World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:10, No:3, 2016

Elman Neural Network for Diagnosis of Unbalance in a Rotor-Bearing System

S. Sendhilkumar, N. Mohanasundaram, M. Senthilkumar, S. N. Sivanandam

***Abstract*—**The operational life of rotating machines has to be extended using a predictive condition maintenance tool. Among various condition monitoring techniques, vibration analysis is most widely used technique in industry. Signals are extracted for evaluating the condition of machine; further diagnostics is carried out with detected signals to extend the life of machine. With help of detected signals, further interpretations are done to predict the occurrence of defects. To study the problem of defects, a test rig with various possibilities of defects is constructed and experiments are performed considering the unbalanced condition. Further, this paper presents an approach for fault diagnosis of unbalance condition using Elman neural network and frequency-domain vibration analysis. Amplitudes with variation in acceleration are fed to Elman neural network to classify fault or no-fault condition. The Elman network is trained, validated and tested with experimental readings. Results illustrate the effectiveness of Elman network in rotor-bearing system.

***Keywords*—**Elman neural network, fault detection, rotating machines, unbalance, vibration analysis.

I. Introduction

THE earliest known type of breakdown maintenance was run-to-failure, where the machine was forced to run until the occurrence of fault. A sizeable portion of the total cost to be attended by this traditional process is considered as rather expensive. It is surprising to visualize how much of present day maintenance activity is of this type. Eventually, maintenance people hit on the thought of periodic preventive maintenance, where machines are disassembled and overhauled on accepted schedules. The assumption is that when machines are renovated before their predictable life, they do not stop service. Predictive maintenance has become popular in the last decade, where the machine is repaired only when it is recognized with a fault. Among the available predictive maintenance techniques, condition monitoring was used universally. Analysis of machines using vibration analysis is a versatile process among condition monitoring techniques.

Imbalance results when the center of the mass of a rotating component does not coincide with the center of rotation. It is practically impossible to fabricate a system which is perfectly balanced; hence, unbalance is a relatively common condition in rotating machines. The causes of unbalance can be due to excess of mass on one side of the rotor, material defects, aerodynamic forces, and changes in temperature. Excessive bearing wear, fatigue in supports, losses in power and disturbances occur due to the presence of unbalance. Heavy vibration occurs radially at 1X harmonic of the running speed and being predominant one compared to other harmonics. The reliable estimation of the state of the rotor unbalance combining amplitude and phase from a single run-down in a possible procedure is explained and suggested by [1]. Further, the interaction between friction induced vibrations and self-sustained lateral vibrations caused by mass-unbalance in an experimental rotor dynamic set-up is stated clearly [2]. Investigation is performed using numerical and experimental bifurcation analyses and the result illustrates a higher level of mass-unbalance, which generally increases lateral vibrations. A neural network simulator is developed and its usage for fault prediction of rotating machinery is illustrated with the help of back propagation learning algorithm [3], adaptive resonance theory (ART) and the learning strategy of Kohonen neural network (KNN) [4]. The success rate of network is also evaluated and compared with other networks. The purpose of neural networks and their applications can be extended towards condition monitoring of bearings [5], dynamic behavior of rotating systems [6]. The presence of vibration in a mechanical system is predicted, trained and tested using the backpropagation neural network for different amplitudes with variations in acceleration [7]. Investigation has been done to compare the performance of bearing fault detection using the various types of artificial neural networks and its relative effectiveness have been illustrated in detail [8], [9]. A neural network approach has been employed for detecting the rotating machinery faults using the feed forward neural network with the nonlinear neurons which can diagnose more than 40 faults in the system [10], using a proposed Elman Neural Network (ENN) [11], [18]. A cost effective method is based on ENN for predicting the anti-germ performance in detergents [15]. The following sections of this paper discuss the diagnosis of unbalance in a single disk rotor-bearing model using frequency domain and ENN.

