Effect of Input Data on the Neural Networks Performance Applied in Bearing Fault Diagnosis

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Abstract. The aim of this paper is to study the effect of input parameters choice of the artificial neural network (ANN), in order to obtain the best performances of fault classification. The purpose of this network is to automate the electric motor bearing diagnosis based on vibration signal analysis. The choice of the components of ANN's inputs (training and testing) has a big challenge for prediction of the machines faults diagnosis. The vibration signals collected from the test rig (Bearing Data Center) are preprocessed, to extract the most appropriate monitoring indicators to analyze the health of the experimental device.

To improve the performance of the neural network, we use three different dataset: the first contains only time indicators, while the second contains the frequency indicators, and the third set is a combination of these two indicators. A comparison between the effects of each feature on the ANN performances, allowed us to choose the optimal structure of input data. The obtained results show that the combined dataset give the best performances compared to the two others dataset.

Keywords: Artificial neural networks · Diagnosis · Bearing faults
Vibration analysis

1 Introduction

Bearings are the most fragile components of rotating machines. Being located between the fixed part and the moving part of these machines, they ensure the transmission of forces and the rotation of the shaft. They must be continuously monitored and any defect should be tracked to avoid costly production downtime.

However, the vibration signals generated by faults in such systems have been widely studied (McFadden and Smith 1985), and there are many signal processing techniques that can be used to extract the defect information from a measured vibration signals (Randall and Antoni 2011; Rai and Upadhyay 2016).

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The artificial neural networks by their capacities of training, classification, and decision, give a solution to the problems of diagnosis bearings by the automatic classification of the vibratory signals, which corresponds to the various states of normal and abnormal functioning of the machines (Alguindigue et al. 1993; Samanta and Al-Balushi 2003; Rajakarunakaran et al. 2008; Li et al. 2000). The artificial neural networks are intended to increase the precision (accuracy) and to reduce errors caused by subjective human judgments.

The accuracy of ANN model highly depends on the setting of network parameters, such as sufficient number of hidden layers, neurons within each layer, and learning rate, as well as activation function. Most of the research in this area suggest some methods to find optimal parameters setting of the neural network (McCormick and Nandi 1996; Giuliani et al. 1998; Jack and Nandi 2000; Al-Araimi et al. 2004; Abhinav and Ashraf 2007; Rao et al. 2012).

However, very little attention has been paid to the effect of the dataset structure used to training and testing the ANNs. Therefore, the main objective of this work is to study the effect of the components choice of the input vector on the performances of the artificial neural network, to be used as a diagnostic tool of bearing defects. Starting from the analysis of signals collected by vibration sensors of the bearing test rig, with the calculation of time indicators (kurtosis, Rms, or crest factor) and frequency indicators. Then, configure them to build the database which will be used for learning and testing the ANN, which will allow us to find the best network configuration (inputs, outputs and parameters), and subsequently to automate the decision on the possibility of the fault bearings.

2 Background

2.1 Rolling Element Bearings

The main components of rolling bearings are the inner ring; the outer ring, the rolling elements, and the cage (see Fig. 1). Typically, the inner ring of the bearing is mounted on a rotating shaft, and the outer ring is mounted in the stationary housing. The rolling elements may be balls or rollers. The balls in a ball bearing transfer the load over a very small surface (ideally, point contact) on the raceways (Randall and Antoni 2011).

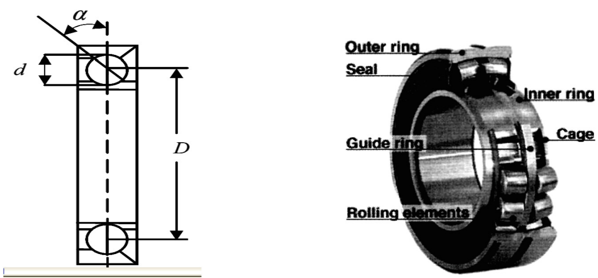

Fig. 1. Components of a rolling element bearing.

Local or wear defects causes periodic impulses in vibration signals. Amplitude and periodic of these impulses are determined by shaft rotational speed, fault location, and learning dimensions. The formula for the various defect frequencies is given by:

Ball pass frequency, outer race:

$$BPFO = \frac{nfr}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{1}$$

Ball pass frequency, inner race:

$$BPFI = \frac{nfr}{2}\left(1 + \frac{d}{D}\cos(\alpha)\right) \tag{2}$$

Fundamental train frequency (cage speed):

$$FTF = \frac{fr}{2}\left(1 - \frac{d}{D}\cos(\alpha)\right) \tag{3}$$

Ball (roller) spins frequency:

$$BSF = \frac{D}{2d}\left(1 - \left(\frac{d}{D}\cos(\alpha)\right)^2\right) \tag{4}$$

Where fr is the shaft speed, n is the number of rolling elements, and f is the angle of the load from the radial plane. Note that the ball spin frequency (BSF) is the frequency with which the fault strikes the same race (inner or outer).

