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A neural network approach to detect winding faults in electrical machine

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Abstract: In this paper, Neural Network (NN) approach is developed and utilised to detect winding faults in an electrical machine using the samples data of electrical machine in both the healthy and different fault conditions (i.e. shorted-turn fault, phase-to-ground fault and coil-to-coil fault). This is done by interfacing a data acquisition device connected to the machine with a computer in the laboratory. Thereafter, a two-layer feed-forward network with Levenberg–Marquardt back-propagation algorithm is created with the collected input dataset. The NN model developed was tested with both the healthy and the four different fault conditions of the electrical machine. The results from the NN approach was also compared with other results obtained by determining the fault index (FI) of an electrical machine using signal processing approach. The results show that the NN approach can identify each of the electrical machine condition with high accuracy. The percentage accuracy for healthy (normal), shorted-turn, phase-to-ground and coil-to-coil fault conditions are 99, 99.6, 100 and 100% respectively.

Keywords: condition monitoring; electrical machine; fault detection; neural network (NN); winding faults.

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1 Introduction

The main cost component constituting the operational and maintenance costs in most processing and manufacturing industries is attributed to the maintenance of electrical machines. The expenses are incurred due to the high dependency on electrical machines for industrial production [1, 2]. These expenses particularly arise, when there is very costly shut-down time as a result of failures/faults in electrical machines. This can result in the loss of valuable products and lives in critical applications in the industries. It is crucial to ensure that these machines do not breakdown, particularly to ascertain the continuity of production and process chains in many industries. Before the breakdown of any machine, it would have exhibited disturbances that change the normal operation on or in the electrical machine. These disturbances result in failures/faults which manifest in the machine inform of unbalanced line currents, pulsations in torque and speed, excessive heating, decreased efficiency and average torque as well as unbalanced air-gap voltages [3, 4]. The risk of failure of the machine could be avoided if the proper diagnostic scheme is designed and implemented to detect failure/impending faults at an early stage. This would prevent production shutdowns, huge financial loss, sudden disruption of the machine and personal injuries if these faults were to be detected at the incipient stage.

The relevant literature shows that early fault detection of the electrical machine is not only important in minimising damage and reducing energy consumption, but also preventing the spread of failure or limiting its escalation in terms of severity [5–7]. Hence, the condition monitoring and fault diagnosis of the machines is important to forestall costly interactions due to failures or faults in the machine. This would prevent huge financial loss, production shutdowns, sudden disruption of the machine and personal injuries provided these faults are detected at the early stage. Over the past 40 years, there have been several research activities on developing new fault diagnosis and condition monitoring techniques for electrical machines, especially the induction machines [8]. Certainly, induction machine is one of the major parts of the industries that cannot be replaced because about 90% of all electrical machines used worldwide in the industry is induction machines [9, 10]. The machine is considered very important because they are extensively used in the industries where it is the core of most of the engineering processes as well as, in many home appliances. Hence, the machine mustn't break down, particularly for process chains continuity and productions in many industries. The risk of the failure or the breaking down of this type of machine can be mitigated provided there is a proper diagnostic and condition monitoring technique. The technique is needed to detect and diagnose the coming failure/faults at an early stage.

From literature, there are many methods for fault detection and diagnosis of the machine [1, 7, 10–12] such as wavelet transform technique, Fourier transform technique, negative sequence current compensation etc. However, there is paucity of literature on the use of machine learning techniques especially the neural networks in the literature. This paper, therefore, looks into the neural network approach to detect winding faults in electrical (induction) machine. The rest of the paper is organised as follows: Section 2 discusses winding fault as well as its statistical proportion which is significant enough to research upon. Section 3 describes the laboratory experiment carried out for the research reported in this paper. Section 4 highlights the early technique used. In Section 5, the description of a neural network approach (algorithm) to detect faults in the electrical machine was discussed. Section 6 contains the results and discussion while the conclusion of the paper is given in Section 7.

2 Winding faults in electrical machine

There is a strong demand for induction machine owing to their robustness, reliability and operational safety. In fact, the most widely used electrical machines are induction machines, nonetheless, when the machine are interrupted or fail due to using incorrectly rated power, imperfections in fabrication or construction, mistakes during repairs, misuse of the machine, etcetera, they will be operating in unhealthy or fault condition(s) [12, 13]. The chart presented in Figure 1 depicts the industrial experience surveys of faults conducted on electrical machines [14, 15]. The surveys were categorised into a group of four (bearing, rotor, stator and other) related faults. The outcome of the surveys of the Electric Power Research Institute (EPRI), IEEE-Industry Applications Society (IEEE-IAS) and Allianz was compared with vis-`a-vis induction machines as shown in the multiple bar chart (Figure 1). According to a statistical study carried out by the EPRI, most failures in electrical machine occurred due to bearing and winding faults [16–18]. The Allianz survey focuses on medium-to-high voltage large induction machines that are used in electric ships. It was specified that stator-related faults are the most prominent for high-power machines. Likewise, according to [19], a survey that focused on electric motors used in offshore applications indicates that the main faults are also due to bearing and stator winding defects. Tavner et al. [20] furnish greater detail and thorough analyses on several real cases of faults in high-powered electrical machines.

