Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 167 (2020) 1594–1603

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

Gearbox Fault Diagnosis using Advanced Computational Intelligence

Subrata Mukherjee[a,*], Vikash Kumar[b], Somnath Sarangi[c] and Tarun Kumar Bera[d]

[a,b]Department of Mechanical Engineering, Thapar Institute of Engineering and Technology, Patiala, Punjab 147004, India
[b,c]Department of Mechanical Engineering, Indian Institute of Technology, Patna, Bihar 801103, India

Abstract

Gearbox is an indispensable element allied with mechanical industries to fluctuate speed and load in accordance with the requirements. More improvements in its mechanical structure and procedure can increase the efficiency of the industries. For those reasons, the gearbox was designed and manufactured very carefully with the zero tolerance of defects. Gearbox failure can lead to an increase in financial loss and decrease in production strength. Vibration signal analysis is used to monitor the gearbox condition. But, non-stationary properties of vibration signal make this procedure very challenging. Therefore, this paper presents a unique gearbox fault investigation technique based on advanced computational intelligence. Firstly, Time Synchronous Averaging algorithm was used to study the nonstationary properties of the raw vibration signal. Then, nine types of time domain arithmetical features were calculated from the pre-processed TSA vibration signal. After that, the J48 algorithm was used for significant features selection of gearbox fault and Naïve Bayes algorithm for features classification of gearbox fault. A computer-aided fault simulator was used for experimental study. MATLAB and WEKA platforms were used for signal processing, features selection, and features classification of the gearbox faults. The performance of the proposed method shows meaningful results for gearbox fault diagnosis.

Peer-review under responsibility of the scientific committee of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019).

Keywords: Gearbox; Time Synchronous Averaging; J48; Naïve Bayes; Signal processing; Features selection; Features Classification

* Corresponding author. Tel.: +91 7430806481.
E-mail address: subratamukherjeetume001@gmail.com

1877-0509
Peer-review under responsibility of the scientific committee of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019).
10.1016/j.procs.2020.03.370

1. Introduction

These days computational intelligence is used for monitoring various mechanical as well as industrial units. It is also useful for the improvement of the production section in the case of mass production. Due to this reason, production potency of industrial machinery is continuously increasing for achieving higher technological advancement. The gearbox is one of the most important key elements of any rotary machinery as well as an industrial workplace. Due to excessive load and huge pressure, gearbox shows some abnormal behaviors which are known as gearbox failures. Mainly, gearbox failure occurs due to the gear tooth damage or bearing damage. Gearbox breakdown can lead to shutting down the whole production unit, which may result in monumental economic losses and heavy personal injuries in any industrial organization. There are many types of techniques that are available to abate this problem but vibration signal analysis is best among them. Most of the fault such as tooth crack, tooth broken, etc. occurs in the gearbox due to excessive load and huge pressure.

Gearbox fault diagnosis can be observed as a pattern recognition problem. As an influential pattern recognition tool, computational intelligence or artificial intelligence (AI) shows promising response in gearbox fault diagnosis. Several AI-based techniques have been used but AI based classifier have been extensively used in fault analysis of the gearbox. Lei et al. [1] reviewed that application of EMD in fault analysis. Z. Peng et al. [2] showed a comparison between HHT and wavelet for fault examination of a bearing. R. Yan et al. [3] reviewed the application of wavelet for fault diagnosis of rotary machinery. Zhao et al. [4] proposed a way based on combinatorial Bayes network for transformer fault diagnosis. J. Seshadrinath et al. [5] conducted an experiment on induction motor fault diagnosis using vibration analysis. V. Muralidharan et al. [6] showed that the comparison between Naïve Bayes classifier and Bayes net classifier using wavelet transform. Nguyen et al. [7] offered a fault diagnosis technique for a bearing using a wavelet kurtogram and VFA. X. Wan et al. [8] studied the different type of dimensionality reduction techniques for gear fault identifications. J. Rafiee et al. [9] proposed a process based on the artificial neural network for gearbox fault analysis. M. Mrugalski et al. [10] used multi-layer perceptron for fault diagnosis of a mechanical system. A. Sadeghian et al. [11] offered a scheme for fault examination of induction motor based on WPD and ANN. J. Sanz et al. [12] showed that the gearbox fault diagnosis techniques using DWT and multi-layer perceptron neural networks. P. Jayaswal et al. [13] presented a fault analysis structure by comparing the ANN and Fuzzy logic based on wavelet transform. K. Salahshoor et al. [14] used fusion SVM for fault analysis of a steam turbine. M. Saimurugan et al. [15] offered a fault investigation technique based on decision tree and SVM for fault inspection for a rotational mechanical system. P. Konar et al. [16] used wavelet and SVM for bearing fault diagnosis. Tang et al. [17] proposed an AI process based on SVM and chaos particle swarm optimization.

