Ball Bearing fault diagnosis using a MLP and WNN neural networks

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Abstract

Developing a special method for maintenance of electrical and mechanical equipment of industrial company is necessary for improving maintenance quality and reducing operating costs. Vibration analysis provides useful information about machine control and performance for the engineers to help them to the production. In this study, two methods based on vibration analysis was presented for fault diagnosis in ball bearings. Vibration signals from the alternator of Massey Ferguson (MF 285) type tractor was studied. Wavelet neural network (WNN) and The Multi-Layer perceptron (MLP) neural network classifier was used in fault diagnosis. The highest accuracy was obtained for (WNN) classifier, which equals to 96.36%.

Keywords: Fault Diagnosis, Ball Bearing, FFT spectrum, Multi-Layer Perceptron (MLP), Wavelet Neural Network (WNN).

1. Introduction

It has been known for many years that the mechanical integrity of a machine can be evaluated by detailed analysis of the vibratory motion (Eisenmann, 1998). Vibration signals carry information about exciting forces and the structural path through which they propagate to vibration transducers. A machine generates vibrations of specific 'color' when in a healthy state and the degradation of a component within it my result in a change in the character of the vibration signals (Williams, 1994).
Machine condition monitoring has long been accepted as one of the most effective and cost-efficient approaches to avoid catastrophic failures of machines. It has been known for many years that the mechanical integrity of a machine can be evaluated by detailed analysis of the vibratory motion (Eisenmann, 1998).
In this research, density data produced by vibration analysis was compared with previous data. Numerical data produced by Fast Fourier Transform were compared with Fast Fourier Transform in healthy Ball Bearing, in order to quantify the effectiveness of the Fast Fourier Transform technique (Wowk, 1991).

2. Materials and Methods

2.1. The Multi-Layer Perceptron (MLP) neural network

A multilayer neural network includes an input layer, an output layer, and one or more hidden layers. Each layer may include many neurons. A neuron in each layer of the network is connected to all the nodes or neurons in the previous layer (Haykin, 1999). An architectural graph of multilayer perceptron with one hidden layer is shown in Figure1.
In the modeling of systems by multilayer neural network, after defining the structure, the neural network weights should be designed in a way that with applying the inputs, a very close output to the real output is achieved. This is called neural network training, which means setting the weights to decrease the errors between network output and real output (Zarei, 2012).

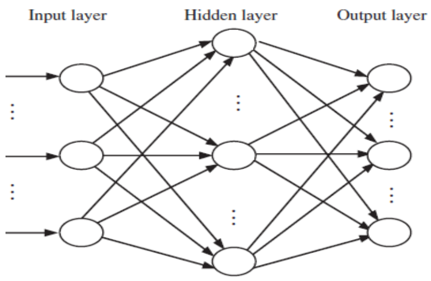


Figure 1. Topology of a two hidden layer MLP

The simplest form of ANN is the perceptron, which consists of one single neuron (see Figure2). Output is defined to be (Vitch, 2005):

$Y=\phi\,(w, x)$ (1)
$w(-\theta, w_1, \ldots\ldots, w_m)$ (2)
$x = (1, x_m, \ldots\ldots, x_m)$ (3)

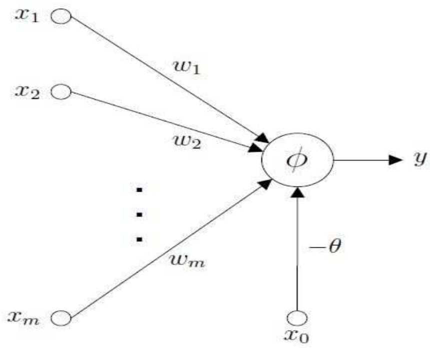


Figure 2. Perceptron with m inputs

2.2. Wavelet neural networks (WNN) neural network

Wavelet neural networks combine the theory of wavelets and neural networks into one. A wavelet neural network generally consists of a feed-forward neural network, with one hidden layer, whose activation functions are drawn from an orthonormal wavelet family. One application of wavelet neural networks is that of function estimation. Given a series of observed values of a function, a wavelet network can be trained to learn the composition of that function, and hence calculate an expected value for a given input.

That is, a feed-forward neural network, taking one or more inputs, with one hidden layer and whose output layer consists of one or more linear combiners or summers. The hidden layer consists of neurons, whose activation functions are drawn from a wavelet basis.