Figure 2 presents the percentage of faults in induction machine components based on the survey carried out by [8, 12] on the distribution of failed components in induction machines.

Stator winding faults account for approximately 38% of all faults as illustrated (Figure 2) [21]. In an analogous trend, in the survey carried out by EPRI in Figure 1, about 36% of all faults in induction machines can be attributed to stator winding faults. This contributes to a significant proportion of the total number of faults. Therefore, there is a need to develop an efficient and reliable fault diagnostic system or method to diagnose these winding faults at the earliest possible stage before they lead to more severe faults that can damage the machine. Stator winding fault(s)

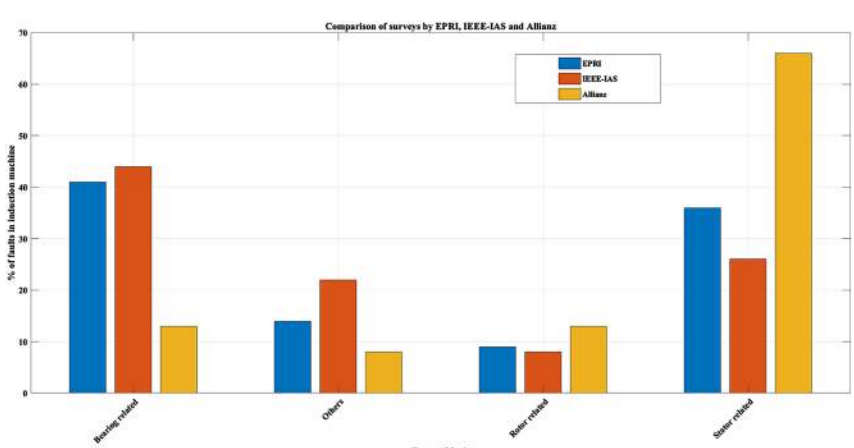


Figure 1: Chart showing the comparison of surveys by EPRI, IEEE-IAS and Allianz.

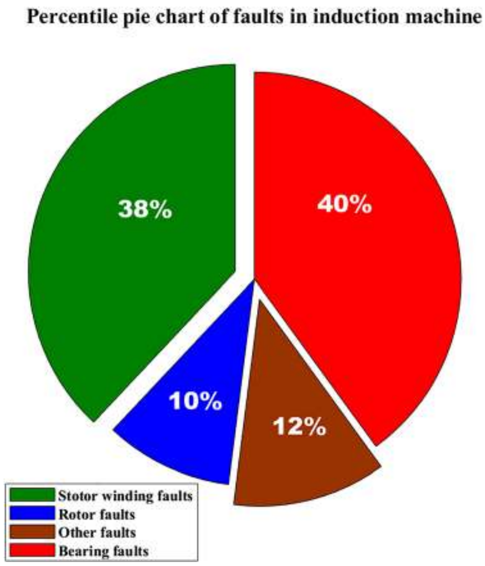


Figure 2: Percentile pie chart of faults in induction machine.

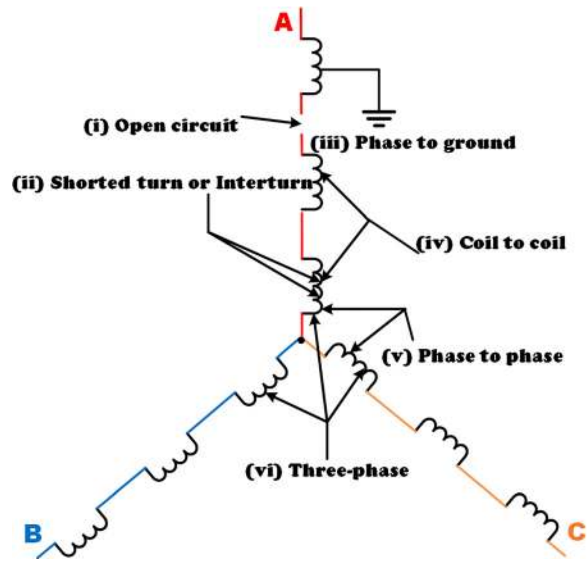


Figure 3: Classification of stator winding faults of an electrical machine.

