Middle-East Journal of Scientific Research 24 (6): 2009-2012, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.06.23585

Fault Identification and Diagnosis of Induction Motor Using Neural Networks

[1]*M. Sudhakaran* and [2]*R. Seyezhai*

[1]Associate Professor, Department of EEE,
Ganadipathy Tulsi's Jain Engineering College, Vellore-632 102, India
[2]Associate Professor, Department of EEE,
SSN College of Engineering, Chennai-603 110, India

Abstract: Now a day's motor faults are identified and analysis during offline. Most of industries machines fault identification is done in online using vibration method. The cost of that method is comparatively high with other method. To minimize the cost and the study of electromagnetic flux is to provide the useful information about various faults in an induction motor during online. The objective of this work is to progress a tool which is used for condition monitoring of single phase induction motors by means of axial magnetic flux measurements and also to design a diagnostics system for induction motors. The Simulation and experimental analysis is developed through Neural Network software.

Key words: Multi LayerPerceptron · Artificial intelligent · Back Propagation method · Training and cross validation · Toroidal flux sensor · Single phase induction motor

INTRODUCTION

Neural networks have developed into an emergent part of research for last few decades and which affects the many manufacturing branches. Neural networks have several applications in industrial electronics which includes power distribution problems and motor drives with harmonic distortion. The present contribution reports insulation failures of inter turn stator winding in induction motor with different load conditions which is evaluated through Data and Signal Processing(DSP) tools which combine Parks Transform (PT) and Cross Wavelet Transform (CWT). For fault severity monitoring, the Rough Set Theory (RST) based classifier are used. Induction machines play an essential task in industries because of their reliable and safe operation but ultimately do wear out. Failures and faults of induction machines which cause unnecessary downtimes and produce huge damages in protection and lost proceeds, this motivate to assess the online condition monitoring. The main aim of condition monitoring for online is to detect the faults and to reduce unpredicted failures and maintenance costs. This paper surveys the recent trends in on-line fault detection and diagnosis of induction motor.

Fault diagnosing the traditional method of defect due to Flux signal analysis. The algorithmic calculation by Runge-Kutta method reduces the computation of read value signals. To monitor the signals, there are three kinds of defective signals [1].Spectrum analyzes the vibration calculation through the defective bearings [2].These data analyze vibration signatures from defect detection via flux monitoring [3]. In neural networks analyze the small fault occurred in diagnostic performance [5]. Two categories arise from physical and analytical redundancy through the fault tolerant with low cost [6]. Analyze the efficiency of vibration faults [4]. To magnet the quantize function under electro motive wavelet thresholds. Here, overcome other than extension advantages to fault diagnosis we can do in future work. An adaptive describes the instrumental fault of analytical redundancy for dynamic systems [7]. The simulated analysis using the capability of measured work done by using embedded controllers through the noise detection [8].

Proposed Method: In induction motor, flux signal is detect from the variation of sensor which convert into magnet signals through waveforms. Acoustic filters in wavelet tool boxes are the given box. Then, we convert to signal processor. Analyze the wavelet from flux signal waveform

Corresponding Author: M. Sudhakaran, Associate Professor, Department of EEE,
Ganadipathy Tulsi's Jain Engineering College, Vellore-632 102, India.

into the sigview work let through the different location to neural network. From the wave form analysis of the different location where the noise is too much varied from motor and slowing motor work.

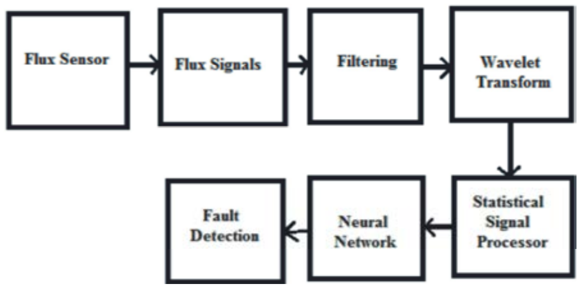

Fig. 1: Block Diagram of Proposed method

RESULTS AND DISCUSSION

Neuro-Solutions for Excel are aim partial application that consist of existing linear regression techniques along with probabilistic and multi-layer perceptions neural networks. It can correspondingly integrate through one of the Neuro-Solutions levels to provide an exact controlling situation to manipulate the data, to generate the reports and to run the experiments batches.

