Performance Analysis of Expert Systems Incorporating Neural Network for Fault Detection of an Electric Motor

M. Khatami Rad, N. Jamali, M. Torabizadeh, and A. Noshadi

Abstract—In this paper, an artificial neural network simulator is employed to carry out diagnosis and prognosis on electric motor as rotating machinery based on predictive maintenance. Vibration data of the primary failed motor including unbalance, misalignment and bearing fault were collected for training the neural network. Neural network training was performed for a variety of inputs and the motor condition was used as the expert training information. The main purpose of applying the neural network as an expert system was to detect the type of failure and applying preventive maintenance. The advantage of this study is for machinery Industries by providing appropriate maintenance that has an essential activity to keep the production process going at all processes in the machinery industry. Proper maintenance is pivotal in order to prevent the possible failures in operating system and increase the availability and effectiveness of a system by analyzing vibration monitoring and developing expert system.

Keywords—Condition based monitoring, expert system, neural network, fault detection, vibration monitoring.

I. INTRODUCTION

NOWADAYS, diagnosis and fault detection for rotatory machinery is a major problem in automation processes due to the faults may cause the machine to break down and decrease its efficiency and performance. Therefore, in order to keep the machine performing at its best condition and avoid malfunction, different methods of fault diagnosis have been developed and used to detect the system failure at an early stage. Maintenance has been considered as an essential activity to keep the production process going. For maintenance planning, some tools such as total productive maintenance (TPM), reliability centered maintenance (RCM), condition based maintenance (CBM) and root cause analysis are sometimes offered as all encompassing solution [1].

One of the best strategies for fault detection is condition based maintenance (CBM) according to vibration analysis tool and it is based on detecting initial failures. Generally, CBM

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can prevent failures from happening at a bad time and fix it before it causes damage. Once the failure has been initiated, this methodology allows trend monitoring and prediction of function failure. Expert systems can be adapted for machine condition based monitoring data interpretation due to the ability to identify systematic reasoning processes. The use of expert systems would allow a greater analysis throughput as well as enabling technicians to perform routine analysis. Some techniques can be used such as neural network, fuzzy logic, and genetic algorithm to identify the model of the system for predicting the failure [2].In this paper, condition based maintenance is utilized to a small size electric motor as our case study using vibration monitoring in alliance with neural network as an expert system for system identification. Neural Network (NN) is the functional imitation of a human brain, which is able to simulate the human decision-making and draws conclusions even when is faced with noisy, complex, and irrelevant information. In neural network, any non-linear system can be modeled NNs without having to acquire knowledge of its actual structure[3].

II. VIBRATION ANALYSIS AND NETWORK DESIGN

Vibration analysis is a technique that follows the condition of machinery operation and its aim is to find possible failure in system [4]. Vibration analysis consists of vibration measurement and its interpretation. In the first part, vibration signals are collected by a sensor in time domain and then these signals are changed into frequency domain. In next step, the collected information from vibration signals can be used to predict catastrophic failures and to increase the lifetime of system respectively [5],[6]. Vibration data of each failed motor was measured and collected in time domain separately, then obtained vibration data has been transformed into frequency domain via Fast Fourier Transform (FFT). Then, vibration data were used to model the system and create an expert system in order to identify the probability of failure and to design improvement alternatives using Neural Network.

Electric motor, due to the rotating nature of its internal components, produces vibrations. So, Accelerometers were used to measure the vibration of motor's components. Accelerometers strategically placed in points next to the motor and allow acceleration of the machine over time to be measured. Therefore, the accelerometer was placed on a vertical, horizontal and axial position on the top part of the electric motor and shows the measurement [7].

World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:5, No:12, 2011

There are many different failures for electric motor, but the most important failures are due to unbalance, misalignment, and bearing fault [8]. In order to design an expert system to be able to predict the failure of electric motor, vibration data of three failed motor related to unbalance, misalignment, and bearing were measured and fed into NN correspondingly to train and test the network. With the obtained data from three different motors, the neural network can be applied for the system identification and modelling. Once the system designed and modelled accurately using neural network, it can be used as an expert system to determine the probability of failure of a working motor when operator measures the vibration of motor and feed the data to the neural network modelled system.

