PATTERN RECOGNITION AND DIAGNOSIS OF SHORT AND OPEN CIRCUIT FAULTS INVERTER IN INDUCTION MOTOR DRIVE USING NEURAL NETWORKS

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Abstract:

Nowadays, feeding induction motors with voltage source inverters under faulty conditions is a major challenge. For this reason, electrical systems must be well thought out to provide good diagnostics for these elements. Consequently, the early detection of faults is very important to establish strategies that allow us to control the operation and take preventive measures to avoid frequent failures. Our aim in this paper is to train multilayer neural networks using features extracted from currents and voltages measurements to detect and classify open and short-circuit switch faults in source voltage inverters. Simulation results show that instead of using several types of features extracted from measurements of several signal cycles as in previous works, a two-component feature obtained from one cycle is sufficient to obtain an excellent accuracy. The normalized mean Clark currents and the power spectrum using the fast Fourier transform have been used as features for open switches and short-circuit faults respectively.

1 Introduction

Source voltage inverters feeding induction motors are widely used in industrial process. They constitute key element in driving process at variable speeds. The most common inverter faults are mainly caused by damaged power semiconductor switches [1,2]. Power semiconductor switch faults can be divided into short-circuit faults and open circuit faults. When a short circuit fault occurs, an overcurrent occurs and the system must be shut down immediately [3]. Compared to short-circuit faults, open-circuit faults do not cause the system to stop [4]. The system continues to operate but in a degraded mode. The detection of open or short-circuit switches fault in power converter have been extensively studied in previous works to improve the reliability and availability of the power converters.

The majority of these methods are based on signal analysis. The main advantage of these methods is that they only require measurements of line currents or line-to-line voltages [5-8]. In the literature, the diagnosis of open circuit faults using neural networks is considered as a pattern recognition problem [9-13]. The most commonly used methods consist of two key steps; feature extraction and fault classification. In the time domain, features are extracted directly from the three stator currents or the Clark currents transform [14-15]. For instance, current angle and diameter were considered as features in [16]. These features can be used to classify single faults only. For the detection of multiple faults, the mean, area, and angle extracted from Clark currents are considered [4,17]. In the frequency domain, among the most commonly used techniques for open-circuit fault detection in power-converter drives are the Fourier transform [18] and the wavelet-based multi resolution analysis [19-20]. For instance, in [18] the fault-signature spectrum obtained from the three-phase currents is considered as feature. Also, a dimensionally reduced FFT by principal component analysis is proposed. On the other hand, the wavelet coefficients were used as a feature vector [20]. Principal component

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analysis could be used to reduce the dimensionality of the feature vector [21,22]. The extracted feature vector will be used for classification using different machine learning algorithms such linear classifiers like k-nearest neighbors (kNN), decision tree, support vector machine (SVM) and neural network (NN) [7,23].

The aim of this paper is the use of neural networks to detect and classify open and short-circuit switches fault in source voltage inverter. Instead of using several types of features, or measurements of several signal cycles as in previous works, in the proposed approach, a two components feature obtained from one cycle is sufficient to obtain an excellent accuracy. The normalized mean Clark currents and the power spectrum using fast Fourier transform have been used as feature for open switches and short-circuit faults respectively. The rest of this paper is organized as follows: Section 2 presents the basic DTC procedure. In Section 3, the fault diagnosis system is analyzed for single and multiple open switches and short-circuit faults. Section 4 presents the proposed method. Section 5 contains simulation results. Section 6 contains the conclusion.

2 Basic DTC

As seen in Figure 1, two loops correspond to the stator flux and torque magnitudes. The reference values T_e^* , ϕ_s^* for the torque and the flux compared with the actual values T_e , ϕ_s induce errors ε_T ,ε_F . These errors feed into two hysteresis blocks, respectively. Depending on the values of the two hysteresis comparators and the position of the stator flux over six control ranges, the switching table selects a suitable vector. The inverter in six-stage operation has six active vectors and two zero vectors. Thus, the output voltage vector of the inverter minimizes the flux and torque errors and determines the direction of flux rotation [12, 24-28].