Hence, from the literature review, it is clear that maximum amount of research work used various advanced signal processing techniques for studying the raw vibration response of the gearbox. Some authors also suggested the combined approach of vibration response and statistical learning for gearbox fault diagnosis. Concept of dimensionality reduction in gear tooth crack was also introduced in the literature review. Some literature also proposed the combined approach of WPD-SVM, SVM-ANN, ANN-Fuzzy logic and SVM-CPSO for gearbox fault diagnosis. Some authors compared Naïve Bayes and Bayes Set, ANN and SVM.

This paper is one such attempt to apply computational intelligence techniques i.e., J48 and Naïve Bayes algorithm to the TSA vibration signal for time-domain features extraction, selection and classification of gearbox fault diagnosis. This work also deals with the reduction of non-stationary properties which is considered as noise.

The remaining part of this paper is presented in this way: In section 2, Experiment Investigations. Section 3, Theoretical concept. Section 4, Result and discussion. Section 5, Conclusion and Future work

2. Experiential Investigations

2.1. Experimental Setup

Experimental investigations were carried out by Spectra Quest Machinery Faults Simulator, which is a combination of a Computer-Aided DAQ. Fig.1 shows the experimental setup. A single-stage bevel gearbox was used for fault diagnosis, which has 27 teeth in driver gear and 18 teeth in driven gear with the contact ratio of 1.5. Fig.2 shows the single-stage bevel gearbox setup. One healthy and two faulty condition gearsets were used for experimental studies. Fig.3 shows the two faulty gearsets i.e. chipped tooth gear and missing tooth gear.

