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Diagnosis of Stator Turn-to-Turn Fault and Stator Voltage Unbalance Fault Using ANFIS

Sk Moin Ahmed*, Haitham Abu-Rub*, Shady S. Refaat*, Atif Iqbal**
* Departement of Electrical and Computer Engineering, texas A&M University at Qatar
** Departement of Electrical Engineering, Qatar University

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ABSTRACT

An induction machine is a highly non-linear system that poses a great challenge because of its fault diagnosis due to the processing of large and complex data. The fault in an induction machine can lead to excessive downtimes that can lead to huge losses in terms of maintenance and production. This paper discusses the diagnosis of stator winding faults, which is one of the common faults in an induction machine. Several diagnostics techniques have been presented in the literature. Fault detection using traditional analytical methods are not always possible as this requires prior knowledge of the exact motor model. The motor models are also susceptible to inaccuracy due to parameter variations. This paper presents Adaptive Neuro-fuzzy Inference system (ANFIS) based fault diagnosis of induction motors. The distinction between the stator winding fault and supply unbalance is addressed in this paper. Experimental data is collected by shorting the turns of a health motor as well as creating unbalance in the stator voltage. The data is processed and fed to an ANFIS classifier that accurately identifies the faulted condition and unbalanced supply voltage conditions. The ANFIS provides almost 99% accurate and computationally efficient output in diagnosing the faults and unbalance conditions.

Corresponding Author:

Sk Moin Ahmed,
Departement of Electrical and Computer Engineering,
Texas A&M University,
Doha, Qatar
Email: moin.sk@qatar.tamu.edu

1. INTRODUCTION

Condition monitoring and fault diagnosis of electrical machines is extremely important in any industrial set-up as fault in a single machine can have drastic consequences. Thus, extensive research efforts are being put forth to develop various methods of fault diagnosis as summarized in [1-5]. Broadly classified, faults can be of electrical or mechanical nature. A three-phase induction motor may experience several types of electrical fault conditions, such as over load, ground fault, line-to-line fault, unbalanced supply voltage, over voltage, under voltage, single phasing, and turn-to-turn fault [6, 7]. Single phasing situations occur when one of the three-phases of the motor is open. This situation increases the positive and negative sequence currents and excessive heating is hence produced. Unbalanced supply voltage results in negative sequence voltage. It also leads to an increase in positive and negative sequence current components. Similarly, turn-to-turn short and coil open faults can cause line current unbalance. Ground and line faults are detected by observing the zero sequence components of the current.

The inter-turn fault of stator windings usually starts as an undetected insulation failure between two adjacent turns. As a result, it slowly develops to a short circuit isolating a number of turns. In some cases, the fault occurs due to an electric arc connecting two points of the winding. From the past literature analysis, it is obvious that the presence of various faults is simply determined by the stator current analysis most commonly referred as Motor Current Signature Analysis (MCSA) [1]. The stator currents and voltages are usually preferred for diagnostics purposes because the needed sensors are usually available in the existing drive system. In most of the cases, MCSA relies on the model based diagnostic techniques. The stator winding fault detection using a model-based approach is extensively discussed in the literature [8]. The major drawbacks of model-based techniques are the requirements of precise motor parameters and the need of speed signals in addition to the voltage and current. The induction motor model that is developed is independent of rotor speed in [9] and, thus, the diagnostic method is also independent of the torque variation.

To overcome the dependence on the parameter of machines, a method to extract the component produced by the fault from the estimation error is presented in [10]. The negative sequence component of the estimation error is used in this paper. This component is computed by projecting the current estimation error in an inverse-sequence reference frame.

A more precise stator winding fault diagnostic technique that is able to detect even a single turn fault is presented in [11]. The proposed technique can detect incipient fault and is highly sensitive. The fault signature used is the positive and negative third harmonic line current. The proposed technique is independent of structural asymmetry and supply imbalance. It is shown that both positive and negative third harmonic is generated from interaction of specific time and permeance harmonics. It is further shown that the order of time and permeance harmonics for the positive and negative sequence third harmonic components is different and hence both are included for the fault diagnosis. The least squares method is utilized for estimating inherent structural asymmetry and supply-imbalance-related third harmonic components. The final fault signatures (residues) used are the error in the estimated value and measured value of the third harmonic components. The major drawback of the proposed method is the need of a robust observer system to estimate the accurate value of the third harmonic components.