The WNN in this paper is designed as a three-layer structure with an input layer, a hidden layer, and an output layer. Each layer has one or more nodes. Figure 3 shows the schematic diagram of the three-layer WNN. Morlet wavelet is widely used as the activation function in the nodes of the hidden layer (Ghohizadeh, & Salajegheh, 2008 Chen, & Yang 2006). It is expressed by Eq.4 and shown in Figure 4.

$$w(t) = e^{-\frac{t^2}{2}} \cos 5t \qquad (4)$$

The back propagation algorithm is commonly adopted for the training of WNN in the literature [Lin & shen, 2005. Subasi & Alkan, 2005] and it is also employed in the designed WNN of this paper.

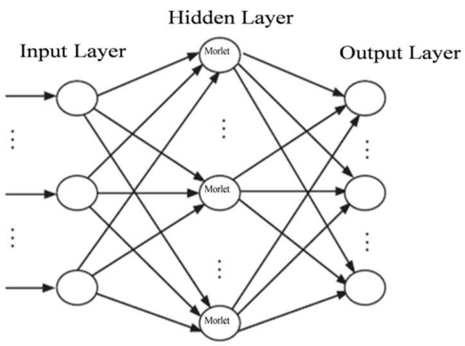


Figure 3. Schematic diagram of the three-layer WNN

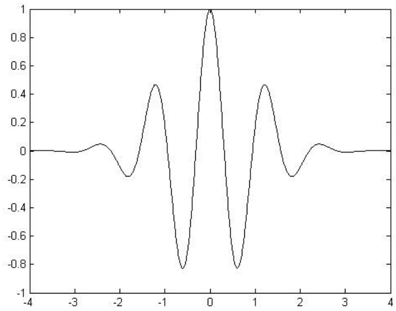


Figure 4. Morlet wavelet activation function

The output of a wavelet neural network is a linear weighted combination of the wavelet activation functions. Figure 5 shows the form of a single-input wavelon. The output is defined as:

$$\psi_{\lambda,t} = \psi(\tfrac{u-t}{\lambda}) \qquad (5)$$

Where λ and t are the dilation and translation parameters respectively (Vitch, 2005).

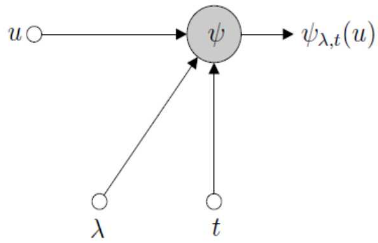


Figure 5. A Wavelet Neuron

2.3. Feature Extraction

Vibration signals contain a large set of data for each sample therefore some statistical and frequency domain functions are applied to reduce feature vectors. Feature extraction method is a dimensionality reduction technique is widely applied in condition monitoring. Seven features were extracted from RMS values of vibration velocity of signals by using the statistical and vibration parameters. Some of used Parameters are: Maximum, mean, Skewness, The central moment of 4, Crest Factor, Shape Factor, Impulse Factor, The central moment of 3 and the central moment of 5. These features are shown in Table 1.

Table 1. features and their formulas

Formula	Feature Description
$\frac{\sum_{K=1}^{K} S(K)}{K}$	*mean*
$Max(\lvert S(K)\rvert)$	*Max*
$\frac{\sum_{K=1}^{K} (S(K)-F_1)^4}{(K-1)}$	*The central moment of 4*

$\frac{Max(\lvert S(K)\rvert)}{RMS(S(K))}$	*Crest Factor*
$\frac{RMS(S(K)}{\frac{1}{K}\sum_{K=1}^{K}\lvert S(K)\rvert}$	*Shape Factor*
$\sqrt{\frac{\sum_{K=1}^{K}(S(K)-F_1)^3}{(K-1)F_4^3}}$	*Skewness*
$\frac{F_2}{\frac{1}{K}\sum_{K=1}^{K}\lvert S(K)\rvert}$	*Impulse Factor*
$\frac{\sum_{K=1}^{K}(S(K)-F_1)^3}{(K-1)}$	*The central moment of 3*
$\frac{\sum_{K=1}^{K}(S(K)-F_1)^5}{(K-1)}$	*The central moment of 5*

2.4. Characteristic defect frequency

Local defects or wear defects cause periodic impulses in vibration signals. Amplitude and period of these impulses are determined by shaft rotational speed, fault location, and bearing dimensions. The frequency of these impulses, considering different fault locations as in Figure 6 is obtained by (6)–(8) (Tandon, & Choudhury, 1999 Zarei & Poshtan, 2007).
Ball defect frequency is two times the ball spin frequency and can be calculated as:

$$f_{bd} = \frac{\mathrm{P_d}}{2\mathrm{B_d}} n_b \left(1 - \left(\frac{\mathrm{B_d}}{\mathrm{P_d}}\right)^2\right) \quad (6)$$

