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AN OPTIMAL MULTILAYER PERCEPTRON-BASED NEURAL NETWORK FOR DETECTION AND CLASSIFICATION OF FAULTS IN A THREE-PHASE PERMANENT MAGNET SYNCHRONOUS MOTOR

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ABSTRACT

Permanent Magnet Synchronous Motor (PMSM) is subjected to various operating, environmental, and other conditions; due to which incipient faults occur. If these faults are undetected, lead to catastrophic failure. For reliable and safe operation of PMSM. Online condition monitoring, fault detection, and diagnosis were required. Many researchers have proposed various techniques for fault detection and diagnosis, which requires good domain knowledge and costly pieces of equipment. This paper presents an optimal multilayer perceptron (MLP) neural network for fault detection and classification, which is simple, reliable, and cost-effective. Two faults are created on a three-phase permanent magnet synchronous motor stator inter-turn and eccentricity with varying load conditions. The experimental data is generated on 1 hp, 3 phase, 4 poles, 1500 rpm permanent magnet synchronous motor during healthy and faulty conditions. Various sensors are inbuilt internally and externally into the PMSM motor for the measurement of different parameters. 12 different measurable parameters include three-phase motor intake current, three-phase motor applied voltage, power factor, winding temperatures, and bearing sound. The proposed classifier with 12 input parameters is designed and verified for optimal performance for fault identification and classification, Nearly 100% classification accuracy is achieved.

KEYWORDS: Permanent Magnet Synchronous Motor, Multilayer Perceptron (MLP), Fault Detection, Fault Classification**.**

1. INTRODUCTION

Electric motors have been widely used in all fields of applications from huge power to low. Electric motors play an important role in the modern lifestyle that we are used to. It is well-known fact that there is a huge demand for electric motors from various fields of applications, however, there is a revolutionary change in the manufacturing process of electric motors from the conventional motor to permanent magnet motors.[1,2]

Permanent magnet brings the following benefits in the construction of electric motors. Permanent magnet motor has better efficiency, high torque, better dynamic performance, and simplified construction and maintenance as compared to conventional motors. Thus permanent magnet synchronous motor covers a wide variety of application fields from stepping motor to ship propulsion.[3,4] Permanent magnet synchronous motor is extensively used for industrial and commercial purposes. They are exposed to a wide variety of environmental and operating conditions; these factors coupled with natural aging and manufacturing defect may lead to incipient faults. If these faults are left undetected, lead to catastrophic failure.[5]

The main types of faults occurring in permanent magnet synchronous motors are commonly categorized as Electrical faults, Mechanical faults, and Demagnetization faults. These faults may be observed in most abnormal symptoms and have specific patterns about motor faults conditions and severity, such as unbalanced air gap, unbalanced voltage and current, increased torque, acoustic noise, and excessive heating. According to EPRI and IEEE survey, the failures of electric motors are grouped as major contributors to faults as shown in Table.1.[6,7]

Table 1: Electric Motor faults occurrence.

Survey Report	Bearing related Fault %	Stator-related fault %	Rotor-related fault %	Others %
EPRI	41	38	10	12
IEEE	40	38	8	22

Many researchers have developed various tools and techniques for incipient fault detection and diagnosis. The importance of incipient fault detection at an early stage prevents loss of production, and loss of valuable human life, which results in cost savings and prevention of permanent damage of costly permanent magnet synchronous motor.[8] The various conventional techniques for detection and diagnosis are available with their advantages and limitations, such as motor current signature analysis,[9] Finite element analysis,[10] Fast Fourier transform,[11] Wavelet Analysis,[12,13] Winding configuration, Modified winding configuration, temperature analysis, zero, positive and negative sequence analysis,[14,15] HF single Injection.[16] and acoustic noise and torque pulsation.[17]

Artificial intelligence technique has gained importance for fault detection and diagnosis, control process, and image processing. Artificial intelligence systems can detect and interpret the fault data. Various artificial intelligence technology has been developed in recent years, such as expert system,[18] artificial neural network,[19,25] fuzzy logic, neuro-fuzzy, and adaptive neuro–fuzzy.ANN.[26,28] gain popularity over other techniques, as it is inexpensive, reliable, simple, and non-invasive to detect similarities among large data. This technique does not require the heuristic knowledge of faults and mathematical models, however, the ANN can perform online fault detection and classification through the use of an inexpensive monitoring device. These devices obtain the necessary information in a non-invasive manner.

The purpose of this paper is to develop an alternative method for fault detection and diagnosis using a neural network as compared to an existing scheme which requires good domain knowledge and costly equipment. In this scheme, twelve stastical parameters such as three-phase voltages, three-phase currents, stator healthy winding temperature, stator faulty winding temperature, bearing temperature, motor body temperature, acquoistic noise and power factor are used to develop a multilayer perceptron neural network model for fault detection and classification. Nearly 100% classification acccuracy was achieved. This method is simple, reliable, and economic as compared to the existing scheme.

1 FAULT CLASSIFICATION USING ARTIFICIAL NEURAL NETWORK

The following procedure is proposed for fault detection and classification.

Fault created on PMSM.

Data generation and collection.

Data selection.

Fault classification

This paper proposed two faults created on permanent magnet synchronous motor, stator inter-turn (IT) and eccentricity. Eccentricity is categorized into three parts namely static eccentricity (SE), dynamic eccentricity (DE), and mixed eccentricity (ME). For creating a Fault PMSM motor of 1 hp, three-phase, 4 poles, 1500 rpm, 415 V, 50 Hz is used.

