APPLICATION OF PATTERN RECOGNITION TECHNIQUES FOR FAULT DETECTION OF CLUTCH RETAINER OF TRACTOR

Mostafa Bahrami[1]*, Hossein Javadikia[1], Ebrahim Ebrahimi[2]
[1]Department of Mechanical Engineering of Agricultural Machinery, Faculty of Agriculture,
Razi University, Kermanshah, Iran
[2]Department of Mechanical Engineering, Faculty of Engineering,
Kermanshah Branch Islamic Azad University, Kermanshah, Iran
*Corresponding author: mostafa.bahrami.2@gmail.com

Abstract: *This study develops a technique based on pattern recognition for fault diagnosis of clutch retainer mechanism of MF285 tractor using the neural network. In this technique, time features and frequency domain features consist of Fast Fourier Transform (FFT) phase angle and Power Spectral Density (PSD) proposes to improve diagnosis ability. Three different cases, such as: normal condition, bearing wears and shaft wears were applied for signal processing. The data divides in two parts; in part one 70% data are dataset1 and in part two 30% for dataset2. At first, the artificial neural networks (ANN) are trained by 60% dataset1 and validated by 20% dataset1 and tested by 20% dataset1. Then, to more test of the proposed model, the network using the datasets2 are simulated. The results indicate effective ability in accurate diagnosis of various clutch retainer mechanism of MF285 tractor faults using pattern recognition networks.*

Keywords: clutch retainer mechanism, fault detection; neural network, pattern recognition

INTRODUCTION

Tractors are popular in agricultural applications. A faulty clutch retainer mechanism of MF285 tractor may cause many problems, so recognizing faults is important for an agricultural works on time.

Different approaches for fault detection have been studied and diagnosis successful proposed. Most of these techniques involve vibration analysis because they are easy to measure and highly reliable (Tran et al., 2009).

The current fault diagnosis techniques are using classical techniques in time or frequency domain predominantly based on intelligent modeling systems, such as: Fuzzy-based; Vibration-based fault diagnosis of pump was studied by using fuzzy technique (Wang and Hu, 2006) and on-line fault detection and classification in transmission line was based on Fuzzy logic(Adhikari et al., 2016), ANN-based; An ensemble of dynamic neural network identifiers was studied for fault detection and isolation of gas turbine engines (Amozegarand Khorasani, 2016), Detection of broken rotor bar faults in induction motor at low load was studied by using neural network (Bessam et al.,2016), Early fault diagnosis of rotating machinery was based on wavelet packets-empirical mode decomposition feature extraction and neural network (Bin et al., 2012), a novel technique for selecting mother wavelet function was studied by using an intelligent fault diagnosis system (Rafiee et al., 2009), Induction motors bearing fault detection was studied by using pattern recognition techniques(Zarei, 2012), decision tree-based; Feature extraction using wavelets and classification was applied through decision tree algorithm for fault diagnosis of mono-block centrifugal pump (Muralidharan and Sugumaran et al., 2013), Exploiting sound signals for fault diagnosis of bearings was studied by using decision tree (Amarnath et al., 2013) and hybrid systems such as SVM with PSO-based; Multi-fault classification based on wavelet SVM with PSO algorithm to analyze vibration signals was applied from rolling element bearings (Liu et al., 2013) and SVM with fuzzy based; Application of multi-class fuzzy support vector machine classifier was applied for fault diagnosis of wind turbine (Hang et al.,2016), adaptive neuro -fuzzy-based; adaptive neuro-fuzzy technique was applied for analyses of the most influential factors for vibration monitoring of planetary power transmissions in pellet mills (Milovančević et al., 2016) and Fault diagnosis of induction motor was based on decision trees and adaptive neuro-fuzzy inference (Tran et al., 2009), Intelligent Fault Detection of Retainer Clutch Mechanism of Tractor was studied by using ANFIS and Vibration Analysis (Ebrahimi et al., 2013) and other studied such as; A novel fault diagnosis model for gearbox based on wavelet support vector machine with immune genetic algorithm(Chen et al., 2013), Fault feature extraction of gearbox was studied by using over complete rational dilation discrete wavelet transform on signals measured from vibration sensors (Chen et al., 2012), Fault detection of mechanical drives under variable operating conditions was based on wavelet packet Renyi entropy signatures (Boskoski and Juricic, 2012).