II. Experimental Setup

The experimental setup shown in Fig. 1 consists of an AC motor, a self designed coupling, a single-disk rotor. The rotor shaft of length 900 mm is supported by three pillow radial bearings of bearing span of 500 mm from the non drive end and another span of 200 mm from the coupling end. The

S. Sendhilkumar and S. N. Sivanandam are with the Karpagam Institute of Technology, Coimbatore, India (phone: +919486172845, e-mail: ssk333c@yahoo.co.in).

N. Mohanasundaram is with the Karpagam Institute of Technology, Coimbatore, India (e-mail: itismemohan@gmail.com).

M. Senthilkumar is with the Production Engineering Department, PSG College of Technology, Coimbatore, India (e-mail: msenthil_kumar@hotmail.com).

diameter of rotor shaft is 12 mm holding a disk of outer diameter 50 mm, weighing 886 grams with provision for introducing unbalance is mounted on the mid-way of the bearing supports [12]. The necessity of self designed coupling is to differentiate between the driver and driven unit of test rig. The bearing pedestals and motor support are firmly mounted on steel base plates. Using radial screws, the disk is fixed on the rotor shaft and the variation of speed is measured using tachometer.

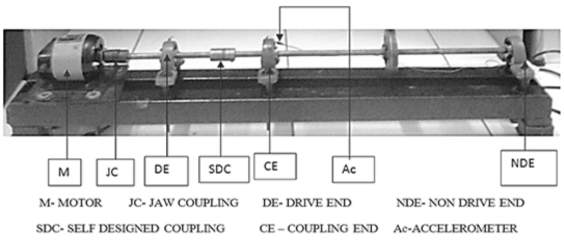


Fig. 1 Experimental setup

A. Instrumentation Used

The instrumentation used in the experiments includes a non-contact accelerometer with voltage range of ±5 V, dynamic range of over 100 dB. Data rates on input channels of USB-9233 range from 2 to 50 kHz, and with a sensitivity of 0.9 g. An effective continuous signal extraction system is developed for monitoring the rotor signatures using LABVIEW software with NI sound and vibration tool kit. The extracted signals are diagnosed with the help of time domain analysis like RMS and PEAK to PEAK and frequency domain analyses like power spectrum analysis.

B. Error Back Propagation Algorithm

Error back propagation algorithm consists of two passes through different layers of network: A forward pass and a backward pass. In the forward pass, input vector is applied to the input node of network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as actual response of the network. The synaptic weights of networks are fixed during forward pass. The backward pass starts at the output layer by passing error signals leftward through the network and recursively computing the local gradient for each neuron. This permits the synaptic weights of network to be all adjusted in accordance with an error-correction rule. The algorithm is stopped when the error has become small and within the set tolerance error value. Finding the best set of weights and biases for the neural network is the objective of training and is an iterative process. For each iteration, back-propagation algorithm computes a new set of neural network weight and bias values generates output values which are closer to the target values. So, Back-propagation algorithm calculates the gradient of the error and then propagates the error backward through the network for modifying the weights and biases [13], [17].

C. ENN

A recurrent network [14] has a context layer containing context units with a fixed weight of 1 such that contents of hidden layer are copied to context layer on a one-to-one basis [11], [13], [16] is shown in Fig. 2 called ENN. The context units save previous output values of hidden layer neurons and are fed back fully connected to hidden layer neurons and hence serve as additional inputs to the network. The operation of network is performed with the current input from input layer along with neurons saved in the context layer and passed to hidden layer, which processes them and passes to output layer. In this paper, neural networks have been used to perform fault diagnosis based on extracted information features. Back propagation algorithm (BP) is used as a learning algorithm as it is straightforward for implementation and, most importantly, often performs well in comparison to other methods [8]. The neural network has been developed in MATLAB.