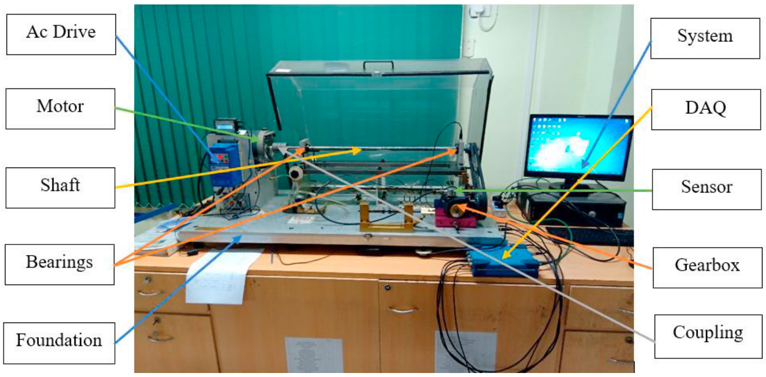


Fig.1 Experimental Setup

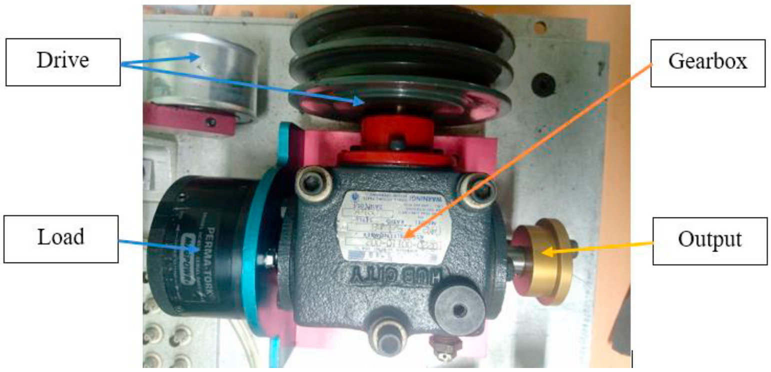


Fig.2 Single Stage Bevel Gearbox

Fig.3 Chipped and Missing Tooth Gears

2.2. Experimental Procedure and Proposed Method

This experimental work was carried out under three different gearbox conditions with the three different speed conditions i.e., 15Hz, 25Hz and 35Hz. Three different load excitations i.e., 0lb., 2lb., and 4lb. were also introduced in the experimental studies. Firstly, TSA algorithm was used for pre-processing of the raw vibration response. Then, nine types of time domain features were extracted from the TSA vibration response. After that, the J48 algorithm was used for feature selection and the Naïve Bayes algorithm was used for feature classification of the gearbox faults. Fig.4 displays the flowchart of the proposed method.

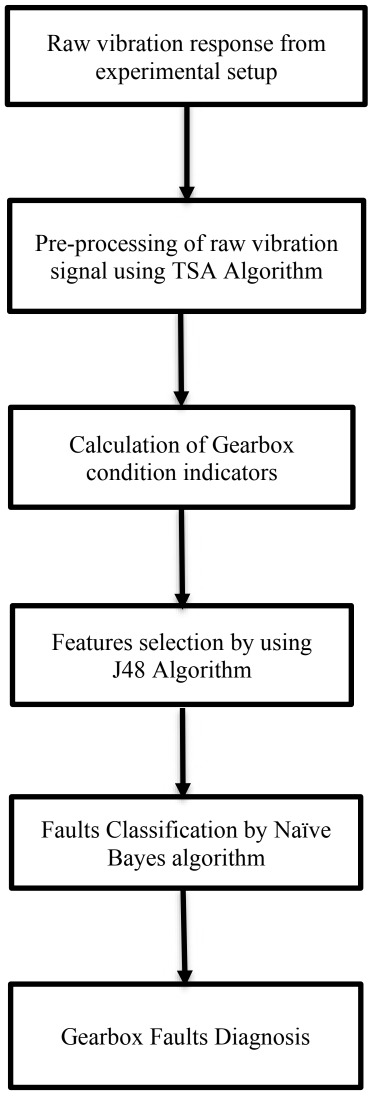


Fig.4 Flow chart of Proposed Method

3. Theoretical Concept

3.1. Time Synchronous Averaging Algorithm

TSA [1-10]is an effective time-domain pre-processing method to condense the consequence of the noise in a repetitive vibration signal. Mathematically, TSA is expressed as

$$Ai(t) = \frac{1}{Pi}\sum_{i=0}^{P-1} C(t + iTn) \tag{1}$$

Where, Pi is the number of the Avg. segments and $Ai(t)$ is the averaged signal.

3.2. J48 Algorithm

Features selection is the basic process for identifying the classes from a set of records that contains attributes. Decision trees [5-15] are one of the common approaches for the purpose of features selection. Decision trees can be constructed by various algorithms, but the most popular algorithm is C4.5. The ability to identify and classify in every step is the vital factor which has won the trust of many experts. J48[5-15] is one of the most common approaches that is used for constructing decision trees. In the WEKA platform, J48 is a Java implementation of the C4.5 algorithm.