It is necessary for the tractors to be available at the time required because time is a vital factor in agricultural systems. The aim of this study is early fault detection of clutch mechanism before tractors were stopped totally. In this paper provides a procedure based on a pattern recognition technique for fault diagnosis of clutch retainer mechanism of MF285 tractor using the artificial neural networks. Artificial neural networks (ANNs) proven as a reliable technique to diagnose the condition and have good learning capability.

MATERIALS AND METHOD

Time domain and frequency domain features

Time domain features and frequency domain features consist of Fast Fourier Transform (FFT) phase angle and Power Spectral Density (PSD) are usually used for fault recognition of rotating machine. The main aim of this section is to extract acceptable features from collected data. Each original signal set was divided by the data points, and each segment is processed to extract the following features (Zarei, 2012; Ebrahimi and Molazade, 2010).

In follow there are several relationships for extracting features of data points of signal in time domain and frequency domain. These features are used as input of neural network model.

Mean value

$$T_1 = \frac{\sum_{n=1}^{N} x(n)}{N} \tag{1}$$

Standard deviation

$$T_2 = \sqrt{\frac{\sum_{n=1}^{N}((x(n)-T1)^2}{N-1}} \tag{2}$$

Root mean square (RMS)

$$T_3 = \sqrt{\frac{\sum_{n=1}^{N}(x(n))^2}{N}} \tag{3}$$

Peak value

$$T_4 = \max|x(n)| \tag{4}$$

Shape factor

$$T_5 = \frac{T_3}{\frac{1}{N}\sum_{n=1}^{N}|x(n)|} \tag{5}$$

Impulse factor

$$T_6 = \frac{T_4}{\frac{1}{N}\sum_{n=1}^{N}|x(n)|} \tag{6}$$

Crest factor

$$T_7 = \frac{T_4}{T_3} \tag{7}$$

Sample standard deviation

$$T_8 = \sqrt{\frac{n\sum_{n=1}^{N} x^2(n) - \sum_{n-1}^{N}(x(n))^2}{n(n-1)}} \tag{8}$$

Sample variance

$$T_9 = (T_8)^2 \tag{9}$$

Kurtosis

$$T_{10} = \frac{\sum_{n=1}^{N}(x(n)-T_1)^4}{N \times (T_9)^2} \tag{10}$$

Skewness

$$T_{11} = \frac{n}{(n-1)(n-2)}\sum_{n=1}^{N}\left(\frac{x(n)-T_1}{T_8}\right)^3 \tag{11}$$

Where x(n) is a signal series for n= 1,2,. . .,N, N is number of data points.

Data acquisition

To study the clutch retainer mechanism of MF285 tractor failure, our experiment does with three speeds (1000, 1500 and 2000 r/min) and three conditions, i.e., normal condition, bearing wears, shaft wears. In this paper, the signal was got by an accelerometer mounted on the outer case of a clutch retainer, when it was loaded in the speeds.

The experimental setup to collect dataset also consists of analyzer system (APC- 40, APC Ltd, Korea), an accelerometer (VMI-102. VMI Ltd, Sweden) tachometer (DT-2234B) and shock absorbers rubber under the base of test-bed are shown in Figure 1. Experimental setup was designed to install clutch retainer mechanism of MF285 tractor, electric motor and load mechanism with shock absorbers under bases to cancel out vibrations. The number of iteration for each case (for example normal condition in speed of 1000) is 130 and the time of each data equation is 4 second. The rotational speed of the system was measured by tachometer.

