Diagnosis of Shorted-Turns Faults in Electrical Machine using Neural Network

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***Abstract*—This paper discusses the diagnosis of shorted-turn faults in the electrical machine using Neural Networks (NN). This leads to a design process of a work-flow for the NN. The work-flow has three stages: data acquisition, training algorithm and diagnosis and detection of machine condition. Samples data of electrical machine in healthy and shorted-turn fault conditions were collected by interfacing data acquisition device with a computer laboratory. A two-layer feed-forward network with back-propagation algorithm is created and configured with data collected for NN training. The network model gives a high correlation coefficient of $R = 0.9992$, $R = 0.99917$ and $R = 0.99923$ in the training, validation and test phase respectively as well as the overall correlation which is $R = 0.9992$. This connotes that the NN model gives a high correlation coefficient between predicted outputs (NN) and targets (Fault Index (FI)). Using the NN model, the healthy and shorted-turn electrical machine are predicted correctly and this is compared with the diagnosis done using FI. Thus, with an NN, a robust and reliable method to diagnose shorted-turn fault in the electrical machine can be achieved.**

***Index Terms*—electrical machine, fault diagnosis, fault index (FI), neural network(NN), shorted-turn**

I. Introduction

WHEN there is a presence of disturbance that alters the performance of a normal operation on or in the electrical machine, then a fault is suspected. Such faults lead to various manifestations which include, pulsations in torque and speed, unbalanced line currents, unbalanced air-gap voltages, decreased efficiency and average torque, excessive heating, and consequently increased losses. The high dependency on electrical machines, especially in critical applications in the industries often results in very expensive shut-down time due to such failure and loss of valuable lives [1]. In most manufacturing and processing operations, approximately 50 % of the operational cost could be attributed to maintenance [2].

Over ninety percent of all electrical machines used worldwide in the industry are induction machine. It is very important to make sure that these machines do not breakdown, especially to ensure the continuity of production and process chains in many industries. The risk of failure of this type of machine could be avoided if the proper diagnostic scheme is designed and implemented to detect failure/impending faults at an incipient 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, indicates that early fault detection of induction machines 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 [3], [4], [5]. Hence, fault diagnosis, condition monitoring and prognosis of electrical machines is essential to prevent costly interactions due to failures or faults in the machine. There are many methods of faults detection and diagnosis for the machine, however, a machine learning technique, such as neural networks would require further investigation to adequately detect and diagnose shorted-turn faults. [6], [2], [7], [3], [8].

II. Laboratory Set-up for Data Capturing for Neural Network Training

Laboratory experiments were carried out on two sets of identical induction machines with the rating parameters $1.5kW$, $380V/220V, 50Hz$, 4-pole as shown in Figure 1. Switches are connected to the stator winding on phase A of one of the machines to create a shorted-turns fault in the winding faults on the phase. When the switch is in ”OFF” position, and the machine is operating at the no-fault condition, the data obtained during this time are captured as healthy(normal) condition. When the switch is in ”ON” position, and the machine is still operating, a shorted-turn fault is created and the data obtained are captured shorted-turns fault conditions. The data are captured 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. This is the number of samples captured for a $50Hz$ supply according to the instruction manual of the HIOKI power quality analyser. The data is recorded in the computer interfacing the HIOKI and this represents the sets of data for the induction machine healthy state. In a similar manner, when the switch (ON) for the shorted-turn faulty state, about 2056 samples of data (stator currents and voltages) is also captured from the HIOKI Power Quality Analyser. These data is also recorded in the computer interfacing the HIOKI and it represents the sets of data for the induction machine with a stator (winding) shorted-turns fault conditions. Figure 2 shows the comparison of the phase-A current of both healthy and faulty conditions on the machine. A close look at healthy and shorted-turn fault condition is in agreement with a

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similar comparison carried out by [9], [8]. From Figure 2, the peak value of the current for an induction machine in the healthy condition is $2.32A$ and the peak of stator currents for shorted-turns faults condition is $3.48A$. There is an increment of about 50% for shorted-turns. This abnormality is observed and it could grow into more severe winding faults which can destroy the machine if it continues to run.

