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Feed Forward Back Propagation Artificial Neural Network Based Faulty Switch Identification of the Three Phase Three Level Converter Based Drive for the Three Phase Induction Motor

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Abstract: Three phase induction motors are the work horse in the electrically driven industrial applications. The modern day power electronic control systems have contributed much for the speed, torque and power control schemes of the three phase induction motor drives. In this study, an online faulty switch indication method is designed and demonstrated using simulations in the Matlab/Simulink environment. An experimental verification is also presented that has been developed in the ARM processor LPC 2148. The back propagation feed forward artificial neural network has been the core of the system in identification of the faulty switch based on a pattern mapping scheme considering the current drawn by the motor and the terminal voltage across the motor.

Key words: Uninterrupted Power Supply UPS, Static Compensator (STATCOM), Feed Forward Back Propagation (FFBP), type Artificial Neural Network (ANN), reactive power compensation

INTRODUCTION

The modern day industry relies on electrical drives and the mostly used are of the three phase squirrel cage type of the induction motor family. Power electronic converters are widely used for convenient speed and torque control systems. The three phase three leg switching arrangement popularly known as the Graetz Bridge is widely used for this purpose.

Though the power electronic convertor based drives are flexible but their reliability still under question. Power electronic devices which when subjected to unpredictable dv and di get damaged (Yusuffa *et al*., 2011). Therefore, in the event of a fault and a subsequent damage in order that the down time is reduced and productivity is increased it is necessary that automated fault location schemes are made available and automatic redundant correction systems are available (Brahma and Girgis, 2004).

Typically in a fuse protected system where each Power device is protected by a series switch whenever a heavy current flows through the device because of a short circuited power electronic device it so, happens the series fuse blows and the circuit becomes an open circuit. Though it was a short circuit fault happened in the switch it is actually reported as an open circuit fault because of the series fuse blown out. Now, it can be immediately addressed by an intelligent fault diagnosing system which can locate the open circuited segment and route the current through a bye pass device that comes in the place of the one in the faulty segment (Samantaray *et al*., 2006).

This study presents the step by step development of a novel artificial neural network based faulty segment locating system. The configuration of the neural network used is of the popular feed forward back propagation network.

In the pre learning or pre training mode all possible faults are created and the current and voltage data are collected. Once the data is collected the ANN is trained. The trained ANN is then put in its place in the system and whenever a fault occurs the ANN shows the exact faulty device or devices. Eventually activated by the ANN the redundant system comes into action and the motor runs continuously unaffected by what has happened.

The three phase induction motor: The three phase induction motor is dominant in the industry meant for converting electrical energy into mechanical energy. Simple in construction, operation and a speed torque characteristics make the three phase SCIM suitable for fairly fixed speed applications (Meng *et al*., 2010). The only drawback with the three phase SCIM is that it is very difficult for using it for variable speed applications (Khan *et al*., 2005). Since, a long time the only choice for variable speed drives had been the DC motor. However with the advent of modern power electronic devices and the associated control techniques implemented using digital systems variable speed drives are coming up