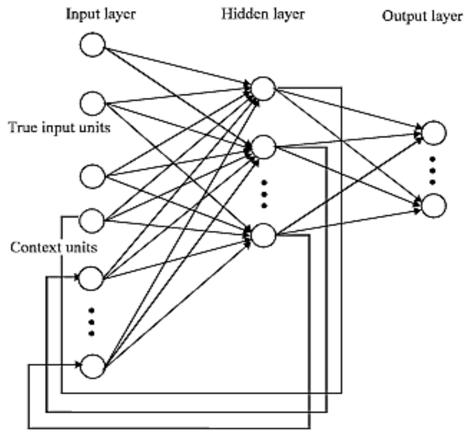


Fig. 2 ENN

D. Training, Modelling and Simulation of ENN

ENN is trained and supervised using the Error Back Propagation algorithm which updates input–hidden, hidden–output, and context–hidden weights to reduce the difference between the output of the output layer and the desired output for various levels of unbalance. The desired outputs are necessary and serve as a reference to calculate errors. The algorithm stops when the error is of negligible value and lies within the set tolerance error value. Modelling and simulation of the Elman Network are executed using MATLAB and the architecture of the ENN and its parameters is shown in Table I. For binary inputs, the data may be represented in binary form (0, 1) or bipolar form (-1, 1). The output of a neuron depends on factor 'input x weight'. If input is '0' then output may be of a small value and Gradient may be constant which results in a long period of Convergence or the total absence of any convergence implies learning can be improved that if input is in the bipolar form (1,-1). Back propagation network with n different weights w_1, w_2, .., w_n, and the i-th correction for weight w_k is given by

$$\Delta w_k(i) = -\gamma\, \partial E\, \partial w_k + \alpha\, \Delta w_{k\,(i-1)} \quad (1)$$

where γ and α are the learning rate and momentum factor respectively. Accelerating the convergence to a minimum of the error function can be done by increasing the learning rate up-to the optimal value. Reduction in oscillations occurs due to the introduction of a momentum rate during the process of iteration. The best possible convergence can be achieved by either trial and error or a random search of tuning the learning parameters. Since the optimal parameters are highly dependent on learning task, no general strategy can be developed to deal with this kind of problems. When the learning rate is less, progress of learning is very slow with high accuracy. More oscillations in error are produced with low accuracy and fast convergence, when the learning rate is high.

E. Input Parameters for NN

Three levels of unbalance (0.032, 0.064, 0.096 gr) are introduced at a radius of 30 mm in the rotor disk. All experiment tests were conducted at speeds of 500 rpm, 1000 rpm, 1500 rpm and 2000 rpm respectively to record the acceleration at bearing locations. For each speed, 1024 samples are extracted per second using NI USB-9233 accelerometer. Parameters of vibration are extracted from the bearing locations in the vertical direction. The network is modelled as a two-class problem, trained and tested accordingly, which informs the presence or absence of any fault. Among the captured vertical signal data sets from the bearing location, (1024 x6) data set were used for training and remaining (1024 x3) data sets were used for testing of the network at 900 rpm, three different location of unbalance plane. The analysis is conducted for learning rates of 0.1, 0.2 and 0.3. Even for a learning factor of 0.2, there is no convergence of results and the error is high. Oscillations of a large number are witnessed when the learning rate is high. The momentum factor is introduced to make the learning faster by arresting the oscillations. When it is set lesser than 0.9 the convergence is very slow or does not converge. In this research work, the learning rate is set to be 0.1 and momentum factor is set to be 0.9. The number of hidden layer neurons plays a vital role in the performance of the diagnosis. There is no hard and fast rule for finalizing the number of hidden layers neurons. If more number of neurons is present, the calculations of error may take time and the rate of convergence could be slower.