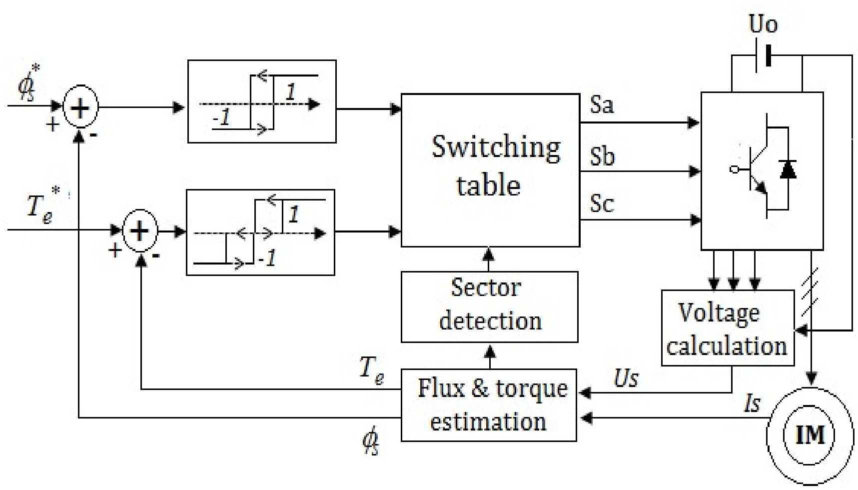


Figure 1. Basic DTC block diagram.

The inverter output U_s is obtained via the switching status (S_a, S_b and S_c) and the DC voltage source that fed the inverter U_0. It is formed as follows [29]:

$$U_s = \sqrt{\frac{2}{3}} U_0 \left(S_a + S_b e^{i\frac{2\pi}{3}} + S_c e^{i\frac{4\pi}{3}} \right). \tag{1}$$

The stator flux vector formed in tow-phase axes (α, β) are estimated by integrating the stator back-electromotive force signal [29,30]:

$$\begin{cases} \varphi_{s\alpha} = \int_0^t (V_{s\alpha} - R_s I_{s\alpha}) dt \\ \varphi_{s\beta} = \int_0^t (V_{s\beta} - R_s I_{s\beta}) dt \end{cases}. \tag{2}$$

The next equation calculates the stator flux modulus [29]:

$$\phi_s = \sqrt{\varphi_{s\alpha}^2 + \varphi_{s\beta}^2}. \tag{3}$$

The angle θ_s is set by [30] :

$$\theta_s = tan^{-1} \frac{\varphi_{s\beta}}{\varphi_{s\alpha}}. \tag{4}$$

The calculated currents $(I_{s\alpha}, I_{s\beta})$ and the estimated flux magnitudes $(\varphi_{s\alpha}, \varphi_{s\beta})$ are used to evaluate the electromagnetic torque given by [29]:

$$T_e = \frac{2}{3} p\left(I_{s\beta}\varphi_{s\alpha} - I_{s\alpha}\varphi_{s\beta}\right), \tag{5}$$

where p is the number of poles.

3 System of fault diagnosis

The basic structure of the voltage source inverter is shown in Figure 2. It contains six insulated-gate bipolar transistors (IGBTs), which operate in a complementary manner, and six free-wheeling diodes. The inverter supplies fully symmetrical three-phase sinusoidal currents and voltages. Pulse width modulation technique is used to control the IGBT switches. As shown in Figure 2(b), the faults of the voltage source inverter are divided into short circuit and open circuit. When the switch fault is open, the IGBT remains off. Open circuit faults do not cause the system to shut down, and the system continues to operate in degradation mode. In the case of a short circuit, an overcurrent is detected by the standard protection system and the system is shut down.

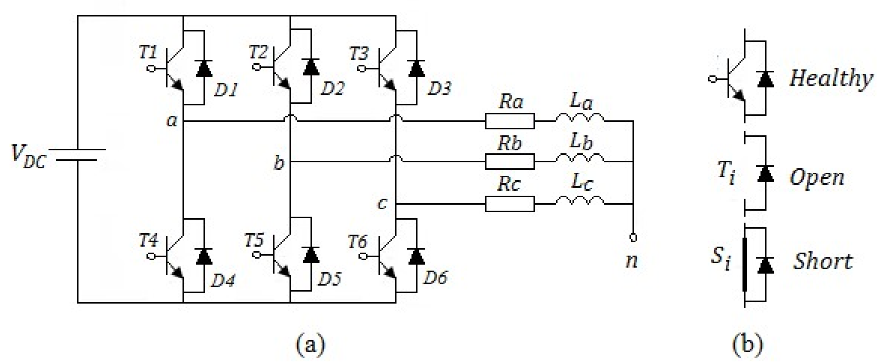


Figure 2. Diagram of a VSI feeding three-phase induction motor (a) and typical faults (b).

