

Simultaneous Detection of Broken Rotor Bar Fault and PQ disturbances in the Supply to Induction Motor Using Neuro-Fuzzy

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ABSTRACT: This paper presents a methodology for the detection of broken rotor bar fault and power quality (PQ) disturbances in the supply to induction motor. These faults lead to increase in the temperature and decrease in the efficiency of the induction motor. Wavelet transform is applied to the stator current, for the extraction of the signature of the fault. These wavelet coefficients are fed as input to Adaptive Neuro Fuzzy Inference System (ANFIS). The output of ANFIS network detects both the health of the machine and the nature of the supply. The entire simulation is done using MATLAB SIMULINK. The proposed network has performance efficiency of 92.06%.

KEYWORDS: Adaptive neuro -fuzzy inference system, Induction motor, Discrete wavelet transforms, Broken rotor bar fault, PQ disturbances.

I. INTRODUCTION

Power engineering, in one way or other is related to Power Quality. Power quality (PQ) encompasses the study of deviations of voltage and current waveforms from ideal sinusoidal waves. Good PQ is essential for the reliable working of the connected equipment/load and interconnected loads without much loss of performance. PQ disturbances have become a salient issue to the consumers due to extensive use of non-linear loads and sensitive power electronic equipments. These PQ disturbances include voltage surges/sags, over voltage, under voltage, flickers, interrupts and harmonics. These PQ disturbances have predominant impact on the operation of the motor by affecting torque, speed, efficiency, cause mechanical shock and also reduce the lifetime of the motor. This in turn leads to safety concerns, unreliable operation, damage of capital –intensive appliances and mainly huge economic loss.

With the growing population and technological trends, requirement for clear electric power is persistently increasing. In the present scenario, electrical motors have become the integral part of the world to meet various requirements. Induction Motors are far and wide used electrical motors by virtue of its ruggedness, reliability, low cost and better performance. Induction motors finds its applications in various fields where synchronous operation of a machine is not required such as industrial drives, agricultural pumps, cranes, conveyors etc., IM works on the principle of mutual induction. The currents in the rotor bars are induced due to the variation of the flux produced in the stator linking the rotor. Hence any variation in the supply parameters or machine parameters leads to abnormal operation of the motor. If these abnormalities are prolonged then it may lead to faults resulting in the failure of the motor.

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Faults in electrical machines are broadly classified as [1]

1. Stator faults (38%)
2. Rotor faults (10%)
3. Bearing balls faults (40%)
4. Other faults (12%)

When these faults are superimposed with the PQ disturbances then identification of health of the motor becomes difficult. Hence this calls for the continuous monitoring of the health of the motor. Condition monitoring plays an important role in the identification of various PQ disturbances and to ensure reliable operation of the machine. Along with monitoring of the machine, monitoring of the supply parameters is also required as good Power Quality is necessary for the reliable operation of the motor. There are many commercially available tools to monitor induction motors to ensure high degree of reliability. In spite of many condition monitoring tools, many companies are still facing unexpected system failures and reduced motor lifetime. Also in computation of fault using FFT, the frequencies similar to those used for rotor bar breakage detection can be generated due to low frequency oscillating torque loads and voltage imbalance. In such cases, FFT would not produce good results. STFT on the other hand uses constant window size for all frequencies, thus gives good time resolution but poor frequency resolution. To overcome these problems, Wavelet transform is used as it imbibes the features of variable frequency, variable time window. Because of this ability of time localization and multi resolution analysis, it makes wavelet an attractive technique for fault detection. Classification of the faults is done with the help of hybrid learning algorithm such as Adaptive neuro-fuzzy inference system-ANFIS, which is fusion of neural network and Fuzzy. It is known for its knowledge extraction feasibility, domain partitioning, rule structuring and modifications [2-9].