are often initiated with failure in insulations between the turns of the individual windings in either stator of the machine [22–24]. The inter-turn or shorted-turn which short-circuits a few nearby turns of a phase winding leads to insulations failure in the stator of the machine. The current circulating in the shorted-turns generates heat and increases the temperature in the affected area as the machine continues to operate. The increase in the temperature leads to further little damage in the insulation of the affected area [22, 23]. The shorted-turn fault could extend to a short circuit between two coils of the same phase (coil to coil fault) which is a potential severe fault. There is also an open circuit fault when winding gets disconnected as well as a phase-to-ground fault when any of the phases is connected to the ground. On rare occasion, there could be a short circuit between turns of two phases (phase to phase fault) or a short circuit between turns of all three phases (three-phase fault). Phase-to-phase and three-phase fault are very dangerous and most severe winding faults, but they seldom occur.

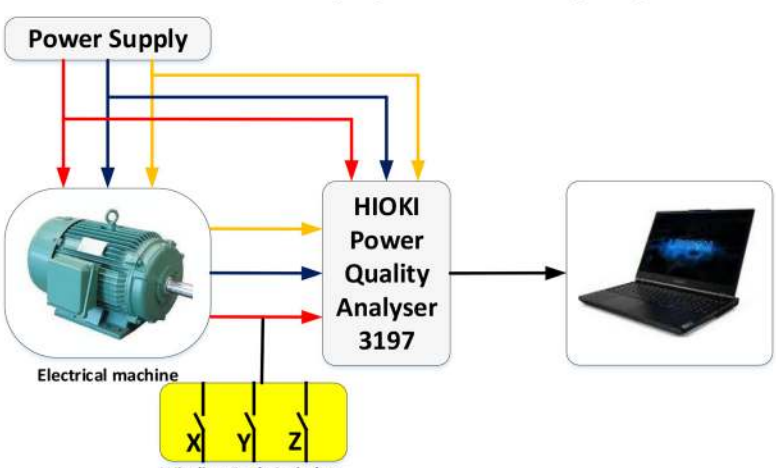
Figure 3, illustrates the schematic diagram of the classifications of the electrical machine stator winding faults. The classifications include: (i) Open circuit fault when winding gets disconnected in any phase; (ii) Inter-turn or shorted-turns faults within a coil (i.e., short circuits of turn to turn within a coil); (iii) Phase-to-ground short circuit faults; (iv) Coil-to-coil short circuit faults within the same phase winding (v) Phase-to-phase short circuit faults; and (vi) Three-phase faults.

The general opinion of the users and manufacturers of the electrical machine is that there is a longer lead-time between the inception of shorted turns up to failure in the winding. Even if there is no enough knowledge about the time interval from the shorted-turns fault to insulation failure, but it is clear that transition and its rate depend on the severity of the fault. In other words, the number of shorted-turns has gradually and slowly increased to insulation failure. Thus, the earlier the shorted-turn faults are detected the better for the machine. If this is not detected on time, it could lead to a more severe fault and further to the machine accidental shut-down. In this paper, four cases of electrical machine conditions are considered for the neural network diagnosis approach.

3 Laboratory experiment for neural network training data collection

Laboratory experiments were carried out on two sets of identical induction machines with the rating parameters 1.5 kW, 380 V/220 V, 50 Hz, 4-pole as shown in Figures 4a and 4b. Switches X, Y and Z are connected to the stator winding on phase *A* of one of the machines to create winding faults on the phase. Each of the switches X, Y and Z are connected to create *shorted-turns, phase-to-ground* and *coil-to-coil* winding faults respectively. It should be noted that only two turn of shorted-turn were connected to Switch X, a single turn to the ground was connected to Switch Y and a single coil to coil was made to Switch Z (Figure 4b). When any of the switches are in “OFF” position, and the machine is operating at no-fault condition, the data obtained during this time are captured as a healthy (normal) condition. However, when any of the switches are in “ON” position, and the machine is still operating, a fault is created and the data obtained are captured as the particular type of fault condition labelled on the switch. These data are collected by the HIOKI 3197-Power Quality Analyser measuring device and are interfaced with the computer for application further analysis. When the machine is in operation, about 2056 samples of data (stator currents and voltages) is captured from the HIOKI Power Quality Analyser in 200 ms, this is 10 waveforms for the power supply of 50 Hz [25]. This is the number of samples captured for a 50 Hz supply according to the instruction manual of the HIOKI power quality analyser [25] 2056 for 10 waveform. The data is recorded in the computer interfacing the HIOKI as shown in the experimental set-up of Figures 4a and 4b. When the switch (OFF), the samples of data (stator currents and voltages) captured from the HIOKI Power Quality Analyser are recorded as healthy conditions. Whereas, when each of the three faults is switched (OFF), the samples of data (stator currents and voltages) captured from the HIOKI Power Quality Analyser are recorded as fault condition created within the windings of the machine. Figure 5 depicts the comparison of the phase-A current of both healthy and each of the three winding fault conditions on the machine. A close look at healthy and shorted-turn fault condition is in agreement with similar comparison carried out by [10, 26]. It is evident in Figure 5 that the peak value of the current for a *healthy* condition is 2.32A. However, the peak of stator currents for *shorted-turns*, *phase-to-ground* and *coil-to-coil* faults are 3.48 A, 4.69 A and 0.27 A respectively. There are increments of 50 and 102% for shorted-turns, phase-to- ground faults respectively, while there was an 88% decrease in the coil-to-coil fault which could destroy the machine if it continues to be in operation.

