IGBT Fault Detection for Three Phase Motor Drives using Neural Networks

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Abstract

Motor drives are widely used in industry for controlling the speed of three phase AC motors. Faults in motor drives degrade motor performance and can cause catastrophic failures. IGBT switch faults are one of the main roots of electrical faults in inverters and motor drives. In this paper, a method based on neural network is implemented to detect and isolate switch faults in a three phase voltage source inverter. Only the output signals of the inverter are monitored. The entropy of the phase current and voltage is selected as the switch fault feature. Single and multiple short and open circuit switch faults are isolable with this method.

1. Introduction

Nowadays, the ability to maintain healthy operation of any system is of great importance from efficiency, productivity, and safety aspects. Every machine is subject to faults. Although many types of faults can be prevented during the design stage, there always exist probabilities of system failure due to device ageing, overloading, and unpredicted situations. To prevent the fault propagation and prevent unexpected shut-down of the vital systems, industries are highly interested in fault tolerant systems. The first step towards having fault tolerant systems is fault detection and isolation (FDI). Fault diagnostic systems also can reduce the maintenance cost of the machines by eliminating unnecessary scheduled maintenance services.

A large number of hybrid electric vehicles consist of three phase induction motor drives. The precise torque control of these motors has been made possible by power electronics with controllable solid state switches. However, the solid state switches can fail by sticking open or shorted regardless of the control signal. Power electronic inverters are considered as the weakest link in the electro-mechanical systems because of the high probability of failure of the semiconductor switches. In current technologies, given the high reliability required in almost all systems, the ability to detect a system fault at the earliest possible stage is of primary interest [15].

Over the last decades, a number of intelligent systems approaches have been investigated in signal fault diagnosis. Model-based approaches [9], fuzzy logic, artificial neural networks, and case-based reasoning (CBR) are popular techniques used in various fault diagnostics problems in electrical systems [14]. There exist a good amount of work in the literature on fault diagnostics for power electronics inverter [2, 13, 8, 3, 5, 12, 16, 10, 4]. A novel method based on fault dictionary that uses entropy as a preprocessor to diagnose faulty behavior in switched current circuit was proposed in [18]. They used a neural network for diagnosing soft faults in electronic components of switch current integrated circuits.

In this research, a model-based fault diagnostic system using neural network is studied for detecting multiple switch faults in a motor drive. The systems is models by a three phase voltage source inverter and a three phase RL load is considered. A fault dictionary is built to capture 73 different fault modes with the higher rate of occurrence. The voltage and current signals are collected via output detectors. To reduce the dimension of the fault dictionary, Entropy and mean value of the detected signals are extracted. These features are used to train a neural network system as the fault diagnosis engine. Simulation results shows these fault isolation method is capable of addressing major single and multiple faults switch faults with high accuracy.

The model of the inverter and the switch faults are described in Section 2. Section 3 describes the entropy function and the feature extraction process. The neural network structure and the fault isolation method comes in Section 4. The fault detection and isolation results come in Section 4.3 and limitations of the presented method are discussed. The paper is concluded in Section 5.

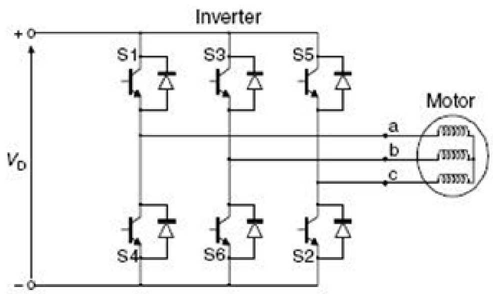


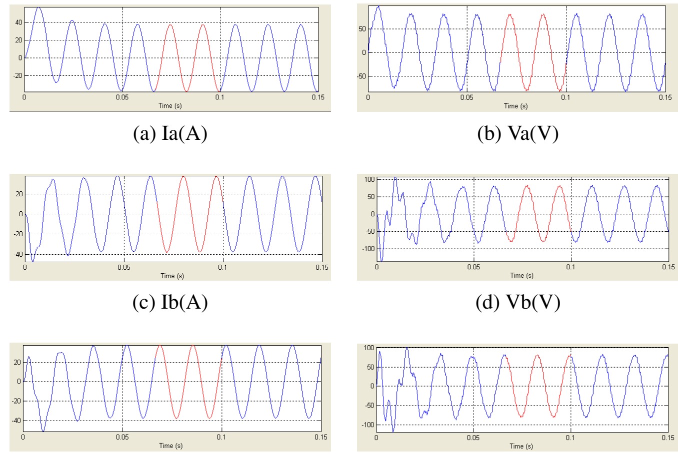
Figure 1: Basic structure of an inverter system