2.2 Bearing Fault Diagnosis Technique

A wide variety of techniques based on various algorithms were developed for the detection and diagnosis of faults in rolling element bearings and have been introduced to inspect raw vibration signals. These algorithms can be classified into time domain, frequency domain, time-frequency domain, and higher order spectral analysis (Nataraj and Kappaganthu 2011).

2.3 Multi-Layer Perceptron (MLP)

The multi-layer perceptron (MLP) is the simplest and most known structure of the neural networks. This structure is shown in Fig. 2, is relatively simple with a layer of inputs, a layer of outputs and one or more hidden layers. Each neuron is not only connected to the neurons of the preceding layers, but also to all the neurons of the following layer (Bishop 1995).

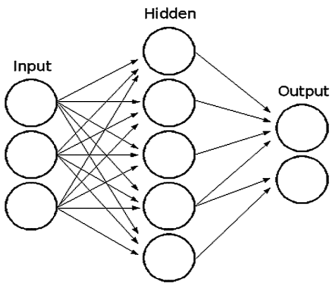

Fig. 2. Multi-layer perceptron general architecture.

The learning of the multilayer perceptron is supervised, and consists of adapting the weights of the neurons so that the network is capable of performing the requested task.

The conventional method for learning the multilayer perceptron is the back-propagation algorithm, which was developed in particular by Rumelhart and Parkenet le Cun in 1985. This algorithm relies on the minimization of the quadratic error between the computed outputs and those desired.

3 Materials and Methods

3.1 Data Acquisition

An experimental test rig built to predict the defects in rolling bearings is shown in Fig. 3.

This website provides access to ball bearing test data for normal and faulty bearings (Case Western Reserve University, bearing data Center 2006). Experiments were conducted using a 2 horsepower (hp) Reliance Electric motor, and acceleration data were measured at locations near to remote from the motor bearings. These web pages are unique in that the actual test conditions of the motor as well as the bearing fault status have been carefully documented for each experiment.

Motor bearings were seeded with faults using electro-discharge machining (EDM). Faults diameter ranging from 0.17 mm to 0.71 mm in diameter were introduced separately at the inner raceway, rolling element (i.e. ball) and outer raceway. Faults bearings were reinstalled into the test motor and vibration data were recorded for motor loads of 0 to 3 hp (motor speeds of 1797 to 1720 RPM). Vibration data were collected using accelerometers, which were attached to the housing with magnetic bases. Accelerometers were placed at the 12 o'clock position at both the drive end and fan end of the motor housing.

The time domain presentation of signal is shown in Fig. 4.

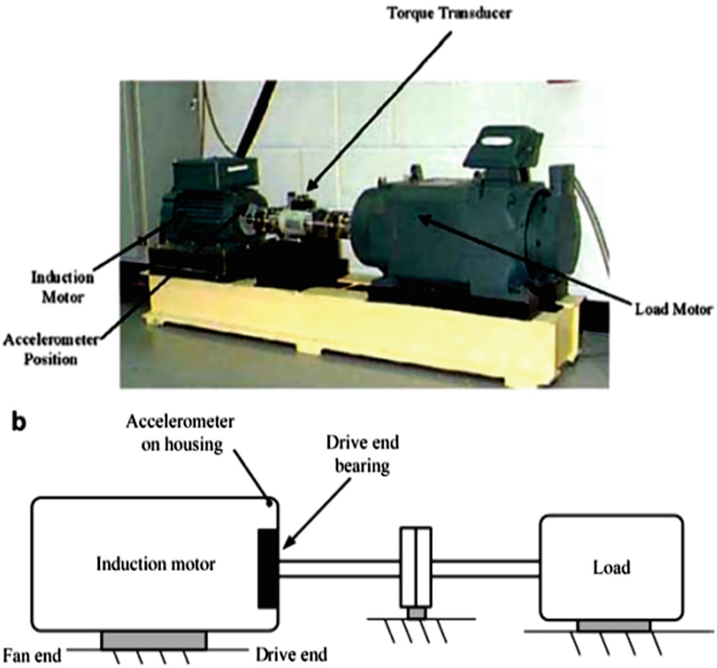

Fig. 3. (a) The bearing test rig; (b) the schematic description of the test rig. (Huang et al. 2010)