Inner race defect frequencies are given by

$$f_{id} = \frac{n_b}{2}\,\mathrm{N}\left(1 + \frac{\mathrm{B_d}}{\mathrm{P_d}}\right) \quad (7)$$

Outer race defect frequencies are given by

$$f_{od} = \frac{n_b}{2}\,\mathrm{N}\left(1 - \frac{\mathrm{B_d}}{\mathrm{P_d}}\right) \quad (8)$$

In these relations, fs is the shaft rotation frequency, nb is the number of balls, d is the roller diameter, D is the pitch diameter of the bearing, and a is a contact angle as shown in Figure 6.

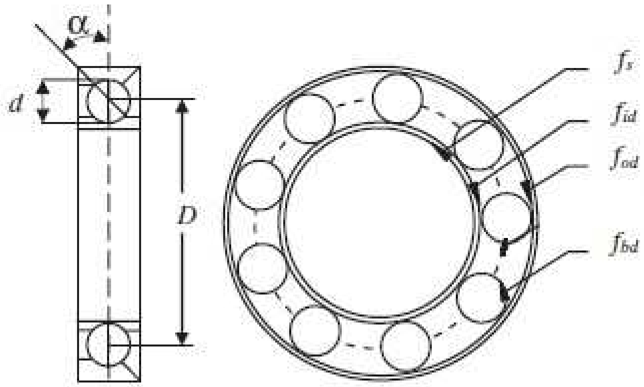


Figure 6- Bearing dimension and characteristic defect frequencies

3. Experimentation and testing

The test bench of an Alternator ball bearing is shown in Figure 7 the number of Ball Bearing was 6201SKF, with seven balls. Details of the Ball Bearing are given in table 2.

Figure 7. Alternator of Massey Ferguson

Table 2. Detail of Ball Bearing

Ball Bearing	Description
Number of Balls	7 Balls
Ball diameter	66.4 mm
Pitch diameter	263.9mm
Contact angle	0 degree

A bearing data set containing nine subsets is obtained from the experimental system under the five different conditions. The five conditions are described in Table 3.

Table 3. Description of the faulty bearings

Condition	**Label**
normal condition	a
ball fault	b
fault in the inner race	c
fault in the outer race	d
housing rub fault	e

These faulty bearings are shown in Figure 8. Each data subset corresponds to one of the nine conditions and it consists of 50 samples. Each sample is a vibration signal containing 16384 sampling points. Figure 9: (a) – (e) give raw data samples for the nine bearing health conditions: (a) normal condition, (b) ball fault, (c) fault in the inner race, (d) fault in the outer race, and (e) housing rub fault.