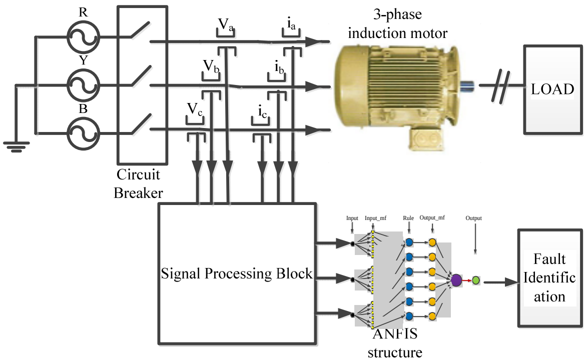
The stator winding faults create unbalancing in the line current, and similar unbalancing is also created due to asymmetrical winding resistances, the circuit connection resistances [12, 13] and supply unbalance. The later is not classified as fault conditions. Some work has been done to identify and distinguish the unbalancing due to faults and the unbalancing due to the inherent asymmetry in the winding and supply [14]. However, the distinction between these two phenomena is highly challenging under no-load conditions. This issue is addressed in this paper.

The traditional monitoring systems have a number of drawbacks such as inflexibility, high cost, and hardware limitations that are highly dependent on specialized instruments. Recently, the monitoring and fault detection of electrical machines have taken a new turn from traditional techniques to artificial intelligence [15-18].

Artificial intelligence techniques are considered significant in condition monitoring and fault diagnosis of electrical machines, reviewed in [19-20]. Neural network and fuzzy logic techniques have their own shortcomings as discussed in [21] and thus a specific combination of these two techniques, known as Adaptive Neuro-Fuzzy Inference System (ANFIS), have evolved as a better alternative solution [22]. The ANFIS technique offers the best training feature of neural network and heuristic interpretation of the process results similar to fuzzy logic theory, thus providing a powerful tool that can be employed in conjunction with the condition monitoring and fault diagnostic applications. The use of ANFIS is growing in popularity in this niche application area and a significant amount of literature is available [23]-[26]. Mechanical fault diagnosis using ANFIS is also discussed in [27-29] for induction motor drive systems. The technique presented in [27] utilizes stator current signature analysis using wavelet packet decomposition to diagnose the broken rotor bar and rotor eccentricity. Bearing fault and inter-turn insulation failure of main winding of a single-phase induction motor is considered in [26]. Stator current, rotor speed, motor winding temperature, bearing temperature and motor noise are considered as input to the ANFIS. However, additional noise sensors are not very reliable and the data collected from such sensors is not very precise. The bearing failure diagnostic used in [30] uses vibration data as one type of input to the ANFIS. Nevertheless, the vibration sensors are also prone to disturbances from the environmental condition. Furthermore, if the grounding of the machine is improper, then the sensor may not give reliable output. The eccentricity related issues also lead to similar vibration and, thus, the distinction between this fault and bearing failure may be difficult.

This paper proposes the application of an ANFIS-based fault diagnostic scheme for stator turn-to-turn fault. Since the stator winding faults creates unbalancing and the unbalancing is also possible in the line, the proposed method distinguishes between the input supply unbalance and stator winding fault conditions. Both the stator winding fault and unbalanced conditions are detected by a single ANFIS structure that is experimentally tested on a three-phase induction motor. The three phase stator currents and voltages are sensed for each of the faulty and normal cases. The three phase currents and voltages are passed through a signal-processing block where these signals are converted to three signals which are fed to the ANFIS for fault identification and classification of fault and unbalancing. The three signals that are fed to the ANFIS are the magnitudes of the negative sequence current, positive sequence current and negative sequence voltage.

The block diagram of the diagnostic system is shown in Fig. 1. The testing results of the ANFIS diagnostic system give over 99% accuracy in fault detection.