3.1. Open circuit faults

Open circuit faults can be classified into three categories: single switch faults, double switch faults in the same bridge arm, and double switch faults in different bridge arms. All possible faults are shown in Table 1 [31].

Single open switch fault

To see the effect of an open switch fault, consider the case when the switch T1 is open. The current cannot flow in the phase A through the upper bridge arm when this current is positive; the output current of phase A is zero. During this half period, the phase current of the remaining phases are distorted due to the three-phase current balance. When the phase current is in the negative range, the current can flow in the phase A through the lower bridge arm via the freewheel diode D4. The same consideration applies to the other switches [31].

Double-switch faults in the same bridge arm

In the case of a double switch fault in the same bridge arm, the current in the considered phase is zero. Consequently, the currents of the other phases are distorted; they are out of phase. For example if T1 and T4 are open, $i_b(t) = -i_c(t)$ [31].

Double-switch faults in different bridge arms

In this case, consider T1 and T2 are open. During the interval [2kπ, 2kπ + 2π/3], the current of phase A is zero following the open switch fault of T1. The current of phase B which is negative in this interval passes through the diode D5. The current of phase C passes normally but with a slight distortion. The currents of phases B and C are in phase opposition. In the interval [2*k*π + 2π/3, 2*k*π + π], the current in the phase A remains zero. The current of phase B which normally will become positive does not flow following the fault of switch T2. Since the two currents are zero, the current of phase C will necessarily be zero. In the interval [2*k*π + π, 2*k*π + 5π/3], the current of phase A flow through the freewheel diode D4 and the current of the phase B remains zero. This situation leads to a distortion of the current of the phase C. In the last interval, [2*k*π + 5π/3, 2*k*π + 2π], the three currents flow normally through D4 and D5 and the the upper bridge arm [31].

3.2. Short circuit faults

When a short circuit occurs, stator currents increase dramatically, leading to catastrophic inverter failure [3]. Therefore, using stator currents to detect short-circuit faults is not useful. On the other hand, the normalized mean value of the stator voltage in the (α, β)-space for the six short-circuit switches is almost zero, so the short-circuit switch fault cannot be detected. To remedy this, the stator voltages in the frequency domain are used.

Table 1. Faults types and their corresponding labels.

Fault types	Fault location	Corresponding label
Healthy mode	-	H
Single open switch fault	T1, T2, T3, T4 T5, T6	T1, T2, T3, T4 T5, T6
Double open-switch fault in the same bridge arm	T1-T4, T2-T5, T3-T6	T14, T25, T36
Double open-switch fault in different bridge arms	T1-T2, T1-T3, T1-T5, T1-T6	T12, T13, T15, T16
	T2-T3, T2-T4, T2-T6, T3-T4	T23, T24,T26,T34
	T3-T6 T4-T5, T4-T6, T5-T6	T36, T45, T46,T56
Single short-circuit fault	S1, S2, S3, S4 ,S5, S6	S1, S2, S3, S4 ,S5, S6

4 Proposed method

Figure 3 depicts the proposed open and short switch faults detection in the diagnosis system using the current and voltage measurements.

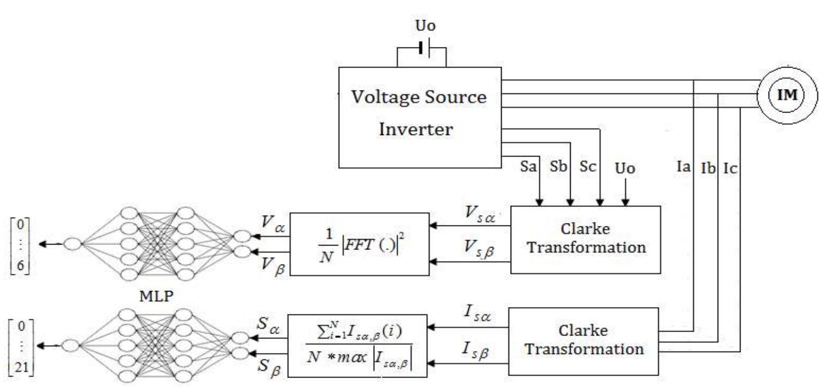


Figure 3. Proposed fault diagnosis system.

