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A PATH FOR HORIZING YOUR INNOVATIVE WORK

FAULT DETECTION IN THREE PHASE INDUCTION MOTOR USING ARTIFICIAL INTELLIGENCE

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Abstract: This paper describes early detection of faults in induction motor as well abnormal voltage condition would eliminate damage in the motor. In this paper feed forward neural network and ANFIS techniques are used for the detection of bearing fault and voltage unbalance condition. More than one parameter of the motor are use for detecting such a fault with stator current. The signal transform with ceptral coefficients analysis technique are used to extract features of the motor parameter. The main aim of this paper is to analyse the simulation data and provide a generalised method for detection of faults in the three phase induction motor with neural network and ANFIS technique.

Keywords: Feed Forward Neural Network, ANFIS, Bearing Fault, Voltage Unbalance

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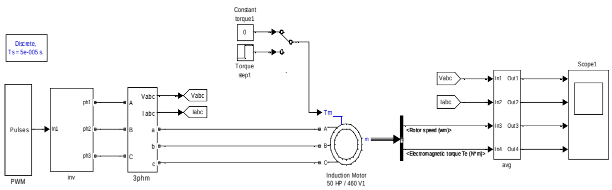
INTRODUCTION

Induction motor is used in many fields of industrial production system, due to their advantages like quick start, less maintenance etc. Long term working failure is very crucial for production system. Like other types of electrical machines these motors are exposed to a wide variety of environmental conditions electrical and mechanical errors. Because of these motor defects will bring about labour and maintenance cost. Bearing problems are also caused by improperly forcing the bearing onto shaft or into the housing. This produces physical damage. However voltage applied to the motor are not exactly the same, unbalanced currents will flow in stator winding, the magnitude depend upon the amount of voltage unbalance this effect may overheat to the point of burnout. The main aim of this work is to develop software based model for prediction and detection of unbalance voltage condition and bearing faults in induction motor. The objective of this to present feed forward neural network and ANFIS techniques for accurate detection and classification of this fault.

2.Software Model of Induction Motor

Simulation model of an induction motor are used for generating the data for voltage unbalance condition and bearing fault. The motor parameters which include supply voltage, current, torque and speed at corresponding condition i.e. motor under No load, half load, and full load condition. Simulation model of Induction motor under consideration is Asynchronous, squirrel cage model with stator and rotor wye connected. It is a 2 pole model supplied with 460v, 50Hz, 5.4HP, 4KW, and 1430rpm. Torque model indicates the loading condition of the motor. If the torque is of constant value it indicates no load condition. When this torque step size increases it indicates loading condition of the motor. Thus according to the torque value loading condition changes and bearing fault introduces using uniform random number. Following shows the motor model. These are designed to collect the sufficient testing data for the neural, neuro fuzzy system.



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3. Feature Extraction

The main problem facing the use of ANN is the selection of the best input and creating the highly accurate network. For that feature selection is the important process. To generate the inputs from the above database short time Fourier transform is used so as to extract the components from the long time domain signals.

A.Short-Time Fourier Transform

All the parameter that is current, voltage, torque, speed is gone under the STFT.*Short-Time Fourier Transform* (STFT), maps a signal into a two-dimensional function of time and frequency. However, we can only obtain the information with limited precision, and that precision is determined by the size of the window. To overcome this drawback of the Fourier transform we are taking the mel frequency coefficients of the signals so as we can take the features from equally spaced bands.

B.Mel-frequency cepstral coefficients (MFCCs)

The mel-frequency cepstrum (MFC) is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency. Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC. in the MFC, the frequency bands are equally spaced on the mel scale, which approximates the signals response more closely than the linearly-spaced frequency bands used in the normal cepstrum. This frequency warping can allow for better representation of signal. MFCCs are commonly derived as follows:

Take the Fourier transform of (a windowed excerpt of) a signal.

Map the powers of the spectrum obtained above onto the mel scale, using windows.

Take the logs of the powers at each of the mel frequencies. The MFCCs are the amplitudes of the resulting spectrum.

