Fault Detection Analysis for Three Phase Induction Motor Drive System using Neural Network

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Abstract. One of the most important components of the industrial process is known to be the three-phase induction motor. This device, however, is prone to electrical and mechanical faults, which may cause a substantial component or financial losses. The fault analysis received growing attention due to a need to increase reliability and to decrease potential output loss due to machine breakdown. Thus, the purpose of this paper is to present a simple and reliable fault analysis based on the Neural Network (NN) is proposed. The NN method is a simpler approach without a diagnostic professional to review data and diagnose issues. Various fault disputes of induction motor are developed and analysed using the NN method. The main types of faults considered are over-voltage, under-voltage, and unbalanced voltage faults. The trained network is tested with simulated fault current and voltage data.

1. Introduction
The three-phase induction motor is one of the most common machines used in industrial processes to convert electric energy into mechanical energy. This is mainly due to the low maintenance, reliability, robustness to hostile environments, and fast adaptation to multiple load conditions [1]. With these attractive features, the three-phase induction motor can present electrical or mechanical faults to the system. The electrical fault can happen because weather conditions. This includes lighting strikes, heavy rains, heavy winds, deposition of salt on overhead lines and conductors, accumulation of snow and ice on transmission lines, etc. Such environmental conditions disrupt the supply of power and affect electrical installations. The failure of the equipment often causes various electrical equipment, such as generators, motors, transformers, reactors, switching devices, and short-circuit faults due to malfunction, deterioration, cable insulation failure and winding. These failures result in the flow of high current through the devices, which affects it any further. In addition, electrical faults are often triggered by human mistakes, such as the selection of incorrect device or device ratings, the forgetting of metallic or electrical components after servicing or repair, and the switching of the circuit during maintenance [2].

Reliable operation of the electrical machine provides energy efficiency and financial benefit to the industry. Faults that may affect the smooth operation of the machine are therefore crucial for the safety which paid special attention of investigators in this area. Parameter monitoring of the machine
is important in industry to detect and diagnose the type of fault at an earlier stage. If the faults are not detected in process system, fault can affect to the electrical system like as over current flow and low impedance for current flow occurring high current is drawn form the supply causing relay tripping and insulation damaged. It is also a concern to working workers at the time because the occurrence of faults can also cause shocks to people. The magnitude of the shock at the site of the fault depends on the current and voltage and can even lead to death. These faults cause electrical flow interruptions, damage to machinery, and even the death of humans. Consequently, failures that may affect the smooth operation of the system are crucial to safety, which has given attention to investigators in this field. Hence, the system of failure detection is important for the proper prevention of operational downtime and repair [1 - 3].

Fault detection and classification in three-phase induction motor is necessary to prevent the unexpected failure of electric motors such as stator faults, rotor faults and unbalanced voltage faults. If these faults are not identified in the early stage, it may become catastrophic to the operation of the motor. Research for the fault detection and analysis has been carried out over the last few years. There are two approaches for fault detection which is a model-based method and a knowledge-based method. The model-based method used a mathematical form to analyse each of the problems that occurred. With a model-based method to analyse, it reduces the time consuming for each fault that always faced. In wind turbine system time is important for the operation system. The higher the time of rotation, the higher the fault can occur if the system is shutdown. Analysis with the model-based method is more preferred for mathematical models which can explain the system and evaluations can be done more efficiently. Knowledge-based method is different from model-based method where it required only a large amount of historic data compare to a priori known model [4-6].

Knowledge-based method is also referred as data-based method. Methods that extract quantitative information can be broadly classified as non-statistical or statistical methods. Neural networks (NN) and fuzzy logic (FL) are two methods in non-statistical classifier. An NN is a set of nodes linked by connections with weights representing the strength of those connections. The nodes are organized into layers and data is propagated through successive layers. FL is an approach of partitioning a feature space into fuzzy sets and utilizing fuzzy rules for reasoning, which essentially provide approximate human reasoning. In statistical method, the qualitative knowledge methods are mainly composed of principal component analysis (PCA), partial least squares (PLS), independent component analysis (ICA), statistical pattern classifiers and support vector machine (SVM). PCA is the most popular statistically-based monitoring technique, which is utilized to find factors with a much lower dimension than the original data set so that the major trends in the original data set can be properly described. PLS is one of the dominant data-driven tools for complex industrial processes. ICA plays an important role in real-time monitoring and diagnosis for practical industrial processes as it allows latent variables not to follow a Gaussian distribution. The SVM is a relatively new machine learning technique relying on statistical learning theory, which is capable of achieving high generalization and of dealing with problems with low samples and high input features. The SVM is regarded as a potential technique for classifying all kinds of data sets [7-8].