In the case of feed-forward NN training it is necessary to present not only input vectors but also target outputs. For the three-output detectors these outputs were defined as follows:

- [1; 0; 0]: for an unbalance problem
- [0; 1; 0]: for a misalignment problem
- [0; 0; 1]: for a bearing fault

There are two input nodes namely frequency and amplitude, each node related to a moment input; and an output layer consisting of three nodes, each node corresponding to one of the three primary faults under consideration (see Fig. 1). The number of hidden layers can be varied. The number of neurons in each hidden layer can also be varied.
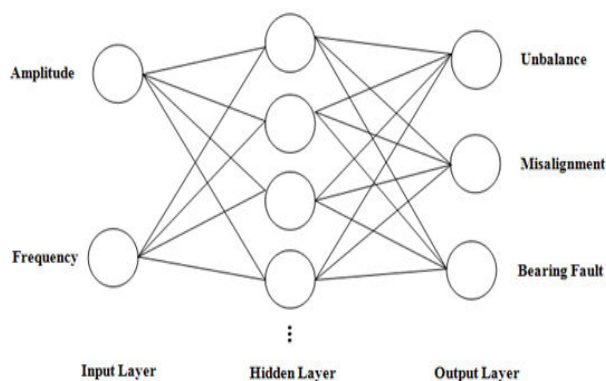

Fig. 1 Schematic diagram of NN

Once the learning process starts, the neural network is so designed that the weights and the thresholds between different layers adjust automatically, so as to minimize the mean square error, between the actual network output and the targeted output. In minimizing the error, the other network parameters like moment, learning rate, number of hidden layers and nodes in each layer are to be adjusted [9].

III. NETWORK TRAINING AND TESTING

In this paper, an expert system is developed using Neural network (NN) to identify electric motor failures. MATLAB software package was utilized for design and develop the system using neural network. Neural network was chosen because of its ability to model a multi-input multi-output (MIMO) system and predict the future outputs from the modeled network. As a matter of fact, neural network has privilege on solving classification, identification, and forecasting problems based on historical data. Different types of neural network topologies have been tested to find the best model for the system. The developed model measures the vibration of an electric motor and extracts necessary information to be fed to a neural network in order to train it. The output of the neural network is statistically analyzed to come up with a failure prediction.

All steps for applied NN are as follow in summary:

- Initialize weights and bias units to small values

- Input layer uses a tansig transfer function with (2×84) inputs

- Hidden layer with 10 and 20 hidden neurons (uses a tansig transfer function) and output layer has (3×84) output units

- Gradient descent back-propagation to find optimised weights and bias units of each layer

- Simulate network for a normal input data to validate and test the modeled network

The network designed for this case consists of (2×84) inputs i.e. failures' frequencies and their corresponding amplitudes, four hidden layer and each layer with 10 hidden neurons, (3×84) outputs i.e. three different failures, two training function such as a Bayesian regulation back propagation training function (trainbr) and Gradient descent with momentum back propagation (traingdm) for comparative study, and the learning function which hyperbolic tangent sigmoid function (Tansig) was used. The NN designed for traingdm and trainbr are shown in Figs. 2 and 3 respectively.
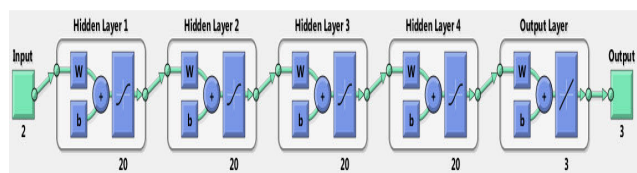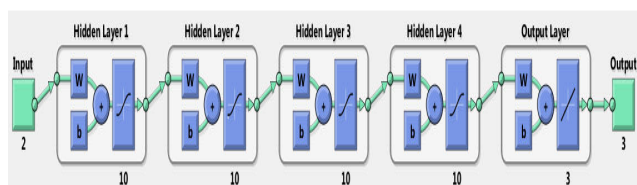

Fig. 2 Traingdm Network

Fig. 3 Trainbr Network

World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:5, No:12, 2011

IV. NEURAL NETWORK RESULTS

Each input was associated with a type of failure. For instance, first 28 inputs for unbalance motor, second 28 inputs for misalignment motor, and third 28 inputs for bearing fault. Then, inputs were fed into the NN for system modelling and for this reason characteristic of each fault should be shown in the form of binary in output.In fact, for first 28 inputs, the suitable output of 1 should be assumed. Output 2 should be assumed one for 28 to 56 inputs, and also output 3 for input 56 to 84 should be assigned one as well. Hence, system could be modelled with different NN and various training such as traingdm and trainbr and two most accurate results will be shown in the following figures.