1.1 FAULT CREATED ON PERMANENT MAGNET SYNCHRONOUS MOTOR

1.1.1 Stator Inter-turn fault

To create the effect of stator inter-turn fault in a three-phase PMSM motor. The one phase winding has been modified by taking out six tapping for shorting. Without disturbing the remaining two phases. After every two turns one tapping is taken out in a step of 2,4,6.8.10.12. The additional extra wires of very small distance are attached to the end turn and the other end of these external wires is attached to the designed chromium sheet mounted near the motor terminal to created the fault. Which is shown in figure.1.1

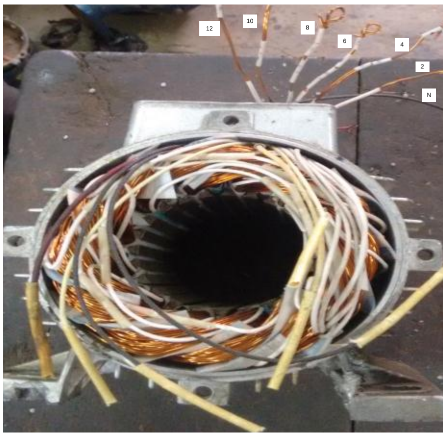


Figure 1-1: The Stator of PMSM with stator inter-turn.

1.2 Eccentricity Fault

Eccentricity faults are the most common mechanical faults in electric machines. The air gap between the stator and rotor is uniformly distributed in a healthy machine. In other words, the stator symmetrical axis, rotor symmetrical axis, and rotor rotation axis are all aligned, and the system is balanced. In an eccentricity faulted system, the symmetrical axes of the stator, rotor, and rotation axis of the rotor are displaced from each other, and the air gap is no longer uniform, resulting in asymmetric flux distribution and a radial force between the stator and rotor. This force grew stronger as the severity increased. The unbalanced magnetic pull (UMP) could have several effects on the machine, including noise, vibration, torque oscillations, shaft bending, and bearing wear. This may cause the rotor and stator to rub as the eccentricity increases over time.

Eccentricity faults can be caused by a bent shaft, incorrect alignment during motor assembly, bearing tolerance, and mechanical stresses applied to the motor. If the rotor shaft assembly is sufficiently rigid, the level of eccentricity remains constant. Detecting eccentricity at an early stage is critical for protecting the machine from severe damage and for easy maintenance, which leads to cost savings and complete motor shutdown.

Eccentricity faults are generally classified into three types Static eccentricity, Dynamic eccentricity, and Mixed eccentricity.

1.2.1 Static Eccentricity

Static eccentricity is a case in which the rotor symmetrical axis is shifted from the stator symmetrical axis but is still running on its axis (rotation axis of the rotor). During static eccentricity, the position of the minimum air gap remains fixed in space. Static eccentricity may be caused by an oval stator or misaligned mounting of bearing incorrect positioning of the stator and rotor assembling of machines, or various stresses applied to the machine stator.

The static eccentricity ratio is defined as the air gap variations to the original air gap length.

$$E_s = \frac{\epsilon_s}{g_0} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (1)$$

Where ϵ_s is the radial distance between the rotor symmetrical axis and stator symmetrical axis and g_0 is the uniform air gap length in healthy conditions.

1.2.2 Dynamic Eccentricity

Dynamic eccentricity is a case in which the symmetrical axis of the rotor is shifted from the stator symmetrical axis and rotation axis of the rotor, During dynamic eccentricity, the position of the minimum air gap rotates in space along with the rotor. The cause of dynamic eccentricity can be a bent shaft, bearing wear and movement, misaligned mounting of the bearing, and mechanical resonance at a critical speed. Dynamic eccentricity in a new machine can be controlled by the “run-out” of the rotor.

The dynamic eccentricity ratio is defined as the radial distance between the rotor axis and stator axis to the uniform air gap length.

$$E_d = \frac{\epsilon_d}{g_0} = \frac{|\epsilon_d|\omega_r t}{g_0} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(2)$$

Where ϵ_d is the radial distance between the rotors axis and stator axis

1.2.3 Mixed Eccentricity

Mixed eccentricity is a case in which the rotation axis of the rotor is different than the stator symmetrical axis and rotor symmetrical axis. In other words, is a combination of static and dynamic eccentricity.

$$E_m = \frac{\epsilon_s}{g_0} + \frac{\epsilon_d}{g_0} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(3)$$

To create the effect of static, dynamic, and mixed eccentricity fault in a three-phase PMSM motor. A round pulley of 6 inches in diameter,2 inches in width, and a four bores of 10 mm in diameter is used to create the fault. The pulley is connected to the shaft to create the eccentricity fault externally without disturbing the motor eccentricity. Static eccentricity was induced by connecting a balanced load on both sides of the created bore. Dynamic eccentricity was induced by connecting a load on one side of the bore and in mixed eccentricity, an unbalanced load is connected on both sides of the bore. Figure 1-2 shows the schematic of healthy condition and eccentricity conditions of permanent magnet synchronous motor.

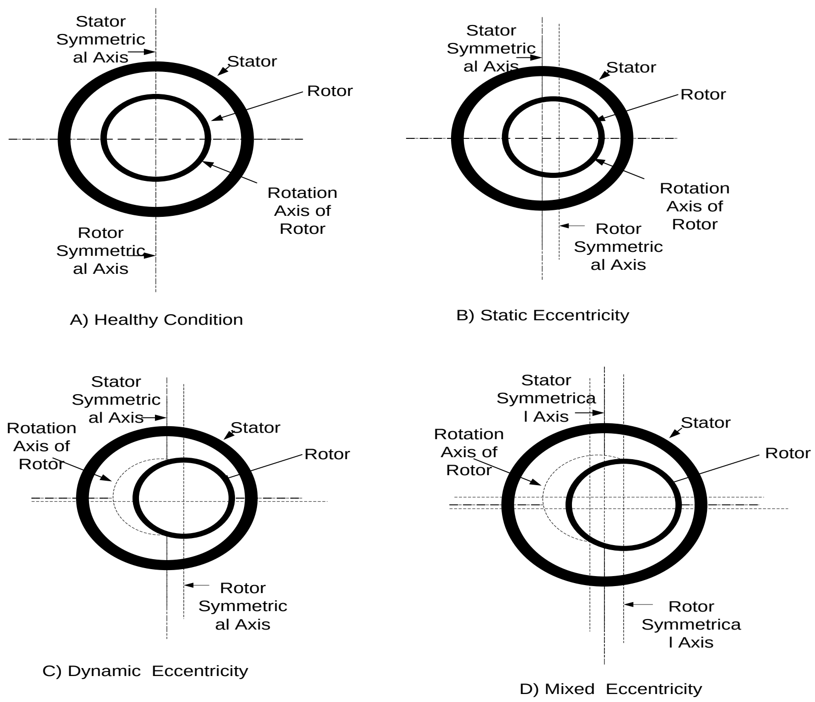


Figure 1-2: Shows the Schematic of Eccentricity Faults.