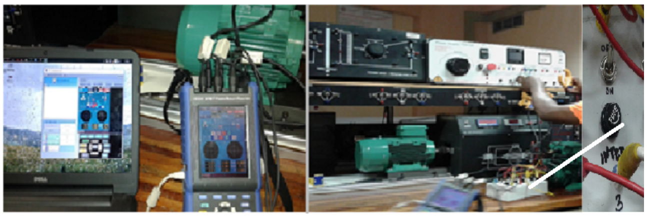

Fig. 1. Experimental Set-up for data capturing [6]

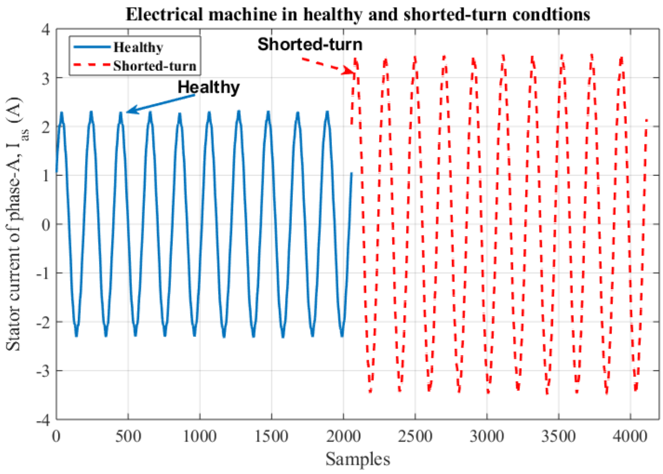

Fig. 2. Comparison of Stator Currents of Healthy and shorted turns fault Induction Machine

III. Fault Index (FI) of Electrical Machine

An algorithm to determine the Fault Index (FI) of an electrical machine was developed by [10], [6]. Using the application of district wavelet transform, the author(s) [10], [6], [11] were able to generate the energy-frequency plots for the stator currents captured from electrical machine under some winding faults and healthy state conditions. The severity of the state of the machine are classified into Normal, Medium, or High, using the fault index (FI) as stated in Equation 1. This was possible using the maximum energy value, E_n, of the healthy (normal) condition and the corresponding frequency, f_n which were the set energy, E_t, and set frequency, f_t, respectively. Whereas for any of the fault conditions, the maximum energy value, E_f, and corresponding frequency, f_f, were also noted for each the fault condition.

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

Where E_x, represents either normal or faulty state peak energy.
Figure 3 shows the results of the analysis carried out by [6], [12] to also detect the shorted-turn faults in induction machines using discrete wavelet transform. The maximum values of the energy and corresponding frequency for each condition obtained from the Figure 3 are presented in Table I [6]. Using a computer with $2.60GHz$ core $-i5-4210M$ processor, it takes approximately 38 secs 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, about 41 secs passed before it obtained 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 paper, the most severe faults are not considered. In the next section, a neural network approach is presented to diagnose shorted-turn as well as show some relationships to neural network approach.

TABLE I
Maximum values of the energy and corresponding frequency [6]

State of Machine	Max. Energy (J)	Cor. Freq (Hz)	Phenomena Period	FI
Healthy	1507	0.02626	38.08 Sec	1.000
Shorted-Turns Fault	3942	0.02432	41.12 Sec	2.616

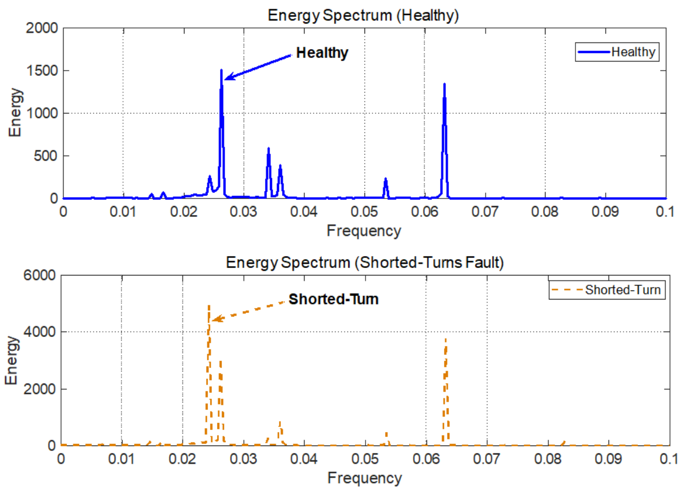

Fig. 3. DWT-Energy plot for Healthy and shorted fault Conditions

IV. Neural Network Work flow Algorithm

The work flow for the neural network design process for this research work has three primary stages as depicted in Figure 4. The stages are IV-A data acquisition, IV-B training algorithm and IV-C diagnosis and detection of machine condition.