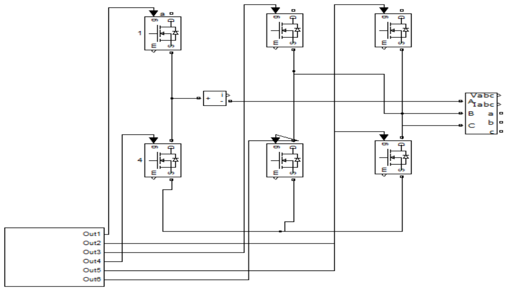

Fig. 1: Three leg bridge for variable voltage variable frequency drives

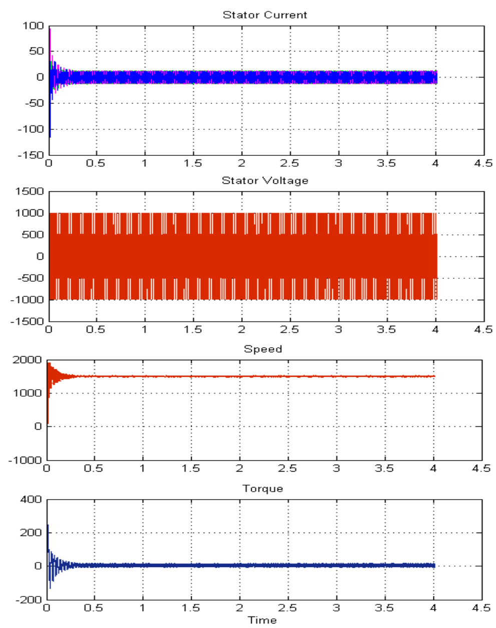

Fig. 2: Terminal voltage, current, speed and torque in normal condition

recently (Rodriguez and Arkkio, 2008). The popular variable voltage variable frequency drive uses a three leg bridge of MOSFET or IGBT switches arranged as shown in Fig. 1. The three phase bridge derives power from a DC source and converts it into the three phase voltage or current format of any desirable frequency and amplitude. The speed of the SCIM is governed by the formula Ns = 120 f/P where f is the frequency and P is the number of poles of the machine. In this formula Ns is the synchronous speed of the rotating magne

tic field produced by the three phase winding when energized by a three phase voltage with a phase shift of 120°. The terminal voltage, current, speed and torque of the induction motor are waveforms of the three phases SCIM are as shown in Fig. 2 and 3.

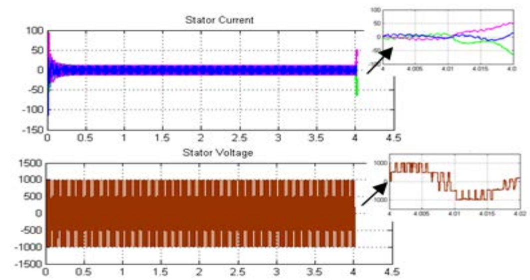

Fig. 3: Terminal voltage and current with switch 1 fault

The motor draws a heavy starting current while the speed rises from stand still condition towards the rated speed and after the motor speed reaches the rated value the current falls down to the normal steady state operating value. The ANN based fault location system as described in this paper has relevance to the steady state only. There are six vectors of interest. They are the three phase voltages and currents. These are the only directly measurable electrical quantities from the physical system. Only these parameters are considered for the faulty switch location system.

Under normal circumstances the voltages and currents are as shown in Fig. 2. With a switch s1 open at instant of 4 sec the voltages and current waveform suddenly change as shown in Fig. 3.

The three phase currents and voltages are continuous. Hence to be processed in a digital processor they need to sampled and in this application the number of samples considered are 1000/20 m sec period. The 20 m sec base period is considered because it is the period of each the AC cycle.

MATERIALS AND METHODS

Sampling: Sampling starts simultaneously in a the three voltage vectors and current vectors right from the zero crossing of the first phase and it continues until a fixed 1000 samples are got from all the six channels.

The three phase induction motor is a linear load comprising of some resistance and a large inductance of the three phase coils. Being, a linear load there exists a finite relationship between the voltages and currents not influenced by time. That is the system is linear and time invariant. Therefore, under steady state at any instant, there exists a certain mapping among the three voltages and the three current values. This fact is the basis of the implementation of the idea proposed and verified successfully as presented in this study.

In every sampling window of approximately 1000 samples spanned over a period of 20 m sec each sample is a vector of six elements and this corresponds to a particular switch condition which is also a vector of six elements being either 0-1 depending upon whether a switch is open or closed at that instant (Tan and Lim, 2004).

Under steady state the data produced by the 1000 vectors of six elements each will be of a certain format if all the six switches operate properly. If any of the six switches goes open circuited then thereafter the voltage and current pattern gets deviated in a characteristic manner which is characteristic to the open circuit or removal of that particular switch.

When a certain switch is open circuited the resulting data pattern deviates from the original one that was obtained when all the switches were intact and operational. With a certain switch of the six switched bridge converter now open each of the six elements of each of the 1000 sample vectors now deviate differently. At the end of the collecting the 1000 samples the standard deviation of each element over the 1000 samples is numerically estimated. This gives rise to a six element single vector of standard deviations. This vector corresponds to the pattern of six bits representing each of the six switches and if the result was obtained with the first switch open then this data pattern becomes 0 1 1 1 1 When the first switch is restored and the second switch is opened the resulting vector of six element standard deviation will be mapped to the pattern 1 0 1 1 1 1. Thus, a set of six input patterns and a corresponding set of six output patterns are used to train the neural network.