1.3 DATA GENERATION AND DATA ACQUISITION SYSTEM

For experimentation and data generation the specially designed 1 Hp, three phases, 4 poles, 1500 rpm, and 50 Hz permanent magnet synchronous motor is used which is shown in figure 1-3.

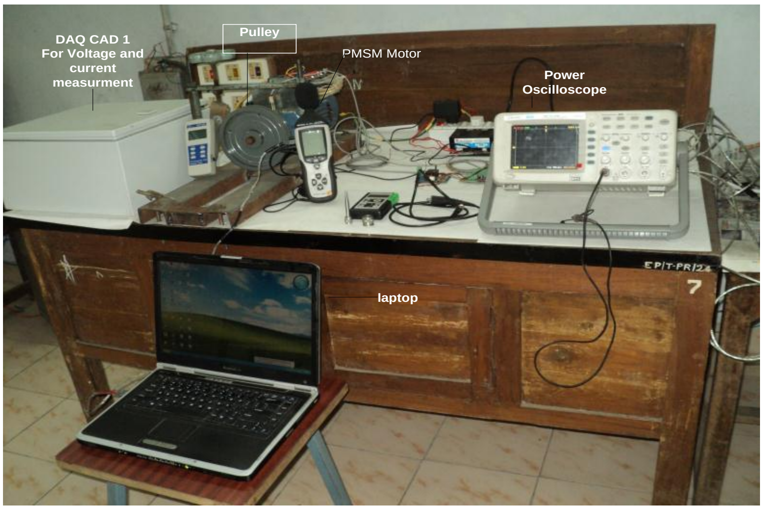


Figure 1-3: Shows the experimental Setup.

Data Acquisition card 1 is used to measure the three-phase motor intake current by using hall effect sensors, three-phase voltage, and power factor. Data Acquisition card 2 is used to measure the temperatures of the motor .healthy winding temperature, faulty winding temperature, bearing temperature, and motor body temperature. Data Acquisition card 3 is used to measure the speed and sound of the motor. All these parameters were recorded with the motor running on no-load, rated load, and greater than the rated load for healthy and faulty conditions .with specially designed software in VB 6.0 on a personal computer using RS232 to USB port.

1.4 Data Selection

The first step to designing a neural network is the selection of generated data set. Most relevant data providing fault information should be selected from the generated data set. To avoid the complexity and to improve the classifier performance. In this paper Multilayer perceptron neural network was used.

2 Fault classifier

2.1 Multilayer Perceptrons (MLP) based NN classifier

Multilayer Perceptron (MLP) neural network is proposed as a fault classifier for the detection and diagnosis of stator inter-turn and eccentricity (static, dynamic, and mixed) faults in a three-phase permanent magnet synchronous motor. The number of input processing elements (PEs) must be equal to that of the number of input statistical parameters so 12 input processing elements are used in the input layer. Five processing elements are used in the output layer for five conditions of the PMSM motor namely Healthy condition (H), stator inter-turn (IT), static eccentricity (SE), dynamic eccentricity (DE) and mixed eccentricity (ME). For data processing MATLAB 18.0, Neuro Solution 5.0, and XLSTAT-2010 are used. The Multilayer Perceptron is used with supervised learning and has led to the successful implementation of the backpropagation algorithm means the learning algorithm used in the multilayer perceptron is the backpropagation algorithm. The backpropagation algorithm was performed using two basic steps. The first one called propagation applies value to the input neuron. The input neuron performs the function product of the sum of input features with the respective weight associated with it. After passing through the activation function produce the desired response from the neuron. The value is then compared with the target output for that signal. The second step occurs in the reverse way i.e., from output to the hidden layer, from hidden to the input layer, The error produced by the network is used in the adjustment process of its internal parameters such as weight, bias, and other parameters associated with those layers.

The generalized training algorithm used in backpropagation is as follows.

2.1.1 Feature Scaling

Feature scaling is used to convert a large dynamic range to a standard scale to make it easier for machine learning. The features or attributes have been scaled in the range of 0 to 1 by an easy equation.

$$X = \frac{x_i - \mu_i}{\sigma_i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where x_i is the original data set, μ_i is the mean value (average of the data), σ_i is the standard deviation and X is the normalized data. Where (i= 1,2……n) All data used herein was collected at 10 milliseconds using a sample rate is 5 Khz producing 6000 data points for various faults.

2.1.2 Initialization of weight

Step 1: Initialize the weights to a small random value.

Step 2: While the stopping condition is false, do steps 3-10.

Step 3: For each training pair do steps 4-9.

2.1.3 Feed Forward

Step 4: Each input unit receives the input signal ($x_{i,}$ i=1,2…...p) transmit this signal to all units in the hidden layer, here the input layer transfer function is a linear transfer function.

Step 5: Each hidden unit ($z_{j,}$ 1,2….m) sums its weighted signals.

$$z_{inj} = v_{oj} + \sum_{i=1}^{m} x_i v_{ij} \quad \dots\dots\dots\dots\dots\dots (5)$$

Applying the activation function $z_j = f_2(z_{inj})$ here f_2 is the activation function for the hidden layer.is $\tan h(x) = {e^x - e^{-x}}/{e^x + e^{-x}}$, after applying the activation function, the signals are sent to all units in the output layers.