2. Inverter Model

The basic structure of a three phase voltage source inverter is shown in Fig. 1. In this model S_1 to S_6 are Insulated Gate Bipolar Transistors (IGBTs) which can be on or off. Sinusoidal pulse width modulation (SPWM) is a common technique for controlling the switches. The average value of voltage fed to the load is controlled by turning the switch between supply and load on and off at a high frequency. The longer the switch is on compared to the off periods, the higher the power supplied to the load is.

The simplest way to generate a PWM signal is the intersective method, which requires a triangle waveform and a comparator [8]. When the value of the reference signal is more than the modulation waveform, the PWM signal is in the high state, otherwise it is in the low state. After appropriate filtering, the desired sinusoidal waveform can be obtained which is the fundamental frequency of the switching signal.

Figure 2 depicts the inverter model which is simulated in MATLAB. The output of the inverter is connected to a three phase RL load through a low pass filter. Sensors are placed on the load to monitor the three phase voltage and current signals. Figure 3 shows the current and voltage of all three phases in no fault mode. The measurement sampling time is set to $T_s = 1/60/3240 = 5.14e-6$ s.



(a) Ia(A)

(b) Va(V)

(c) Ib(A)

(d) Vb(V)

(e) Ic(A)

(f) Vc(V)

Figure 3: Monitored signals in no-fault mode of operation.

2.1. Switch Faults

In this study, two major types of faults are considered:

- **Short circuit faults**
  Short circuit faults are one of the common failures in IGBTs. In this situation, the IGBT falls in the on state and remain in this situation regardless of the gate voltage value. To model this type of fault, an ideal switch is used in parallel with each IGBT as shown in Fig. 4a. The switch is initially open. By closing the switch at the desired time, an artificial fault is inserted. The combination of the IGBT and this switch simulates an IGBT with a Drain-Source short circuit fault

- **Open circuit faults**
  Open circuit faults are the other type of common failures in IGBTs. In this situation, the .IGBT falls in the off state and remain in this situation regardless of

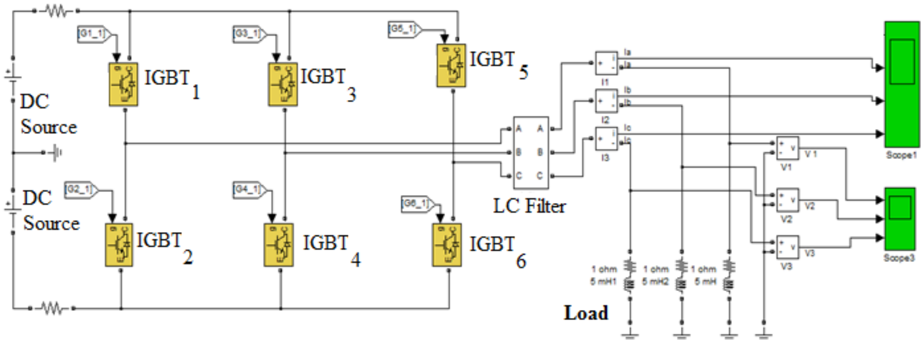
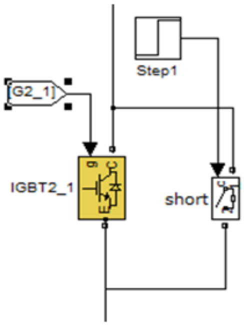
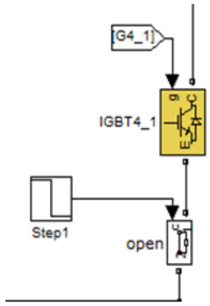


Figure 2: The MATLAB SIMULINK model of three phase inverter.



(a) Simulink model for emulating short circuit faults.



(b) Simulink model for emulating open circuit faults.

Figure 4: Simulink models of IGBT faults.

the gate voltage value. To model this type of fault, an ideal switch is used in series with each IGBT as shown in Fig. 4b. The switch is initially closed. By opening the switch at the desired time, an artificial fault is inserted. The combination of the IGBT and this switch simulates an IGBT with a Drain-Source open circuit fault.