3.3. Naïve Bayes Algorithm

In this work, the *Naïve Bayes* [1-10] algorithm was used for classification of gearbox faults which is based on Bayes Principal. Mathematical expression of the Bayes theorem written as follows

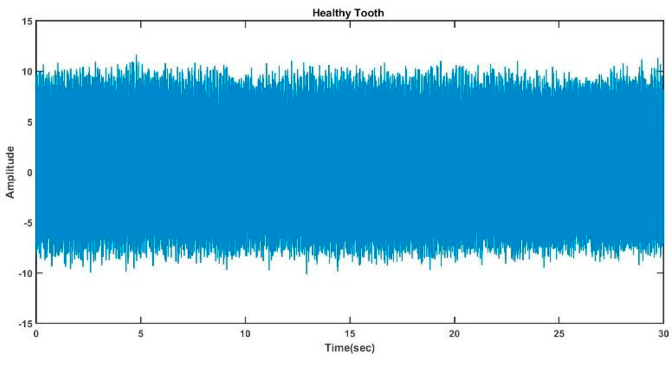
$$Ta(v \mid m) = (Ta(m \mid v)Ta(v))/(Ta(m)) \tag{2}$$

Where, $Ta(v \mid m)$ and $Ta(m \mid v)$ known as a discriminative and generative model.

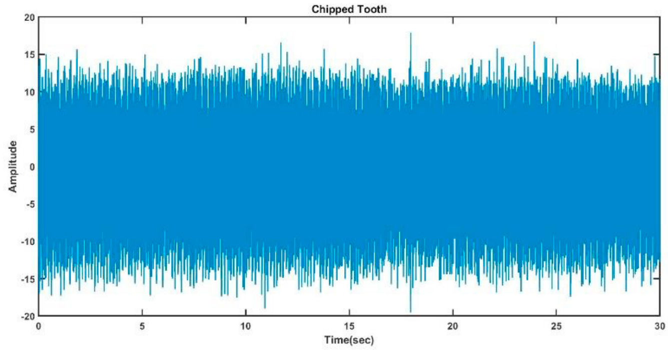
4. Results and Discussions

4.1. Noisy Vibration Signature of the Gearbox

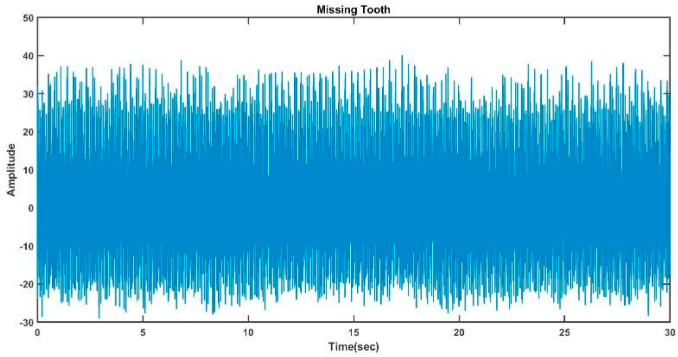
Raw vibration response of the gearbox is a combination of the stationary and non-stationary properties. These non-stationary properties of the raw vibration response are treated as noise. Fig.5 shows the noisy vibration response of the gearbox with three different gearbox conditions.



(a)



(b)

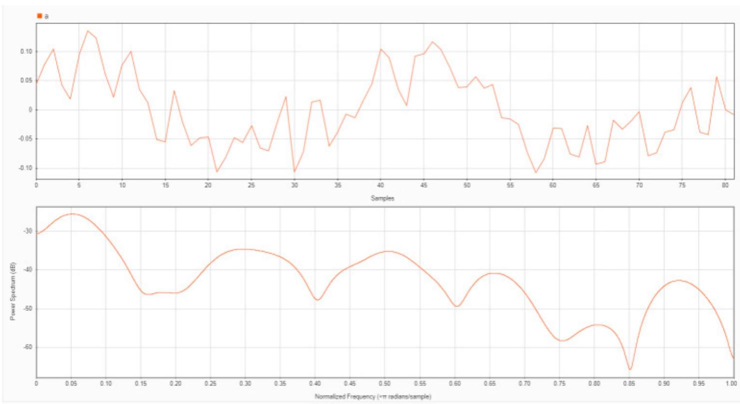


(c)