C. *Discrete wavelet transform*

In discrete wavelet transform we are also used here for taking into account only the low frequency components of the signal under consideration because low frequency component characterize a signal. After applying these methods we applying the haar transform on the signal to calculate the energy of the signal. This energy signal is then used to generate sufficient

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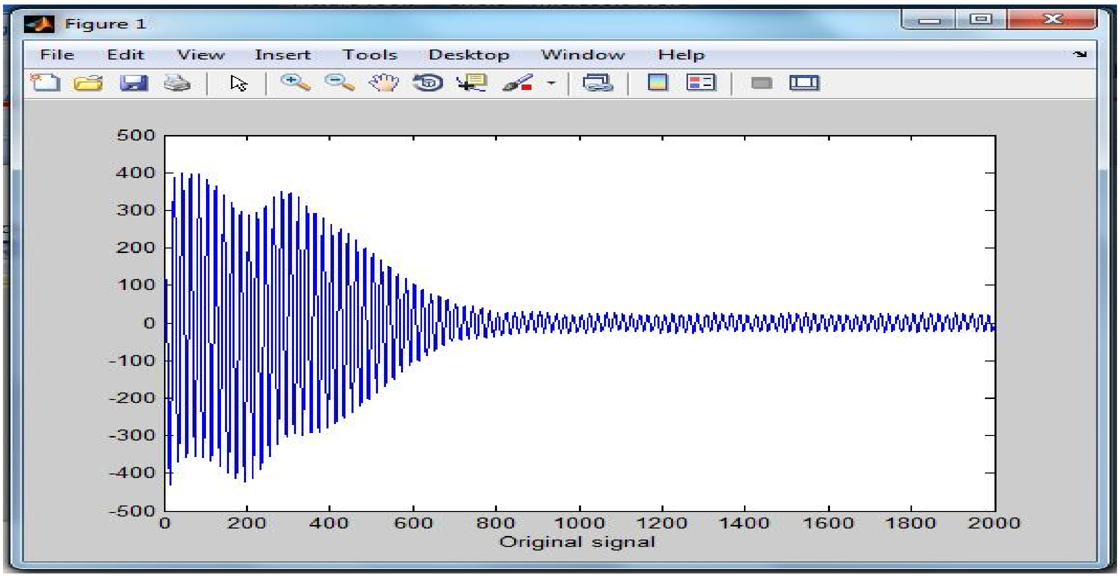
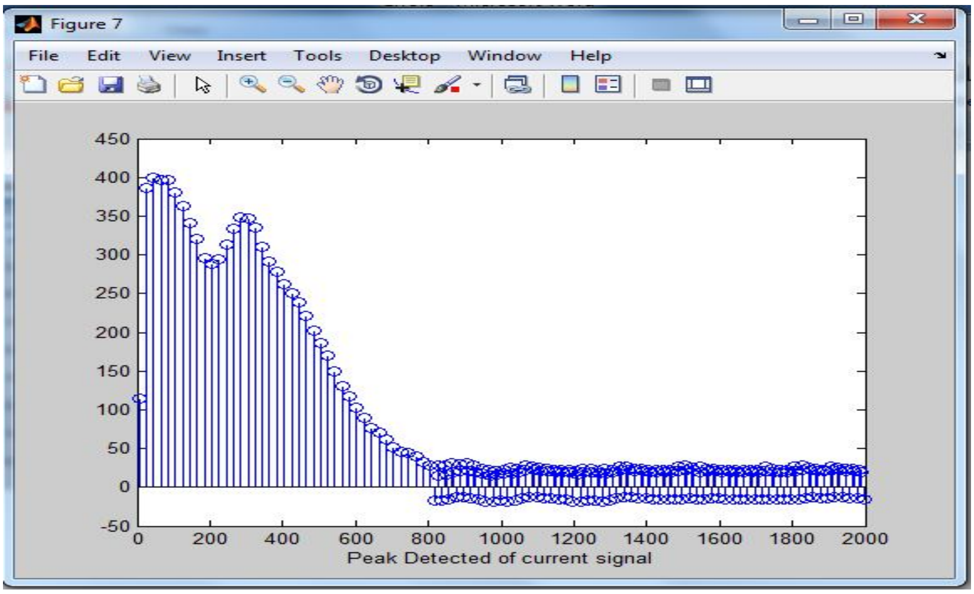
data for the training of the network. This database consists of normal as well faulty data.The following shows the results for the parameters under the consideration