2.2. Representation of Faults

We use a binary code to represent each fault mode. Each code consists of nine bits. The first six least significant bits represent the faulty switch. In no fault mode all these six bits are equal to zero. If any of these six bits is 1 the corresponding switch is faulty. The fault type is determined by the three most significant bits. Table 1 shows the fault mode and their assigned code. For example, 100 001000 means an open circuit fault exists in the 3^{rd} switch and 011 010010 means the 2^{nd} and 5^{th} switches are short circuited.

Fault Mode	Fault Code
Normal	111
Single switch open	100
Single switch short	101
Two switches open	000
Two switches short	011
One switch open and One switch short	001

Table 1: Fault modes and their corresponding binary code.

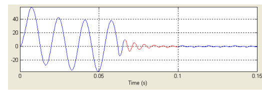
A combination of the short and open circuit faults may occur in the inverter which is called a fault mode. As the probability of having more than two faults at the same time is very rare, we consider maximum two faulty switches at the same time in the inverter.

$$N = \binom{6}{1} + \binom{6}{1} + \binom{6}{2} + \binom{6}{2} + \binom{6}{1} * \binom{5}{1} = 72 \quad (1)$$

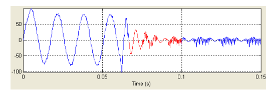
Equation 1 calculates the number of fault modes, N. Adding the no-fault mode, there will be 73 fault modes to be diagnosed.

2.3. Fault Database

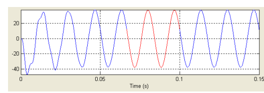
To train the fault diagnosis neural network, all the fault modes should be simulated. Three phase voltage and current signals are sampled and stored in data form to build the fault database. Figures 5, 6, 7, 8, 9, and 10 depicts some examples of the monitored signals for different fault modes.



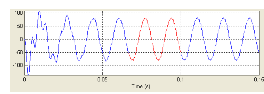
(a) Ia(A)



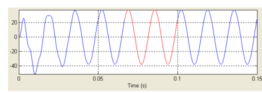
(b) Va(V)



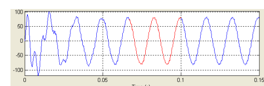
(c) Ib(A)



(d) Vb(V)

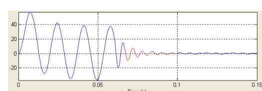


(e) Ic(A)

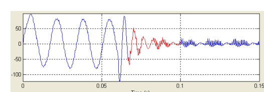


(f) Vc(V)

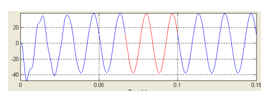
Figure 5: Three phase current and voltage output when an open circuit fault occurs in switch 1 at t=0.06s.



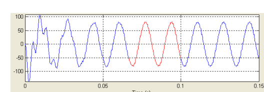
(a) Ia(A)



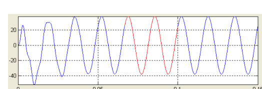
(b) Va(V)



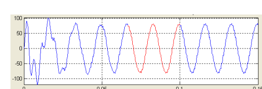
(c) Ib(A)



(d) Vb(V)



(e) Ic(A)



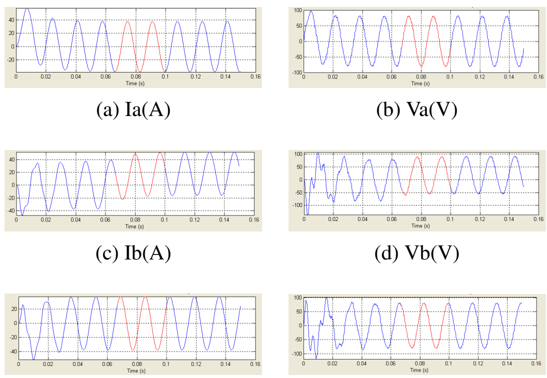
(f) Vc(V)

Figure 6: Three phase current and voltage output when an open circuit fault occurs in switch 2 at t=0.06s.

Using only one set output for the neural network to learn and diagnose all the faults is too limited [2]. Thus, we collected 24 sets of output for each fault mode, and all the samples were stored to form a fault dictionary. To collect these sets, we run the system under different conditions. We assumed that the circuit parameters can change within 10% of their nominal values. These parameters include internal resistance, R_i, and amplitude of the DC voltage source, V, internal resistance and snubber resistance, R_s, of each IGBT, and the load parameters, R_L and L. Table.2 shows some circuit condition sets and the value of circuit parameters for each set.