A. Data acquisition

This involves the collection of the electrical machine data (stator currents and voltages) into the computer for analysis and diagnosis purpose. For the purpose of this research, a measuring device (HIOKI 3197-Power Quality Analyser) that captures all the data required before and after the fault condition has been acquired. The frequency, f_s of the captured signals is very important for

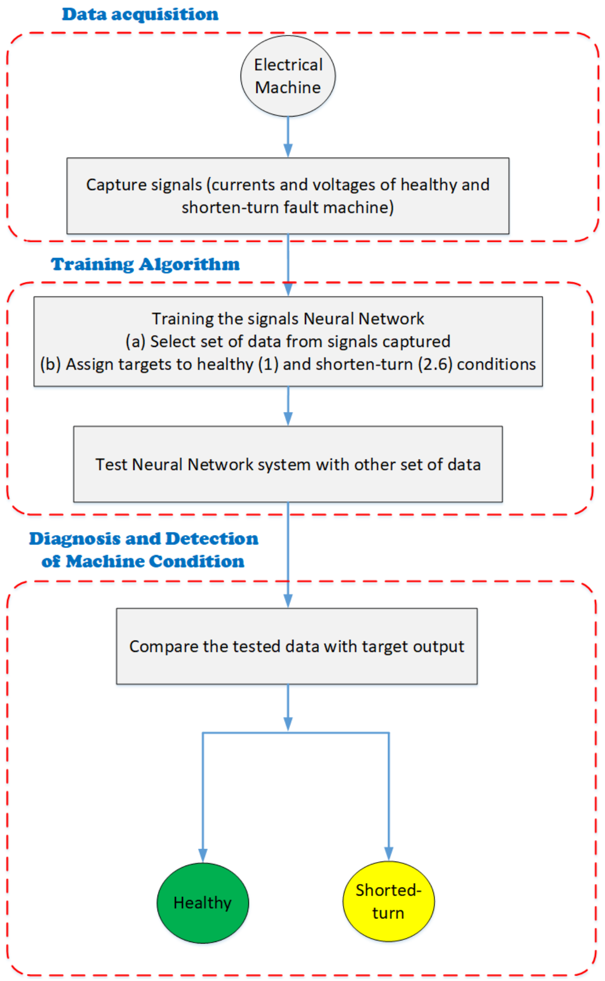

Fig. 4. Neural network work flow algorithm

the analysis. In this case, the number data captured for samples for $50Hz$ (i.e $20ms/cycle$) is $2056samples/sec$ based on the findings from the device manual ($10cycle/sec$).

B. Training Algorithm

After the collection of data stage, the next stage is the training algorithm. This involves, neural network creation on both healthy and shorted-turn data collected into the computer. A two-layer feed-forward network with back-propagation algorithm is created with input data as the 4112 sets of data (2056 each from healthy and shorted-turn data). Using FI in information in Table I, a target of 1 is assigned to healthy and 2.616 is assigned to shorted-turn conditions. After a neural network has been created, it must be configured. The configuration step consists of examining input and target data, 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 [13]. The network learns by training the data inputs and outputs. 70% of the total samples which is about 2878 data samples is configured for training, 15% which is about 617 data samples is configured for validation and 15% which is the same as validation is configured for testing. In other words, 70% will be used for training, 15% will be used to validate that the network by generalising and stopping training before it is overfitting. The last 15% will be used as a completely independent test of network generalisation. All these % values were obtained by default selection from the NN-training tool. The training is initialised and the network are updated each time an input is presented to the network.

C. Diagnosis and Detection of Machine Condition

The diagnosis and the decision of the machine conditions are the third stage of the Neural network workflow algorithm. 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 from the network. If the sets of data tested is 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 is close the targets-outputs for shorted-turn, the machine is operating with shorted-turn condition.

V. Results and Discussion

When the work flow algorithm described in section IV is properly followed, the network is trained and validated. The network object can be used to calculate the network response to any input. Figure 5 depicts the 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 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. Train stops when the validation error stop decreasing. The red line shows the error on the test data indicating how well the network could generalised the training data. Figure 6 shows the training

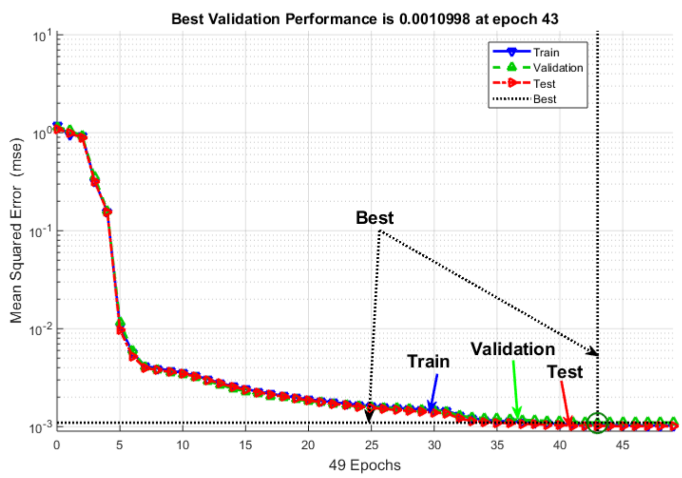

Fig. 5. Performance plot

state plot. It depicts the progress of other training variables, such as the gradient magnitude, the number of validation checks, etc. The error histogram plot in Figure 7 shows the distribution of the network errors. Figure 8 depicts the regression plot and it means the a regression plots between