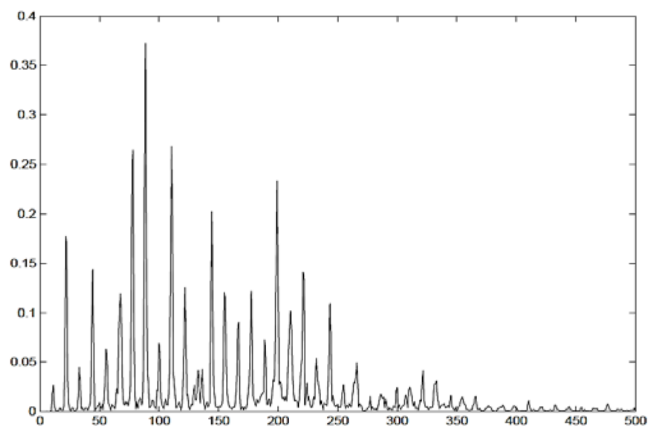
TABLE I
ARCHITECTURE OF ENN

Number of Input Neurons		1
Number of Output Neurons		2
Number of Hidden Layers		1
Number of Hidden Neurons		Varied to find optimum (3,5,7,9,11,13,15)
Activation Function	Input Hidden Layer	TAN Sigmoid
	Output Layer	Linear
Performance function (error)		MSE (Mean Square Error)
Training Algorithm		Back Propagation
Learning Rate		0.1
Momentum factor		0.9

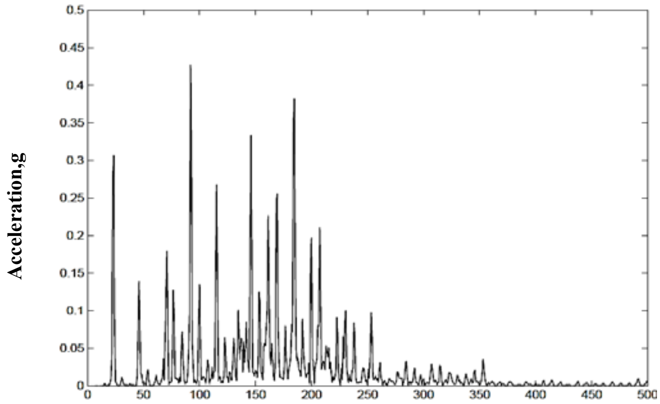
Accuracy is not possible when the number of hidden neurons is less than 3 that is why the hidden neuron starts from 3 and is increased later to 5,7,9,11,13 and 15. When the number of hidden neurons goes beyond 11, the number of epochs (learning time) is much more. Considering the above discussed aspects the architecture of neural network is designed and shown in Table I.

III. RESULTS AND DISCUSSIONS

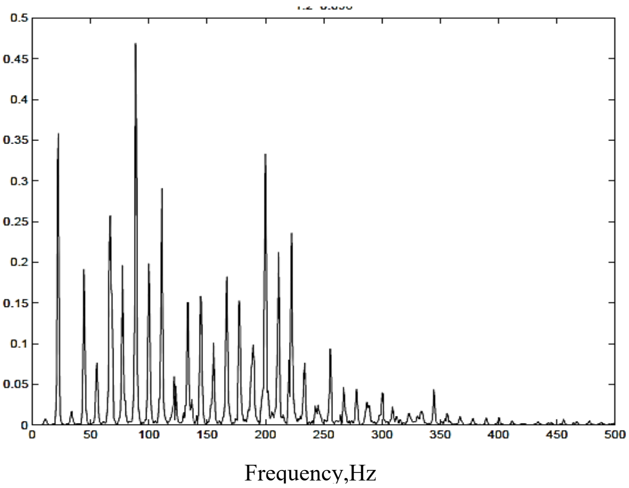
The effects of unbalance are investigated using a test rig as shown in Fig. 1. The shaft must first be balanced manually. After achieving a perfect balance in offline conditions, a base line data is generated at an aligned condition which can be used for further comparison after introducing unbalance. Spectral comparisons are made across the three bearing stations. The variation of spectrum is illustrated in Fig. 3 for variation of unbalance. Fig. 3 illustrates the spectrum of acceleration at a speed of 4000 rpm for various unbalance with rotor at the mid of two bearings. The maximum magnitude of acceleration occurs in range of 75-85 Hz with a value of 0.35 m/s^2, 0.42m/s^2, 0.45 m/s^2 for 4000 rpm with 0.032 gr, 0.064 gr, 0.096 gr of unbalance variation respectively. The maximum magnitude arises still earlier in comparison to the previous condition as unbalance is varied. For each condition the amplitude of vibrations is measured and is plotted where the horizontal axis is frequency in orders of RPM. Speed seems to have the most dominant effect on vibration spectra and severity. The various acceleration spectrums are shown in Figs. 3 (a) and (b) for rotor at the middle of two bearings with varying amount of unbalance for different speeds. The spectrum of test rig without any unbalance is taken as base spectrum for further comparison with varying unbalance. Fig. 3 shows the spectrum has 1X components predominant one which is due to presence of unbalance. The experiment is conducted for 13 different varying speeds, 60% data is considered for training of network, parameters for 20% is considered for testing, parameters for 20% is considered for validating network. The developed NN model comprises of 1 input neurons, 3/5/7 hidden neurons and 2 output neurons, weighting factor W_1 is either 3x3 or 3x5 or 3x7, bias function is 3x1 or 5x1 or 7x1, activation function is TAN Sigmoid, weighting factors W_2 is 3x2 or 5x2 or 7x2 and bias function is 2x1 and linear activation function.