Table 2: Different sets of circuit parameters which are used in training stage.

	DC Source		IGBT1		IGBT2		IGBT3		IGBT4		IGBT5		IGBT6		Load	
Set	V	$R_i(\Omega\ )$	$R_i(\Omega)$	$R_s(\Omega)$	$R_i(\Omega)$	$R_s(\Omega)$	$R_i(\Omega)$	$R_s(\Omega)$	$R_i(\Omega)$	$R_s(\Omega)$	$R_i(\Omega)$	$R_s(\Omega)$	$R_i(\Omega)$	$R_s(\Omega)$	$R_L(\Omega)$	L(H)
1	400	0.01	55e-3	1e5	55e-3	1e5	55e-3	1e5	55e-3	1e5	55e-3	1e5	55e-3	1e5	3	5e-3
2	400	0.02	50e-3	0.9e5	50e-3	0.9e5	50e-3	0.9e5	50e-3	0.9e5	50e-3	0.9e5	50e-3	0.9e5	2	5.5e-3
3	500	0.02	60e-3	1.1e5	60e-3	1.1e5	60e-3	1.1e5	60e-3	1.1e5	60e-3	1.1e5	60e-3	1.1e5	2.5	4.5e-3
4	600	0.025	60e-3	1e5	55e-3	0.9e5	55e-3	1.1e5	50e-3	0.9e5	60e-3	0.9e5	50e-3	1.1e5	4	7e-3
5	600	0.01	55e-3	1e5	50e-3	0.9e5	60e-3	0.9e5	60e-3	1.1e5	50e-3	1.1e5	55e-3	0.9e5	4.5	6e-3
6	500	0.015	60e-3	0.9e5	60e-3	1e5	50e-3	1.1e5	55e-3	1.1e5	55e-3	0.9e5	50e-3	0.9e5	3.5	7.5e-3
7	600	0.03	50e-3	1.1	55e-3	0.9e5	55e-3	0.9e5	60e-3	1e5	60e-3	1e5	50e-3	1.1	3.5	5e-3
8	400	0.0009	55e-3	1e5	60e-3	1e5	50e-3	1.1e5	60e-3	1e5	55e-3	1e5	60e-3	1.1e5	5	3e-3
9	460	0.0008	45e-3	1.1e5	45e-3	1.2e5	65e-3	1.2e5	55e-3	0.8e5	65e-3	0.8e5	50e-3	0.8e5	4	4e-3

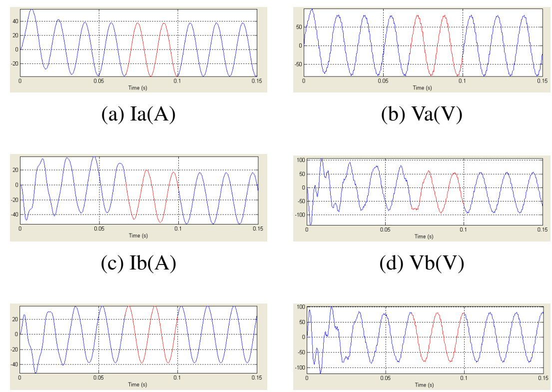


(a) Ia(A) (b) Va(V)

(c) Ib(A) (d) Vb(V)

(e) Ic(A) (f) Vc(V)

Figure 7: Three phase current and voltage output when a short circuit fault occurs in switch 3 at t=0.06s.



(a) Ia(A) (b) Va(V)

(c) Ib(A) (d) Vb(V)

(e) Ic(A) (f) Vc(V)

Figure 8: Three phase current and voltage output when a short circuit fault occurs in switch 4 at t=0.06s.

3. Feature Extraction

The aim of feature extraction is to reduce the dimension of the fault dictionary so that each mode of fault can be represented by only a few features. Usually, Max, Min, Median, Mean, Standard deviation, or Zero-frequency component of the power spectrum of the signal are used as the features. However, using only one of the features above are not good enough to uniquely represent a signal. Usually, a combination of these features is used together to identify a mode of fault. This makes the fault dictionary too big and increases diagnosing difficulty and training time. To overcome this problem, we selected one feature namely the entropy of the signal. Entropy was previously used by [18] as a novel feature extraction method which simplifies the fault dictionary's architecture and reduces the fault diagnosis time.