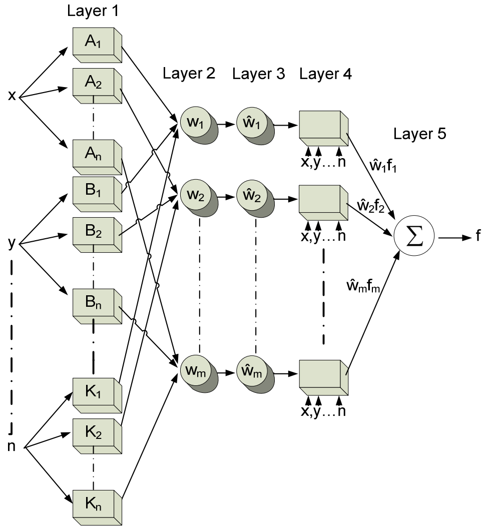


Figure. 1. Block diagram of the diagnostic system Figure. 2. A typical ANFIS structure

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSYTEM: OVERVIEW

ANFIS is a hybrid controller structure using a fuzzy logic inference system and the architecture of a neural network having five-layer feed-forward structure. Thus, the ANFIS offers the advantages of learning capability of neural networks and the inference mechanism of fuzzy logic. A typical architecture of ANFIS having *n* inputs, one output, and *m* rules is illustrated in Fig. 2 [20]. Here *x*, *y*, *z* and up to *n*are inputs, *f* is output, the cylinders represent fixed node functions, and the cubes represent adaptive node functions. This is a Sugeno type fuzzy system, where the fuzzy IF-THEN rules have the following form:

Rule 1: If x is A_1 and y is B_1,… …..n is κ_1 then $f_1 = (p_1 x + q_1 y + r_1 z + ...\upsilon_1)$

Rule 2: If x is A_2 and y is B_2,……..n is κ_2 then $f_2 = (p_2 x + q_2 y + r_2 z + ...\upsilon_2)$.

Rule m: If x is A_m and y is B_m,…..n is κ_m then $f_m = (p_m x + q_m y + r_m z + ...\upsilon_m)$

The operation of each layer is as follows: the output node *i*in layer l is denoted as O_i^l. Layer 1 is a fuzzification layer. Every node *i*in this layer is an adaptive node with node function given by:

$$O_i^l = \xi_{A_i}(x)\,, O_{i+n}^l = \xi_{B_i}(x)\,,$$
$$O_{i+2n}^l = \xi_{C_i}(x)\,.....\,O_{i+nn}^l = \xi_{\kappa_i}(x) \qquad (1)$$

Where *i=1,2,3…..n,*

and*x*is the input to i^{th} node; O_i^l is the membershipgrade of x in the fuzzy set A_i. The generalized bellmembership function is a popular method forspecifying fuzzy sets because of its easy inclusion in numerical calculations, and is defined as:

$$\xi_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \qquad (2)$$

Training of the ANFIS controller is done using hybrid learning procedure which combines back-propagation gradient descent and the least squares optimization method for identification of premise and consequent parameters.

3. PROPOSED STATOR TURN AND UNBALANCE SUPPLY FAULT DETECTION PRINCIPLE

Among several faults occurring in an electrical machine, stator fault is very common. According to a reasonable estimate, it is nearly 35-40% of all faults [5].

Stator turn fault may occur due to undetected insulation failure in several turns of a stator coil within one phase, causing a large circulating current to flow, subsequently generating excessive heat in the shorted turns. The other reason of stator turn fault is found to be the large number of PWM voltage pulses from the drive, which cause partial discharges between turns in the stator. These partial discharges eventually erode the magnet wire insulation, resulting in subsequent failure.

Voltage unbalance at the motor stator terminals causes phase current unbalance well out-of-proportion to the voltage unbalance. It degrades the performance and shortens the life of a machine. Unbalanced currents as a consequence of unbalance voltages lead to increased vibrations, torque pulsations, mechanical stresses, motor overheating and increased losses which results in a shorter winding insulation life. The most common causes of voltage unbalance are:

1. Unbalanced or unstable utility supply
2. Faulty operation of power factor correction equipment
3. Unevenly distributed single-phase loads on the same power system
4. Unbalanced transformer bank supplying a remote three-phase load
5. An open circuit on the primary distribution system
6. Unidentified single-phase to ground faults

The indicators of stator turn fault and stator voltage unbalance faults are increased in the negative sequence current and voltages respectively. This paper considered three key parameters to identify the deterioration of the stator turn fault as well as stator voltage unbalance fault. They are the magnitude of negative sequence current, positive sequence current and negative sequence voltage. These three parameters are fed to ANFIS for fault classification and identification.