The artificial neural network: An artificial neural network is network of neurons arranged in a number of layers. Each layer has a number of neurons and each neuron has an activation function. All the neurons in each layer are connected to all the neurons in the next layer and the connecting elements are known as synapses and each synapse has its weight usually different from the other synapses and the weights of each neurons are modified in the training phase of the ANN.

The feed forward back propagation algorithm: The neural network under consideration is an unidirectional network. There is no feedback connection. Considering the number of neurons in the input, hidden and output layers the total number of synapses in this network is 6×9 and 9×6 accounting to a total of 108 synapses. To start with the weights of the synapses are randomized. vector corresponds to the pattern of six bits representing each of the six switches and if the result was obtained with the first switch open then this data pattern becomes 0 1 1 1 1 When the first switch is restored and the second switch is opened the resulting vector of six element standard deviation will be mapped to the pattern 1 0 1 1 1 1. Thus,

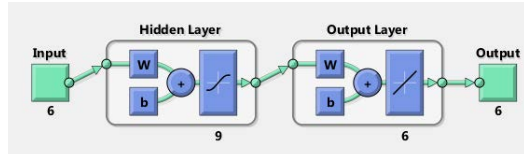

Fig. 4: Neural network structures

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The layer that accepts the input vector is called the input layer and the layer at the other end that gives out the output vector is called the output layer (Ribeiro *et al*., 2003). The number of neurons in the input layer and that at the output layer corresponds to the number of elements in the input vector and the elements of the output vector, respectively.

The general structure of the multi-layer feed forward back propagation neural network is shown in Fig. 4. In this example the input layer has six neurons and the output layer also has six neurons with one hidden layer with nine neurons.

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With a randomized set of synaptic weights if the first set of input vector [×11-16] is placed at the input neurons of the input layer of the neural network then these input elements are individually manipulated by the activation function of each of the neuron and each neuron gives an output (m11-16). The output m11 of the first neuron passes through all the synapses running between the first neuron in the input layer and those in the second layer.

Since, each of the nine synapses running from the first neuron of the first layer to all the neurons in the hidden layer has its own weights randomized (w11-19) each of the neuron in the hidden layer receive the set of information marked as (m11×w11 m11×w12 m11×w13 m11×w14 m11×w15 m11×w16 m11×w17 m11×w18 m11×w19).

Similarly the first neuron in the hidden layer receives information from all other neurons in the first layer duly weighed by Eq. 1: the corresponding synaptic weights. The total input to the first neuron in the hidden layer will be:

$$\sum_{j=1,2,\ldots 9}^{1,2,\ldots 6} m_i \times W1_j \tag{1}$$

Similarly all other neurons in the hidden layer gets similar inputs from the all the neurons of the input layer. As given by Eq. 1, the total inputs to any one of the