Pattern recognition neural networks

A multilayer neural network incorporates an input layer, and one or more hidden layers, an output layer. 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; Zarei, 2012).

In this paper, to create a model by use of a pattern recognition network, this is a feed-forward network with tan-sigmoid transfer functions in the two hidden layers and the output layer. As in the function-fitting, use changeable neurons in two hidden layers. The output layer of network has three neurons, because there are three classes related with each input vector such as; normal condition, bearing wears, shaft wears.

A multilayer perceptron architectural with one hidden layer is shown in Figure 2. The neural network weights should be designed in a way that with applying the inputs, a close output to the real output is reached. This is called neural network training, which means setting the weights to decrease the errors between network output and real output (Zarei, 2012).

a- Data capture platform b- Tachometer c- Piezoelectric accelerometer

Figure 1. Experimental setup.

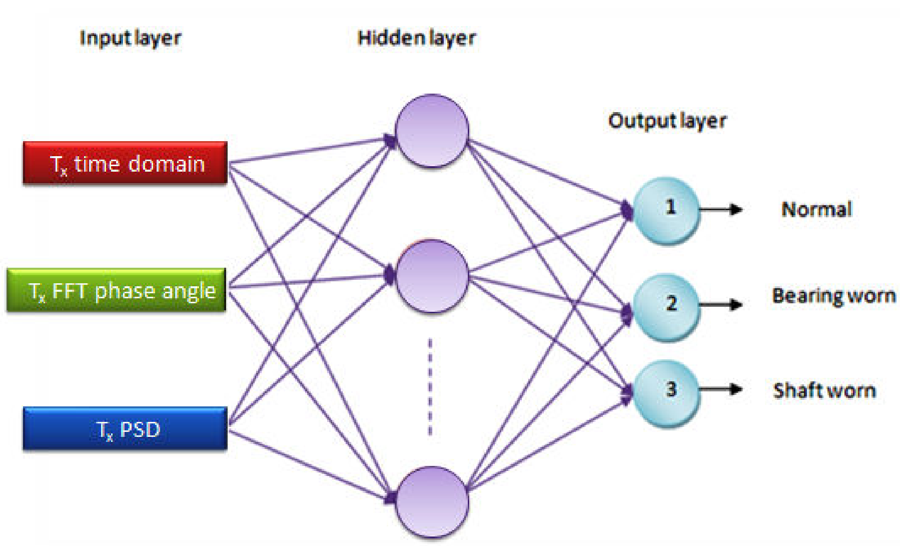

Figure 2. An architectural of multilayer perceptron

RESULTS AND DISCUSSION

The aim of this paper is to design an ANN using time and frequency domain features. For this purpose, the frequency domain features consist of Fast Fourier Transform (FFT) phase angle features and Power Spectral Density (PSD) features and time domain features, including the Mean value, Standard deviation, Root mean square (RMS), Peak value, Shape factor, Impulse factor, Crest factor, Sample standard, Sample variance, Kurtosis, Skewness of the vibration signal (T_1 to T_{11}), are considered as the inputs of the network. So, the three input vectors for the training step of the ANN is constructed as T_x of Fast Fourier Transform (FFT) phase angle & T_x of Power Spectral Density (PSD) & T_x of time domain features (x=1,2..11).

To design a proper network, a network with four layers, including inputs, two hidden layers and outputs was constructed firstly. Then numbers of neurons in hidden layers are changed to get the best of an architectural neural network. 780 samples are got (130 sample normal condition at speed of 1000 r/min, 130 sample normal condition at speed of 1500 r/min, 130 sample normal condition at speed of 2000 r/min and for bearing wears and shaft wears conditions too) that divides in two parts; in part one 70% data are dataset1 and in part two 30% for dataset2.