A series of experiments are conducted for detection of inter-turn short circuits in the stator windings of a three-phase induction motor and unbalance voltage condition. The three phase induction motor chosen for the experiment operate in open loop condition fed by a three phase auto transformer supply. The motor used in experimental tests is a three-phase, 50 Hz, 2-pole, 2.2kW, squirrel cage induction motor, rated at 380 V, 5 A and 1425 rpm, driving a DC motor via a flexible coupling. The DC motor acted as a generator and its power output was dissipated in a variable resistor bank. The stator currents and voltage signals are sampled at a sampling rate of 12 kHz using a VIBDAQ 4+ data acquisition card. The VIBDAQ 4+ is a portable 4-channel data acquisition card with USB 2.0; the VIBDAQ 4+ is equipped with four independent 24 bits A/D converters, which gives an excellent phase match between channels. The whole system is shown in Fig. 3. Nine different situations are taken into consideration. These situations are repeated with three different types of load condition, namely No Load, Half Full Load and Full Load condition. The nine different situations are:

1. Normal condition 2. 1% turn fault 3. 5% turn fault4. 10% turn fault5. 1% voltage unbalance
6. 2% voltage unbalance7. 3% voltage unbalance8. 4% voltage unbalance9. 5% voltage unbalance

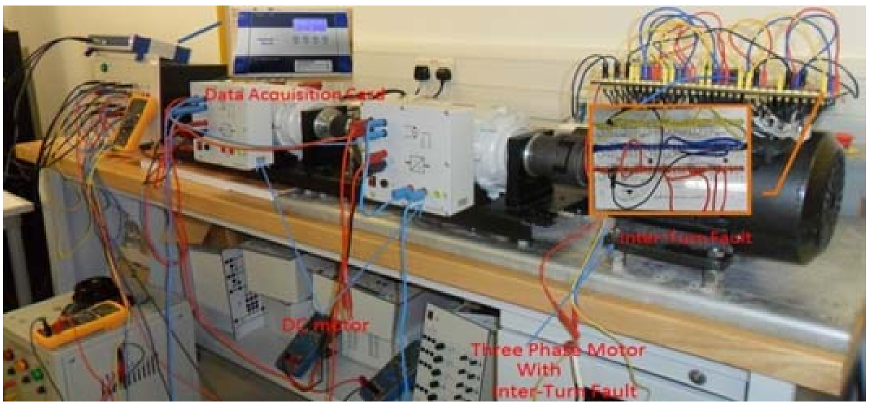


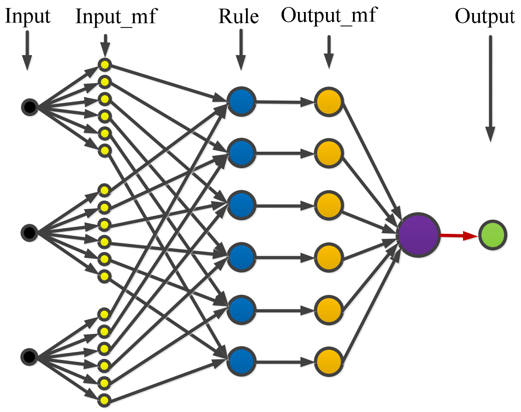
Figure 3. Experimental setup

The data obtained from normal, turn fault and different unbalanced supply voltages are utilized for ANFIS training and testing. Out of 10,000 collected data only 200 data is taken for training. The six set (three currents and three voltages) of 200 data each are fed to a signal processing block. The choice of 200 for the number of data is optimal from computational point of view. The outputs of the block are the magnitude of negative sequence current, positive sequence current and negative sequence voltage. These three parameters are fed to ANFIS structure. Another set of 200 data are used for testing the performance of the ANFIS. The rest of the data are used for checking the performance of the ANFIS.

4. ANFIS BASED DIAGNOSTIC RESULTS

The neuro-adaptive learning method works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. Fuzzy Logic Toolbox software computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. In the present case the initial model for ANFIS training is generated by applying subtractive clustering on the data. Subtractive clustering, [21], is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. The cluster estimates can be used to initialize iterative optimization-based clustering methods and model identification methods (like ANFIS).

The ANFIS model generates six input membership functions of Gaussian structure with the help of subtractive clustering method. The model is run for 200 Epochs. The structure of the ANFIS model is shown in Fig. 4. The post training input membership functions are displayed in Fig. 5.