The main aim of this paper is to detect broken rotor bar fault in induction motor operating at full load subjected to supply PQ disturbances. The entire simulation is carried out using MATLAB SIMULINK software. A 3 phase squirrel cage induction motor of 3.2KW, 400V, 50Hz, 4 poles is selected to perform the simulation. Figure 1 shows the simulink model of the proposed test bench.

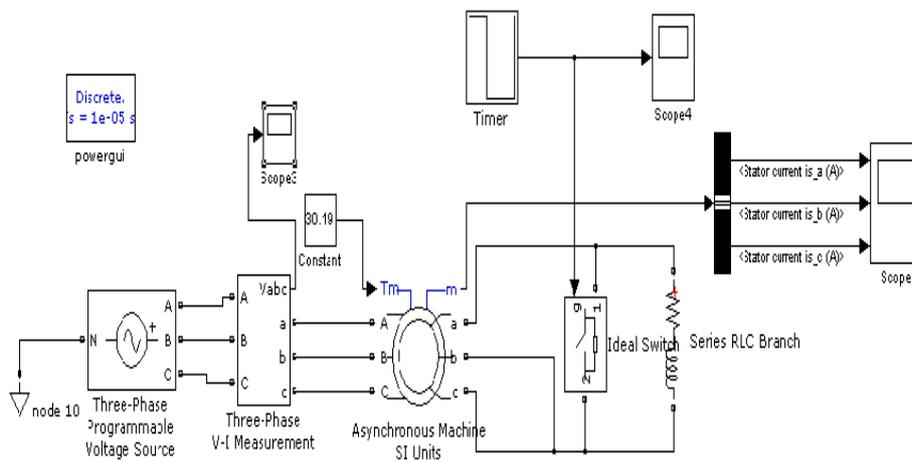


Fig. 1: MATLAB / SIMULINK model of the proposed technique.

The rotor bar is broken at 0.3 sec after the start up in the steady state region. The stator current of the induction motor is sampled with a sampling frequency of 100 KHz and processed by 11th level Daubechies-9 (DB9) wavelet for extracting the signature of the fault. DB9 has emerged as the most suitable wavelet for our application, after several comparisons between different wavelets. These wavelet coefficients are given as inputs to ANFIS which is used for the classification purpose. The output of the ANFIS model gives the status of both the machine and the supply.

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II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Adaptive neuro fuzzy inference network (ANFIS), as the name indicates, is a network structure consisting of a number of nodes connected through directional links. Each node depicts a process unit, and the links between nodes specify the causal relationship between the connected nodes. The learning rule enumerates a way the parameters (of the nodes) should be updated to minimize a prescribed error measure. By merging the positive features of neural network and fuzzy, a simple fault detection technique is developed.

The important steps of the neuro-fuzzy modelling approach are:

- Fuzzification of the input physical variables.
- Computation of the degree of satisfaction for the available linguistic terms.
- Conjunction of the premise and the fuzzy inferred parameters.
- Defuzzification of the output.

There are two methods that ANFIS learning employs for updating membership function parameters:

- Backpropagation for all parameters (a steepest descent method)
- A hybrid method consisting of backpropagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions.

Here ANFIS uses sub-clustering to generate fuzzy inference system (FIS) model for the input data set and then uses Backpropagation algorithm to train the parameters of a Sugeno type fuzzy inference system (FIS). The training process continues till the desired number of training steps (epochs) between the desired and the generated output is achieved. Backpropagation algorithm identifies premise and consequent parameters of first order, Sugeno type fuzzy system for predicting the levels of sag and swell for both balanced and unbalanced supply.

The fuzzy logic takes into account the imprecision and uncertainty of the system that is being modelled while the neural network gives it a sense of adaptability. Using this hybrid method, at first an initial fuzzy model along with its input variables are derived with the help of the rules extracted from the input output data of the system that is being modelled. Next the neural network is used to fine tune the rules of the initial fuzzy model to produce the final ANFIS model of the system. ANFIS has an edge over the other techniques of soft computing as it exhibits features of both neural network and fuzzy.