The line currents as well as the voltages of the three phases with respect to the neutral are represented in the $\alpha\beta$-reference frame by a simple vector addition of these three-phase variables. these two new vectors are btained by applying the Clarke-Concordia transformation. Therefore, the measured currents (I_{sa}, I_{sb}, I_{sc}) are transformed into two dimension $(I_{s\alpha}, I_{s\beta})$ by [17]:

$$\begin{cases} I_{s\alpha} = \frac{2}{3} I_{sa} - \frac{1}{3} I_{sb} - \frac{1}{3} I_{sc} \\ I_{s\beta} = \frac{1}{\sqrt{3}} (I_{sb} - I_{sc}) \end{cases} \tag{6}$$

In the same way, the stator voltage components in the (α, β) reference are obtained by applying Concordia transformation on the output voltage of the three-phase VSI which are given by [29]:

$$\begin{cases} V_{s\alpha} = \sqrt{\frac{2}{3}} U_0 \left(S_a - \frac{1}{2} S_b - \frac{1}{2} S_c \right) \\ V_{s\beta} = \sqrt{\frac{1}{2}} U_0 (S_b - S_c) \end{cases} \tag{7}$$

We extract features using the normalized mean value of signals in equations (6) for open switches faults and the power spectrum using the discrete Fourier transform for the short-circuit faults case.

4.1. Feature extraction

Feature extraction is critical for developing an efficient problem detection and diagnosis system from the output three-phase current signal. It was used to extract data and train a neural network to detect faults.

For open switch fault, we have used a method based on the normaized mean value of currents. The measured currents I_{sa}, I_{sb}, I_{sc}, transformed into $I_{s\alpha}, I_{s\beta}$ by equation (6) are used to calculate the features S_α, S_β using the folowing equations [16]:

$$\begin{cases} S_\alpha = \dfrac{\sum_{i=1}^{N} I_{s\alpha}(i)}{length(I_{s\alpha}) * max(abs(I_{s\alpha}))} \\ S_\beta = \dfrac{\sum_{i=1}^{N} I_{s\beta}(i)}{length(I_{s\beta}) * max(abs(I_{s\beta}))} \end{cases} \tag{8}$$

Where N is the number of samples contained in Is_α or Is_β. The choice of N depends on the diagnosis decision time. $S_{\alpha,\beta}$ is a normalized mean obtained from the N available measurements of $I_{s\alpha}$ $(I_{s\beta})$. In open circuit choosing surface calculation as feature extraction because it gives three symmetric levels (negative, zero, positive) to present lower switch default, healthy switch, and upper switch default. The data are well organized and the fault classification will be simple and easy. To create the dataset, we manually produce faults by opening the IGBTs gates in the used Simulink model. Figure 4 shows the obtained features using equation (8) for some single and multi-open switches faults.

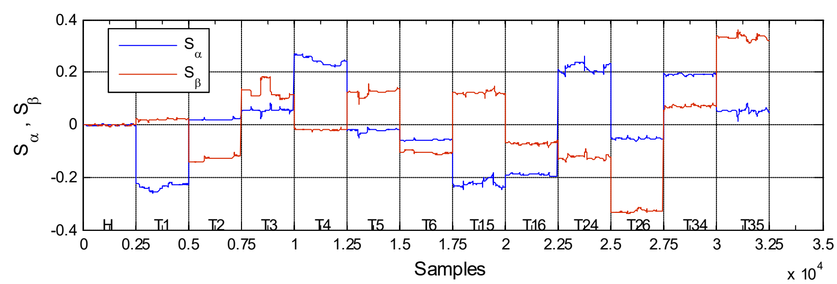


Figure 4. Feature extraction under open circuit switch fault occurrence.