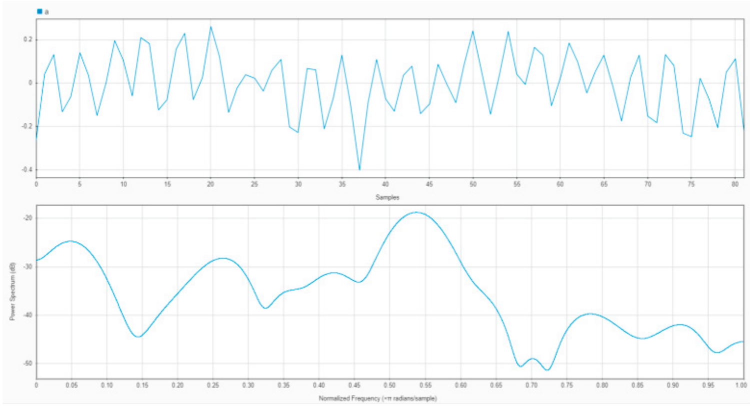
Fig.5 Noisy vibration response of (a) Healthy tooth (b) Chipped tooth and (c) Missing tooth Gearbox

4.2. Noiseless Vibration response of the Gearbox

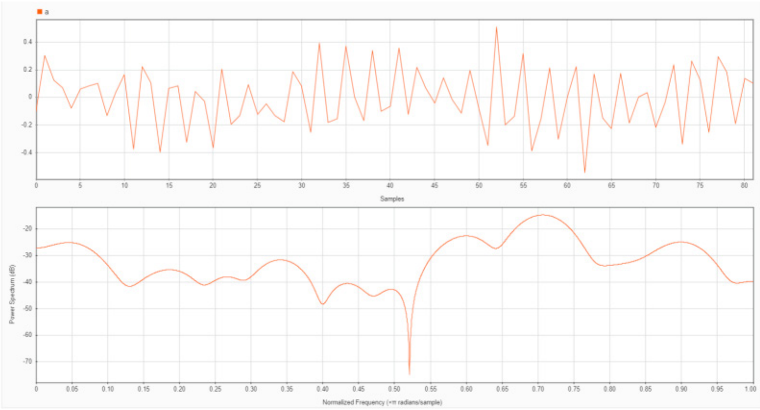
Time synchronous averaging was used to remove the noise from the raw vibration response. Fig.6 shows the time-synchronous averaging of noisy vibration responses of each gearbox condition along with the power spectrum of noiseless vibration responses.



(a)



(b)



(c)

Fig.6. TSA with the Power spectrum of (a) Healthy tooth (b) Chipped tooth and (c) Missing tooth Gearbox.

4.3. Feature Selection by using J48 Algorithm of Noiseless vibration response of the Gearbox

In this work, nine types of time domain features were taken out from the noiseless vibration response which served as an input in the J48 algorithm. J48 is also used to select the significant features. Fig.7. shows three significant features, namely peak value, clearance factor, and approximate entropy.

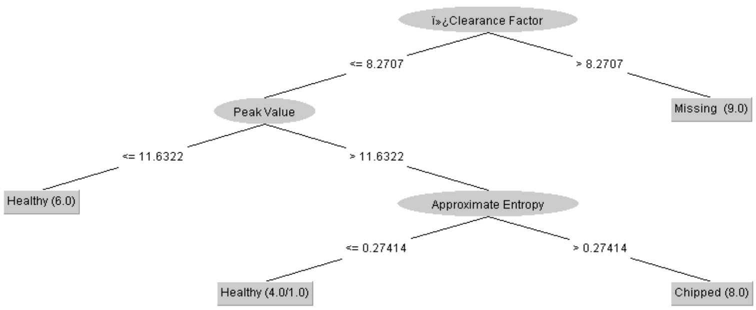


Fig.7. Features selection by J48 algorithm

4.4. Feature Classification by using Naïve Bayes Algorithm of Noiseless vibration response of the Gearbox

This section describes the classification procedure of gearbox fault features by using the Naïve Bayes algorithm. WEKA platform was used for classification of the gearbox fault. Three significant features peak value, clearance factor, and approximate entropy were used as an input in the Naïve Bayes algorithm. Table 1 displays the confusion matrix created by the Naïve Bayes algorithm.