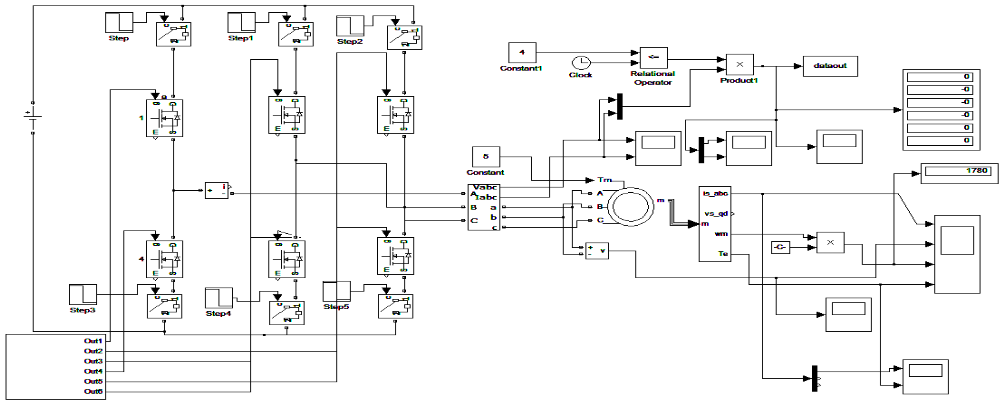

Fig. 5: Main circuit topology

neurons in the hidden layer will be processed by the receiving neuron according to the activation function. The out of each of the neuron in the hidden layer will be (h1-h9). These 9 outputs are then passed on to the output layer through the synaptic weights between the hidden layer neurons and the output layer neurons (Diallo *et al*., 2005). Thus, each of the neuron at the output layer gets as information given by Eq. 2:

$$\sum_{j=1,2,\dots 9}^{1,2,\dots 6} h_i \times W_{ij} \tag{2}$$

Example: h1×W14 means the input received by the 4th neuron in the output layer from the first neuron of the hidden layer through the synaptic weight between the first neuron in the hidden layer and the 4th neuron in the output layer.

Training phase: Since, all the synaptic weights have been randomized it is not necessary that when all the neurons of the output layer gets their inputs the output vector of the output layer need not be expected value. Now, it is possible that each element of the actual output vector exhibits an error with respect to the expected output. This error has to be minimized. The only freedom available is to alter the weights of the synapses. The synaptic weights of the synapses between the output and the hidden layer are adjusted and similarly those between the input and the hidden layer are adjusted. These adjustments of the synaptic weights are carried out until the expected output is obtained.

The next input vector is now placed at the input of the neural network. The corresponding output may not match the expected output. Again the synaptic weights are adjusted. This process is repeated again and again strategically changing the synaptic weights until the output of the neural network becomes equal to the expected output with deviations well within the allowable tolerance level for all cases of inputs. Now the ANN is said to be trained. After the ANN is trained, during run time for every input the ANN receives it will give the relevant output as dictated by what it has learnt.

Average error calculation: During every sampling window of 20 milliseconds 1000 samples of the three phase voltages and currents are made. The array of the samples is as given by sample ref $[v1_j\ v2_j\ v3_j\ i1_j\ i2_j\ i3_j]$ where, j = 1, ..., 1000. The first sample in the sampling window is sampleref $[v1_1\ v2_1\ v3_1\ i1_1\ i2_1\ i3_1]$ and the last sample in the sampling window is sampleref $[v1_{1000}\ v2_{1000}\ v3_{1000}\ i1_{1000}\ i2_{1000}\ i3_{1000}]$.

The set of 1000 samples obtained in a sampling window when all the switches are intact will be treated as the reference sample set. When a certain switch is opened then again we can get a sample data set over a similar sampling window of 20 m sec. Every element in each column of the sample set may now become different as compared to the corresponding reference. If, for example the sample set obtained with one switch open be given by sample sw1 $[v1_j\ v2_j\ v3_j\ i1_j\ i2_j\ i3_j]$. Now the error in each element of the two matrices are given Eq. 3.

Sample_error $[v1_j\ v2_j\ v3_j\ i1_j\ i2_j\ i3_j]$ = sampleref $[v1_j\ v2_j\ v3_j\ i1_j\ i2_j\ i3_j]$-samplesw1 $[v1_j\ v2_j\ v3_j\ i1_j\ i2_j\ i3_j]$. The average error will be e_error=Sample_error:

$$\frac{\begin{bmatrix} \sum_{j=1}^{1000} v1_j & \sum_{j=1}^{1000} v2_j & \sum_{j=1}^{1000} v3_j \\ \sum_{j=1}^{1000} v4_j & \sum_{j=1}^{1000} v5_j & \sum_{j=1}^{1000} v6_j \end{bmatrix}}{1000} \tag{3}$$

A typical pattern of the average error will be as shown below Ave-error = [0.07 0.07 0.002 0.001 0.003 0.005] and this corresponds top the switch pattern [0 1 1 1 1 1] while the pattern of the ave_error for the healthy condition is [0 0 0 0 0 0] and the switch condition is [1 1 1 1 1 1] indicating that all the six switches are intact.