Figs. 4 to 6 show the effect of using traingdm training function and using different neural network configurations. Fig. 4 indicates the results obtained from modelling the system using traingdm training function for unbalance motor. In fact, for first 28 inputs of the network, the corresponding outputs should be 1 and for the rest of data the corresponding output should be 0. In other word, the trained output1 (dash line) which represents the model of unbalance motor should be matched to the desired output1 then the system is said to be modeled accurately.
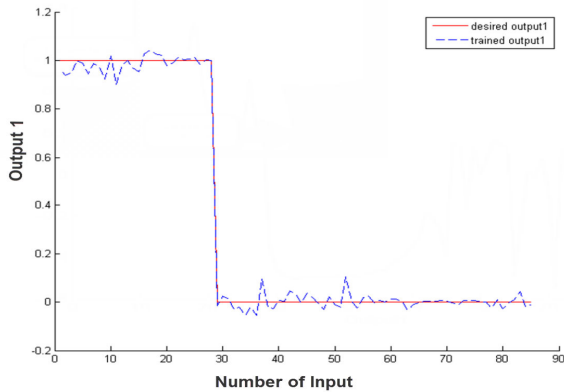

Fig. 4 Accuracy of traingdm for unbalance motor

Fig. 5 shows the trained network using traingdm for misalignment failure. The second 28 data in the Fig. 5 should be 1 to represent the misalignment failure. In other word, the trained output2 (dash line) should be matched to the desired output2.
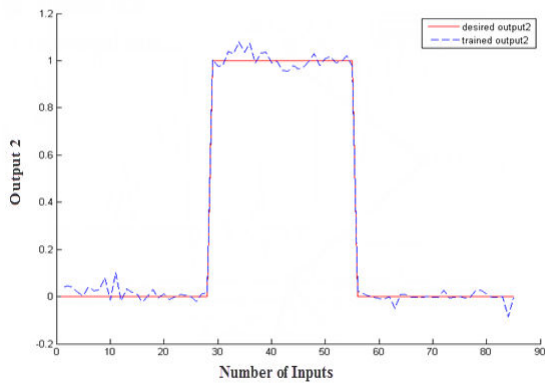

Fig. 5 Accuracy of traingdm for misalignment motor

Desired and actual outputs of the failed system due to bearing fault are depicted in Fig. 6. Last 28 points in the Figure should be corresponded to the 1 output that it showed the system model accurately. In other word, the trained output3 (dash line) should be matched to the desired output3.
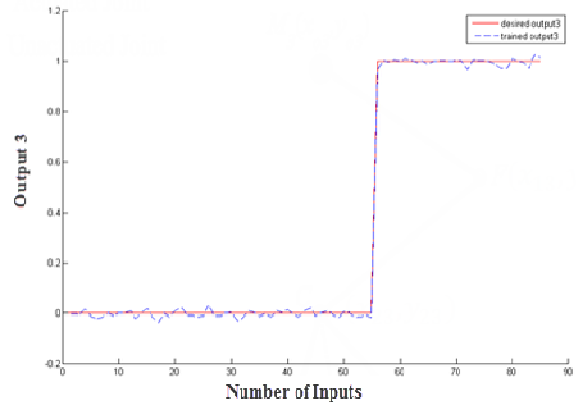