At first order the part one (dataset1) was used. The dataset1 used for training (60%) and validation (20%) and test (20%) of neural networks. After make of neural network models for more tests of the designed networks, the networks are simulated by dataset2.
The results for eleven network structures for T1 to T11 are shown in Table 1 (dataset1) and Table 2 (dataset2). In the net structure, changeable neurons are used in two hidden layers. The best of network structure is related to T1 (mean value), where the probability of correct classification for these structures is reviewed. Besides, Confusion matrix for output of network related to dataset1 for T_1 is shown in Figure 3(training 60%, validation 20%, testing 20% and total 100%) and more test of network by datset2 for T_1 is shown in Figure 4. The class of 1 is normal condition, class of 2 is bearing wear and class 3 is shaft wear condition. To analyze the network response by considering the outputs of the trained network and comparing them to the expected results (targets) confusion matrix was used. The diagonal cells in each table were shown in Figures 3 and 4. The number of cases that were correctly classified and the off-diagonal cells show the misclassified cases. The blue cell in the bottom right shows the total percent of correctly classified cases (in green) and the total percent of misclassified cases (in red). For example, in Figure 4, 80 data points are normal (class 1), 77 data points are bearing wear (class 2), 77 data points are shaft wear (class 3). Same results in considering the output of the network and comparing them to the expected results (targets) is shown. The results for all set training, validation and testing for dataset1 and again testing by dataset2 show very good recognition

Table 1 Comparison of different networks using dataset1 features

Feature No.	Net. structure	Probability of correct classification			Average decision rate, %
		Normal condition, %	Bearing wears, %	Shaft wears, %	
T_1	[5 8]	100	100	100	100
T_2	[8 10]	87.8	100	98.4	95.4
T_3	[7 8]	100	100	100	100
T_4	[6 10]	100	100	93.4	97.8
T_5	[15 15]	100	100	92.2	97.4
T_6	[8 10]	100	100	100	100
T_7	[8 10]	100	100	96.2	98.7
T_8	[8 12]	100	100	95.1	98.4
T_9	[10 20]	93.3	100	100	97.8
T_{10}	[28 21]	40.6	68.3	50.8	53.3
T_{11}	[8 11]	100	100	85.2	95.1

Table 2 Comparison of different simulated networks using dataset2 features

Feature No.	Net. structure	Probability of correct classification			Average decision rate, %
		Normal condition, %	Bearing wears, %	Shaft wears, %	
T_1	[5 8]	100	100	100	100
T_2	[8 10]	81.3	100	96.1	92.3
T_3	[7 8]	100	100	100	100
T_4	[6 10]	100	100	93.5	97.9
T_5	[15 15]	100	98.9	94.0	97.6
T_6	[8 10]	100	100	100	100
T_7	[8 10]	100	100	94.8	98.3
T_8	[8 12]	100	100	100	100
T_9	[10 20]	81.3	100	100	93.6
T_{10}	[28 21]	46.3	85.7	49.4	60.3
T_{11}	[8 11]	100	100	87.0	95.7

