

Comparative Analysis of Characteristics of Multilayer Perceptron Neural Network for Induction Motor Fault Detection

Zareen J. Tamboli¹

Department of Electronics and Telecommunication,
Sanjay Ghodawat's Group of Institutes,
Kolhapur, India

Email: zareenjtg@gmail.com

S.K.Apte²

Department of Electronics and Telecommunication,
Sanjay Ghodawat's Group of Institutes,
Kolhapur, India

Email: k.sanjivani17@gmail.com

Abstract: In the paper, induction motors faults are studied and detected with the use of Multilayer Perceptron neural network. Multilayer Perceptron neural network is trained and tested in this paper. Simple parameters like set of currents are taken as an input and fed to a Multilayer Perceptron neural network. Different parameters like Mean Square Error (MSE) are calculated and used for analysis of losses and hence faults.

Keywords: Currents, Faults, Induction Motors, Multilayer Perceptron, Neural Network

I. INTRODUCTION:

Multi Layer perceptron (MLP) is a feed forward neural network with one or more layers between input and output layer. Feed forward means that data flows in one direction from input to output layer (forward). This type of network is trained with the back propagation learning algorithm. MLPs are widely used for pattern classification, recognition, prediction and approximation. Multi Layer Perceptron can solve problems which are not linearly separable. Hence it is used to detect whether a given three phase Induction Motor is faulty or healthy.

II. EXPERIMENT:

A three phase Induction Motor is used for the practical purpose. Experimental setup like no-load test and blocked rotor test are conducted for acquiring the set of data from healthy motor and faulty motor. Initially the readings are taken from a healthy motor and taken as reference. Then different set of readings are taken from faulty motor under different loads and three more sets of data are defined.

A three-layer (input, hidden, and output layer) MLP network is used as shown in Fig. 1. The number of neurons in the input and output layers are set to 4 and 1 respectively, whereas the number of neurons in the hidden layer is usually decided by trial and error [1]. In general, the neuron number in the hidden should be moderate. Neither too few nor too many hidden layer neurons are expected because the former would cause the MLP network failure to learn from the training set and the latter may tend to memorize but cannot generalize the training set [2]–[3]. Furthermore, it has been suggested that one hidden layer is sufficient for any arbitrary classification problem, with ample hidden layer neurons [1]. Here we have selected the number of neurons to be 20.

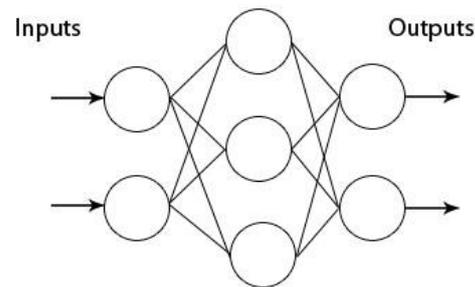


Figure 1: Neural Network

There are weights fully connecting the neurons in the hidden input layer and the hidden output layer. Weights are chosen randomly at the beginning. Inputs are fed forward into the input layer neurons. Each neuron in the hidden layer adds up the weighted inputs, and transforms the weighted sum by means of an activation function to simulate the activation of this neuron. A popular activation function is the sigmoid function, which generates, depending upon the threshold of the neuron, an output value in the range 0–1. This output value mimics the neuron's activation.

Hidden layer neuron activations are sent forward to the output layer neurons, and are dealt with the same manner to generate the MLP network final output. The MLP network is given with training cases of inputs with the desired outputs. At each presentation of a training case, the MLP network generates outputs.

We calculate the squared output errors according to desired and generated outputs. After calculating the squared output errors, we use the generalized delta rule to modify weights and thresholds of the MLP network. When all training set cases have been dealt with, which is regarded as a learning cycle, the learning rate will change by multiplying another constant called the change of the learning rate.

The manner in which the weight and threshold modifications propagate backward from the output layer to the hidden layer explains the term "back propagation." After a few training cycles, the MLP network is tested by an independent test set of healthy motor readings. The MLP

network is considered trained when the output errors of the independent test set are adequately low.

III. RESULTS AND DISCUSSIONS:

This demonstration illustrates the use of a Multi-Layer Perceptron network for regression problems. The data is generated from a noisy sine function. The network has 3 hidden units and a weight decay coefficient of 0.01. After initializing the network, we train it use the scaled conjugate gradients algorithm for 100 cycles.

From the readings after 100 iterations, we see that the accuracy of the network for fault detection of motor goes on increasing upto 90 percent i.e. it means that out of 100 faulty motor readings it can detect upto 90 faulty readings.