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network outputs and network targets. The training, validation and test phases that contain all networks for the NN model generated are $R = 0.9992$, $R = 0.99917$ and $R = 0.99923$ respectively. The combination of the three phases give a correlation of $R = 0.9992$. This implies that the model gives high correlation coefficient between predicted outputs and targets. Thus this is robust and precise to diagnose shorted-turn fault in the electrical machine.

In addition to the aforementioned description of Figures 6

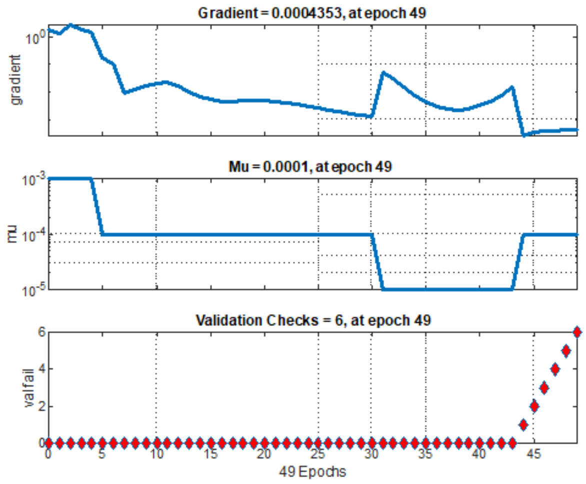

Fig. 6. The training state plot

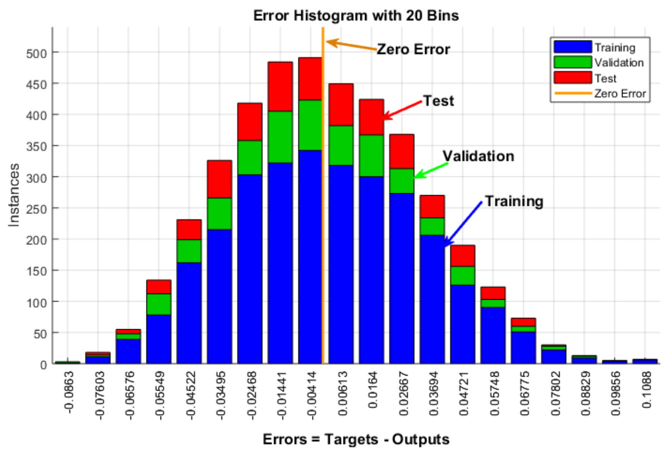

Fig. 7. The error histogram plot

to 8, the output of the network is compared to the target (FI) as shown in Figure 9. The FI (see Table I) for Healthy is 1 and then Neural network (NN) prediction for same sets of data 2056 is approximately equal to 1. Similarly, the neural network prediction for the same sets of data for machine with shorted-turn faults is about the same as the FI which is 2.6. Thus the network has shown in Figure 8 that it can be used to estimate the network response to any input (either data from healthy or shorted-turn fault). Furthermore, 200 samples of data for is obtained for both machine with healthy and shorted-turn conditions. This sets of data are taken outside the ones used as inputs to the network. This is done in order to validate the network created, configured and trained to diagnose shorted-turn faults in the electrical machine. Figure