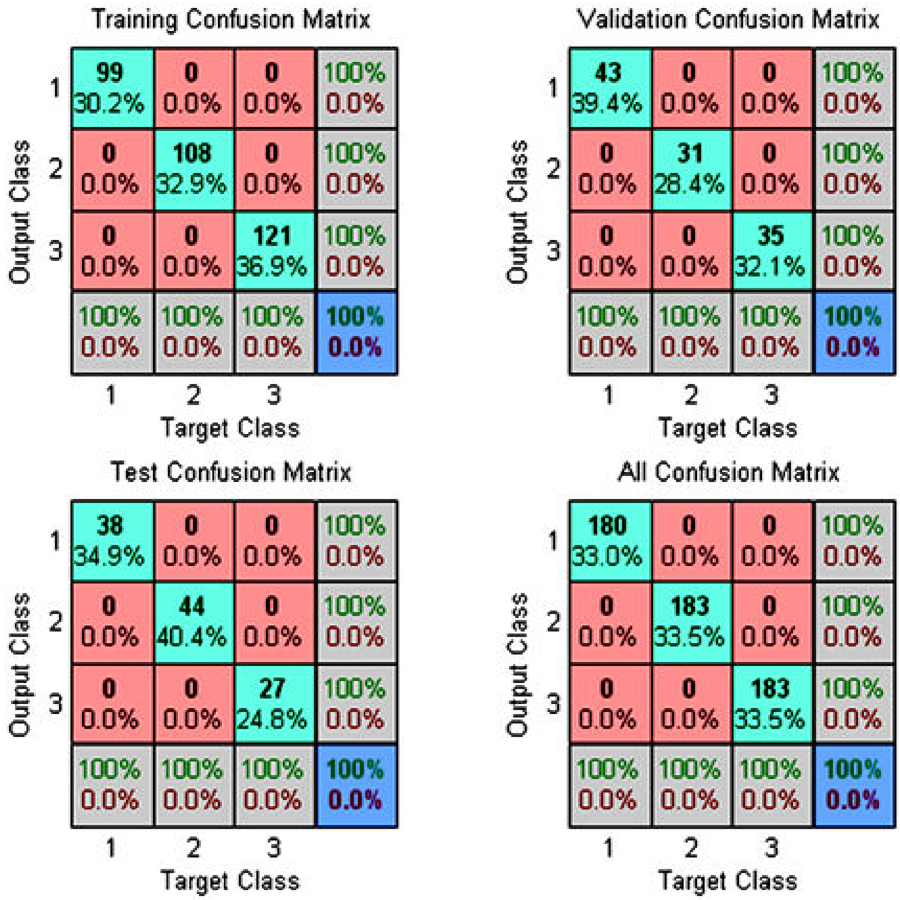

Figure 3. Confusion matrix of dataset1 on T_1

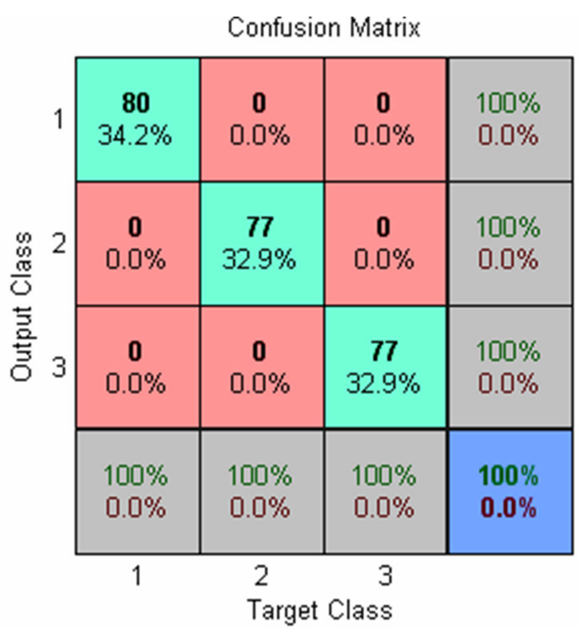

Figure 4. Confusion matrix of dataset2 onT_1

CONCLUSIONS

The aim of this study was application of neural networks as pattern recognition model to intelligent fault diagnosis of a clutch retainer mechanism of MF285 tractor. An experimental set-up was designed, and the proper data was acquired in three conditions, such as: normal condition, bearing wears and shaft wears. Then data is processed and 11 time and frequency domain (FFT phase angle and PSD) features by statistical equation are got. Eleven different pattern recognition networks were designed, first of uses 70% data is applied as the inputs of the networks and then the other 30% data uses as the simulating of the networks. It is shown that using mean value feature has most accurate (decision accurate rat is 100%) for fault diagnosis.

Acknowledgment

Special thanks to Mr. Mohamad Hadi Jalili and Mr. Nasrolah Astan for helping this research.