Step 6: Each output unit ($y_{ink,}$1,2……. n) sum its weighted input signals from the output of hidden layers

$$y_{ink} = w_{ok} + \sum_{j=1}^{p} z_i w_{jk} + \sum_{j=1}^{p} x_i v_{ij} \quad \dots\dots\dots\dots\dots\dots (6)$$

Applying the activation function to calculate the output of the network.

$$y_k = f_3(y_{ink}) \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (7)$$

Where f_3 is the activation function of the output layer, which is given as is $\tan h(x) = {e^x - e^{-x}}/{e^x + e^{-x}}$

2.1.4 Backpropagation Error Calculation

Step 7: Each output unit (y_k, K=1,2……..n) receives a target pattern corresponding to an input pattern, the error term is calculated as,

$$\delta_k = (t_k - y_k) f y_{ink} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (8)$$

Step 8: Each hidden unit ($z_{j,}$ 1,2….m) aum its delta input from units in the hidden layer

$$\delta_{inj} = \sum_{k=1}^{n} \delta_i w_{jk} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (9)$$

The error information term is calculated as

$$\delta_j = \delta_{inj}\, fz_{inj} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (10)$$

2.1.5 Updating of Weight and Biases

Step 9: Each output unit (y_k, K=1,2……..n) update its bias and weights (j= 0, 1,2……p) the weight term is given as $\Delta w_{jk} = \eta\delta_k z_k$ and bias correction term is given as $\Delta w_{0k} = \eta\delta_k$ Therefore

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk} \ldots\ldots\ldots\ldots\ldots\ldots. (11)$$

$$w_{ok}(new) = w_{0k}(old) + \Delta w_{0k} \ldots\ldots\ldots\ldots\ldots\ldots. (12)$$

Step 10: Each hidden unit ($z_{j,}$ 1,2….m) update its bias and weights (i= 0, 1,2……n) the weight term is given as $\Delta v_{jk} = \eta\delta_j x_i$ and bias correction term is given as $\Delta v_{0j} = \eta\delta_j$ Therefore

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij} \ldots\ldots\ldots\ldots\ldots\ldots. (13)$$

$$v_{oj}(new) = v_{0j}(old) + \Delta v_{0j} \ldots\ldots\ldots\ldots\ldots\ldots. (14)$$

When some training data differs from the majority of data, the approach described above is advantageous. When an unusual pair of training patterns are presented, a low learning rate is used to avoid major disruptions in the learning direction. The weight shift is in a direction that is a combination of the current gradient and the previous gradient.

When momentum is added to the weight update formula, the convergence rate increases. To use momentum, the weights from one or more previous training patterns must be saved. Thus, using momentum, the network travels in the direction of the combination of the current gradient and the previous direction for which the weight correction is made, rather than the gradient itself. The primary goal of momentum is to accelerate the convergence of the error propagation algorithm. This method makes the current weight adjustment with a fraction of the most recent weight adjustment.

The new weight update is given as

$$w_{jk}(t+1) = w_{jk}(t) + \eta\delta_k z_j + \mu_n[w_{jk}(t) - w_{jk}(t-1)] \ldots\ldots\ldots\ldots (15)$$

Where η is the learning rate and μ_n is the momentum factor.

$$v_{jk}(t+1) = v_{jk}(t) + \eta\delta_j x_i + \mu_n[v_{ij}(t) - v_{ij}(t-1)] \ldots\ldots\ldots\ldots (16)$$

Step 10: Test the stopping condition

The stopping condition could be error minimization, the number of epochs, the target value equaling the desired value, and so on.

The randomized data is fed to the neural network and is retained 32 times with different randomized weights to remove the biasing effect and to ensure true learning and generalization for the different hidden layers. It is observed that MLP with a single hidden layer gives better performance. The network is trained with varying PEs in the hidden layer minimum MSE on training and CV is obtained when 18 PEs are used in the hidden layer which is shown in fig.2.

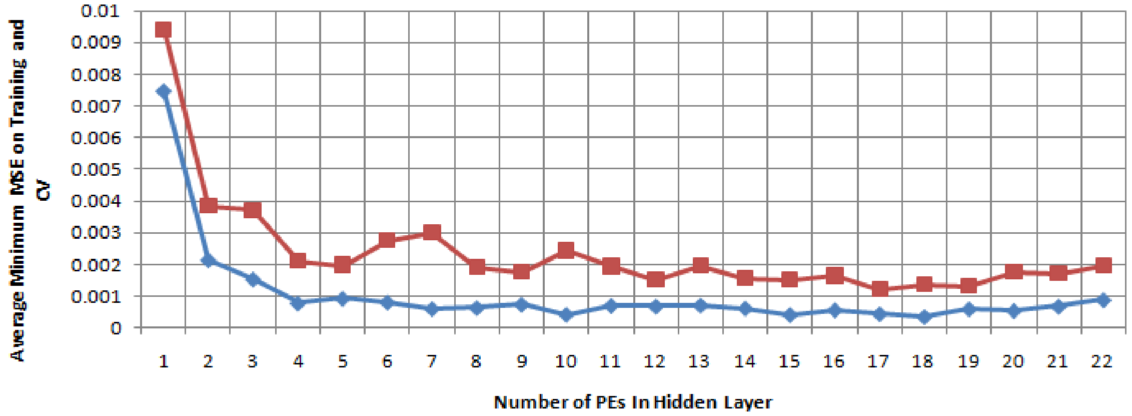


Figure 2: 1Average minimum MSE variation on training and cross validation with number of Pes in hidden layer.

Various transfer functions and learning are used for training the network. average minimum MSE on training and CV are compared in fig 2-2 and average classification accuracy is compared in fig 2-3. It is found that tanhaxon is the most suitable transfer function and LM is the most suitable learning rule among the various learning rule namely step, Momentum (MOM), conjugate gradient (CG), Leverberg Marqual (LM), quick propagation (QP) and delta bar delta (DBD) which is shown in fig 2-4 by comparing average minimum MSE on training and CV and in fig 2-5 average classification accuracy is compared.