Fig. 6 Accuracy of traingdm for bearing fault

Fig. 7 shows accumulative errors of three trained and desired outputs for traingdm.
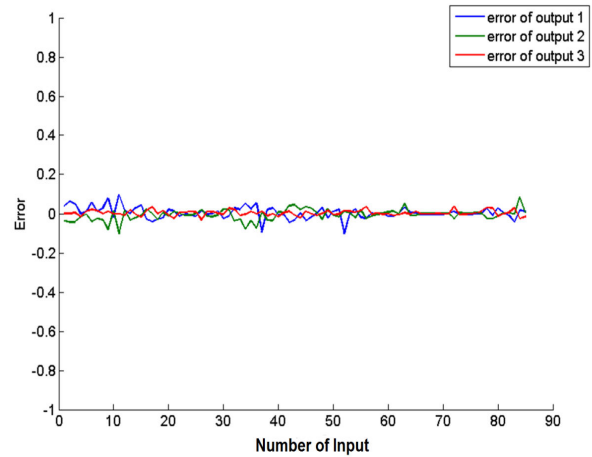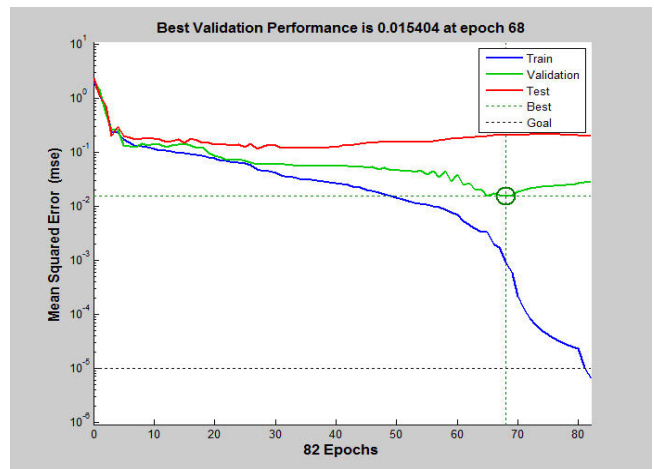

Fig. 7 Accumulative errors for all outputs

Fig. 8 Traingdm performance

World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:5, No:12, 2011

Training errors, validation errors, and test errors was appeared in Fig. 8. It shows how the system was trained by NN. Each line in the Figure shows the performance improvement of system modelling using neural network in training, testing, and validation sections. Hence, the iteration continues until the optimized value of mean squared error (MSE) of the system is obtained. Also, the best performance was 0.015404 at epoch 68.

In next step, obtained reaults from second method i.e. trainbr method will be discussed. Fig. 9 shows the results obtained from trainbr method and unbalance motor. First 28 points in the Figure are supposed to be 1 to show that the system is modelled accurately. In other word, the trained output1 (dashed line) should be matched to the desired output1.
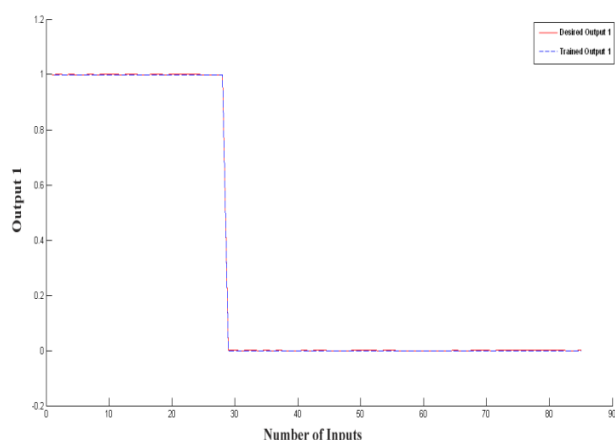

Fig. 9 Accuracy of trainbr for unbalance motor

Fig. 10 also illustrates the misalignment motor modelling using trainbr method.The second 28 inputs should be corresponded to 1 to show the system that is modelled accurately. In other word, the trained output2 (dash line) should be matched to the desired output2. Also, Fig. 11 is related to the trainbr and bearing fault. Last 28 inputs should be corresponded to 1 to show that the system is modelled accurately. In other word, the trained output3 (dash line) should be matched to the desired output3.
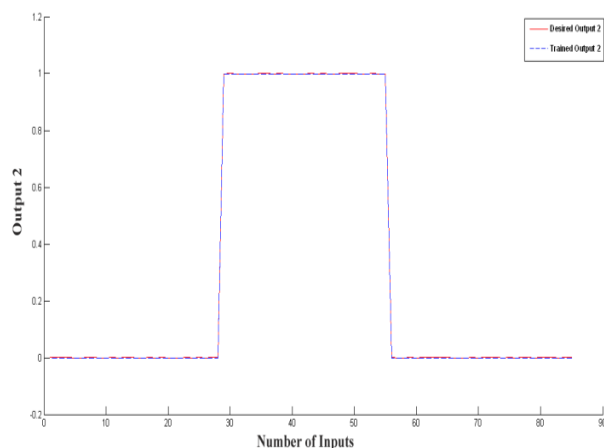