III. PROPOSED METHODOLOGY

The fault detection step involves sampling of the stator current with a sampling frequency of 100 KHz and applying wavelet transform to obtain the signature of the fault. Wavelet transforms compares many stretched and shifted wavelets to the original pulse. They provide a tool for time-frequency localization. For different types of signals, different types of wavelets can be selected that best match the features of the signal we want to analyse. The choice of mother wavelet, the order of the wavelet and the number of decomposition levels plays a crucial role in obtaining an effective output. In the present work Daubechies wavelet-9 (DB9) has emerged as the most suitable wavelet, after several comparative study between different wavelets. The number of levels of wavelet decomposition L is calculated according to the following equation [10]:

$$L \geq \text{int} \left[\frac{\log \left(\frac{f_s}{f} \right)}{\log 2} \right] \quad (1)$$

For a 50Hz signal with a sampling frequency of 100 KHz the number of levels of wavelet decomposition is found to be L=11 as calculated from equation (1). The 11th level wavelet coefficients are fed as input to the ANFIS for further classification purpose.

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The second stage is the classification of nature of the supply using ANFIS. The algorithm for classification using ANFIS is described as follows:

- Preparation of suitable data set for training the ANFIS network
- Output is defined as:
 - 0 for faulty condition
 - 3 for balanced sag
 - 3 for balanced swell
 - 4 for unbalanced sag
 - 4 for unbalanced swell
- Data-set is loaded and for generation of FIS sub-clustering is opted.
- Network is trained by choosing back propagation algorithm method.
- The test data-set is evaluated