Table 1. Confusion Matrix.

Classified as	A	B	C
Healthy (A)	5	0	0
Chipped (B)	1	3	0
Missing (C)	0	0	6

First Row of the Confusion Matrix

1. The first element represents the healthy or good tooth class of the gearbox and successfully classified as a healthy or good tooth class by Naïve Bayes classifier.
2. The second element represents the healthy or good tooth class of the gearbox but misclassified as a chipped tooth class by Naïve Bayes classifier with none.
3. The third element represents the healthy or good tooth class of the gearbox but misclassified as a missing tooth class by Naïve Bayes classifier with none.

Second Row of the Confusion Matrix

1. The first element represents the chipped tooth class of the gearbox but misclassified as a healthy tooth class by Naïve Bayes classifier.
2. The second element represents the chipped tooth class of the gearbox and successfully classified as a chipped tooth class by Naïve Bayes classifier.
3. The third element represents the chipped tooth class of the gearbox but misclassified as a missing tooth class by Naïve Bayes classifier with none.

Third Row of the Confusion Matrix

1. The first element represents the missing tooth class of the gearbox but misclassified as a healthy tooth class by Naïve Bayes classifier with none.
2. The second element represents the missing tooth class of the gearbox but misclassified as a chipped tooth class by Naïve Bayes classifier with none.
3. The third element represents the missing tooth class of the gearbox and classified as a missing tooth class by Naïve Bayes classifier.

Table 2 displays the class-wise precision or accuracy of features where the "TP rate" indicates the True Positive Rate and the FP rate means the False Positive Rate. "TP rate" is for better accuracy and "FP rate" is better positivity. Value of TP and FP must be close to 1 and 0 respectively. Summary of the classification process is given below in Table 3.

Table 2. Comprehensive Accuracy by Class.

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	1.000	0.100	0.833	1.000	0.909	0.866	1.000	1.000	Healthy
	0.750	0.000	1.000	0.750	0.857	0.829	1.000	1.000	Chipped
	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	Missing
Weighted Avg.	0.933	0.033	0.944	0.933	0.932	0.910	1.000	1.000	

Table 3. Summary of the classification process.

An example of a column heading	Parameters	
Correctly Classified Instances	14	93.33 %
Incorrectly Classified Instances	1	6.66 %
Kappa statistic	0.898	
Mean absolute error	0.0609	
Root mean squared error	0.16	
Relative absolute error	13.5141 %	
Root relative squared error	33.2885 %	
Total Number of Instances	15	

5. Conclusion and Future work

In this work, the importance of the TSA algorithm for the gearbox fault diagnosis is discussed. The investigational effort is supported by using three dissimilar gearbox conditions (healthy, chipped and missing condition) with three different speeds and load excitations. TSA algorithm was applied to the raw vibrational signal for reducing the effects of the non-stationary properties which is considered as noise. J48 algorithm was used for feature selection and the Naïve Bayes algorithm was used for feature classification. The classification process shows 93.33% accuracy.

In future, this work will help especially for TSA-IAS combined approach of the gearbox fault diagnosis. This work is also useful for various AI-based hybrid approaches of rotary machinery fault diagnosis. This concept can be applied to mathematical modelling of gearbox for a theoretical understanding of gearbox vibration analysis.

Acknowledgements

This research was supported by Dynamics and Vibration Lab, IIT Patna.