a: Laboratory experiment for data capturing



b: Block diagram of experiment for data capturing

Figure 4: (a) Laboratory experiment for data capturing. (b) Block diagram of experiment for data capturing.

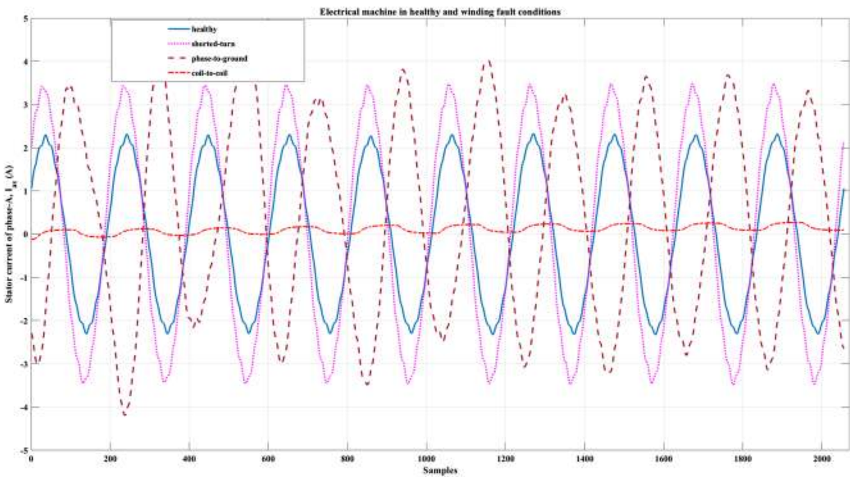


Figure 5: Healthy and fault conditions comparison of induction machine stator currents.

4 Electrical machine fault index (FI)

An algorithm to determine the fault index (FI) of an electrical machine using signal processing approach has been developed by [12, 21]. In the algorithm, a district wavelet transform application [12, 21] was used to generate the energy-frequency plots for the stator currents data captured from the electrical machine under some winding faults and healthy state conditions. The severity of the machine state is classified into Normal, Medium, or High, using the fault index. This was achieved by selecting the maximum energy value, E_n as well as the corresponding frequency, f_n of the healthy (normal) machine condition and assigned them the set energy, E_t and set frequency, f_t, respectively. Whereas for different fault conditions, the maximum energy value, E_f, and corresponding frequency, f_f, were also assigned for each of the fault condition.

The fault index fault (FI) can be written as:

$$\mathrm{FI} = \frac{E_x}{E_t} \tag{1}$$

where E_x, represents either normal or faulty state peak energy.

Figure 6 shows the results of the analysis carried out by [12, 27] to also detect the shorted- turn faults in induction

