These results are useful for identifying the unbalance and looseness fault and are useful in making a maintenance decision, whether the machine is allowed to run or not. The present neural network is classified with 97.5 % accuracy by statistical features in vertical direction. Scope for future work the work can be extended to multi faults.

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