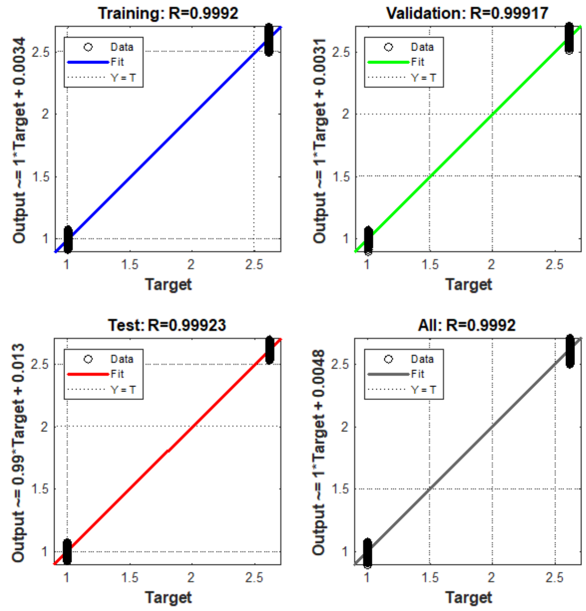

Fig. 8. The regression plot

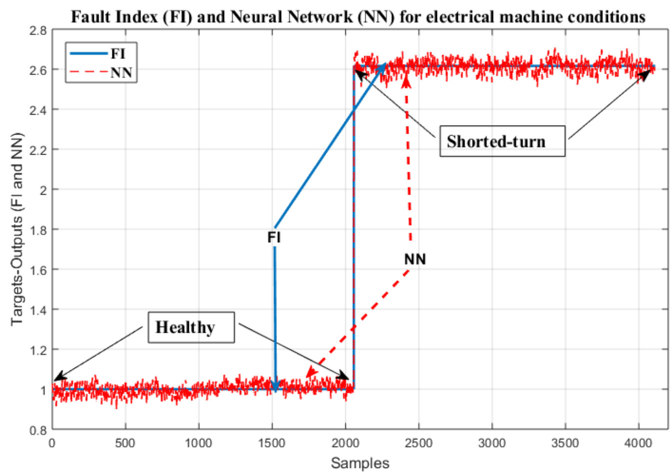

Fig. 9. NN and FI comparison

10 depicts the comparison between the target (FI) and the Neural Network prediction. It can be seen for each sets of 200 data samples for both machine with healthy and shorted-turn conditions, the NN diagnosis the condition around the target (FI) values assigned, 1 for healthy and 2.6 for shorted-turn condition.

VI. Conclusion

This paper discusses the diagnosis of shorted-turn 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 induction machine to develop and test the method. A little details about shorted-turn faults has been addressed and laboratory experiments were carried out on two sets of identical induction machines with the same rating. An algorithm had earlier been developed by [10], [6] to determine the of an fault state of electrical machine using FI. A neural network (NN) approach is now developed to diagnose shorted-turn as

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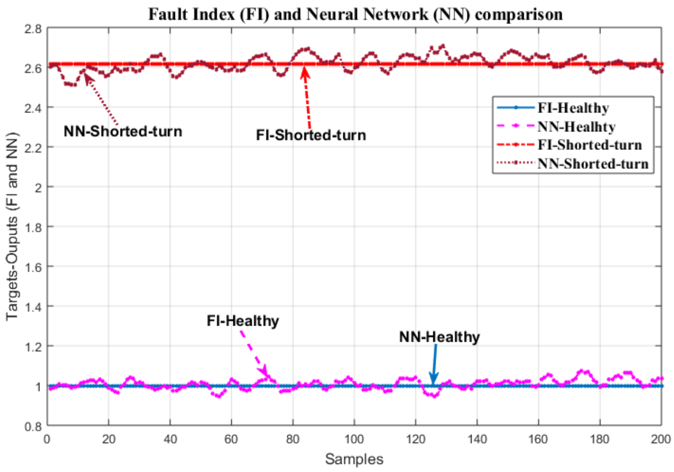

Fig. 10. NN and FI comparison for any other data, e.g (200 sample) of both machine with healthy and shorted-turn conditions each

well and also shows some relationships between FI and NN approach. This leads to a design process of a work flow for the NN. The work flow has three stages: data acquisition, training algorithm and diagnosis and detection of machine condition. The data acquisition involves collection of the electrical machine data (stator currents and voltages) into the computer for analysis and diagnosis purpose. The training algorithm creation, configuration, training and validation of NN from the machine data captured. The diagnosis and the decision of the machine conditions implies, once the network has been trained with the machine data captured, it can be used to test other sets of data to determine the condition of the machine. In order to test the NN, 200 samples of data sets is taken outside the ones used in the network and it is used on the network. When the sets of 200 data samples gives an approximate value of 1, the machine is operating in healthy condition. However, when the sample data gives an approximate value of 2.6, then a shorted-turn fault is detected. There is high correlation coefficient of $R = 0.9992$, $R = 0.99917$ and $R = 0.99923$ in the training, validation and test phases that contain all networks for the NN model respectively in Figure 8. The overall correlation for the (training, validation and test) phases is $R = 0.9992$. This implies that the model gives high correlation coefficient between predicted outputs and targets. Using the NN model, the healthy and shorted-turn electrical machine conditions are correctly predicted in Figure 10. Thus, this is robust and reliable to diagnose shorted-turn fault in the electrical machine.

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