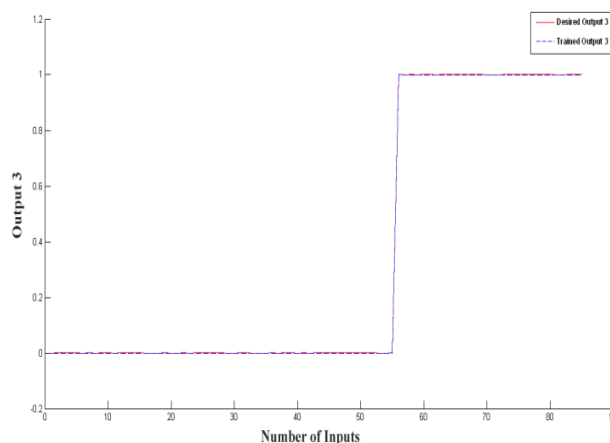Fig. 10: Accuracy of trainbr for misalignment motor

Fig. 11 Accuracy of trainbr for bearing fault

With comparing the results obtained from traingdm and trainbr method, we find out that trainbrmethod has an edge over traingdm in modellingthe corresponding system. Fig. 12 demonstrates the accumulative errors obtained from modelling the system using trainbr method.
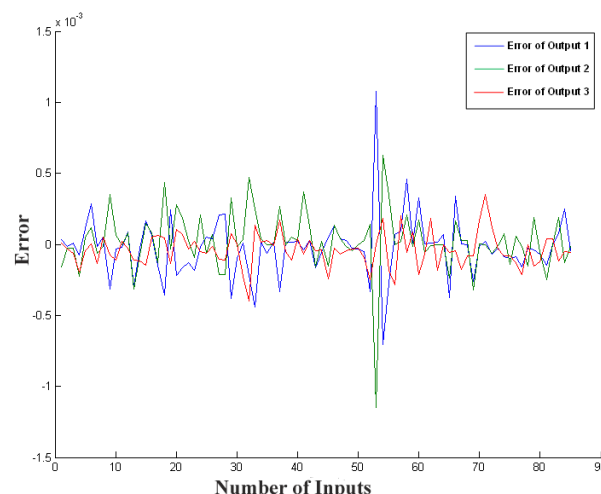

Fig. 12 Accumulative errors for three outputs

The simulation results provide further insight into the superiority of the trainbr method in modelling the electric motor with three separate failures. The results clearly demonstrate that we can predict the type of failure in the system and estimate the system lifetime using artificial neural network with appropriate required parameters.

Training errors, validation errors, and test errors of trainbr learning method appears in Fig. 13. It shows how the system was trained by neural network.

Each line in the Figure represents the system training performance over the iteration. For instance, the blue line relates to training stage, green line relates to validation, and red line relates to testing of the modeled system. Iteration continues till the optimum mean squared error (mse) of the system is obtained. From Fig. 13 can be deduced that the best validation performance was (8.8×10^{-6}) at epoch 203.

World Academy of Science, Engineering and Technology
International Journal of Mechanical and Mechatronics Engineering
Vol:5, No:12, 2011

Fig. 13: Trainbr performance

V. RESULTS VALIDATION

In order to validate the ability of the developed network in predicting the possible failures, vibration data of a failed motor with distinct failure i.e. misalignment failure should be used. Five hundred samples including amplitudes over frequency of the selected failed motor were fed into the expert system as input which had been already designed, and the results obtained from neural network are shown in Fig. 14.

As mentioned earlier, the output for each type of failure was classified according to [1; 0; 0] for unbalance motor, [0;1;0] for misalignment motor, and [0;0;1] for bearing fault respectively. Therefore, final results for validation are shown in 3-dimensional graph. Each axis represents one failure. As a matter of fact, points which located on the x-axis represent the unbalance failure of the motor, points on the Y-axis represent the misalignment motor, and position of points on the Z-axis represent the bearing fault.
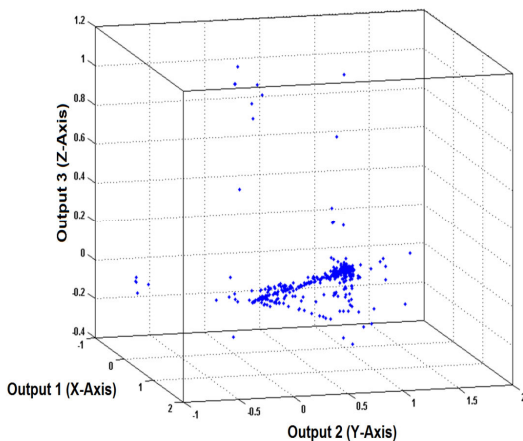
Fig. 14 Simulation result and accuracy

From Fig. 14 we deduce that the distribution of output points is highly concentrated in Y-axis and it represents the failure because of misalignment. Consequently, the expert system was validated and approved that the proposed prognosis NN method is very useful expert system for failure prediction of machinery.