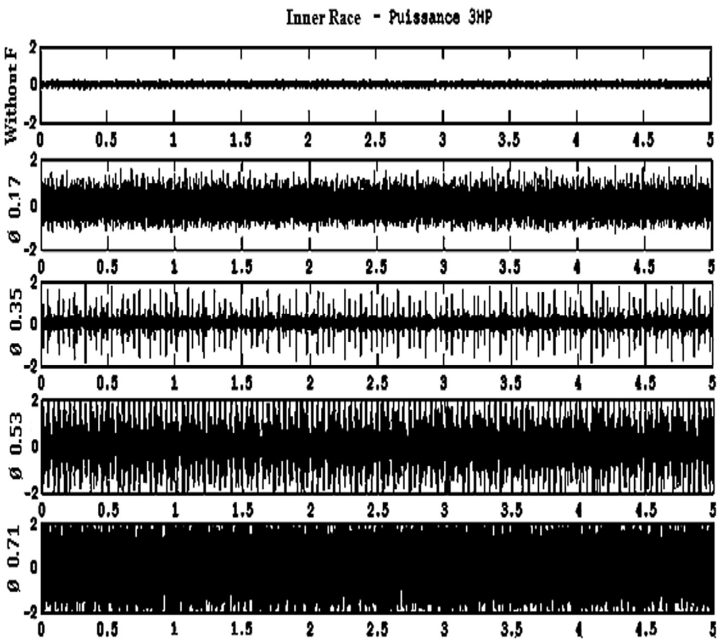

Fig. 4. The time domain signal

3.2 Preprocessing of Vibration Signals

A signal conditioning is required to remove all kinds of useless information, and to facilitate the task of extracting indicators for monitoring the most relevant formants database. We chose to calculate the following indicators: the root mean square value (RMS), crest factor, peak to peak value and kurtosis, and the energy from the spectrum envelope.

After a preliminary analysis (Fedala 2005), we choose to calculate these indicators as follows:

3.2.1 Time Domain Indicators

The time domain indicators (the root mean square value (RMS), crest factor, peak to peak value and kurtosis) are calculated in 5 frequency bands with a total width of 6000 Hz. Each of these 4 bands has a width of 1500 Hz, in addition to a total band that contains the four composed bands. The bands are then calculated within: [1–1500 Hz], [1500–3000 Hz], [3000–4500 Hz], [4500–6000 Hz], in addition to the total band of [1–6000 Hz]. The signal from each slice has been focused and filtered by a bandpass filter.

3.2.2 Frequencies Domain Indicators

As the same methodology used in the calculation of time domain indicators, the Frequencies domain indicator (the energy from the spectrum envelope) is calculated in five frequencies bands of a total width of 6000 Hz, in addition to the six large one that contain other bands with a total width of 6000 Hz. These bands are calculated as follows: [1–1000 Hz], [1000–2000 Hz], [2000–3000 Hz], [3000–4000 Hz], and [4000–5000 Hz], in addition to the total band of [1–6000 Hz].

3.3 Constitution of the Patterns Vector (Networks Input)

The patterns vector is consisted of three different dataset: the first contains only time indicators, while the second contains the frequency indicators, and the third set is a combination of these two indicators. As the main scope of this paper is limited to study the effect of the components choice of the input vector on the performances of the artificial neural network, to be used as a diagnostic tool of bearing defects. The detailed methodology of combining time domain indicator and frequency domain indicator can be found in the literature (Unal et al. 2014) 187–196 (Samanta and Al-Balushi 2003; Jack and Nandi 2002).

The data that must be classified and treated, are stored in an array of type observations/variables.

3.4 Choice of the Classes (Networks Output)

The network outputs vector contains various classes corresponding to each operating conditions from the experimental test rig. We chose five classes, each one of them corresponds to a diameter of the defect. Table 1 represents the labelling of the various studied classes.

Table 1. Labelling of the classes

Class	Fault diameter	Label
1	Without fault	10000
2	0.17 mm	01000
3	0.35 mm	00100
4	0.53 mm	00010
5	0.71 mm	00001

3.5 Data Standardization

To improve the performances of the MLP, it is preferable to normalize the data of the patterns vector. We divided the obtained database into two parts: a training set (70% of database) which train the network, while the remaining database (30%) were used for testing, on which, they have been presented to measure network's performances.

3.6 The Network Configuration

We used a multi-layer perceptron with the following configuration (Fenineche 2008):

- Only one hidden layer.
- 5 neurons in the hidden layer.
- 5 neurons in output layer which corresponding to the various classes.
- Performance Function: MSE (Mean Square Error).

4 Results and Discussion

Table 2 summarizes the values of the MSE error using the various indicators and parameters described above.

In each case, the network is trained until it reaches the values of the stop criteria. The results are obtained after several executions.

Table 2. Performance of the MLP classification

Indicator	MSE
Time	0.0324
Frequency	0.0320
Combined	0.0235

The Figs. 5, 6 and 7 show the performances of ANN for different input data. We have obtained a performance of 0.032 (for MSE) using the time indicators and a performance of 0.036 with the frequency indicators, while the combination of the two sets gives a better performance of 0.0235.