Outer race fault Inner race fault


Ball fault housing fault

Figure 8. Faults in the alternator ball bearings

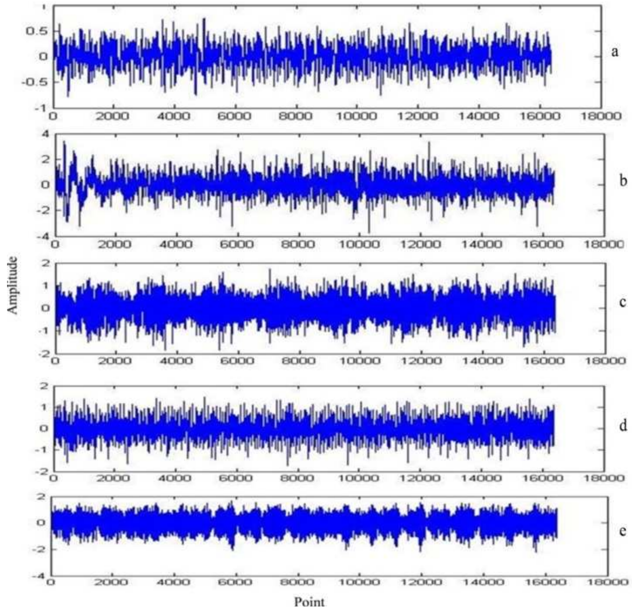


Figure 9. Data samples of the ball bearing

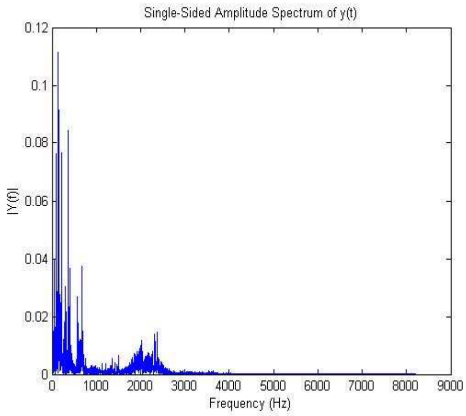
4. Results and discussion

The experimental setup consisted of ball bearing from the alternator of massey ferguson (MF 285). Ball bearings are SKF6201. From the bearing data sheet, pitch diameter equal to 21.99 mm (P_d = 38.5 mm). This bearing has seven balls (n_b = 7) with an approximate diameter of 5.53 mm (B_d=5.53 mm). Finally it is assumed that contact angle is almost zero, i.e. a =0.
Based on these parameter values, and considering that the motor is operating at the measured shaft speed of 1300 rpm (frm = 21.66 Hz), the characteristic vibration frequencies are calculated from (6)-(8) equations as listed in Table 4.

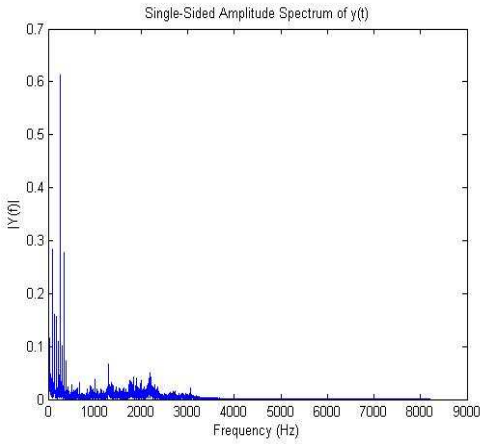
Table 4. Characteristic defect frequencies

Fault location	Characteristic defect frequency
Outer race	f_{od} = 107.34 HZ
Inner race	f_{id} =189.8 HZ
Balls	f_{bd} = 80.6 HZ

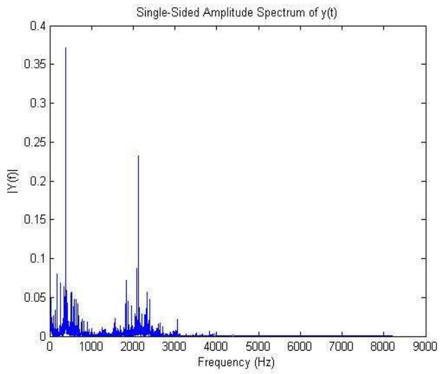
Figure 10 shows the measured vibration spectrum for 5 state normal, ball fault, fault in the inner race, fault in the outer race and housing fault. The frequency spectrum of each fault was different and overall vibration values also were different at the same frequency.
The results showed that area under Fast Fourier Transform carves were indicated a problem. The more area below Fast Fourier Transform curve showed the faults were deeper.


Single-Sided Amplitude Spectrum of y(t)
|Y(f)|
Frequency (Hz)
0.12
0.1
0.08
0.06
0.04
0.02
0
0 1000 2000 3000 4000 5000 6000 7000 8000 9000

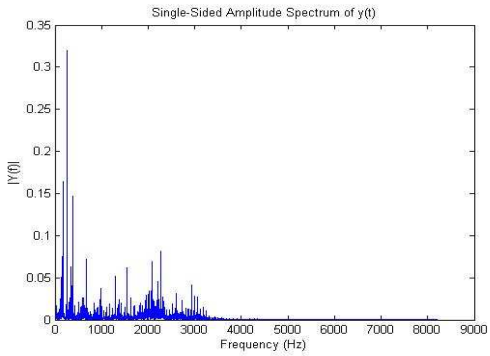
(a)


Single-Sided Amplitude Spectrum of y(t)
|Y(f)|
Frequency (Hz)
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0 1000 2000 3000 4000 5000 6000 7000 8000 9000

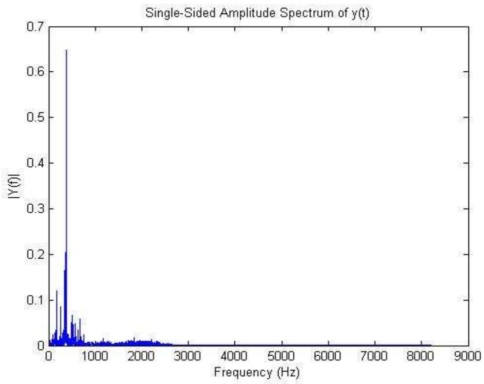
(b)



(c)



(d)



(e)

Figure 10. Original velocity vibration of the signal for three different faults, (a): normal, (b) ball Fault, (c) inner race fault, (d) outer race fault, (e) housing fault

The results showed that area under Fast Fourier Transform carves were indicated a problem. The more area below Fast Fourier Transform curve showed the fault was deeper.