The proposed idea: The proposed idea was verified and validated using Matlab/Simulink simulation. Figure 5 shows the main circuit topology showing the three phase converter and the three phase SCIM. The waveforms of voltage and currents in all the three phases are shown in Fig. 6.

The array of data known as sample ref is obtained for a sampling window of 20 m sec well after the motor reaches the steady state. The curve pertaining to this sampling window is shown in Fig. 7 and 8.

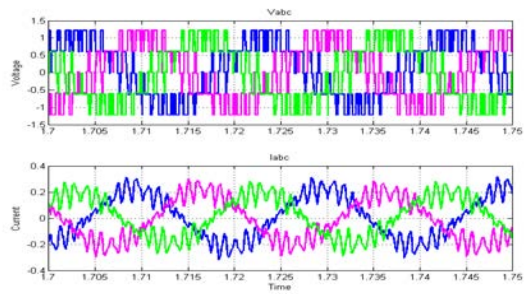

Fig. 6: Three phase voltage and current

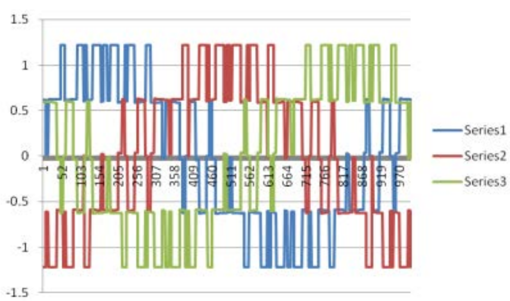

Fig. 7: Voltage waveform for sampling window of 20 m sec

At time t = 5 sec one of the switch is open circuited and the subsequent data is also collected as usual. The error and the average errors are calculated and a final vector of six elements corresponding six errors are obtained. This vector or error average corresponds to the switch data [1 0 0 0 0 0].

In a similar way the data set was collected for the cases of all the possible combinations of switch open circuit cases. That is from the [1 1 1 1 1 1] case which corresponds to all switches intact to the extreme case of [0 0 0 0 0 0] which means all switches are opened 2^6 = 64 combinations are possible and the corresponding ave_error error vector were derived. It is a case of pattern mapping where we have 64 input sets and correspondingly 64 output sets. This data set was used to train the neural network and after training we got the trained ANN that could map the input ave_error vector to the corresponding output vector that would show the switch status.