(a) Unbalance 0.032 gr



(b) Unbalance 0.064 gr



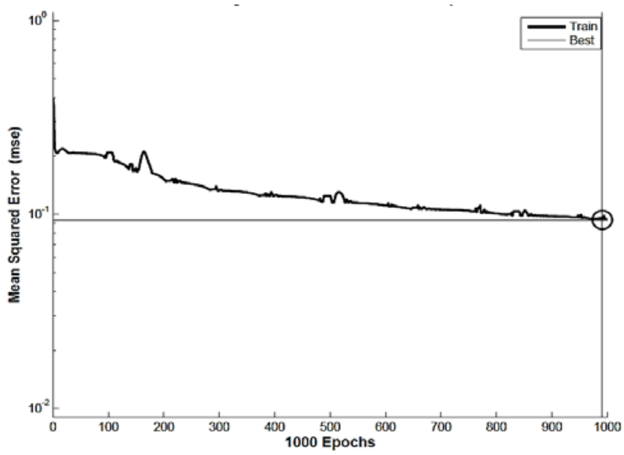
(c) Unbalance 0.096 gr

Fig. 3 Spectrum of acceleration for various unbalance

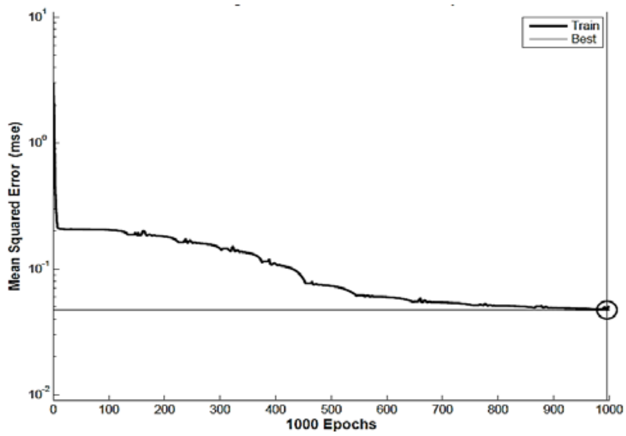
TABLE II
NETWORK OUTPUT

No of Hidden Neurons	3		5		7		9		11	
	Actual Classes									
Predicted Classes	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**	**0**	**1**
0	0	0	0	29	0	10	0	4	0	43
1	28	996	30	965	28	986	26	934	28	952
Precision	0	0.97	0	0.97	0	0.97	0	0.97	0	0.97
Sensitivity	0	1	0	0.97	0	0.99	0	1	0	0.96
Specificity	1	0	0.97	0	0.99	0	1	0	0.96	0
Mean Square Error	0.093785		0.0471		0.047911		0.061533		0.093644	
Accuracy	0.97		0.97		0.96		0.97		0.93	
Epochs	991		996		998		999		1000	