3.1. Entropy

Entropy is a quantitative measure of the information contained in a signal. In fact, the entropy of a random variable can be interpreted as the degree of information that the observation of the variable gives. The more random, i.e., unpredictable and unstructured, the variable is, the larger its entropy will be. Because the switch faults distort the healthy sinusoidal outputs, the entropy of the output can be used as a feature to identify the fault mode.

Entropy is the basic concept in information theory [7]. The entropy of a signal is a measure of unpredictability of the values that signal may take. Entropy H is defined for a discrete-valued random variable X as [7]:

$$H(X) = -\sum_i P(X = a_i) \log P(X = a_i), \quad (2)$$

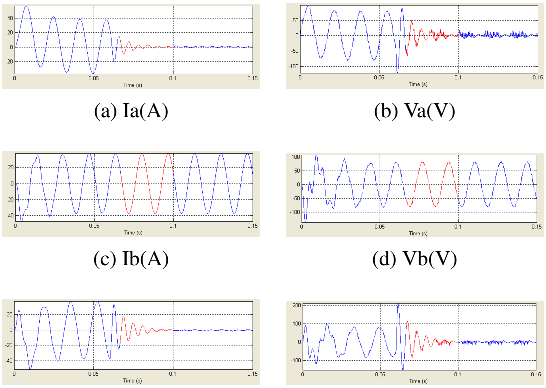
where a_i is the possible value of X, and $P(X = a_i)$ are the probabilities of $X = a_i$. Usually, the logarithm with base 2 is used in Equation 2, where the entropy unit is called a bit [18].

The definition of entropy for discrete-value random variables can be generalized for continues-valued random variables which is called the differential entropy [18]. Equation 3 defines the differential entropy H of a random variable x with density $p(x)$ [7, 11].

$$H(x) = -\int p(x) \log p(x). \quad (3)$$

In [11] the signal's approximate maximum entropy is calculated which is shown in Equ. 4).

$$J(x) \approx \frac{1}{2} \sum_{i=1}^{n} E\{F_i(x)\}^2 \quad (4)$$

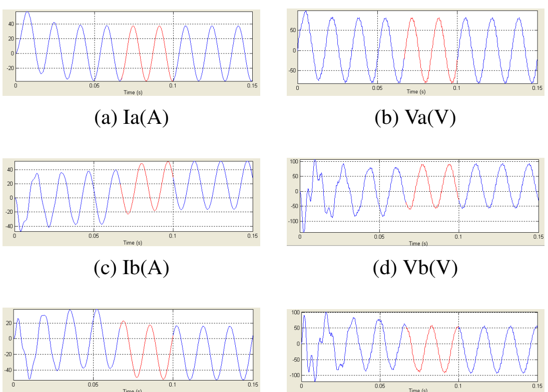


(a) Ia(A) (b) Va(V)

(c) Ib(A) (d) Vb(V)

(e) Ic(A) (f) Vc(V)

Figure 9: Three phase current and voltage output when two open circuit faults occur in switches 2 and 5 at t=0.06s.



(a) Ia(A) (b) Va(V)

(c) Ib(A) (d) Vb(V)

(e) Ic(A) (f) Vc(V)

Figure 10: Three phase current and voltage output when two short circuit faults occur in switches 3 and 6 at t=0.06s.

E calculates the estimated value of information functions, F_i. We can practically take any set of linear independent functions to obtain the set F_i that fulfil the orthogonal assumption [18].

In this paper, we use the approximate maximum entropy proposed in [18].

$$J(x) \approx k_1(E\{G_1(x)\})^2 + k_2(E\{G_2(x)\} - E\{G_2(\nu)\})^2 \quad (5)$$

In Equ. 5, k_1 and k_2 are positive constants and ν is a random variable that meets the standard orthogonal distribution. G_1 function measures the asymmetry, and the G_2 function measures the dimension of bimodality.

Equ. 6 defines G_1 for measuring asymmetry [18],

$$G_1(x) = x\ exp(-x^2/2) \quad (6)$$

and Equ. 6 defines G_2 for measuring bimodality and sparsity.

$$G_2(x) = |x| \quad (7)$$

Based on [18], $k_1 = 36/(8\sqrt{3}-9)$, $k_2 = 1/(2-6/\pi)$, and $\nu = \sqrt{2/\pi}$ are chosen. Thus, the entropy can be obtained as shown in Equ:8:

$$J(x) = k_1(E\{x \exp(-x^2/2)\})^2 + k_2(E\{|x|\} - E\{\sqrt{2/\pi}\})^2 \quad (8)$$

Equation 4 shows the entropy is an even function. Thus, when two signals have the similar values but inverse sign, the entropy will be the same. Therefore, we use the mean value as another feature to differentiate these two signals. In the future, the entropy functions can be modified so that to differentiate between these to cases.