Few methods have been proposed such as SVM, ANN and FL to detect and diagnose faults in induction motors from mechanical failures and electrical faults in [3]. The observation from vibration spectra, that all tests demonstrated good repeatability and without interference problems, ensuring a reliable analysis of the results. SVM showed a technique with excellent results. In comparison with the ANN, the SVM is not dependent on many parameters which influence the percentage of correct detections. On the other hand, although the LF is a technique that produces excellent results, its use is strongly dependent on an expert who knows the process to be analysed. The technique for fault detection for four-switch three-phase inverter fed induction motor drive is discussed in [9]. The proposed method requires only motor currents and DC-link current to be measured for detecting and identifying the power switch in which the open circuit fault or short circuit fault has occurred. A diagnosis controller using ANN for real-time fault detection of power switches is suggested.

Thus, in this work, several types of electrical faults such as over, under and unbalance voltages, are studied. The induction motor is modelled using MATLAB / Simulink. Fault conditions are simulated by varying the supply voltage in Simulink model. The output of the induction motor is
observed during the above operating conditions. The performances of induction motor during the above operating conditions are observed. The analysis of fault will be perform using neural network method.

2. Neural-network Method
A basic structure of ANN is shown in Figure 1. Nodes are represented by small circles and each layer consists of one or more nodes. The lines between the nodes indicate the flow of information from one node to the next. In this feedforward of neural network, the information flows from the input to the output with weights assigned to the connections. There can be several hidden layers in the network. The layers are fully interconnected in one direction from the input layer towards the output layer. The number of neurons in the input and output layers is governed by the number of inputs and outputs of the pattern to be recognised. However, the number of neurons in the middle layer can be selected depending upon the applications. The neural network has to be trained so that it can identify the output patterns corresponding to the input pattern [10-11].

![Figure 1. Basic structure feed-forward neural network [13]](image)

3. Induction Motor Model
Direct torque control (DTC) is one system used in variable-frequency drives to obtain high performance torque control of three-phase AC electric motors. This includes estimating the magnetic flux and torque of the motor based on the motor's calculated voltage and current. The simulation model of the induction motor is shown in Figure 2 with a specification of 200 hp induction motor. The induction motor is fed by a PWM voltage source inverter. The speed control loop uses a proportional-integral controller to produce the flux and torque references for the DTC block. The DTC block measures the estimates of motor torque and flux and compares them with their respective references.
Table 1. Parameters of three-phase induction motor

| Value   | Parameter                        |
|---------|----------------------------------|
| 460 V   | Input voltage                    |
| 60 Hz   | Frequency                        |
| 200 hp  | Power                            |
| 1800 rpm| Speed                            |
| 460 V   | Voltage motor nominal            |
| 3.1 kgm²| Moment of inertia                |
| 2 pole  | Number of a pole                 |

3.1. Implementation of fault detection method

In this work, three type of faults will be analysed and identify which are over voltage fault, under voltage fault and unbalanced voltage fault. Under-voltage and over-voltage supply conditions are commonly occurring power line problems. The efficiency of induction motor decreases when voltage on the induction motor decreases even though all the three phases are balanced. When the percentage balanced under-voltage increases the speed decreases drastically with increase in load. Overloading on induction motor may occur due to various reasons like mechanical load, jam, locked rotor, stalling, and others. Due to overload, the current drawn by the motor is more and hence more heat dissipation in the motor.

In this work, a five-layer feedforward neural network is selected for fault diagnosis of an induction motor as this problem of fault diagnosis is likely a highly complex nonlinear mapping problem because both the inputs and outputs are multiple variables without clear linear relationships. A five-layer feedforward network has proven to have the capability of approximating any function regardless of its complexity. Four inputs are selected to NN such as stator current, rotor speed, electromagnetic torque and DC voltage and three outputs i.e. $Y_1$, $Y_2$ and $Y_3$ corresponding to four conditions as describe in Table 2. As example, the output goes to $Y_1 = 1$, $Y_2 = 1$ and $Y_3 = 1$ if no fault condition exits. Figure 3 shows the architecture of a feedforward neural network with four input, three output and five hidden layer in NN. Figure 4 shows the fault analysis of induction motor using neural network.
Table 2. Neural-network output target

| Fault analysis                  | Y1 | Y2 | Y3 |
|--------------------------------|----|----|----|
| Fault free                     | 1  | 1  | 1  |
| Over voltage fault             | 0  | 0  | 1  |
| Under voltage fault            | 0  | 1  | 0  |
| Unbalanced voltage fault       | 0  | 1  | 1  |