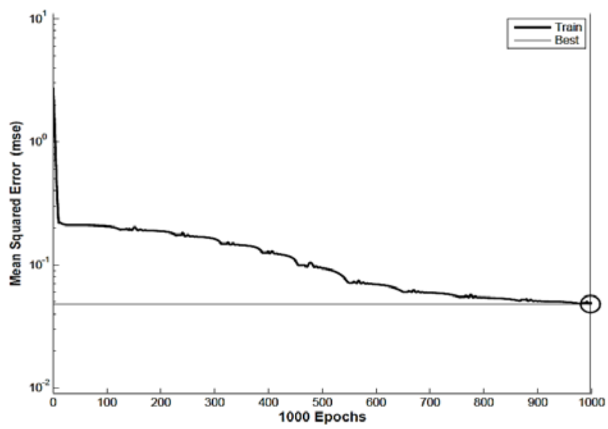
The performance of the developed neural network model was tested using data generated by MATLAB. The set of input values which are used to train the network is around (1024 x 6) and for testing around (1024 x 3). The performance for each hidden layer is studied and its performance curves are shown in Fig. 4 and it is tabulated in Table II. The setting of different values to network parameters and the effects are presented in Table II. The convergence is shown in Fig. 5. The accuracy is also computed on the basis of the number of instances in which classification is correct. An accuracy of 97% is achieved with 5 hidden neurons with 0.0471 mean square error at 996 epochs. In the case of 7 hidden neurons, the accuracy is 96.67% at 998 epochs with the same mean square error. Though both 5 and 7 hidden neurons provide the same value of mean square error, but the training time for 7 is greater than 5, hence the optimized result of unbalance is provided by the network with 5 hidden neurons.



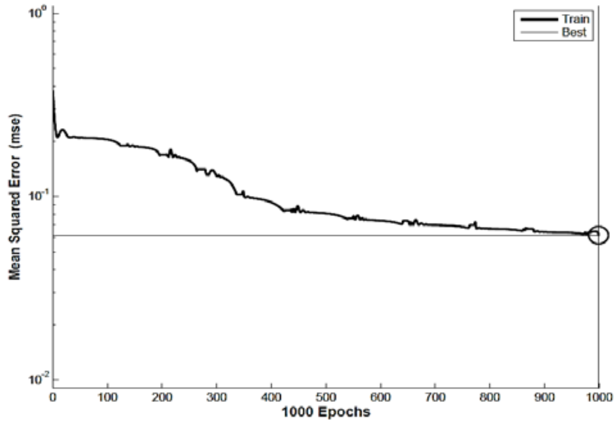
(a) NH-3, Epochs-991



(b) NH-5, Epochs-996



(c) NH- 7, Epochs-998



(d) NH- 9, Epochs-999

Fig. 4 Training Curves for different hidden neurons

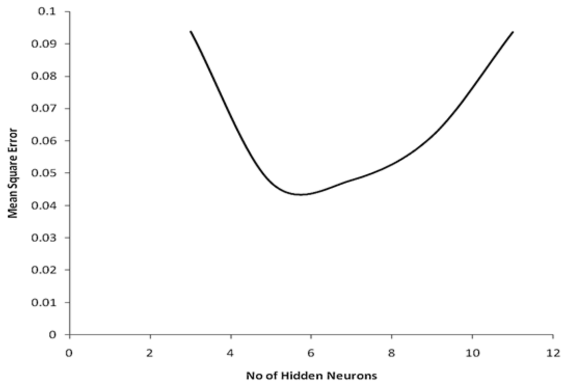


Fig. 5 Performance curve of network model

IV. Conclusions

A test rig with various possibilities of defects is constructed and experiment is performed and investigated. The results are validated with respect to the vibration severity chart. The reasons for unbalance are discussed in this paper. This paper presents a procedure for identification of the unbalance using an artificial neural network. Based on neural network results the optimum results are achieved when number of hidden neurons is 5, learning rate is 0.1 and momentum factor is 0.9. ENN classifies the presence of fault or no fault in system for all the hidden neurons. Classification of fault is accurate and precise when the network possesses 5 hidden neurons, 0.0471 as mean square error and 996 epochs. Vibration analysis can determine the excitation forces in a machine during its processes. These forces are dependent upon machine condition, and knowledge of their characteristics and interactions allows diagnosis of a machine problem. The efficiency and effectiveness of classification are based on faster convergence and accuracy.