References

[1] Y. Lei, J. Lin, Z. He, M.J. Zuo, A review on empirical mode decomposition in fault diagnosis of rotating machinery, Mech. Syst. Sign. Process. 35 (1) (2013) 108–126.

[2] Z. Peng, W.T. Peter, F. Chu, A comparison study of improved Hilbert–Huang transform and wavelet transform application to fault diagnosis for rolling bearing, Mech. Syst. Sign. Process. 19 (5) (2005) 974–988.

[3] R. Yan, R.X. Gao, X. Chen, Wavelets for fault diagnosis of rotary machines: a review with applications, Sign. Process. 96 (2014) 1–15

[4] W. Zhao, Y. Zhang, Y. Zhu, Diagnosis for transformer faults based on combinatorial Bayes network, in 2nd International Congress on Image and Signal Processing, 2009, CISP'09, IEEE, 2009, pp. 1–3

[5] J. Seshadrinath, B. Singh, B. Panigrahi, Vibration analysis based inter-turn fault diagnosis in induction machines, IEEE Trans. Ind. Infor. 10 (1) (2014) 340–350.

[6] V. Muralidharan, V. Sugumaran, A comparative study of Naïve Bayes classifier and Bayes net classifier for fault diagnosis of monoblock centrifugal pump using wavelet analysis, Appl. Soft Comput. 12 (8) (2012) 2023–2029.

[7] P.H. Nguyen, J.-M. Kim, Multi-fault diagnosis of rolling element bearings using a wavelet kurtogram and vector median-based feature analysis, Shock Vib. 2015 (2015) 14, https://doi.org/10.1155/2015/320508, Article ID 320508

[8] X. Wan, D. Wang, W.T. Peter, G. Xu, Q. Zhang, A critical study of different dimensionality reduction methods for gear crack degradation assessment under different operating conditions, Measurement 78 (2016) 138–150

[9] J. Rafiee, F. Arvani, A. Harifi, M. Sadeghi, Intelligent condition monitoring of a gearbox using the artificial neural network, Mech. Syst. Sign. Process. 21 (4) (2007) 1746–1754

[10] M. Mrugalski, M. Witczak, J. Korbicz, Confidence estimation of the multi-layer perceptron and its application in fault detection systems, Eng. Appl. Artif. Intell. 21 (6) (2008) 895–906.

[11] A. Sadeghian, Z. Ye, B. Wu, Online detection of broken rotor bars in induction motors by wavelet packet decomposition and artificial neural networks, IEEE Trans. Instrum. Meas. 58 (7) (2009) 2253–2263

[12] J. Sanz, R. Perera, C. Huerta, Gear dynamics monitoring using discrete wavelet transformation and multi-layer perceptron neural networks, Appl. Soft Comput. 12 (9) (2012) 2867–2878

[13] P. Jayaswal, S. Verma, A. Wadhwani, Application of ann, fuzzy logic and wavelet transform in machine fault diagnosis using vibration signal analysis, J. Qual. Maint. Eng. 16 (2) (2010) 190–213

[14] K. Salahshoor, M. Kordestani, M.S. Khoshro, Fault detection and diagnosis of an industrial steam turbine using a fusion of SVM (support vector machine) and ANFIS (adaptive neuro-fuzzy inference system) classifiers, Energy 35 (12) (2010) 5472–5482

[15] M. Saimurugan, K. Ramachandran, V. Sugumaran, N. Sakthivel, Multicomponent fault diagnosis of a rotational mechanical system based on decision tree and support vector machine, Expert Syst. Appl. 38 (4) (2011) 3819–3826

[16] P. Konar, P. Chattopadhyay, Bearing fault detection of induction motor using wavelet and support vector machines (SVMs), Appl. Soft Comput. 11 (6) (2011) 4203–4211

[17] X. Tang, L. Zhuang, J. Cai, C. Li, Multi-fault classification based on support vector machine trained by chaos particle swarm optimization, Knowl.-Based Syst. 23 (5) (2010) 486–490