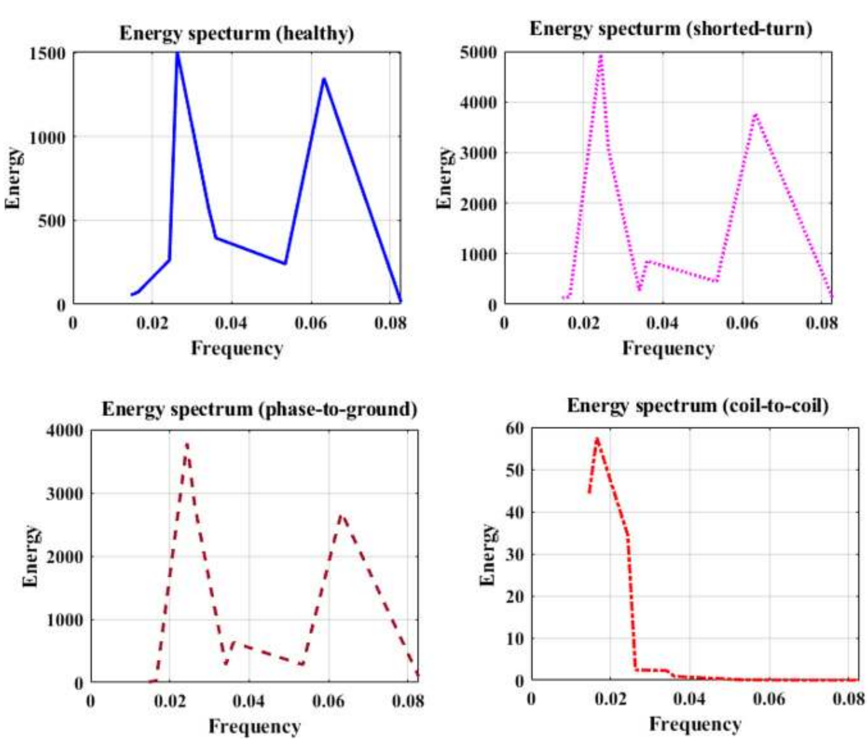


Figure 6: WT-energy plot for healthy and winding fault conditions.

Table 1: Maximum values of the energy and corresponding frequency [12].

State of machine	Max. energy (J)	Cor. freq (Hz)	Phenomena Period	FI
Healthy	1507	0.02626	38.08 s	1.000
Shorted-turns fault	3942	0.02432	41.12 s	2.616
Phase-to-ground fault	3780	0.02432	41.12 s	2.508
Coil-to-coil fault	57.52	0.01654	60.46 s	0.038

machines using discrete wavelet transform. The maximum values of the energy and corresponding frequency for each condition obtained from Figure 6 are presented in Table 1 [12]. Using a computer with 2.60 GHz core i5 4210M processor, it takes approximately 38 s for a healthy electrical machine with no created faults to obtain the peak energy value. In the case of a shorted-turns fault and phase to ground, it took about 41 s before it obtained the maximum energy. When the most severe (coil to coil in a phase) faults within the experiment considered in this research work are created, it takes about 1 min (60 s) to obtain the maximum energy. The discrepancies found in the deviation from the normal condition are used to classify the severity of the state of the machine into Normal, Medium, or High, using the fault index (FI). In the next section, a neural network approach is presented to diagnose the winding faults.

5 Neural network approach

Artificial Neural Networks (ANN) were originally motivated by the biological structures in the brains of animals and humans, which are exceedingly powerful for such tasks as learning, information processing, and adaptation. Good overviews on the biological background can be found in [28, 29]. The most important features of neural networks are a large number of simple units; a strongly connected unit; a highly parallel unit; the robustness against the failure of a single unit; and the learning from data.

The five aforementioned characteristics make an artificial neural network well suitable for quick hardware implementations [28, 30]. The directions of research of neural network can be categorised into two. In the first direction of research, the biologist's, psychologist's and physician's interests are to learn more about and even model the fundamental properties and operation of the animal and human brain. The fundamental properties and operations are still not well understood. The second direction of research is the engineer's interest is to develop a universal tool for problem-solving inspired by the impressive examples of nature but without any pretension to model biological neural network. We would consider the second in the paper because, the most neural network used in engineering are at least related to statistics, mathematics, and optimisation as to the biological character model. A typical block diagram of Neural Network (NN) is shown in Figure 7 [31]. The network is trained or adjusted so that a specific input leads to a particular target-output. The connections between elements largely determine the network function. An NN can be trained to perform a particular function by adjusting the values of the connections (weights) between elements (Figure 7). NNs have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, vision, speech, and control systems. NNs have been proposed and have demonstrated the capability of solving the electrical machine condition monitoring and fault diagnosis problem using a non-invasive, reliable, and inexpensive procedure [32–35].

NNs consist of three layers as shown in Figure 8. They are–the input layer; the hidden layer and the output layer. The input layer comprises of the model inputs and the output layer comprises the model outputs. The hidden layer consists of nodes that attempt to functionally map the model inputs to the model outputs during optimisation [36, 37]. The details about the numerous NN architectures can be found in [31, 37].

5.1 Neural network algorithm

A multilayer perceptron NN model was considered to estimate the state of electrical machine condition. This procedure is a mathematical model that performs a computational simulation of the behaviour of neurons in the human brain by replicating, on a small scale, the brain's patterns in order to produce results from the events

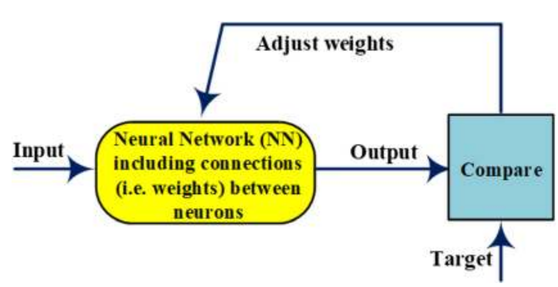


Figure 7: Block diagram of NN.