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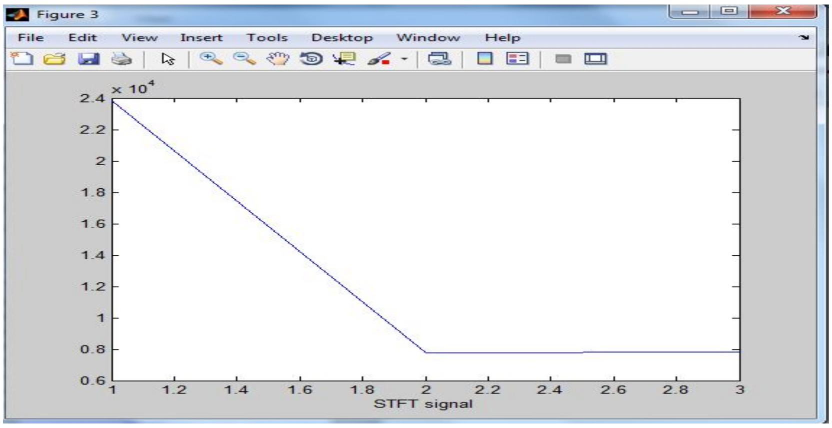
Figure 3
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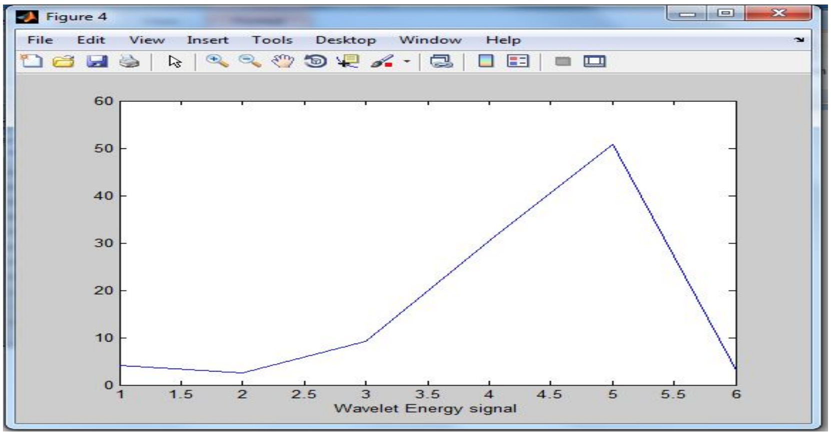
STFT signal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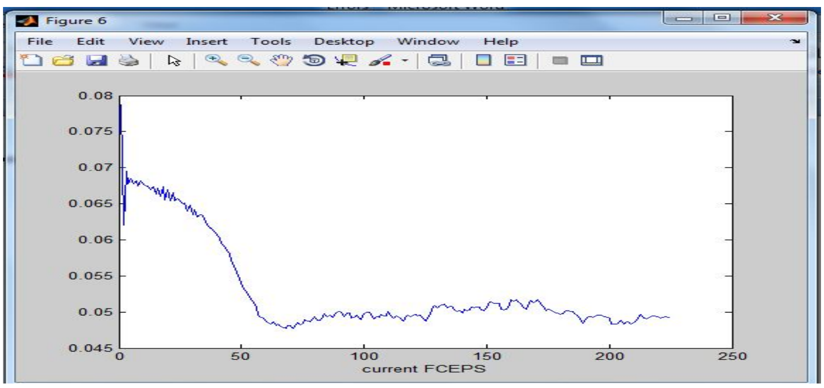
Wavelet Energy signal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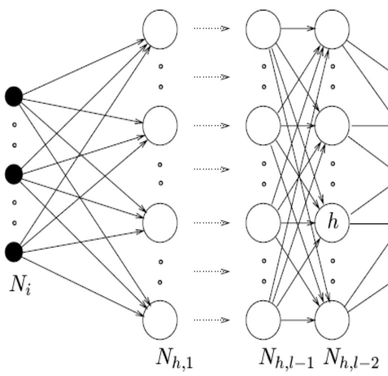
4. FEED FORWARD NEURAL NETWORK