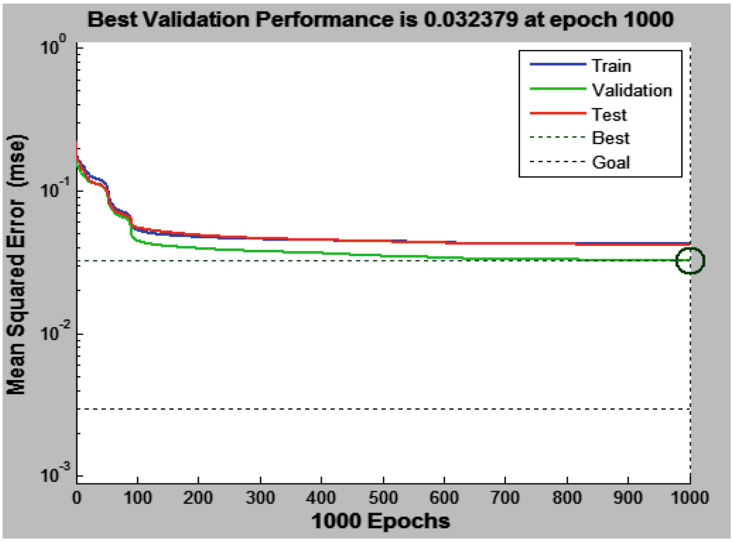

Fig. 5. Performance using the time indicators

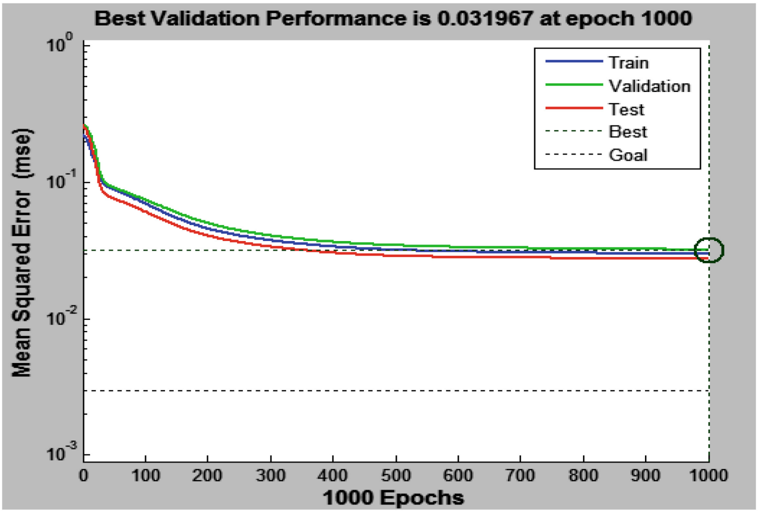

Fig. 6. Performance using the frequency indicators

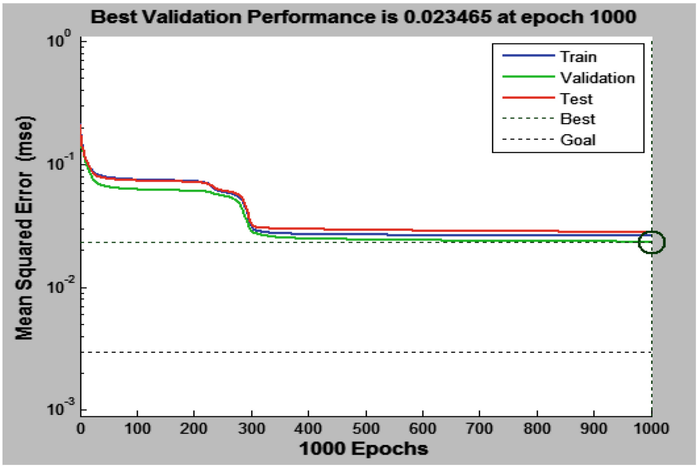

Fig. 7. Performance using the combined indicators

5 Conclusion

The objective of this work is to study the effect of the choice of the elements constituting the pattern vector (inputs) on the performances of the artificial neural network, which has been used as a diagnostic tool for bearing fault diagnosis. Starting from the analysis of the signals collected by vibration sensors of a rolling test rig, and the calculation of time indicators and frequency indicators. Then, they are configured to build the database that will be used to learn and test the ANN, which allows us to find the best configuration of the network (inputs, parameters and outputs) in order to automate the decision on the eventuality of a bearing defect.

The results show that the performance of the artificial neural network is better for the case with the combined indicators. This is because the combined data include all the indicators, which enable them to better presenting the health status of the studied system.

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