Fault defect classification of the two neural networks (MLP) and (WNN) are used for testing and training samples and classification of faults in the tables 5.

Table 5. Serial classification level MLP & WNN networks

Testing	Training	WNN	MLP	Classification result
22	50	A	A	Normal
22	50	B	B	ball fault
22	50	C	C	inner race fault
22	50	D	D	outer race fault
22	50	E	E	Housing fault

In Table 5, 72 samples are acquired for each status in rotating speed 1300 RPM of Tractor, 70% of which are used for training and 30% for testing. In the construction of a MLP & WNN based model normal, ball fault, fault in the inner race, fault in the outer race and Housing fault A, B, C, D and E respectively. Similarly, the 10 features extracted from of the FFT spectrum.

Table 6 and Table 7, shows respectively confusion matrix of the MLP network and WNN network and how to classification for the 4 fault and a normal state that total of 5 classes will be determined.

Table 6 .Confusion matrix for MLP

	A	B	C	D	E
A	22	0	0	0	0
B	0	21	1	0	0
C	0	0	21	1	0
D	1	0	0	21	0
E	0	2	0	0	20

Table 7. Confusion matrix for WNN

	A	B	C	D	E
A	22	0	0	0	0
B	0	21	1	0	0
C	0	0	21	1	0
D	0	0	0	22	0
E	0	2	0	0	20

The results on a test set in a multi-class prediction are displayed as a two dimensional confusion matrix as mention using 5-fold cross validation. Out of 110 instances, Number of cases are 22 for each of A, B, C, D and E bearing respectively. From the Table 5, it is cleared that MLP network with instant has correctly predicted 22, 21, 21, 21 and 20 instances of A, B, C, D and E bearing respectively. The other WNN network with optimized features has correctly predicted 22, 21, 21, 22 and 20 instances of A, B, C, D and E bearing respectively as shown in Table 7.

5. Conclusion

Results showed that vibration condition monitoring and FFT Spectrum technique could detect fault diagnosis of Ball Bearing. Vibration analysis and FFT Spectrum could provide quick and reliable information on the condition of the Ball Bearing on different faults. Integration of vibration condition monitoring technique with FFT Spectrum technique analyzes could indicate more understanding about diagnosis of Ball Bearing.

This paper deals with vibration based fault diagnosis of Ball Bearing four classical states viz. normal, ball fault, fault in the inner race, fault in the outer race and housing fault are on Ball Bearing.

Set of features have been extracted using FFT Spectrum and classified using The Multi- Layer Perceptron (MLP) and The Wavelet neural network (WNN). The accuracy obtained is equal (95.45%) for the (MLP) network and the accuracy obtained is equal (96.36%) for the (WNN). And by comparing these two networks together can be concluded that the (WNN) of Ball Bearing defects investigated in this study to better classification.

5. Acknowledgements

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عیب یابی بلبرینگ توسط شبکه‌های عصبی WNNوMLP

چکیده

توسعه روش‌های پایش‌وضعیت تجهیزات الکتریکی و مکانیکی در صنایع برای بهبود کیفیت و کاهش هزینه‌های تعمییرات ضروری می‌باشد. هدف از پایش‌وضعیت اصلاح وضعیت تجهیزات مکانیکی در شرایط بحرانی برای بهبود عملکرد آنها در صنایع می‌باشد. آنالیز ارتعاشات اطلاعات گسترده‌ای و مفیدی در مورد عملکرد و کنترل ماشین‌آلات در اختیار مهندسان قرار می‌دهد. در این مقاله دو روش مبتنی بر تحلیل ارتعاش برای عیب‌یابی بال‌بیرینگ ارائه می‌شود. سیگنال‌های ارتعاشی از آلترناتور تراکتور مسی‌فرگوسن ۲۸۵ با بال‌بیرینگ‌های سالم و معیوب گرفته شد. از دو شبکه عصبی چندلایه(MLP) و شبکه عصبی ویولتی(WNN) برای عیب یابی یلبرینگ استفاده گردید. بالاترین دقت مربوط به شبکه عصبی ویولتی است که مقدار آن برابر۹۶٫۳۶ می‌باشد.

کلمات کلیدی: عیب‌یابی، بلبرینگ، شبکه عصبی چندلایه، شبکه عصبی ویولتی.