Figure 2 gives the flow chart of proposed methodology

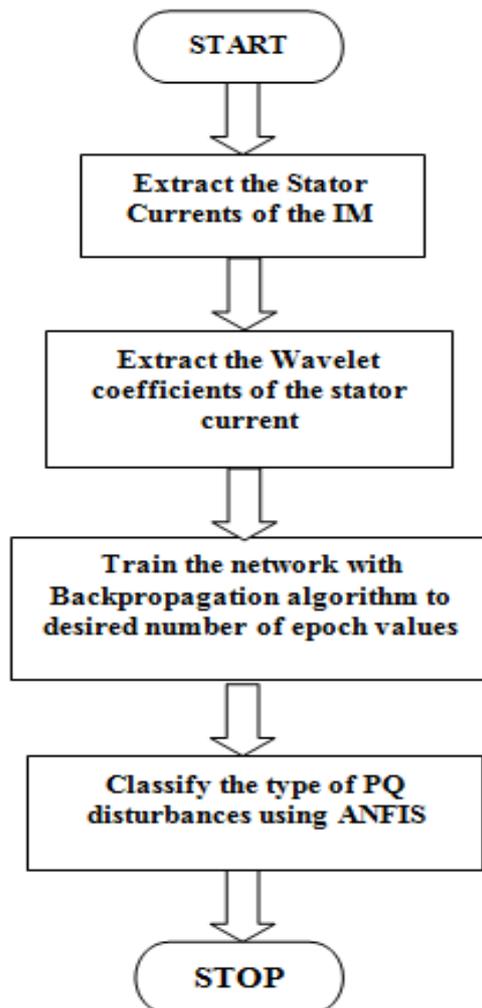


Fig. 2: Flow chart of the proposed methodology

A. ANFIS ARCHITECTURE

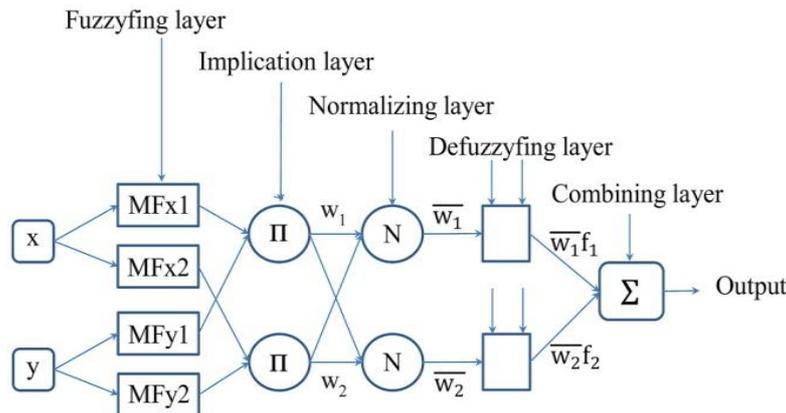


Fig. 3: Structure of ANFIS network

Figure 3 gives the architecture of ANFIS network. The network consists of 5 layers. For the Sugeno model, the rule set is framed based on if-then fuzzy rules. In the ANFIS architecture, it is important to note that nodes of a layer will have a similar function.

Layer 1 (Fuzzyfying Layer): In this layer, the nodes are adaptive (vary based on parameters) along with a node function. There are two inputs “x” and “y” to the node and one output “z”. The input values are scaled and mapped to the domain of variables known as linguistic variables. These variables are determined based on knowledge (intuition) and facts (inference). This layer is a two-step process:

- Assign linguistic variables.
- Assign numerical value to each label.

The linguistic labels which are defined in terms of quantity (small or large) are associated with suitable membership functions. These functions are dependent on parameters called premise parameters exhibiting various forms of membership functions for a fuzzy set.

Layer 2 (Implication Layer): Each node is a fixed node which denotes that it is independent of parameters and the output of this layer is called firing strength of a rule and it is evaluated as a product of incoming signals. Each rule in Fuzzy Clustering (FC) is a node in ANFIS rules layer using dot product (fuzzy AND) to compute the rule matching factor ω_i which is weighted by the firing strength of the rule ω_i .

Layer 3 (Normalization Layer): Each node in this layer is fixed node and it measures the ratio of the rules' firing strength to sum of all rules' firing strength. Hence this layers' output is called normalized firing strength. Each ω_i is scaled into $\bar{\omega}_i$ by calculating the ratio of the firing strength of the respective rule to the sum of the firing strength of all the rules.

Layer 4 (Defuzzyfying Layer): In this layer, the nodes are adaptive as the output is the product of normalized firing strength and the rules. The rules of this layer contain a set of parameters called the consequent parameters.

Layer 5 (Output Layer): This layer has one node and it is a fixed node which calculates the overall output as the summation of all incoming signals.

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For the network that has been trained, the ANFIS model structure is shown in Figure 4.

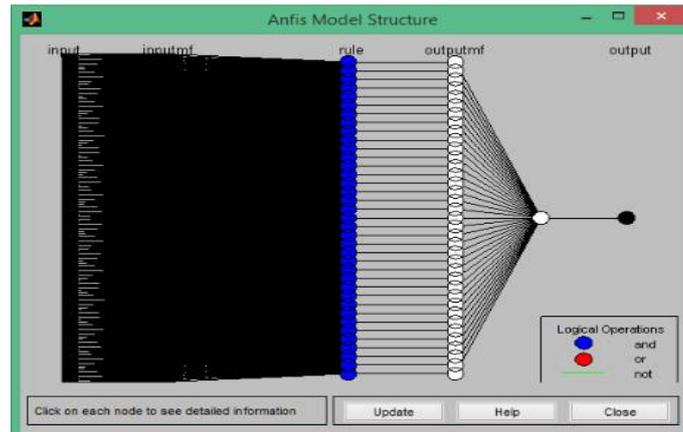


Fig. 4: ANFIS model structure

B. TRAINING ANFIS NETWORK

The training set has been selected to give different combinations of the power supply. 37 input patterns, each containing 212 wavelet coefficients were used for the training of the ANFIS network. The 11th level wavelet coefficients are fed as inputs to the multilayer feedforward ANFIS network for the classification purpose. The ANFIS network is trained using Back propagation algorithm. The ANFIS toolbox has been trained through 20 epochs as shown in Figure5.