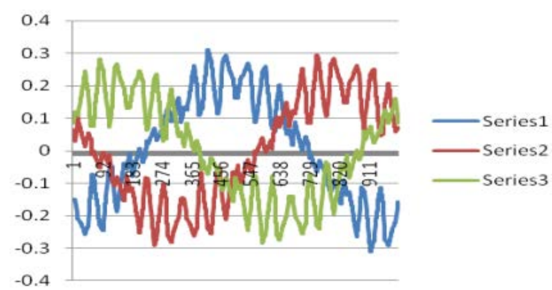

Fig. 8: Current waveform for sampling window of 20 m sec

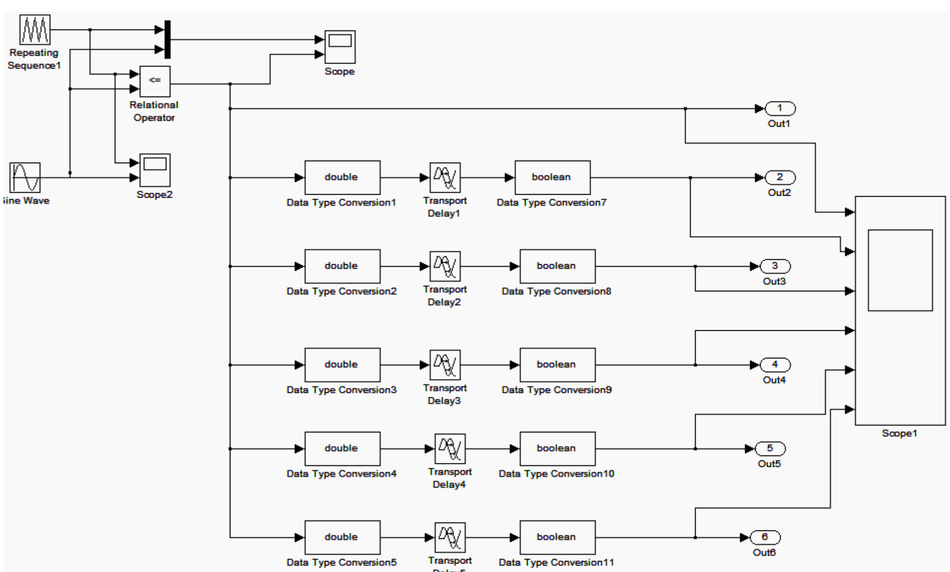

Fig. 9: Subsystem

Correction scheme: The ultimate objective is not just to locate the open circuited switch but also to replace it by routing through a standby switch from a standby set of six switches (Lee *et al*., 2010). Once the standby switch comes in the place of the faulty switch the appropriate switching pulses are also routed to the new switch now in place of the faulty switch. The Matlab Simulink simulation sub system is shown in Fig. 9.

The waveforms of voltage, current, speed and torque are shown in the case of a fault without being addressed and the case of the same fault properly addressed with the required correction (Lee *et al*., 2010).

RESULTS AND DISCUSSION

Figure 10 show the various cases of faults. In all these cases the fault has introduced at the instant of 0.5 sec. Of the 64 possible cases, a set of 9 cases have been presented here. It is interesting to note that the ave_error does not directly exhibit the faulty condition and it needs some expertise to decipher from the ave_error data the corresponding faulty switch pattern.

Figure 10, case 1 indicates the steady state condition, i.e., no switch is at fault. Case 2 indicates the switch 2 is fault. Similarly, voltage and current waveform for fault at each switch is shown in Fig. 10-18.

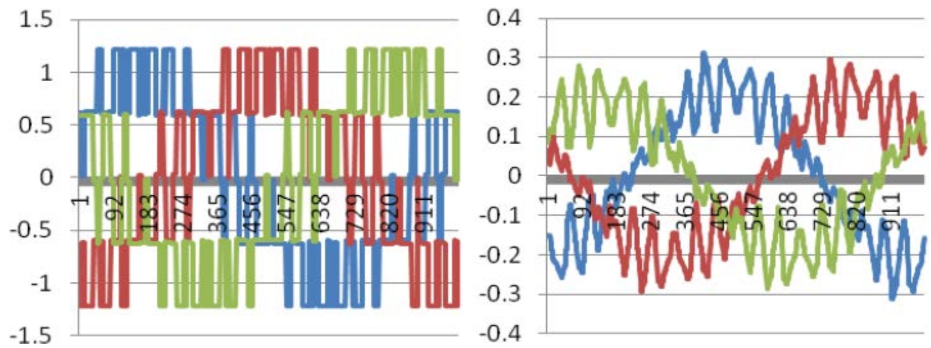

Fig. 10: Voltage and current for various cases of faults [1 1 1 1 1 1]

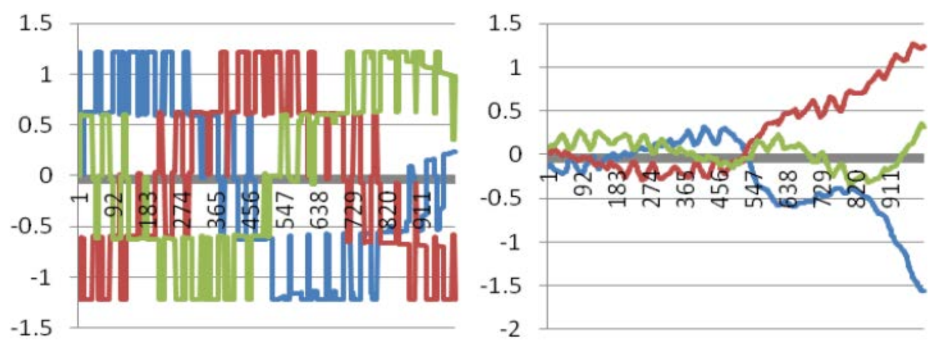

Fig. 11: ANN out put indicating fault switch [0 1 1 1 1 1]