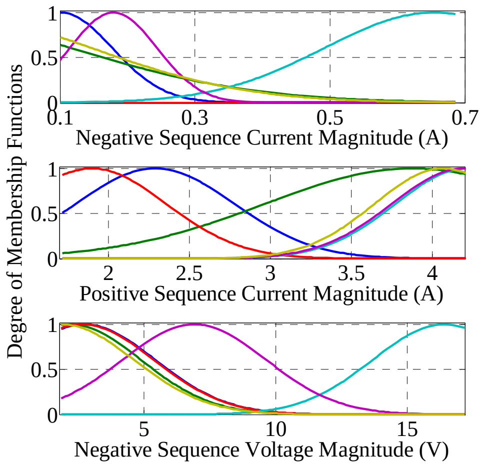


Figure 4. ANFIS structureFigure 5. Input membership functions developed by ANFIS

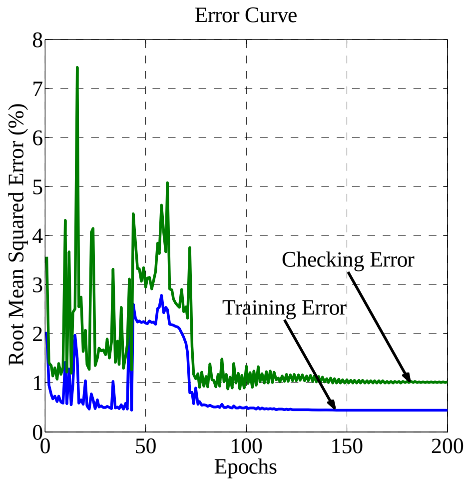


Figure 6. Error curve of the ANFIS controller

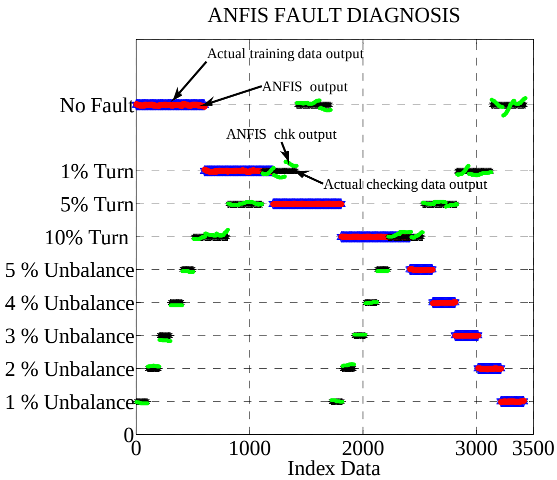


Figure7. Testing and Checking Output for the ANFIS controller

The root mean squared error for the training output is found to be 0.48%. The real fresh data are checked with the developed ANFIS model. The error is about 1%. Both the error curves are plotted in Fig. 6. The ANFIS output range is divided in nine categories. Each category or status of the machine is numerically defined as follows:

No fault: 100, 1% Turn fault: 80, 5% Turn fault: 70, 10% Turn fault: 60, 5% Unbalance fault: 50, 4% Unbalance fault: 40, 3% Unbalance fault: 30, 2% Unbalance fault: 20, 1% Unbalance fault: 10. Each of the faults is created with three different loading conditions a. No Load, b. Half Full Load, c. Full Load.

The trained and checked ANFIS output for different types of fault diagnosis are shown in Fig. 7. The ANFIS performance is found to be excellent. The efficiency of developed ANFIS is about 99% which can be seen from Fig. 6. The input relationships or dependencies for the ANFIS output are also analyzed. These are the unique characteristics of adaptive neuro-fuzzy inference system. Unlike neural network, the input-output mapping in ANFIS is not a black box. The mapping is optimized by neuro adaptive learning techniques by fuzzy modeling procedure to learn information about the data set.

5. CONCLUSION

The main focus of this paper is to use ANFIS for the fault diagnosis of stator turn fault and unbalance supply fault. The ANFIS fault indicator is based on the analysis of magnitude of negative and positive sequence current and the magnitude of negative sequence voltage. The data collected from the experimental test bench were used for off-line training and checking of ANFIS based diagnostic controller. The data are collected for different fault possibilities. The performance of the ANFIS is found to be almost 99% accurate for the diagnosis of fault.

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