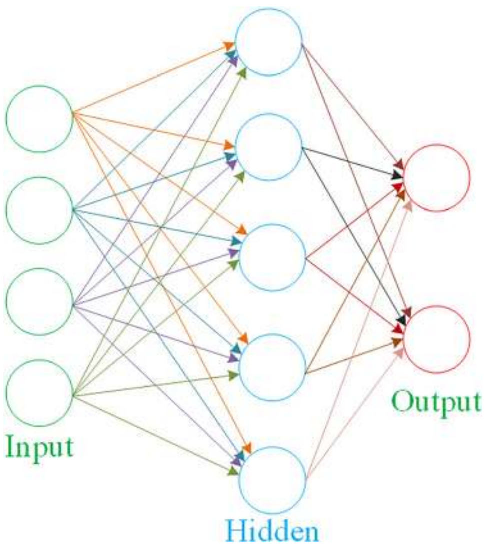


Figure 8: Multilayer perceptron NN schematic map.

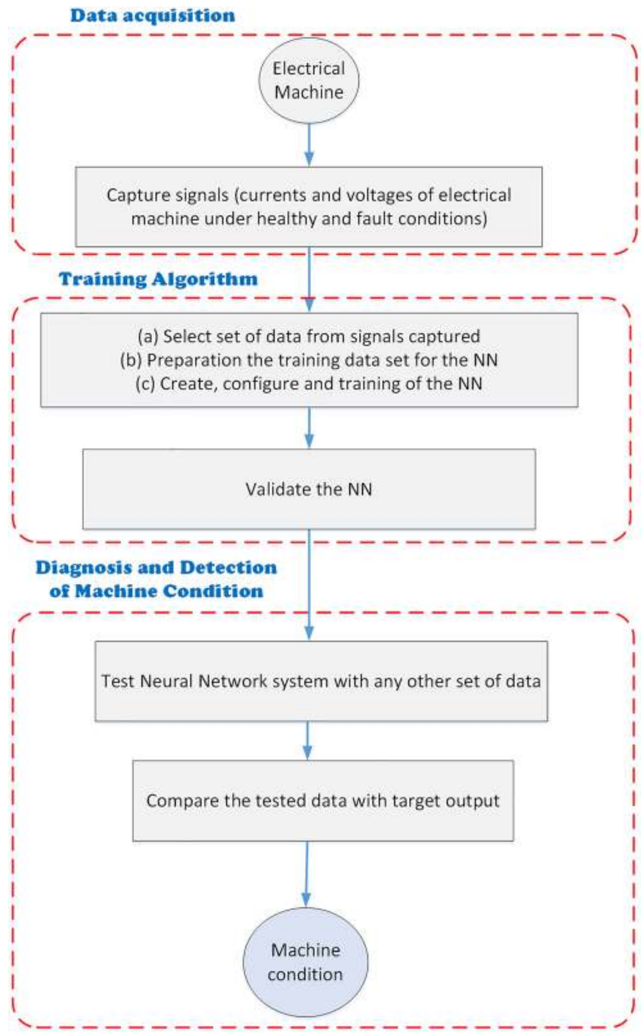


Figure 9: Neural network block algorithm.

perceived, i.e. it is a model based on learning a set of training data.

The Algorithm for the neural network design process discussed in this paper comprises three primary stages as depicted in the algorithm block diagram in Figure 9. The stages are data acquisition, training algorithm as well as diagnosis and detection of machine condition.

5.1.1 Data acquisition

This involves the collection of the electrical machine data (stator currents and voltages) into the computer for analysis and diagnosis purpose. A HIOKI 3197-Power Quality Analyser measuring device was connected to captured all cases of the machine conditions. The frequency, f_s of the captured signals is the same as the frequency of the power supply. In this case, the frequency is 50 Hz. The number of data samples captured with a 50 Hz power supply is 2056 samples which also produces 10 waveforms (Figure 5) [25].

5.1.2 Training algorithm

After the collection of data, the next stage is the pre-processed dataset training. This involves, neural network creation of the data collected into the computer. Then, a two-layer feed-forward network with Levenberg–Marquardt back-propagation algorithm is created with input dataset of healthy and differently three winding fault conditions. Using FI values in Table 1, a target of 1, 2.61, 2.51 and 0.038 are assigned for healthy (normal), shorted-turn, phase-to-ground and coil-to-coil fault conditions respectively. After an NN has been created, it is then configured. The configuration step consists of examining input and target data. The setting the network's input and output sizes to match the data, and choosing settings for processing inputs and outputs that will enable best network performance. The configuration step is normally done automatically, when the training function is called. However, it can be done manually, by using the configuration function [31]. The network learns by training the data inputs and outputs. By default, 70% of the total data samples is configured for training and 15% of the data samples is configured for validation. In other words, 70% would be used for training, 15% would be used to validate the network by generalising and stopping training before it is over-fitting. The last 15% would be used as a completely