The main window of the Neuro-Solutions is opened when the program is propelled. The topmost of window has the main menus which are familiar to dispute commands to the program. The toolbars icons are just below the menus which are shortcuts to the menu commands. Neural components icons are at the bottom of main window. Neuro-Solutions components are classified into families and located in palettes which are similar to the toolbars. The sub windows are denoted as breadboards which are known as Neuro-Solutions documents in which network construction and simulations occurs. This Multi Document Interface (MDI) permits simultaneously to run multiple simulations.

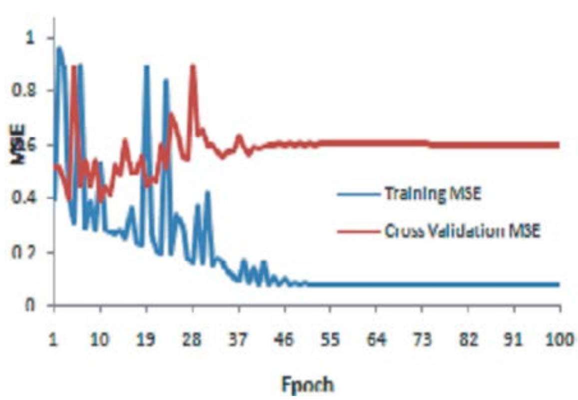

Fig. 2: Train 1 Report MSE versus Epoch

During training the input, the desired data are repetitively offered to the network. Once the network learns, the error will decreases to zero. However, lower error cannot always be a better network which is likely to over train the network. Cross validation is an extremely suggested criterion for stopping the network training. It is not required, even though is highly recommended. Consecutively, several networks attempt by means of training data to find the best works and then practice cross validation for the final training. The next step is to choose how to partition the data into training set and validation set which is also called test set. Network can trained through the training set and the performance of network is checked by the test set. The neural network can locate the input-output map by repetitively analyzing the training set. Training Fig. 4 Net Work, A pre-saved one hidden layer multilayer perceptron (MLP) will be opened within Neuro-Solutions and used for modeling this data. When a training process is run, files are automatically created (using the tagged cross-sections) and loaded into the active Neuro-Solutions network. Each training process displays a dialog box with user definable option corresponding to training process type being run.

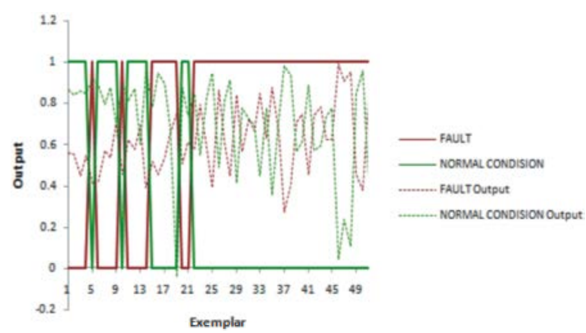

Fig. 3: Desired and Actual Network Output

Levenin the varied parameter is shown in Fig. 3 is a special case of k fold cross validation where, k represents the number of instances in data. Except for a single observation, all the data in each iteration are used for training and the model is tested on single observation. A precision estimate obtained to be nearly unbiased with high difference foremost to defective estimate. When the available data are very rare which can be widely used mostly in bio-informatics because, the dozens of data samples are available.

In this step, we will train the network one time. The dialog box will be preset to use cross validation and train for 100 epochs. Click the "Train Network" button now to train the network. Examine the settings in the resulting dialog box then click OK.

To estimate or compare the learning algorithms is as follows: The k-1 folds of data are used to learn one or more models in each iteration from one or further learning algorithms. Later, the learned models are enquire to build data prediction in validation fold.