In this work, we are using the architecture of the Feed forward neural network, which consists of an input layer, one or more hidden layers, and an output layer. In this type of network, the input is presented to the network and moves through the weights and activation functions towards the output layer, and the error is corrected in a backward direction using the well-known error back propagation correction algorithm. After extensive training, the network eventually establishes the input-output relationships through the adjusted weights on the network.



A. ALGORITHM

Initialization of Weights

Step 1: Initialize weight to small random

values.

Step 2: While stopping condition is false, do

step 3- 10.

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

Feed Forward

Step 4: each input signal xi and transmits this signal to all units in the layer above i.e. hidden layer.

-

Step5: Each hidden unit sums its weighted input signals, $z_{-inj} = v_{oj} + \sum x_i v_{ij}$ Applying activation function $z_j = f(z_{inj})$ and this signal to all units in the layer above i.e. output units. Here activation function is tansig.

Step6: Each output unit (yk, k=1... m) sums its weighted input signals

$y_{-ink} = w_{ok} + \sum z_j w_{jk} + \sum x_i v_{ij}$ and applies its activation function to calculate the output signals. Here activation function used is purelin $Y_k = f(y_{-ink})$

Back propagation of Error

Step 7: Each output unit (y_k, k=1,...,m) receives a target pattern corresponding to an input pattern error information term is calculated as, $\Delta_k = (t_k - y_k) f(y_{-ink})$

Step 8: each hidden unit (z_j, j=1... n) sums its delta inputs from units in the layer above $\Delta_{-inj} = \sum \Delta_j w_{jk}$ The error information term is calculated as, $\Delta_j = \Delta_{-inj} f(z_{-inj})$

Updation of Weight and Biases

Step 9: Each output unit (yk, k=1,...,m) updates its bias and weights (j=0,...,p) The weight correction term is given by , $\Delta w_{jk} = \alpha \Delta_k z_j$ and the bias correction term is given by, $\Delta w_{ok} = \alpha \Delta_k$ Therefore

$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk}$,

$w_{ok}(new) = w_{ok}(old) + \Delta w_{ok}$

Each hidden unit (zj, j=1,...,p) updates its bias and weights(i=0,...,n) the weight correction term, $\Delta v_{ij} = \alpha \Delta_j x_i$,

The bias correction term , $\Delta v_{oj} = \alpha \Delta_j$ Therefore, $v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$,

$v_{oj}(new) = v_{oj}(old) + \Delta v_{oj}$,

Step 10: Test the stopping condition.

The feed forward network used for training Liebenberg marquardt ,the performance measure used are mean squared error so as to reduce the errors occurs in training and testing the data. Training function provides the batch training i.e. updating the weight after each presenting the complete data set. This function gives gradient descent learning with momentum, levenberg-Marquardt algorithm. The most common performance function used for training is the Mean

-

Squared Error which most commonly seen in function approximation network. To train the network using gradient descent with momentum the default learning rate value is 0.01 and momentum value is 0.9. The next parameter is the maximum number times the complete data set may be used for training the net (epochs) are 1000.thus following shows the complete training data for neural network.