3.2. Feature-Fault Matrix

Voltage and current signals of all three phases are monitored. Entropy and the mean value are extracted from each signal. Thus, there will be 12 features for each fault mode. This makes a 12 by 73 feature-fault matrix. Twenty sets of feature matrixes are extracted for the neural network to train and diagnose. I_a, I_b, I_c, V_a, V_b, V_c, are variables of the signal segments sampled from the three phase output. For instance, the features extracted for some fault modes are shown in Table 3.

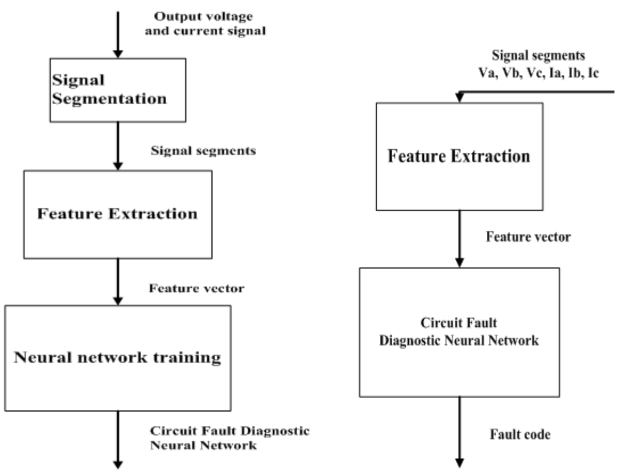
Based on the fault simulation model, data in the fault-feature matrix are collected. A neural network will be trained to be used as the diagnosis engine. Before training, we have to divide the data into two subsets; One subset, called training set, is to use for training the neural network, and the other subset, called test set, is to test if the neural network works good enough for real application [19].

4. Fault Diagnosis

In this step a neural network is trained to be used as the diagnostic engine. Figures 11a and 11b illustrate the computational steps involved in the generation of such a neural network system. There are two computational stages: neural learning and fault diagnostic stage [1].

Table 3: Examples of fault features which are extracted for different fault modes.

Fault mode / Feature	Normal	1 Open	2 and 6 Open	4 Short	4 and 5 Short	3 Short and 4 Open	2 Short and 5 Open
$J(I_a)$	4.41e3	0.39	17.56	4.27e3	2.04e3	4.37e3	3.20e4
$J(I_b)$	4.50e3	4.50e3	6.03e3	3.00e4	2.86e4	4.61e4	2.69e3
$J(I_c)$	4.32e3	4.33e3	57.75	4.19e3	3.15e4	4.34e3	12.48
$J(V_a)$	6.03e4	205.10	1.28e3	5.85e4	3.48e4	5.09e4	5.75e5
$J(V_b)$	5.84e4	5.84e4	2.74e4	2.88e5	1.86e4	6.42e5	3.48e4
$J(V_c)$	5.78e4	5.81e4	2.22e3	5.60e4	1.97e4	4.93e4	568.47
$Mean(I_a)$	-0.04	-0.26	0.26	-0.14	0.18	-0.06	58.65
$Mean(I_b)$	-0.04	-0.04	-0.15	-55.55	-58.73	98.54	0.11
$Mean(I_c)$	-0.04	-0.04	0.26	-0.15	60.24	-0.06	-0.05
$Mean(V_a)$	-0.12	-0.81	0.28	-0.43	0.23	-0.09	102.86
$Mean(V_b)$	-0.12	-0.13	-0.15	-166.65	-98.62	178.62	0.13
$Mean(V_c)$	-0.13	-0.13	0.20	-0.44	104.38	-0.09	-0.05



(a) Computational steps of learning. (b) Computational steps of fault diagnostic.

Figure 11: Learning and fault diagnosis computational steps.

The input to the neural learning stage is a training data set that consists of groups of signals, with each group containing six signals, three voltage signals, Va, Vb, Vc, and three currents Ia, Ib, Ic , acquired at the three phases in the inverter, all generated by our simulation model at normal and the 72 other abnormal operational situation. These groups of signals are segmented and features are extracted on a segment by- segment basis.