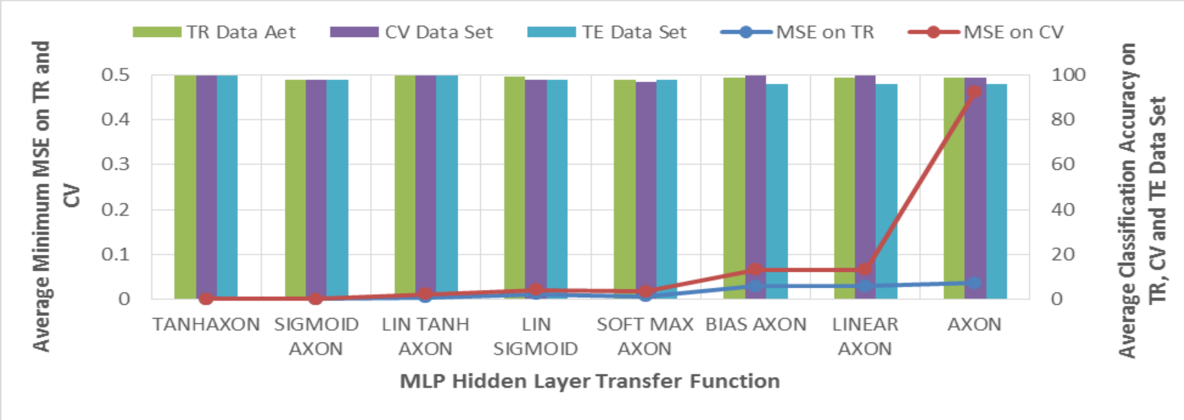


Figure 2-2: Average minimum MSE variation on training and cross validation and Average classification accuracy on TR,CV and TE data set on Hidden Layer Transfer function.

Figure 2-3 Average minimum MSE variation on training and cross validation and Average classification accuracy on TR,CV and TE data set on Hidden Layer Learning Rule.

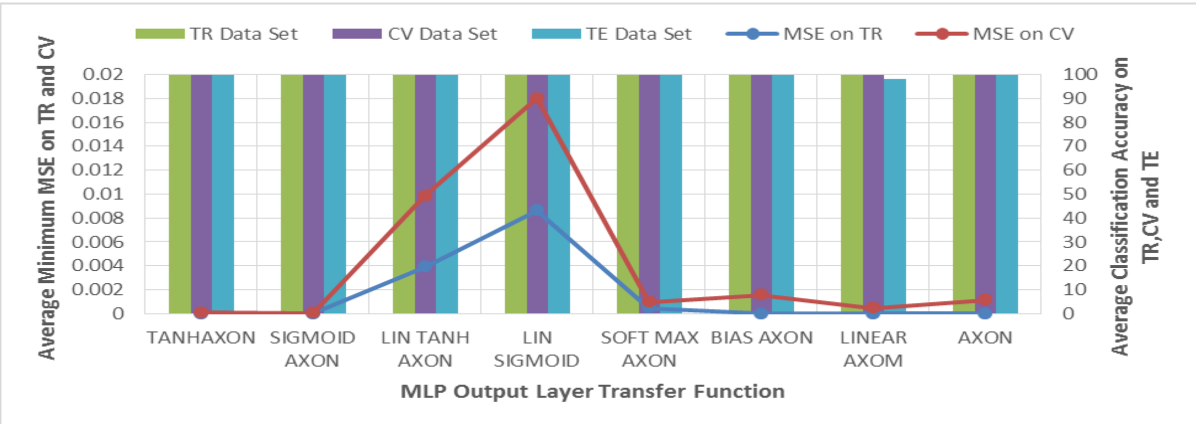


Figure 2-4 Average minimum MSE variation on training and cross validation and Average classification accuracy on TR,CV and TE data set on Output Layer Transfer function.

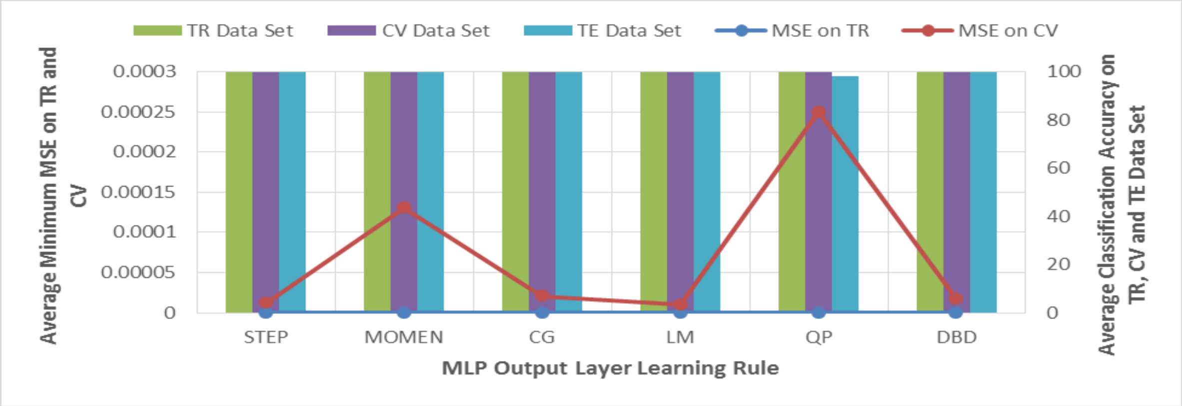
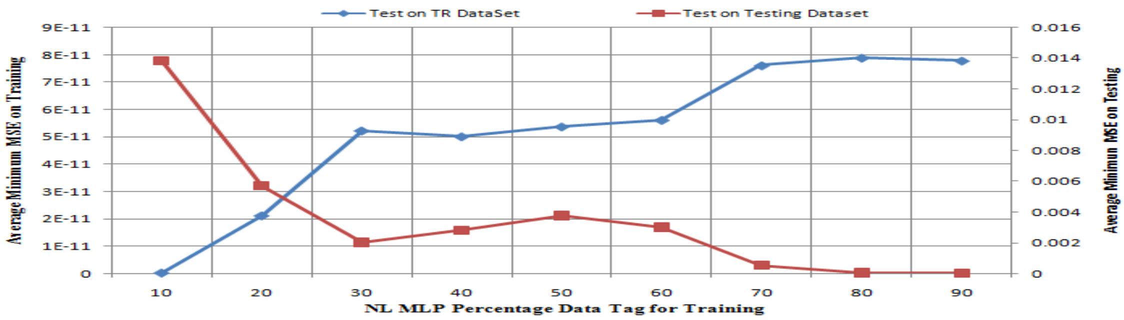
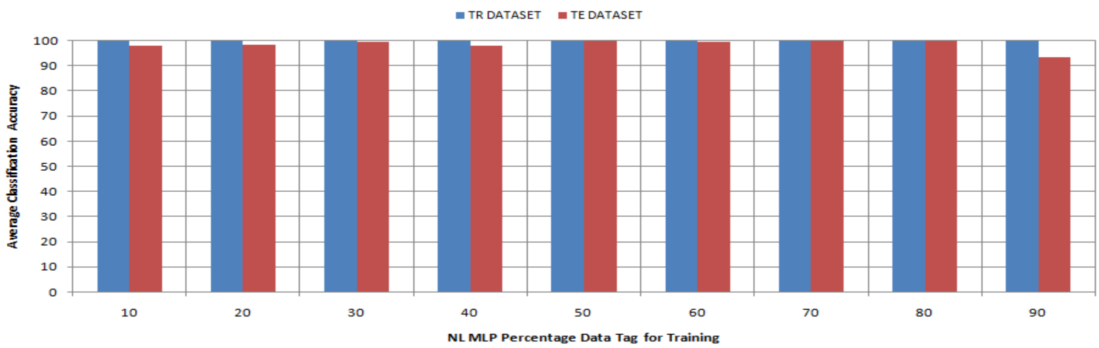