norvaltar = 57.0088

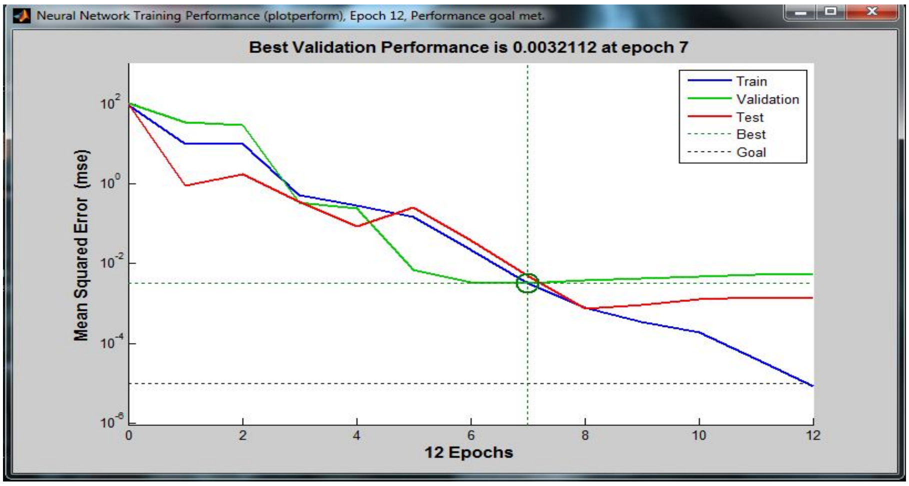
Training with TRAINLM.

Epoch 0/1000, Time 2.044, Performance 97.6094/1e-005, Gradient 931.5699/1e-005, Mu 0.001/10000000000, Validation Checks 0/6

Epoch 12/1000, Time 12.745, Performance 8.1015e-006/1e-005, Gradient 0.10931/1e-005, Mu 0.001/10000000000, Validation Checks 5/6

Training with TRAINLM completed: Performance goal met.

The training data used for the network is 95%, validation data used is 5% and test data is 5%. The data division method used is random i.e. for appropriate training of the network data randomly divided. The activation function used for hidden layer is tansig and for output layer is tanlin. The performance of the network in the form of number of epoch's verses MSE is shown as follows



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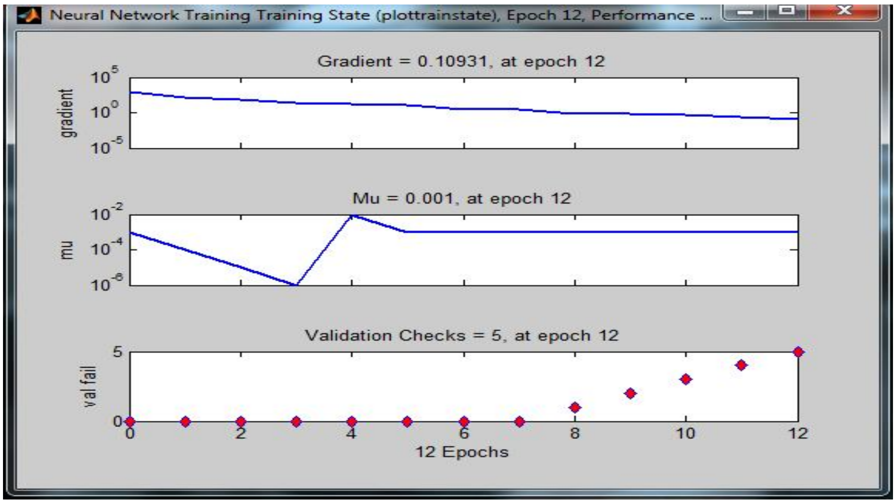
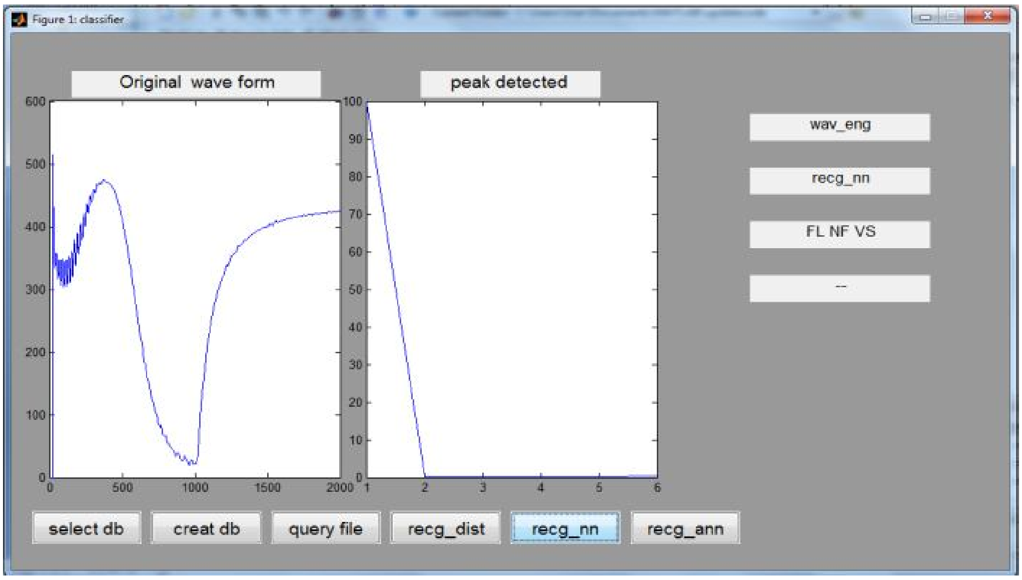
thus training to the network stops when performance is minimized to the goal, the performance gradient fall below min_grad, and validation has increased more than max_fail times since the last times it decreased when using validation. This training state is shown below.