REFERENCES

1. Adhikari, S., Sinha, N. and Dorendrajit, T., 2016. Fuzzy logic based on-line fault detection and classification in transmission line. *SpringerPlus*, *5*(1), pp.1-14.
2. Amarnath, M., Sugumaran, V. and Kumar, H., 2013. Exploiting sound signals for fault diagnosis of bearings using decision tree. *Measurement*, *46*(3), pp.1250-1256.
3. Amozegar, M. and Khorasani, K., 2016. An ensemble of dynamic neural network identifiers for fault detection and isolation of gas turbine engines.*Neural Networks*, *76*, pp.106-121.
4. Bessam, B., Menacer, A., Boumehraz, M. and Cherif, H., 2016. Detection of broken rotor bar faults in induction motor at low load using neural network.*ISA transactions*.
5. Bin, G.F., Gao, J.J., Li, X.J. and Dhillon, B.S., 2012. Early fault diagnosis of rotating machinery based on wavelet packets—Empirical mode decomposition feature extraction and neural network. *Mechanical Systems and Signal Processing*, *27*, pp.696-711.
6. Boškoski, P. and Juričić, Đ., 2012. Fault detection of mechanical drives under variable operating conditions based on wavelet packet Rényi entropy signatures. *Mechanical Systems and Signal Processing*, *31*, pp.369-381.
7. Chen, B., Zhang, Z., Sun, C., Li, B., Zi, Y. and He, Z., 2012. Fault feature extraction of gearbox by using overcomplete rational dilation discrete wavelet transform on signals measured from vibration sensors. *Mechanical Systems and Signal Processing*, *33*, pp.275-298.
8. Chen, F., Tang, B. and Chen, R., 2013. A novel fault diagnosis model for gearbox based on wavelet support vector machine with immune genetic algorithm. *Measurement*, *46*(1), pp.220-232.
9. Ebrahimi, E. and Mollazade, K., 2010. Intelligent fault classification of a tractor starter motor using vibration monitoring and adaptive neuro-fuzzy inference system. *Insight-Non-Destructive Testing and Condition Monitoring*, *52*(10), pp.561-566.
10. Ebrahimi, E., Javadikia, P., Jalili, M.H., Astan, N., Haidari, M. and Bavandpour, M., 2013. Intelligent Fault Detection of Retainer Clutch Mechanism of Tractor by ANFIS and Vibration Analysis. *Modern Mechanical Engineering*, *3*(03), p.17.
11. Hang, J., Zhang, J. and Cheng, M., 2016. Application of multi-class fuzzy support vector machine classifier for fault diagnosis of wind turbine. *Fuzzy Sets and Systems*, *297*, pp.128-140.
12. Haykin, S. 1999. Neural networks: A comprehensive foundation. Dehli: Prentice Hall.
13. Liu, Z., Cao, H., Chen, X., He, Z. and Shen, Z., 2013. Multi-fault classification based on wavelet SVM with PSO algorithm to analyze vibration signals from rolling element bearings. *Neurocomputing*, *99*, pp.399-410.
14. Milovančević, M., Nikolić, V. and Anđelković, B., 2016. Analyses of the most influential factors for vibration monitoring of planetary power transmissions in pellet mills by adaptive neuro-fuzzy technique. *Mechanical Systems and Signal Processing*.
15. Muralidharan, V. and Sugumaran, V., 2013. Feature extraction using wavelets and classification through decision tree algorithm for fault diagnosis of mono-block centrifugal pump. *Measurement*, *46*(1), pp.353-359.
16. Rafiee, J., Tse, P.W., Harifi, A. and Sadeghi, M.H., 2009. A novel technique for selecting mother wavelet function using an intelli gent fault diagnosis system. *Expert Systems with Applications*, *36*(3), pp.4862-4875.
17. Tran, V.T., Yang, B.S., Oh, M.S. and Tan, A.C.C., 2009. Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, *36*(2), pp.1840-1849.
18. Wang, J. and Hu, H., 2006. Vibration-based fault diagnosis of pump using fuzzy technique. *Measurement*, *39*(2), pp.176-185.
19. Zarei, J., 2012. Induction motors bearing fault detection using pattern recognition techniques. *Expert systems with Applications*, *39*(1), pp.68