Figure 2-5: Average minimum MSE variation on training and cross validation and Average classification accuracy on TR,CV and TE data set on Output Layer Learning Rule.

To check the percentage of data tag for training cv and testing the network. Various combination of percentage data is used from 10-90 to 90-10.Average minimum MSE on testing and training is shown in fig.2-6(a) and average classification accuracy on training and testing is shown in 2-6(b).



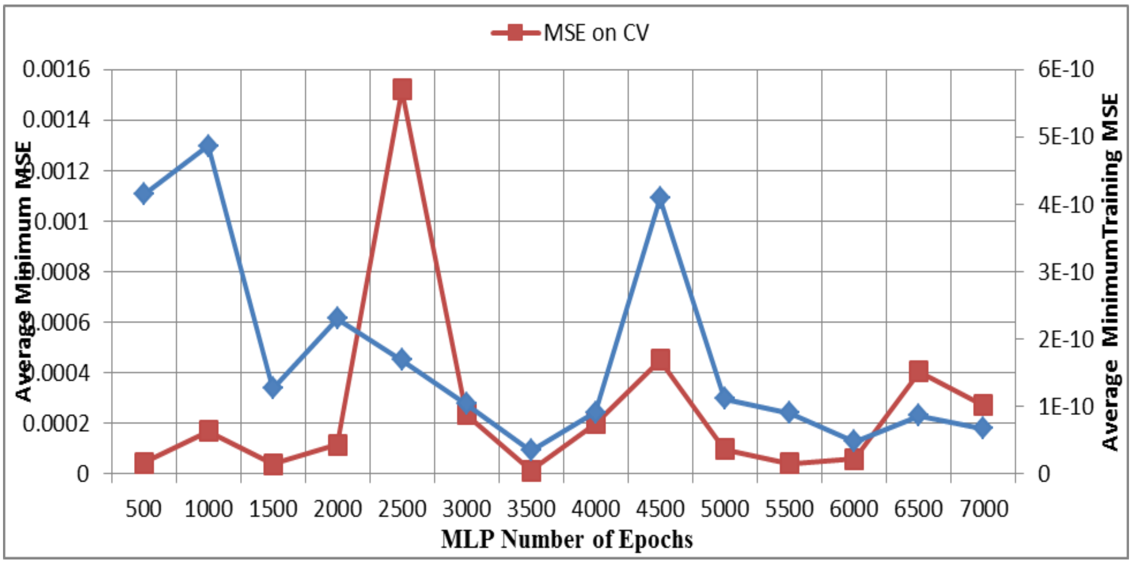
(a)



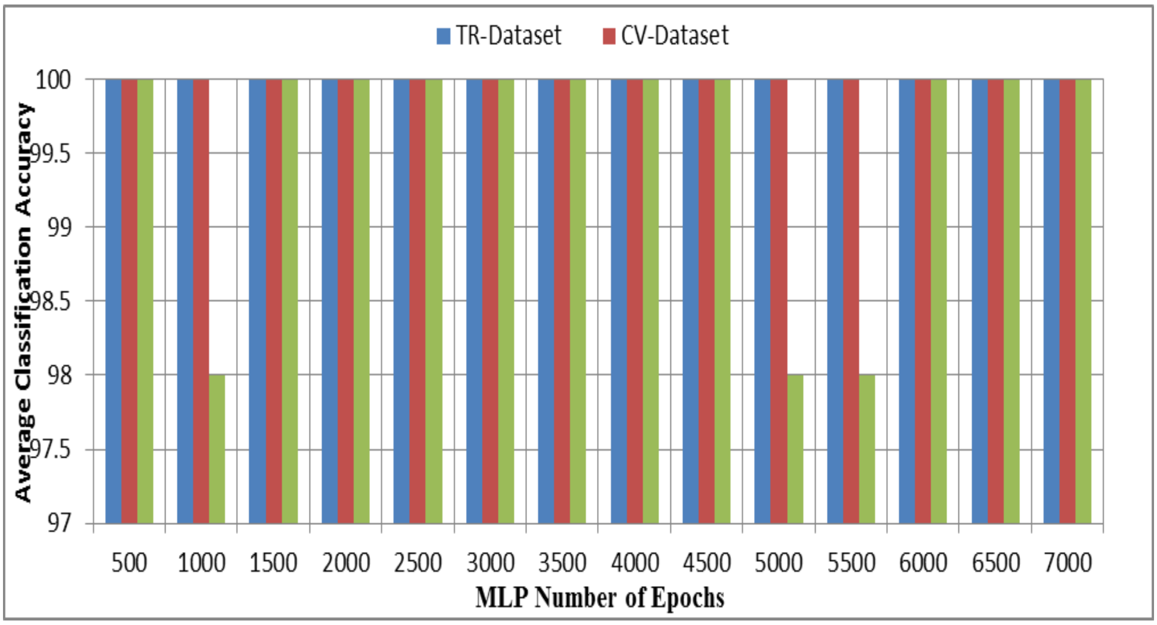
(b)