As we are using the gradient descent with momentum algorithm which calculates the weight change (dW) for a given neuron from the neurons input (p) and error (e).



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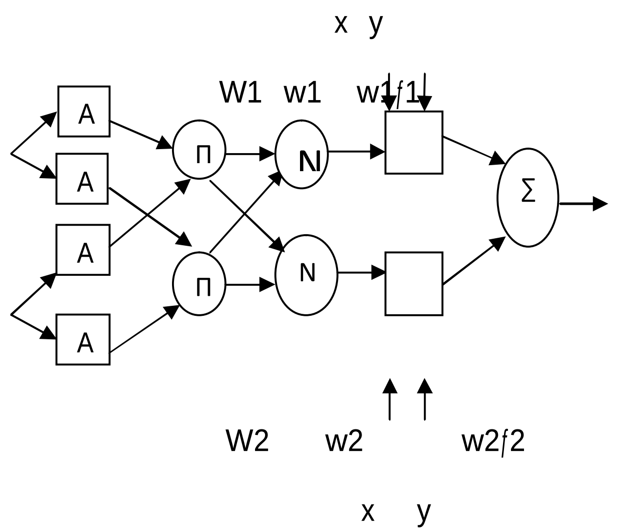
5. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS stands for Adaptive Neuro-Fuzzy Inference System. ANFIS can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership function to generate the stipulated input output. It is a hybrid neuro-fuzzy technique that brings learning capabilities of neural networks to fuzzy inference systems. The outputs from his inference sytem are used to train the network.

Layer 1 Layer 2 Layer3 Layer 4



The circle node shows the fixed nodes and square node has the parameters. Fuzzy inference system under consideration has three input and one output. Rule base contains fuzzy if then rule of sugeno type. The architecture of ANFIS shows that node functions in the same layer are having same membership function.

Layer1: every node in this layer having the node function as Oi=µAi(x)

Where x is input to node I and Ai is linguistic label associated with the node function. The member function used for this layer is bell shaped type

$$\mu Ai(x) = \frac{1}{1 + [\left(\frac{x - ci}{ai}\right) \wedge 2]^{bi}}$$

The generalized bell function depends on three parameters *a*, *b*, and *c*.The parameter *b* is usually positive. The parameter *c* locates the center of the curve. The parameters in this layer are referred as premise parameter.

-

Layer 2: every node in this layer labeled Π which multiplies the incoming signals and sends the product out. For instance

$$W_i = \mu A_i(x) * \mu B_i(y),\ i = 1, 2$$

Each node output representing the firing strength of a rule. Generalized AND function can be used as node function in this layer.

Layer 3: each node in this layer has the node function as

$$O_i = w_i f_i = w_i\,(p_i x + q_i y + r_i)$$

Where wi is the output of layer 2 and (p_i, q_i, r_i) is the parameter set. Parameter is layer will be referred as consequent parameters.