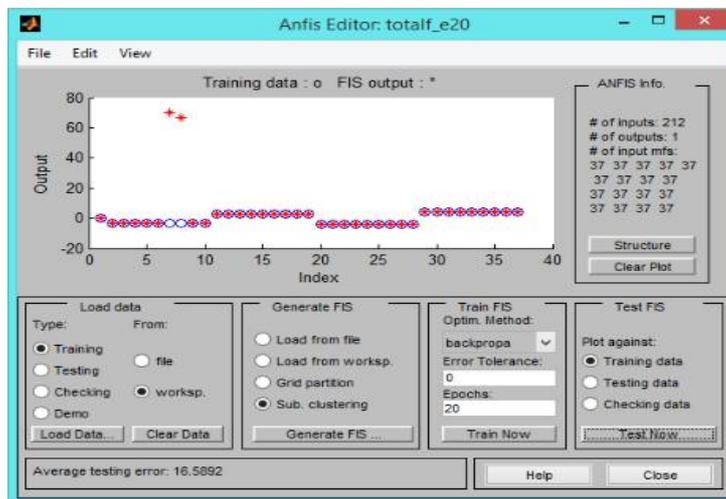


Fig. 5: Training plot

IV. RESULTS AND DISCUSSION

The ANFIS network is trained with 37 different patterns of input. The input consists of

- 1 pattern corresponding to balanced supply at full load torque conditions of the faulty induction motor.
- 9 patterns each corresponding to balanced Sag and balanced swell in the supply.
- 9 patterns each unbalanced Sag and unbalanced swell in the supply.

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The Figure 6 shows the test dataset being evaluated by the network

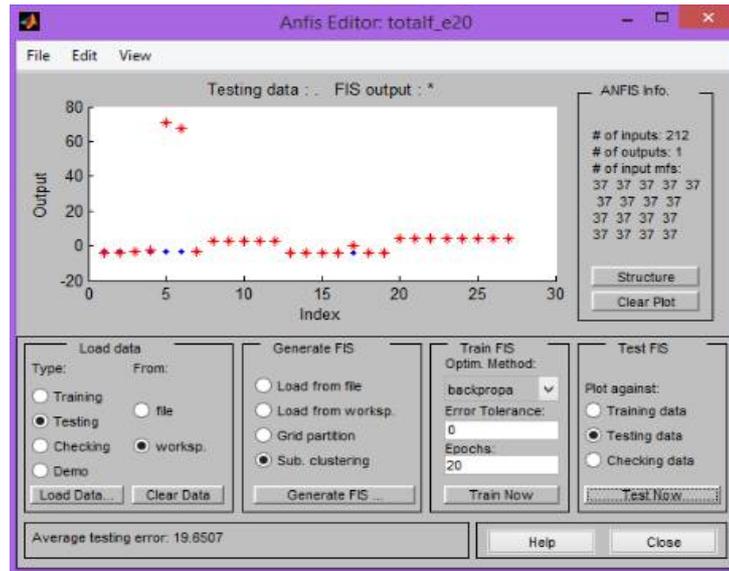


Fig. 6: Testing state plot

Table I gives the classification result of Induction motor at different voltage conditions. The classification accuracy is 100% for trained data, 81.84% for test data and the overall accuracy of the entire network is 92.06% as seen in Figure 7. Further the classification accuracy is found to be 75% for balanced Sag, 100% for balanced swell and unbalanced swell and 93.75% for unbalanced sag as seen in Figure 8.