During the fault diagnostic stage, the segments of the six signals at time t are sent to the feature extraction function. The neural network predicts the output feature vector whether there exists a fault in the circuit at time t, and if it does, the type of fault is indicated as well.

4.1. Neural Network Structure

Multilayer Perceptrons neural networks architecture with Back Propagation (BP) algorithm is selected. The number of neurons in the input layer should be the same as the number of input variables, which is 12 representing the 12 dimensions of the feature vector. The number of output neurons is equal to the number of fault codes which is equal to 9 binary outputs. Figure 12 shows the architecture of the neural network.

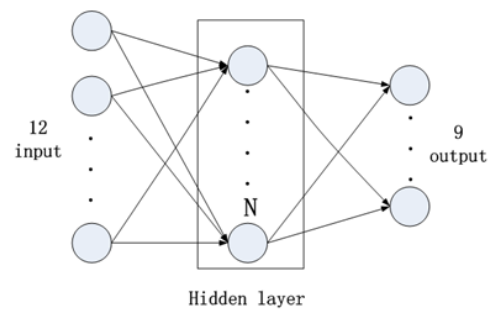


Figure 12: The architecture of the applied neural network.

It has been proven that any rational function can be approached by a network with a sigmoid hidden layer and a linear output layer. So, we select the tansig and logsig functions as the hidden and output layer active functions, respectively [17].

4.2. Training

The learning stage of the neural will result into a multilayer neural network that has the capability of detecting any one of the 72 fault modes in the 6-switch inverter circuit.

In this application, we define the neural network input space as the features extracted from voltages and currents signals in the inverter drive system. The output space consists of class labels, $\{f_0, f_1, \ldots, f_{72}\}$, where f_0 is considered to be the normal operational condition, and f_1 to f_{72} are the 72 fault modes that the neural network system will learn to detect.

In order to train a robust neural network, a number of parameters must be carefully chosen including the number of hidden nodes and learning rate [1]. The learning rate that is selected varies among 0.005, 0.01, 0.05, 0.1 and 0.2, and the number of hidden nodes varies among 10, 14, 18 24 and 28. In each run, the stop criterion is a combination of the maximum epoch number and the threshold of error: if the number of the epoch has reached 100 or the minimum squared error is less than $1e-5$, then the training stops. Among the 24 sets of features 16 sets are used to train the neural networks. The other 4 sets are used for testing. The training set is then delivered to the input neurons and the network is trained to match the goal using the Levenberg-Marquardt algorithm. We evaluated the performances of each type of neural networks and found that the three neural networks with 18 hidden nodes gave the most robust performances.

4.3. Results

After training, a neural network model is build with 12 inputs and 9 outputs. The test date run on this model and results show that the fault mode codes are predicted correctly for all test datasets. Figure 13 depicts the fault diagnostic system and Table 4 shows some examples of the diagnostic results.

4.4. Robustness

In order to test the robustness of the system against noise the authors added noise to all the data generated by model [6]. The noises selected are random number white noise and randomly pulse noise. We selected three test points: the voltage source, inverter output and load. And then added three levels of noise: 5%, 10% and 15%, to the test data generated from these points. After adding noise to the system, the neural network showed its robustness. The average accuracy of the system with the noise was almost 97%.

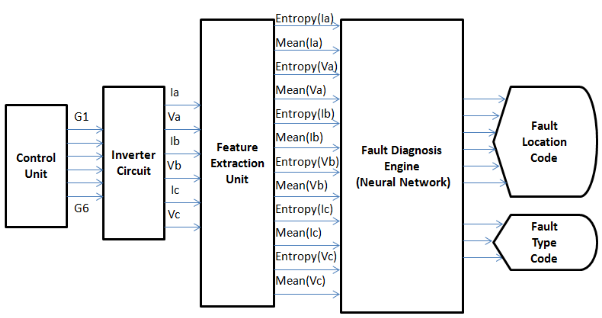


Figure 13: The neural network based fault diagnostic system for three phase voltage source inverter.

4.5. Discussion

A neural network have proven efficiency, in solving different type of problems pertaining to image processing, motor control, financial analysis and pattern classification [6]. The factors that motivate the application of artificial neural network for FDI are as follows:

- The artificial neural networks have the ability to use a large amount of sensory information.
- They have fast response towards sensory inputs.
- They have general mapping capabilities, where as traditional fault detection technique involves detailed modeling of the system.
- The knowledge in a neural network is mainly specified through learning, whereas most other techniques rely mostly on a pre-specified algorithm.
- They have the ability to adapt and continue to improve performance.
- The neural networks are capable of detecting incipient faults.