Figure 3. Multilayer feedforward architecture

Figure 4. Fault analysis induction motor using neural network
4. Result and Discussion

In this work, the normal condition test is simulated with the value of current i(phase) = 500 A, resistance R = 0.02 ohm, voltage = 460 V and frequency f = 60 Hz. Figure 5 shows a diagnostic result diagram on NN in normal condition. In this condition, the output target from neural network is shown as Y_1 = 1, Y_2 = 1 and Y_3 = 1. From figure 4, we can see that NN network able to identify the input to NN is in normal condition by obtaining Y_1 = 1, Y_2 = 0.9992 and Y_3 = 1.001. Different set of tests i.e. normal, over-voltage, under-voltage, and unbalanced voltage faults are analyse using NN and the result is shown in Table 3. In overvoltage fault condition, the starting voltage is simulated at 150 kV and in undervoltage condition, the starting voltage is simulated at 100 V. During unbalance condition, voltage in phase A, phase B and phase C are simulated at 25 MV, 25 mv and 25 kV, respectively. In Table 3, we can see that the NN able to identify and analyse the different test with different analysis faults and obtain output Y_1, Y_2 and Y_3 as been set in NN target.

![Figure 5. Diagnostic result diagram on NN in normal condition](image)

Table 3. Neural network analysis for different faults test

| INPUT | NN Output | FAULT DETECTION ANALYSIS |
|-------|-----------|--------------------------|
| Current | Voltage | Torque | Speed | Y_1 | Y_2 | Y_3 |               |
| 633.96  | 6319.34  | 474.61 | -230.34 | 1   | 0.9992 | 1.001 | Normal |
| 636.43  | 320.65   | 475.47 | -229.04 | 0.9998 | 1 | 0.9995 | Normal |
| 637.19  | 320.22   | 507.47 | -238.57 | 1.002 | 1 | 1.002 | Normal |
| 636.98  | 319.89   | 461.27 | -208.70 | 1.001 | 0.9993 | 1.001 | Normal |
| 637.18  | 320.34   | 525.50 | -245.79 | 1.002 | 1 | 1.002 | Normal |
| 8537.88 | 172.56   | 272.62 | 203268.1 | 1.67x10^{-4} | 7.58x10^{-5} | 0.9992 | Over Voltage |
| 3911.16 | 170.55   | 214.32 | 207046.3 | 1.47x10^{-3} | 1.78 x10^{-3} | 1.002 | Over Voltage |
| 13513.45| 172.52   | 282.21 | 203353.3 | 6.93x10^{-3} | 2.75 x10^{-4} | 1.006 | Over Voltage |
| 4890.95 | 170.78   | 297.35 | 207152.6 | 1.28x10^{-3} | 1.77 x10^{-4} | 1.002 | Over Voltage |
| 7582.097| 172.42   | 230.39 | 203496   | -5.9x10^{-4} | 4.46 x10^{-5} | 0.9986 | Over Voltage |
| -350.61 | 353.82   | 778.45 | 112.74 | -0.00362 | 1 | -0.0037 | Under Voltage |
| -354.31 | 353.81   | 780.36 | 111.39 | -0.00671 | 1 | -0.0067 | Under Voltage |
| -347.53 | 353.77   | 771.68 | 116.48 | -0.00099 | 1 | -0.0010 | Under Voltage |
| -341.18 | 353.72   | 769.74 | 121.29 | 0.004384 | 1 | 0.0044 | Under Voltage |
| -350.96 | 353.82   | 778.51 | 112.41 | -0.00389 | 1 | -0.0040 | Under Voltage |
5. Concluding Remarks
In this work, the fault analysis for three-phase induction motor is presented using neural-network method. A feedforward layered structure of NN is used and trained using the algorithm of backpropagation. The NN method successfully analysed faulty signals such as over voltage fault, under voltage fault and unbalanced voltage fault. However, the training set should have a larger set of data with more fault conditions to improve the accuracy of fault classification.

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