For short-circuit fault leading to over current the use of stator currents to detect short-circuit fault is not practical. Also, normalized mean value of voltages is almost zero. For this reason, the power spectrum constitutes a good alternative for short-circuit fault detection. To compute the power spectrum, we have used the Fast Fourier Transform (FFT) to compute the Discrete Fourier Transform of the two voltage signals $V_{s\alpha}$, $V_{s\beta}$ [32]:

$$F_{v\alpha}(k) = \sum_{n=1}^{N-1} V_{s\alpha}(n) e^{\frac{-j2\pi nk}{N}}, \tag{9}$$

$$F_{v\beta}(k) = \sum_{n=1}^{N-1} V_{s\beta}(n) e^{\frac{-j2\pi nk}{N}}. \tag{10}$$

Where N is the number of samples contained in $V_{s\alpha}$. Then, the power spectrum of the two voltage signal spectrums are used as features [32].

$$V_\alpha = \frac{1}{N}|F_{v\alpha}|^2, \quad V_\beta = \frac{1}{N}|F_{v\beta}|^2. \tag{11}$$

Faults are manually generated to obtain different features in normal and faulty mode. This process is repeated many times under many reference speeds (see Figure 5).

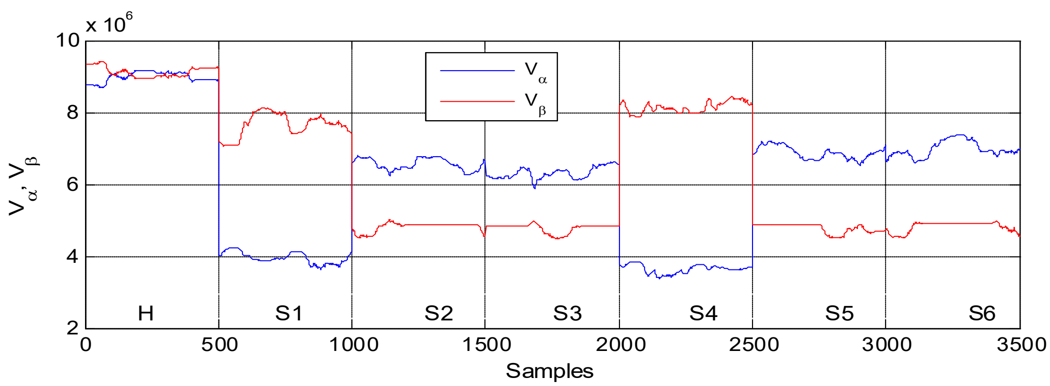


Figure 5. Feature extraction under short-circuit switch fault occurrence.

4.2. ANN Fault classification

Neural networks have shown excellent performance in detecting open circuit faults. The main idea is to train a Multi layer Perceptron (MLP) from a data set consisting of input examples and their corresponding desired outputs. As shown in Fig. 6, the architecture of the used MLP has two hidden layers H_1, H_2 with two input nodes corresponding to the surfaces s_α, s_β in the open switches case and the power spectrums V_α and V_β in the short-circuit case. The output can take values from 0 to 22 for the open switches case and from 0 to 6 in the short-circuit case. This architecture is adopted after multiple training.

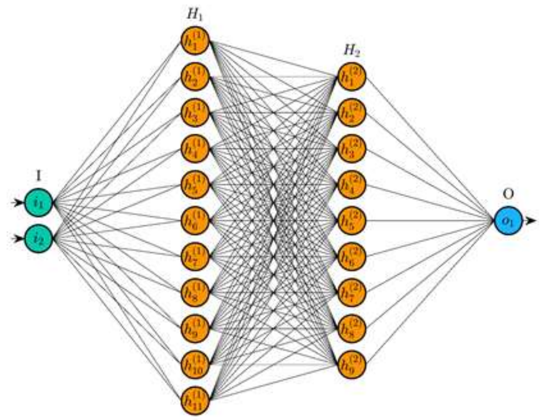


Figure 6. Architecture of the MLP used in the fault detection system.

5 Simulation results

5.1. Input / Output data

To build the dataset, we manually open or short-circuit the switches as indicated in Table 1 and run the simulation under motor speed 40 and 70 round/s and desired torques 0.5 and 1 N.m. In the proposed method, the detection and classification of defects, is performed by the segmentation of the signal using a sliding window. All segments constituting a period of the signal are composed of 450 samples.

The network will be trained with different faulty modes. The input data contains 2000 features for each pattern input. That gives 2000 for a healthy pattern and 2000*21 for fault occurrence. That gives 44000 vectors. For the short-circuit case, 560 features are used where every fault has 80 input features. 50% of these examples of the two cases are used for training, 25% for the validation and 25% for the test.