TABLE I. CLASSIFICATION RESULT OF FAULTY INDUCTION MOTOR FOR DIFFERENT TYPES OF DISTURBANCES FOR TRAINED AND TEST DATA

Sl. No.	Type of Supply	Trained data	Test data	Total	Accuracy
1	Balanced Sag	9/9	3/7	12/16	75%
2	Balanced swell	9/9	5/5	14/14	100%
3	Unbalanced Sag	9/9	6/7	15/16	93.75%
4	Unbalanced Swell	9/9	8/8	17/17	100%
Grand total		37/37	22/27	58/63	92.06%
Percentage column wise		100%	81.84%	92.06%	--

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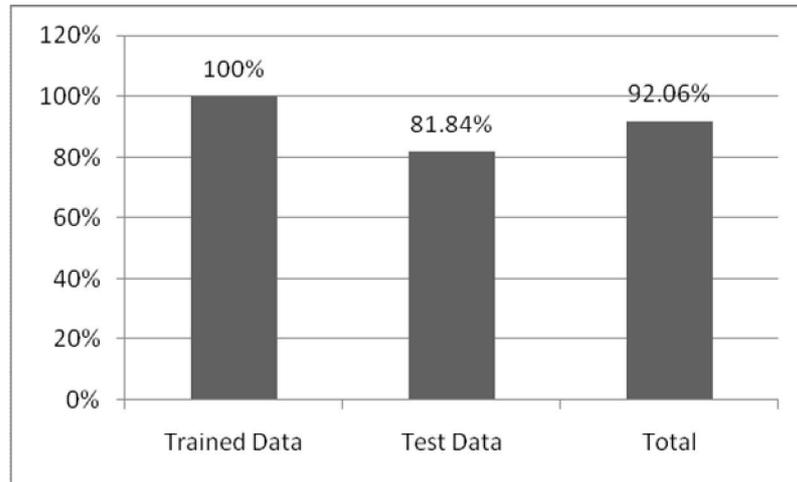


Fig. 7: Percentage classification for trained data, testing data and total data

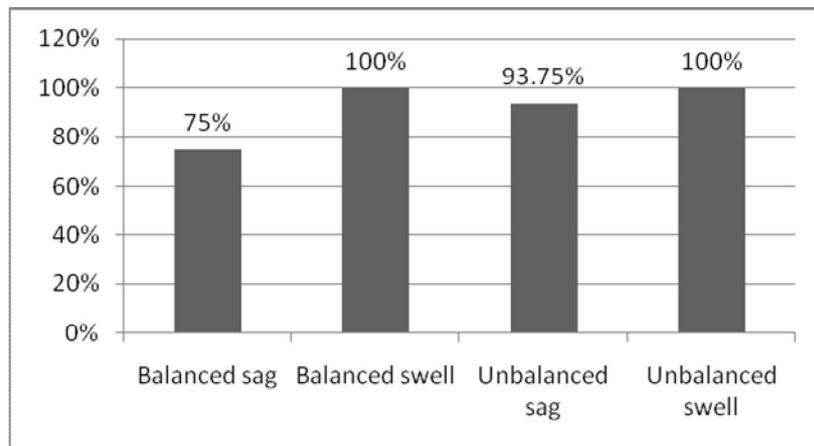


Fig. 8: Classification accuracy of balanced sag-swell and Unbalanced sag-swell in the supply to induction motor

V. CONCLUSION

Fault detection in incipient stages is important for control and protection of induction motor. This paper aims to develop a diagnosis system for simultaneous identification of rotor bar failure in induction motor supply PQ disturbances. By using MATLAB, a model is simulated; DWT is applied to the stator current for the identification of the fault. It is observed that the wavelet coefficients and ANFIS can be used as an efficient tool for the detection and classification of faults. A data set of 37 signals each containing 212 wavelet coefficients was generated for training and an additional 27 signals were used for testing. ANFIS tool is used to classify the faults by generating the FIS model of the given input parameters using sub-clustering technique. Backpropagation algorithm is applied to the model and output is obtained by training the network with 20 epochs. The proposed network has the classification accuracy of 92.06%.

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