VI. CONCLUSION

The main purpose of the research was to develop appropriate failure assessment parameters in condition based maintenance of electric motor and develop the suitable technique for vibration monitoring of electric motor. In this paper, condition based maintenance was applied to electric motor as the case of study, and also, neural network was applied for system identification as an expert system by using the previously obtained data from vibration monitoring of the system. Finally, simulation results successfully demonstrated that the proposed expert system could be utilized to detect the type of failure associated to electric motor and to predict the system useful lifetime.

REFERENCES

[1] V. Narayana, *Effective maintenance management.Risk and reliability strategies for optimizing performance*. Industrial Press, New York, 2004.
[2] J. Lee, R. Abujamra, A. K. S. Jardine, D. Lin, and D. Banjevic, "An integrated platform for diagnostics, prognostics and maintenance optimization", *The IMS '2004 International Conf. on Adv. Maintenance , Modeling, Simulation, Intelligent Monitoring of Degradations*, Arles, France, 2004.
[3] M. Y. Chow and S. O. Yee, "Methodology for On-line Incipient Fault Detection in Single-phase Squirrel - Induction motors using Artificial Neural Networks", *IEEE Trans, on Energy Conversion,* vol. 6,no.3, September 1991.
[4] J. T. Renwick and P. E. Babson, "Vibration analysis-a proven technique as a predictive maintenance tool". *IEEE Trans. Industrial Applications,* vol. 21, no. 2,pp. 324-332, 1985.
[5] I. E. Alguindigue, L. A. Buczak, and R. E. Uhrig, "Monitoring and diagnosis of rolling element bearings using artificial neural networks." *IEEE Transaction of Industrial Electronics,* vol.40, no. 2, pp. 209-217, 1993.
[6] M. AbdKadir, S. Sharifah, and H. Takashi, "Predicting remaining useful life of rotating machinery based artificial neural network, "*Computers and Mathematics with Applications,* vol. 60, pp. 1078-1087,2010.
[7] J. H. Williams, A. Davies, and P. R. Drake, *Condition-Based Maintenance and Machine Diagnostics*, Chapman & Hall, London, 1994.
[8] H. Austerlitz, *Data Acquisition Techniques using PCs.* Academic Press, San Diego, CA, 2003.
[9] P. R. Lippman, "An Introduction to Computing with Neural Nets", *IEEE Transaction on neural networks*, vol. 1, no. 1, pp. 4-27, 1990.

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Amin Noshadi, was born in 1983, Iran. He is M.Eng student in Department of System Dynamics and Control, Faculty of Mechanical Engineering, UniversitiTeknologi Malaysia (UTM), Malaysia. He received his B.Sc. degree in Mechanical Engineering from Ferdowsi University of Mashhad, Mashhad, Iran in 2007. His current research interests include robotics specifically design and control of parallel manipulators, active force control, iterative learning control, fuzzy systems, genetic algorithm, pa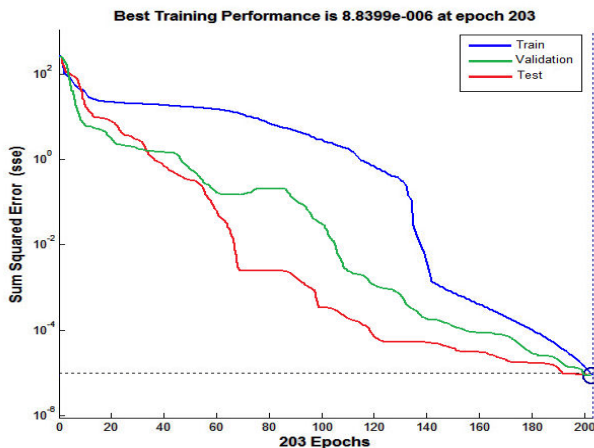rticle swarm optimization, and neural network based systems.