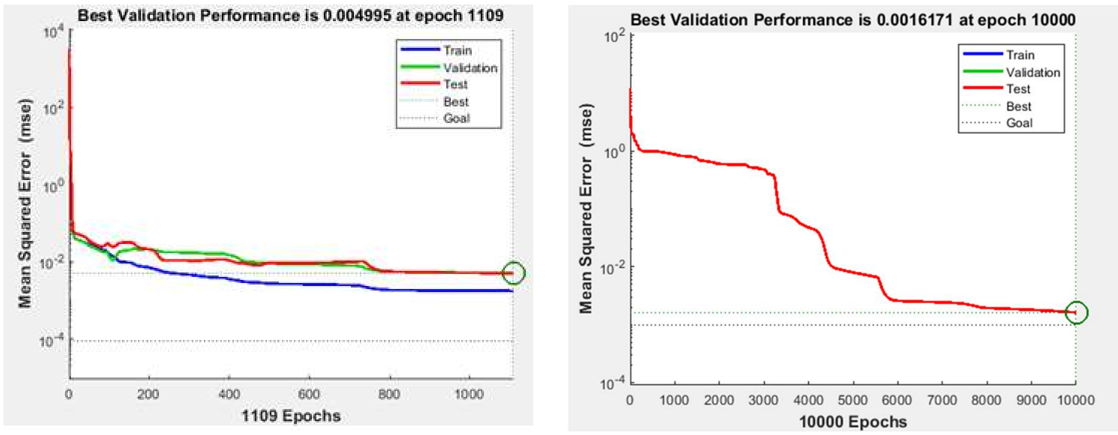
5.2. Neural Network training

After many simulations, we have found that 11 neurons in the first hidden layer and 9 neurons in the second layer is the best configuration in the two cases. The Levenberg Marquardt training algorithm is used due to its rapid training time and regular characteristic properties. The training process will be stopped when the selected Mean Squared Error (MSE) is reached. The MSE is given by [12]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - d_i)^2, \tag{12}$$

where y_i is the output value of the neural network, d_i is the target output, N is the training data number.

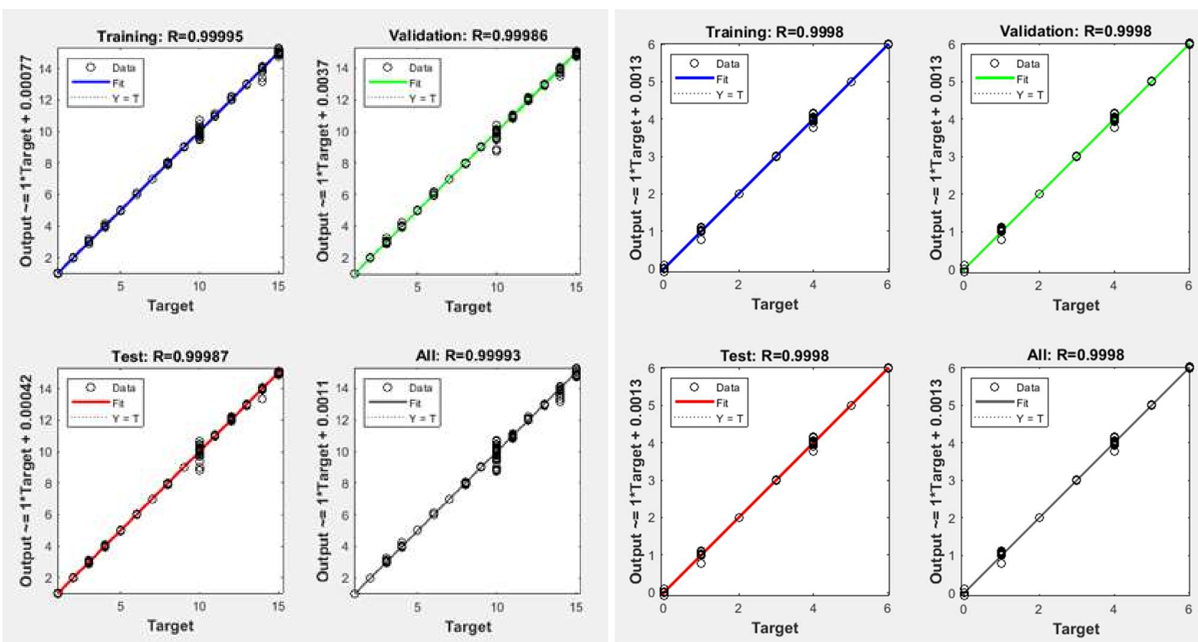
Figure 7 shows the convergence curves for training process for 15 open switches faults. The best validation performance is obtained after 1109 epochs with a MSE of 0.0094. In the short-circuit case, a best performance of 0.0016 is obtained for the all single faults S1,…,S6 after 10000 epochs (see Fig. 7b).