Layer 4: the node in this layer labeled ∑ that computes the overall output as the summation of all incoming signals,

$$O_i = \sum w_i f_i = \frac{\sum \bar{w}_i f_i}{\sum \bar{w}_i}$$

This ANFIS constructed with three input and one output, the membership function are divided into four parts, so input is partitioned into sixteen fuzzy subspaces which results in 64 rules. ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data set.

Following are the ANFIS info:

Number of nodes: 158

Number of linear parameters: 256

Number of nonlinear parameters: 36

Total number of parameters: 292

Number of training data pairs: 60

Number of checking data pairs: 0

Number of fuzzy rules: 64

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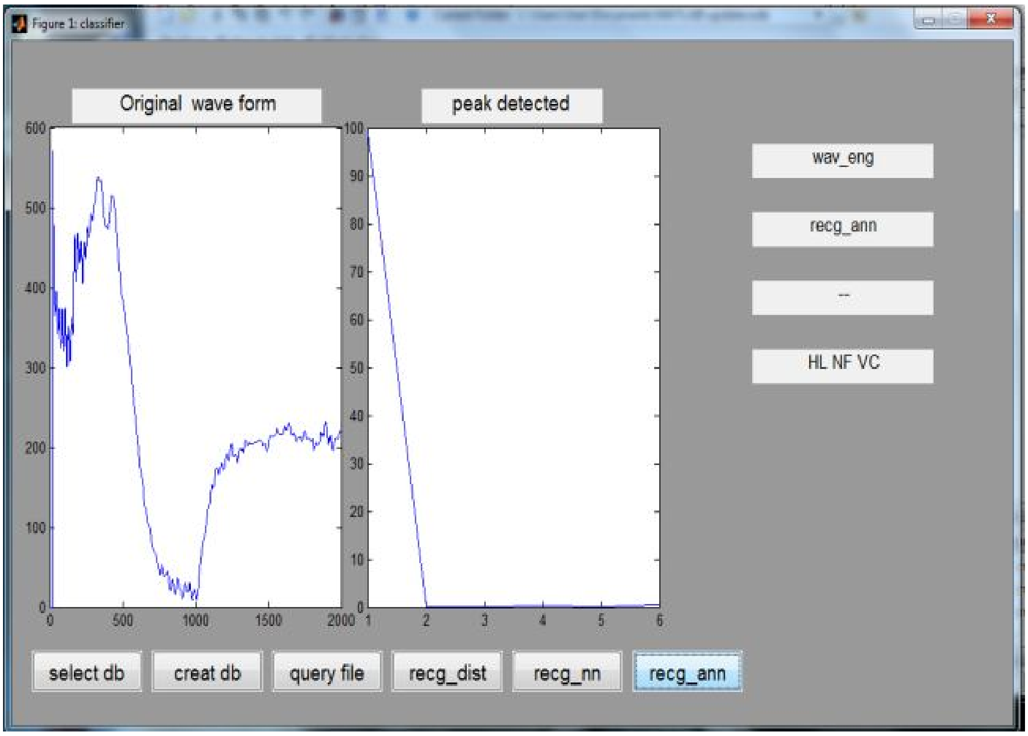
When we start training ANFIS ...Step size decreases to 0.009000 after epoch 5. Again this Step size decreases to 0.008100 after epoch 19. Designated epoch numbers reached. ANFIS training completed at epoch 20. The designed network for detecting faults in three phase induction motor is trained successfully. For more than one input parameter of the motor it provides accurate output due to its fuzzy inference system. The output of the network for the given input is as follows.



6.Conclusion

In this work feed forward neural network based classifier as well ANFIS classifier is evaluated for detection of bearing fault and voltage unbalance condition of the motor. This approach reduces practical data that are needed to design the fault detector. The MFCC and FCeps features from the signal are helpful to detect the fault condition. It may work instead of the variable threshold value of the signal. It is discussed that with the help of five different parameters of the motor networks can be trained well so as it can increase the accuracy for the fault detection of the motor.

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