In each fold, the performance of every learning algorithm is traced by means of approximately scheduled performance metric similar to accuracy. For each algorithm, the completion k samples of performance metric are available. The different methodologies for example averaging are used to find the aggregate calculation from these samples.

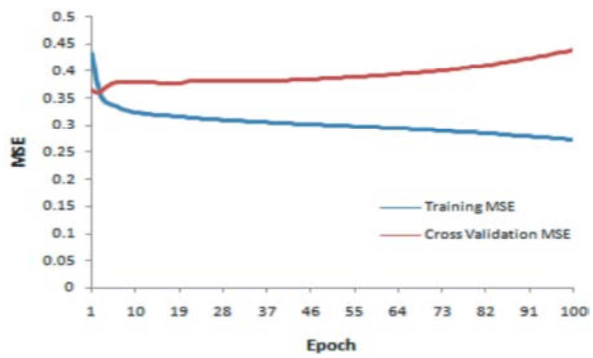

Fig. 4: Train 2Report MSE versus Epoch

Training Results: Notice that a report has been generated within the worksheet named Train 2 Report which summarizes the training results. The plot shows the learning curves for both training data sets and cross validation data sets. The training and cross validation Mean Squared Errors (MSEs) were minimum at the last epoch.

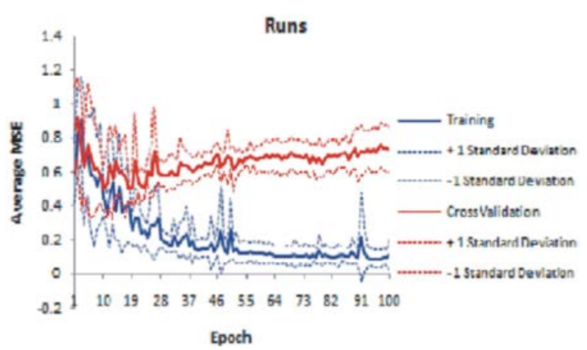

Fig. 5: Average Mean Squared Errors with Standard Deviation Boundaries

The training mean-squared errors and cross validation mean-squared errors were collected for each epoch within the worksheet named Train1 MSE. The actual learning curves will vary with each run of the process since the weights are randomized at the beginning of a training run.

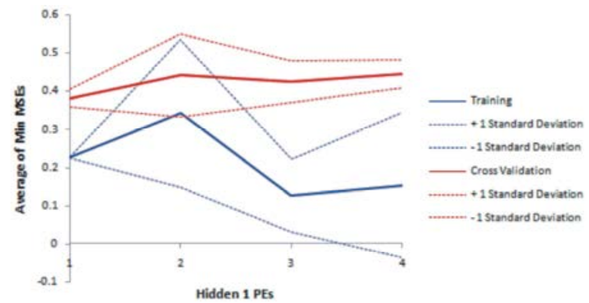

Fig. 6: Average of Minimum Mean Squared Errors with Standard Deviation Boundaries

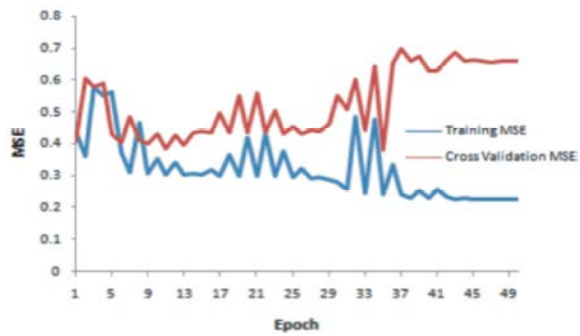

Fig. 6: Train5 Report MSE Vs Epoch

Training Results Fig. 7 Notice that a report has been generated within the worksheet named Train5 Report. This report summarizes the training results. The plot illustrations the learning curves for both training and cross validation data sets.