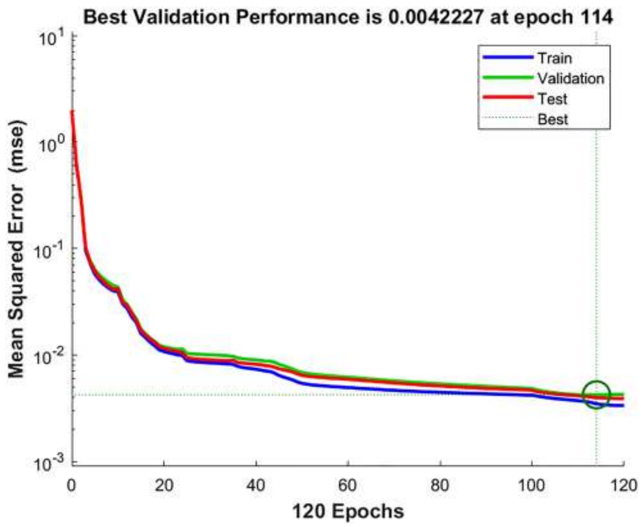


Figure 10: Validation performance.

independent test of network generalisation. All these percentage values were obtained by default selection (random data division) from the NN- training. The training is initialised and the network is updated each time an input is presented to the network.

5.1.3 Detection of machine condition

After training the pre-processed dataset via a neural network, we proceed to the detection of the machine condition. Once the network has been trained with the machine parameters, it can be used to test other sets of data to determine the condition of the machine. If the sets of data tested are close the targets-outputs for healthy then it can be said that the machine is working without fault. However, if the sets of data tested are close to the targets-outputs for any of the winding faults, the machine is operating with on fault condition (shorted-turn, phase-to-ground or coil-to-coil).

6 Results and discussion

The algorithm described in Section 5.1 is followed, the network is trained and validated. The network object can be used to calculate the network response to any input. Figure 10 depicts the validation performance plot of the network. It shows the value of the performance function versus the iteration number (epoch). It plots training, validation, and test performances. It indicates how the

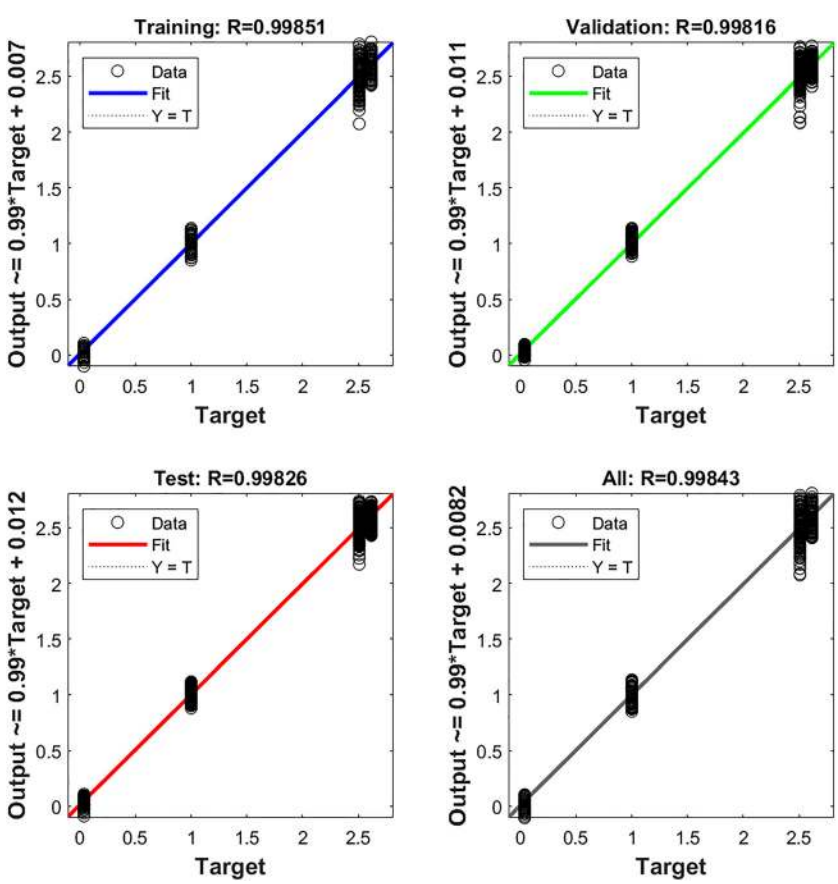


Figure 11: The regression plot.