Figure 2-6: a) Average minimum MSE variation with test on testing and training dataset tagged for training b) Average classification accuracy with test on testing and training dataset tagged for training.

Various number of epochs is used for training of network by varying the number of epoch to small value of epoch 500 to maximum number of epoch 7000.It is found that at 3500 epochs the best result is obtained which is shown in fig 2-7(a) by comparing the average minimum MSE on training and CV as shown in fig.2-7(b) the average classification accuracy is compared on tr, cv and test.

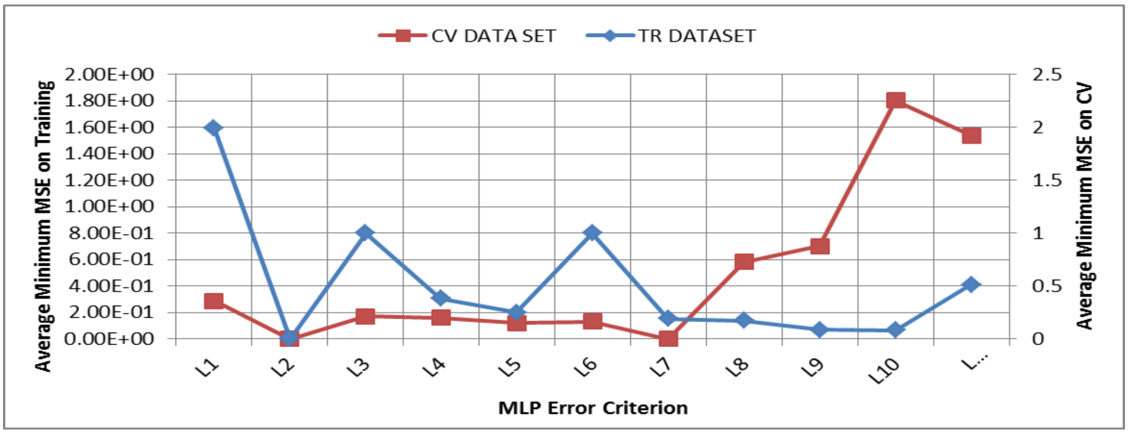


(a)

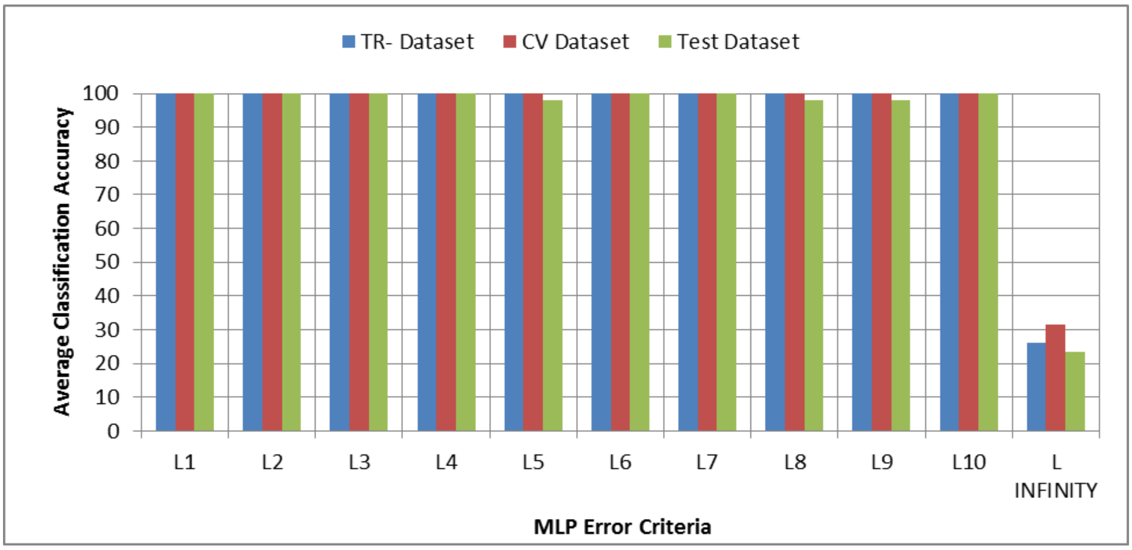


(b)

Figure 2-7: a) Average minimum MSE variation on training and cross validation dataset with number of epochs b) Average classification accuracy on TR,CV and TE Data Set with number of epochs.