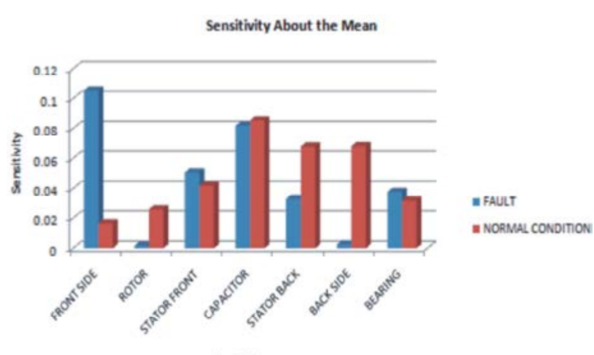

Fig. 7: Sensitivity about the Means

The Table 1 shows the network output for varied input side.

Table 1: Network Output For Varied Input Side

Sensitivity Analysis	Fault Condition	Normal Condition
FRONT SIDE	0.059523393	0.006343623
ROTOR	0.045753929	0.000193133
STATOR FRONT	0.018365882	0.016573314
CAPACITOR	0.051656015	0.005516895
STATOR BACK	0.002445451	0.039217914
BACK SIDE	0.020844035	0.020031768
BEARING	0.016962331	0.027408359

The Training Mean Squared Errors (MSE) and Cross validation Mean Squared Errors (MSE) are collected for each epoch within the worksheet. The actual learning curves will vary with each run of the process since the weights are randomized at the beginning of a training run.

CONCLUSION

A fault diagnosis real time application on motor fault identification new approach for neural network using Neuro dimension is presented. Flux magnet touch is a concept where by any normal surface with no internal circuitry and hardware for flux sensitivity. The flux is converted into a touch sensitive surface by using sigview techniques. On-line condition monitoring involves attractive measurements on a machine while it is operating in order to detect faults with the aspire of reducing both unpredicted failures and maintenance costs using artificial intelligence. Its provide them new ways of interaction for human and machine.

REFERENCES

1. Konstantions, N. Gyftakis, Dionysios V. Spyropolos, Joy C. Kappaatou and Epaminondas D. Mitronikas, 2001. A Novel approach for Broken Bar Fault Diagnosis in Induction Motors Through Torque Monitoring. IEEE Transactions On conversion, 28(2).
2. Andrzej, M. Trzynadlowski and Ewen Ritchie, 2000. Comparative Investigation of Diagnostic Media for Induction Motor: A Case of Rotor Cage Faults. IEEE Transactions On Industrial Electronics, 47(5).
3. Zhenxing, Liu, Xianggen, Yin, Zhe Zhang and Deshuchen, 2004. Online Rotor mixed Fault Diagnosis Way Based on Spectrum Analysis of Instantaneous Power in Squirrel Cage Induction Motor. IEEE Transactions on Energy conversion, 19(3).
4. Nandi, S., H. Toliyat and X. Li, 2005. Condition monitoring and fault diagnosis of a review. IEEE Transaction on Energy Conservation, 20(4): 719-729.
5. Milimonfared, J., H.M. Kelk, S. Nandi, A.D. Minassians and H.A. Toliyat, 1999. A Novel approach for broken-rotor-bar detection in cage induction motors. IEEE Transaction on Industrial Application, 35: 1000-1006.
6. Dorrell, D.G., L. Frosini, G. Galbiati and M.F. Hsieh, 2009. Analysis of axial voltages and inter-bar currents in cast copper cage rotors during DC current injection as an aid to identify casting faults. IEEE proceeding 35th Annual Conference Industrial Electron, pp: 3-5.
7. Zhang, P., Y. Du, T.G. Habetler and B. Lu, 2011. A survey of condition monitoring and protection methods for medium-voltage induction motors. IEEE Transaction on Industrial Application, 47(1): 34-46.
8. Henao, H., H. Razik and G.A. Capolino, 2005. Analytical approach of the stator current frequency harmonics computation for detection of induction machine rotor faults. IEEE Transaction on Industrial Application, 41(3): 801-807.