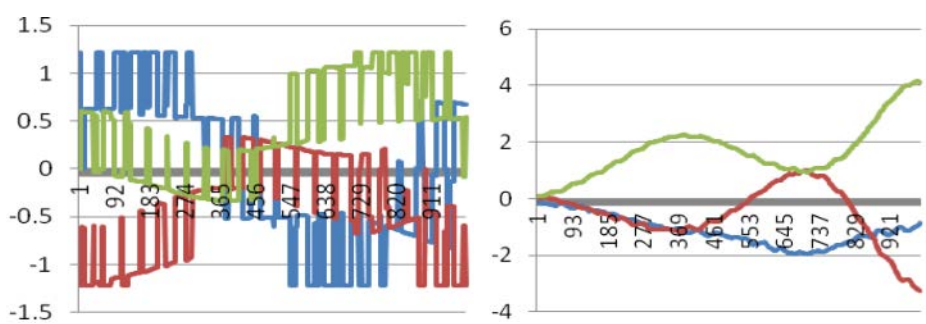

Fig. 12: ANN out put indicating fault switch [1 0 1 1 1 1]

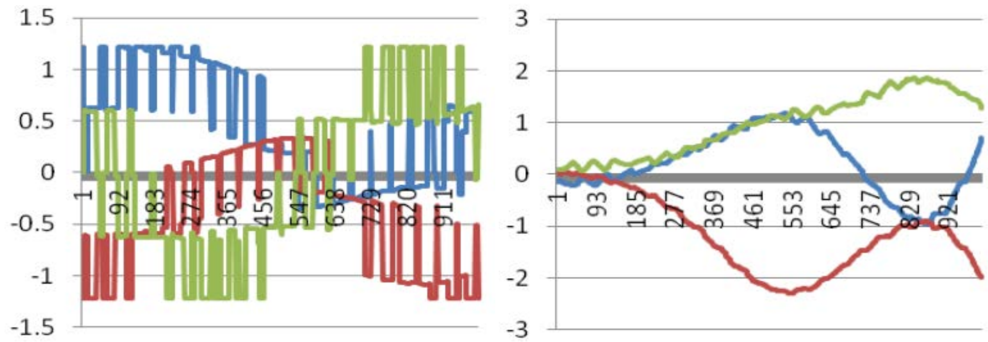

Fig. 13: ANN out put indicating fault switch [1 1 0 1 1 1]

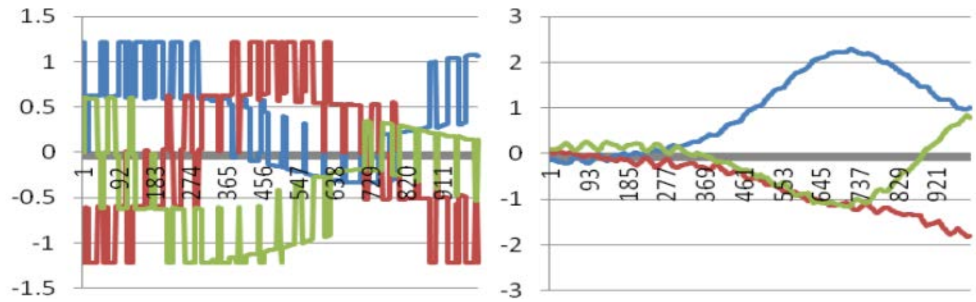

Fig. 14: ANN out put indicating fault switch [1 1 1 0 1 1]