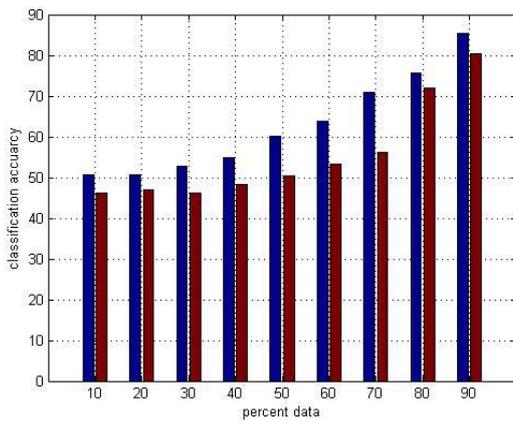


Figure 2: Graph showing classification accuracy of the network.

IV. MEAN SQUARE ERROR(MSE):

Another factor that is considered for detection of fault in Induction Motor is the comparison of the Mean Square Error(MSE) of the healthy motor and the faulty motor. In statistics, the mean squared error (MSE) of an estimator measures the average of the squares of the "errors", that is, the difference between the estimator and what is estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance of the estimator. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root-mean-square error or root-mean-square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

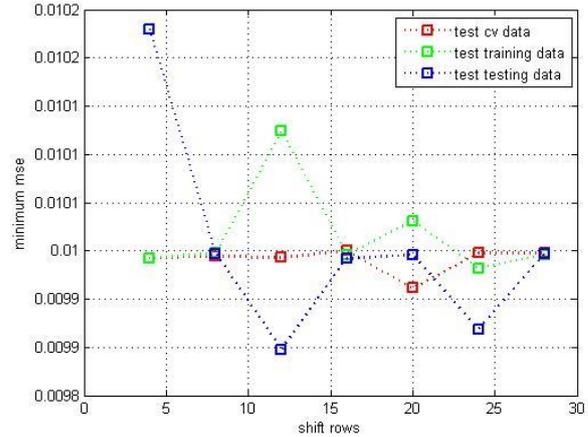


Figure 3: Graph showing MSE of the faulty motor readings

The difference between the MSE of healthy motor and faulty motor is calculated in excel sheet and if the difference is not zero, the motor is considered to be faulty. The detection of fault is done by comparing the MSE readings of the healthy motor and faulty motor. MSE plays an important role in the analysis.

When the data currents of the faulty motor are grouped together and the MSE of the group is taken into consideration, the following graph is obtained. It helps us in detecting after what interval of time the losses are taking place. If the following graph is taken into consideration, it shows that there is a fluctuation in the cv data and the training data after an specific interval of 50 sec of running. The data is divided in 70% training data, 20% testing data and 10% cv data. CV data is used to cross verify whether the given data is tested with high efficiency.

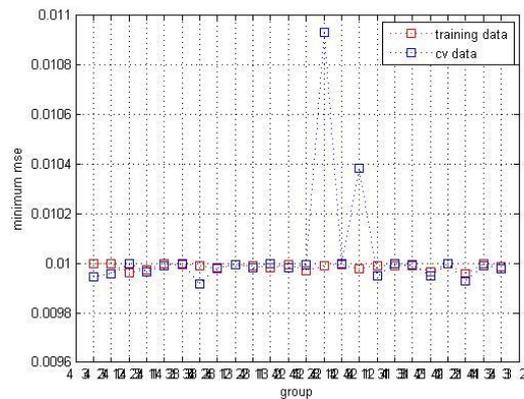


Figure 4: Graph showing MSE of the faulty motor group readings

References:

- [1] IEEE transactions on components, packaging and manufacturing technology, vol. 1, no. 3, march 2011 application of extracted rules from a multilayer perceptron network to moulding machine cycle time improvement
- [2] S. Haykin, Neural Networks and Learning Machines . Upper Saddle River, NJ: Pearson, 2009, p. 169.

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- [3] M. Negnevistsky, Artificial Intelligence . Reading, MA: Addison-Wesley, 2002, p. 174
 - [4] M. T. Hagan, H. B. Demuth, and M. Beale, Neural Network Design Boston, MA: PWS-Kent, 1996, pp. 11–17.
 - [5] D. W. Patterson, Artificial Neural Networks . Englewood Cliffs, NJ: Prentice-Hall, 1996, pp. 206–207.
 - [6] R. J. Schalkoff, Artificial Neural Networks . New York: McGraw-Hill, 1997, pp. 209–210.
 - [7] S. Kumar, Neural Networks . New York: McGraw-Hill, 2005, p. 99.
 - [8] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, Neuro-Fuzzy and Soft Computing . Englewood Cliffs, NJ: Prentice-Hall, 1997, pp. 235–236.
 - [9] IEEE TRANSACTIONS ON NEURAL NETWORKS, VOL. 12, NO. 6, NOVEMBER 2001 Sensitivity Analysis of Multilayer Perceptron to Input and Weight Perturbations Xiaoqin Zeng and Daniel S. Yeung , Senior Member, IEEE

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