(a)



(b)

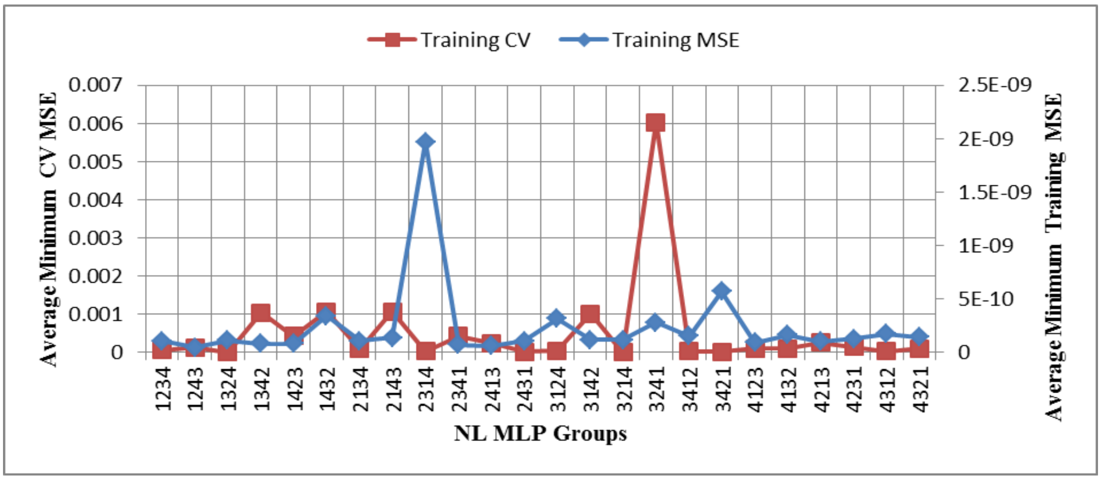
Figure 2-8: a) Average minimum MSE variation on training and cross validation dataset with error criterion b) Average classification accuracy on TR,CV and TE Data Set with error criterion.

With above experimentation, The MLP based NN classifier is designed with following classifications.

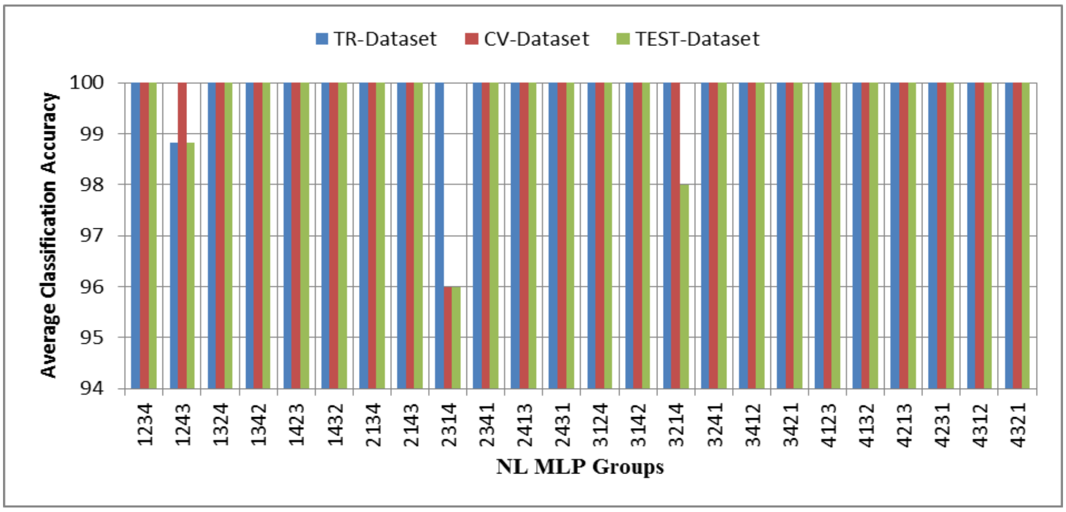
Number of inputs 12, Number of hidden layer 01, Number of PEs in hidden layer 18, Number of Pes in output layer 05, Number of epochs 3500, exemplars for training 70 %, exemplars for cross validation 15 %, exemplars for testing 15 %. Number of connection weight 323, Error criterion L2.

Layers of MLP	Transfer Function	Learning Rule
Hidden	Tanhaxon	LM
Output	Tanhaxon	LM

To check the versatility of the network on the basic of learning ability and classification accuracy. The data is divided into four parts naming 1,2,3,4.for no load ,rated load and greater than rated load. Preparing 24 different combination of group data. Forming 1234 ,1243 group likewise. First two part of the group are tagged as training data, similarly third and fourth part of the group is tagged as cv and testing data. The network is trained and test on this different combination of data. The average minimum MSE on training and cv is shown in fig 2-9(a). The average classification accuracy on tr, cv and test is shown in fig 2-9(b).



(a)



(b)

Figure 2-9: a) Average minimum MSE variation with test on testing and training dataset with MLP Groups b) Average classification accuracy with test on testing and training dataset with MLP Groups.

3 RESULT AND DISCUSSION

This paper presents an artificial neural network based approach for fault detection and classification of three phase permanent magnet synchronous motor for two types of incipient faults namely stator inter turn and eccentricity. An optimal MLP Neural Network are designed and trained to classify different types of faults, stator inter turn, static eccentricity, dynamic eccentricity and mixed eccentricity. For MLP NN various transfer function and learning rule are used for different number of hidden layer and processing elements in hidden layer. It is observed that tanhaxon transfer function and LM learning rule in hidden and output layer gives optimum result with 3500 epochs. To check the versatility and learning capability of network the networked is trained on different group of dataset.

Average minimum MSE on testing and cross validation is going to observe reasonable low as 9.910608E-06 and 0.002076308 respectively and average classification accuracy on testing and cross validation is 99.99% and 99.98% respectively. This method is used for fault detection and classification, without any prior knowledge of fault. And is used in real world application.

4 CONCLUSION

This paper proposes a novel approach to intelligent incipient fault detection and classification of three phase permanent magnet synchronous motors based on a multilayer perceptron neural network. To detect stator inter-turn and eccentricity faults in three phase permanent magnet synchronous motors, simple static parameters such as three phase voltages, three phase currents, healthy winding temperature, faulty winding temperature, bearing temperature, motor body temperature, acquoistic noise, and power factor are used. The first layer hidden layer tanh-LM was discovered to be suitable as a transfer function and learning rule in the design. Tanh-LM is identified as an effective transfer function and learning rule in the output layer. For generalisation, the network is rigorously trained and tested with different data sets and operating conditions such as no load, rated load, and greater than rated load.It has been found that the network is able to detect the fauts in three phase permanent magnet synchronous motor with average classification accuracy of nearly equal to 100%. Since the proposed classifier is to be used in real time with minor modification.

ACKNOWLEDGMENT

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