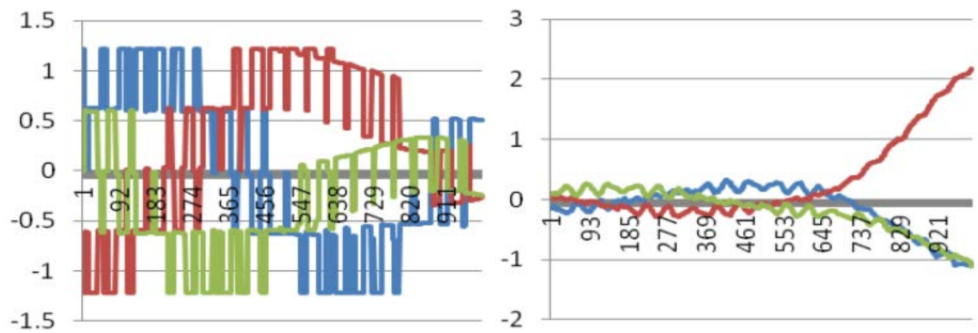

Fig. 15: ANN out put indicating fault switch [1 1 1 1 0 1]

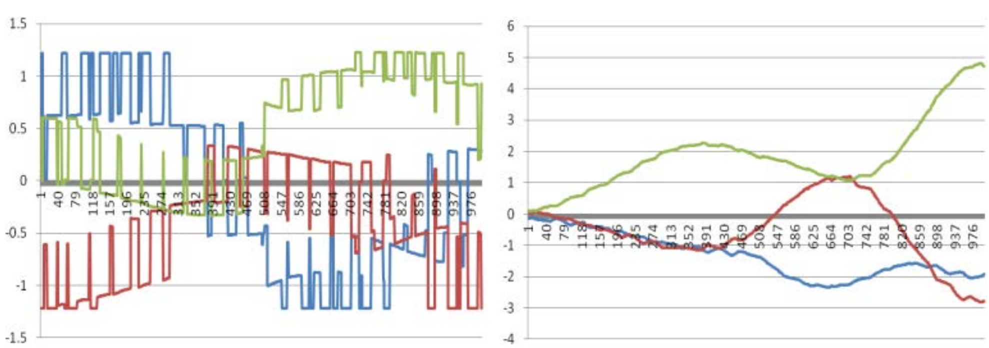

Fig. 16: ANN out put indicating fault switch [1 1 1 1 1 0]

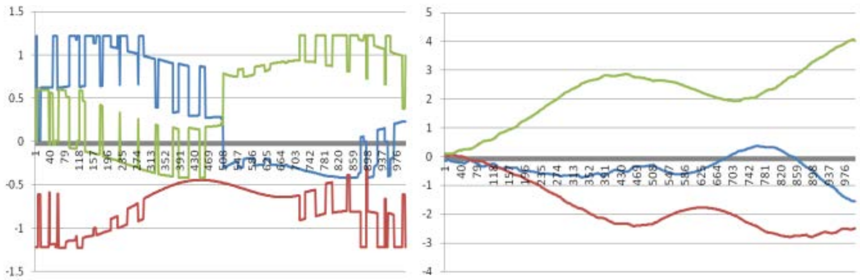

Fig. 17: ANN out put indicating fault switch [0 0 1 1 1 1]

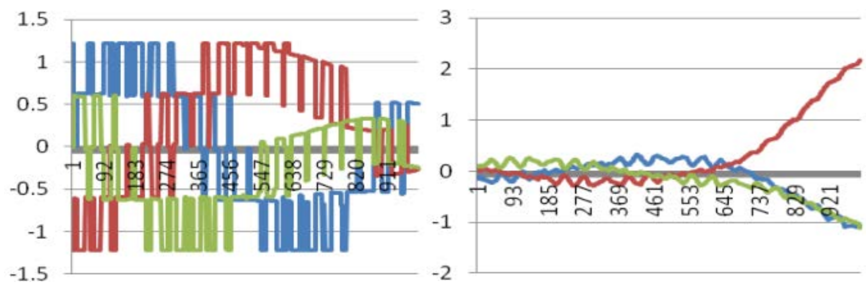

Fig. 18: ANN out put indicating fault switch [0 0 1 1 1 1]

CONCLUSION

The objective behind the proposed methodology is to find out the faulty switch as it may happen in real time by observing the resulting three phase voltages and currents through a sampling window. The proposed idea has been validated using the Matlab/Simulink simulation.

The same method can be extended for advanced and complicated converters like Matrix convertors, etc., which have more number of switches. The proposed methodology can also be realized in real time hardware system using the modern micro controllers like the ARM 7 processor typically LPC 2148.

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