Based on the study of the system performances on the noise-free data and the data with different levels of noise, it can be concluded that the proposed Neural Network systems are robust to data noise. However, they have some limitations; A neural network can never detect an unknown fault. Therefore all the considered faults must be emulated [2] which requires several run of the system for every fault modes. However, it might not be possible for many industrial cases to be run under faulty condition. To overcome this issue, a precise model of the system as well as the model of the faults is required. Fortunately, the model of the system components and model of the faults for the power electronic system are possible to obtain. Nevertheless, the accuracy of the diagnostic system

Table 4: Testing results obtained for single switch fault modes.

Fault mode	Neural Network Outputs (Diagnosis result)									Rounded output
Normal	1.0000	0.9937	0.9986	0.0000	0.0014	0.0032	0.0008	0.0004	0.0000	111 000000
$IGBT_1$ open	1.0000	0.0010	0.0020	0.9977	0.0019	0.0005	0.0004	0.0007	0.0005	100 100000
$IGBT_1$ short	0.9988	0.0000	0.9958	0.9898	0.0019	0.0022	0.0000	0.0026	0.0002	101 100000
$IGBT_2$ open	1.0000	0.0008	0.0014	0.0000	0.9986	0.0000	0.0004	0.0010	0.0007	100 010000
$IGBT_2$ short	1.0000	0.0002	0.9982	0.0019	0.9972	0.0000	0.0015	0.0012	0.0000	101 010000
$IGBT_3$ open	1.0000	0.0004	0.0008	0.0000	0.0000	0.9977	0.0020	0.0013	0.0001	100 001000
$IGBT_3$ short	0.9994	0.0000	0.9990	0.0005	0.0016	0.9970	0.0007	0.0001	0.0014	101 001000
$IGBT_4$ open	1.0000	0.0004	0.0018	0.0005	0.0016	0.0017	0.9973	0.0002	0.0009	100 000100
$IGBT_4$ short	1.0000	0.0000	0.9978	0.0000	0.0003	0.0006	0.9978	0.0021	0.0008	101 000100
$IGBT_5$ open	1.0000	0.0005	0.0007	0.0001	0.0016	0.0000	0.0006	0.9987	0.0002	100 000010
$IGBT_5$ short	0.9998	0.0000	0.9983	0.0002	0.0050	0.0005	0.0022	0.9982	0.0001	101 000010
$IGBT_6$ open	1.0000	0.0000	0.0027	0.0012	0.0000	0.0003	0.0009	0.0007	0.9984	100 000001
$IGBT_6$ short	1.0000	0.0009	0.9997	0.0003	0.0000	0.0005	0.0015	0.0015	0.9958	101 000001

relies on the precise model and knowledge of the system and its faults.

In our previous work [4] we proposed a model based approach for switch fault detection in a single phase inverter. This model base approach is robust to the fault occurrence time, but, a detail mathematical description of the system and all the circuit components is needed. The results show the neural network diagnostic method is robust to the components tolerances. However, the performance of the neural network diagnostic system is not yet evaluated for different fault occurrence times. In the simulations we inserted all the faults at t= 0.06 s. However, in the real application, the faults may occure in any time instance. In the future we will change the fault occurrence time and study the diagnostic accuracy of the FDI system. Entropy functions can be chosen so that the fault features have the minimum sensitivity to the fault occurrence time.

5. Conclusion

In this paper, a diagnostic approach for the detection and isolation of a broad range of open circuit and short circuit faults in electric drive inverters in open-loop systems was presented. A model of the electric drive inverter with a three phase RL load and a control mechanism was developed to simulate the normal and faulty modes of operation of the power electronics inverter. The voltage and current of all three phases were monitored in several faulty modes and stored in a fault data base. Entropy and mean value of the output signals were extracted to build the feature-fault matrix. A multiple class neural network framework was trained as the diagnostic engine using the feature-fault matrix. The accuracy of the diagnostic results has reached more than 97% in presence of noise. The system performance is evaluated on the basis of time elapsed to detect a fault after its occurs. The simulation results show that the proposed system takes less than 20 ms on an average to successfully detect and isolate a fault.

In future, the sensitivity of the entropy function to the switch fault occurrence time should be evaluated. The entropy function will be modified to uniquely capture each fault mode so that the neural network structure can be simplified.

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