References

[1] J. K. Sinha., A. W. Lees., M. I. Friswell., Estimating unbalance and misalignment of a flexible rotating machine from a single run-down. Journal of Sound and Vibration, 2004, p. 967-989.

[2] N. Van de Wouw, H. Nijmeijer and N. Mihajlovic., On The Coupling Between Torsional and Lateral Vibrations In A Rotor Dynamic System With Set-Valued Friction. ASME 2007 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, September 4-7, 2007.

[3] N. S. Vyas, D. Sathishkumar, Artificial neural network design for fault identification in a rotor-system. Mechanism and Machine Theory, Volume 36, 2001, p. 157-175

[4] B. S. Yang, T. Han, J. L. An, ART-KOHENEN neural network for fault diagnosis of rotating machinery, Mechanical Systems and Signal Processing, Volume 18, 2004,p. 645-657.

[5] David Baillie and Joseph Mathew, Diagnosing rolling element bearing faults with artificial neural networks, Acoustics Australia, Volume 22, Issue 3, p. 79-84

[6] M. Kalkat, S. Yildirim, I. Uzmay, Rotor Dynamics Analysis of Rotating systems using Artificial neural networks, International journal of rotating machinery, Volume 9,2003, p. 255-262.

[7] M. Kalkat, S. Yildirim, I. Uzmay, Design of artificial neural networks for rotor dynamics analysis of Rotating machine systems, Mechatronics, Volume 15, 2005, p. 573-588.

[8] B. Samanta, Khamis R. Al-balushi, Saeed A. Al-Araimi, Bearing fault detection using artificial neural networks and genetic algorithm, EURASIP Journal of Applied signal Processing, Volume 3, 2004, p. 366-377.

[9] H. Taplak, S. Yildirim, I. Uzmay, Design of artificial neural networks for rotor dynamics analysis of Rotating machine systems, Journal of scientific and industrial research, Volume 64, 2005, p. 411-419.

[10] H. Navhi, M. Esfahanian, Fault identification in rotating machinery using artificial neural networks, Proceedings of the Institution of Mechanical Engineers, Part-C Journal of Mechanical Engineering Science, 2005,219, p. 141-158.

[11] Elman, J. L., Finding Structure in Time. Cognitive Science Volume 14, Issue 2, 1990, p. 179–211.

[12] M.Senthil Kumar, S.Sendhil Kumar, Condition monitoring of rotating machineries through vibration analysis, Journal of Scientific and Industrial Research, 0022-4456,Vol 73, April 2014, p. 258-261

[13] ZhiQiang Zhang, Zheng Tang and Catherine Vairappan, A Novel Learning Method for Elman Neural Network Using Local Search, Neural Information Processing – Letters and Reviews, Vol. 11, No. 8, 2007.

[14] D. L. Wang, X. M. Liu and S. C. Ahalt, On temporal generalization of simple recurrent networks," Neural Networks, Volume 9, 1996, pp. 1099-1118.

[15] Anqi Cui, Hua Xu , Peifa Jia, An Elman neural network-based model for predicting anti-germ performances and ingredient levels with limited experimental data, Elsevier Expert Systems with Applications, Volume 38, 2011, p. 8186–8192.

[16] Cheng-Yuan Liou, Jau-Chi Huang, Wen-Chie Yang, Modelling word perception using the Elman network, Elsevier Neurocomputing, Volume 71, 2008, p.3150– 3157.

[17] Zhihang Tang, Rongjun Li, An Improved Neural Network Model and Its Applications", Journal of Information & Computational Science Volume 8, Issue 10, 2011, p. 1881–1888.

[18] Junru Gao, Yuqing Wang, The Research on the Methods of Diagnosing the Steam Turbine Based on the Elman Neural Network, Journal of Software Engineering and Applications, Volume 6, 2013, p. 87-90