network mean squared Error (MSE) drops rapidly as it learns. The blue line shows the decreasing error on the train data, the green line shows the validation error. The train stops when the validation error stops decreasing. The red line shows the error on the test data indicating how well the network could generalise the training data. The default performance function for feed-forward networks is MSE (i.e. the average squared error) between the network outputs y and the target outputs t which can be obtained using (2). The lower the values of MSE, the better the network. Zero means no error. The MSE from Figure 10 is 0.00423 and this is a good result.

$$\text{mse} = \frac{1}{N}\sum_{1=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{1=1}^{N}(t_i - y_i)^2 \tag{2}$$

Figure 11 depicts the regression plots between network outputs and network targets. The training, validation and test phases that contain all networks for the NN model generated are R = 0.99851, R = 0.99816 and R = 0.99826 respectively. The combined value of the regression gives a correlation of R = 0.99843. This implies that the model gives high correlation coefficient between predicted outputs and targets. Thus this is a robust and precise approach to detect the condition of the electrical machine.

In addition to the aforementioned description of Figures 10 and 11, the output of the network is compared to the target (FI) as shown in Figure 12. The FI (see Table 1) for values for each state of the machine is compared with the (NN) prediction for same sets of data and these are presented in Table 2. The results in Table 2 show that the NN approach can identify each of the electrical machine condition with high accuracy. The percentage accuracy for healthy (normal), shorted-turn, phase-to-ground and coil-to-coil fault conditions are 99, 99.6, 100 and 100% respectively. In other words, the values obtained with NN similar to the ones with FI.

Table 2: FI and NN comparison.

State of machine	FI	NN	Percentage accuracy
Healthy	1	1.01	99.0%
Shorted-turns fault	2.62	2.63	99.6%
Phase-to-ground fault	2.51	2.51	100%
Coil-to-coil fault	0.038	0.038	100%

Furthermore, a 200 dataset is obtained for each of the conditions (healthy and fault) of the machine. This sets of data are taken outside the sample used as inputs to the network. This is done in order to check the validation the network created, configured and trained to diagnose each condition of the electrical machine. Figure 12 shows the comparison between the (FI) and the Neural Network approach. It can be seen for each set of 200 data samples for each of the conditions (healthy and fault) of the machine that the NN can detect the condition of the machine correctly. Thus, the values of the FI for each condition is approximately the same as the average values of the NN approach.

7 Conclusion

In this paper, we present the detection of winding faults in the electrical machine using Neural Networks (NN). We believe that the method is generally applicable to all types of electrical machines, even though we have concentrated on the induction machine to develop and test the method. Some vital details about winding faults have been explained and laboratory experiments were carried out on two sets of identical induction machines with the same rating. A neural network (NN) approach is developed to detect the condition (healthy and fault) of an electrical machine. The NN approach can identify each of the

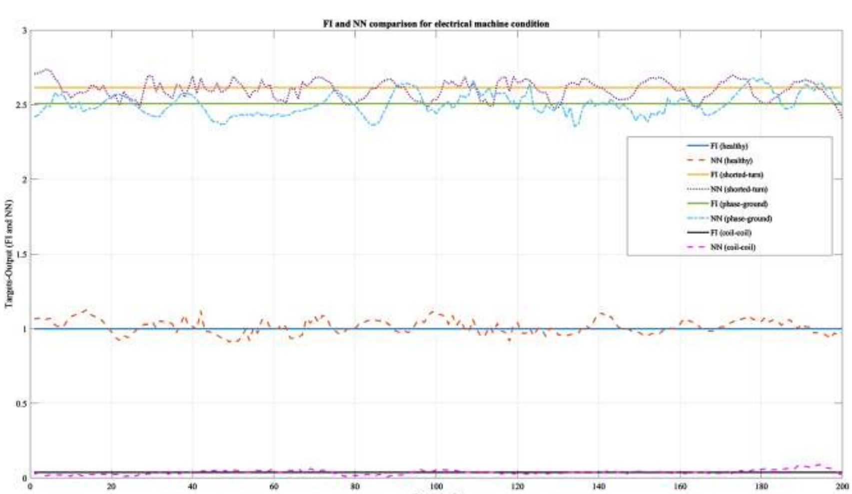


Figure 12: NN and FI comparison for any other data, e.g. (200 samples) of both machine with healthy and each of the three fault conditions.

electrical machine condition with high accuracy. The percentage accuracy for healthy (normal), shorted-turn, phase-to-ground and coil-to-coil fault conditions are 99, 99.6, 100 and 100% respectively. In other words, the values obtained with NN similar to the ones with FI.

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