(a) *(b)*

Figure 7. Training process for (a) open-switches and (b) short-circuit cases.

Figure 8 shows the performance of the neural network during the training phase. The prediction ratio is almost 99.99% for training, validation and testing process in the open and short-circuits cases.



(a) *(b)*

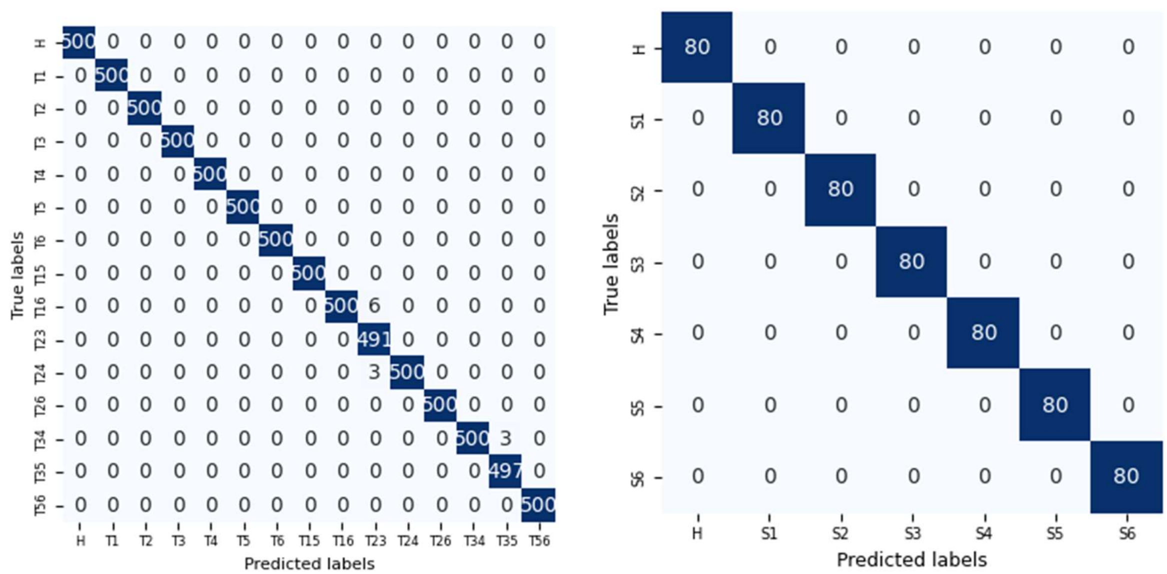
Figure 8. Behavior of the MLP during training, validation and testing process for (a) open-switches and (b) short-circuit cases.

5.3. Performance Evaluation

To evaluate the performance of the trained MLP, the accuracy and confusion matrix metrics were used to measure the correct or the misclassification of the different errors [33]. Accuracy is an essential metric for evaluating the result. It is the ratio of correctly predicted errors to total errors and is evaluated using the test data. The accuracy for the open switch case is 99.84%, while complete accuracy is achieved in the short circuit case. The confusion matrix is defined in table which allows us to visualise the performance of the MLP for the two faults type. Each row of the matrix presents the true labels, while each column represents the predicted labels. The confusion matrix shows the accuracy per class. As we can see from the confusion matrix, the accuracy is 100% for single open-switches and short-circuit faults. For multiple open switches fault, 12 misclassified from 7500 faults are noticed.

6 Conclusion

In this paper, fault detection in an inverter-fed induction motor is studied using neural networks. Single and multiple open switches as well as short circuit faults were considered. The features used are extracted from stator currents and voltages represented by the Clarke-Concordia transform in the -reference frame. The mean normalized currents and voltages were used for training the neural network. All mean currents or mean voltages form the inputs of the neural network. All current or voltage signals are segmented in every current or voltage cycle. Simulation results show that using only two features, the multilayer perceptron can achieve significant accuracy in detecting open or short-circuit fault in a three-phase inverter feeding an induction motor.



(a) *(b)*

Figure 9. Confusion matrix for test data (a) open-switches and (b) short-circuit cases.

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