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Deep Learning Approach for open switch Fault Diagnosis in Matrix Frequency Converter

***Abstract**. This document proposes a new method for detecting and locating open circuit faults in a matrix frequency converter (MC) based on the technique of pattern recognition by neural networks. The converter input and output current signals are used for this purpose. For this, a database of current signals under healthy conditions and defective for different operating conditions was established. After transforming these signals into a Concordia lair, a process of deep learning by a convolutional neural network was carried out. To verify the robustness of our proposed approach, a simulation of a MC system with a defective power electronic switch supplying an asynchronous motor controlled by DTC-SVM under different conditions of torque and speed was developed. The diagnostic results demonstrate the feasibility and effectiveness of the proposed method. It made it possible to locate the faulty switch precisely and quickly*

***Streszczenie.** Zaproponowano nową metodę wykrywania i lokalizowania uszkodzeń obwodu otwartego w przekształtniku matrycowym (MC) w oparciu o technikę rozpoznawania wzorców przez sieć neuronową. W tym celu wykorzystywane są sygnały wejściowe i wyjściowe prądu przekształtnika. Utworzono bazę danych sygnałów prądowych w warunkach znamionowych i z uszkodzeniem dla różnych warunków pracy. Po przekształceniu tych sygnałów w środowisku Concordia przeprowadzono proces głębokiego uczenia się przez splotową sieć neuronową. Aby zweryfikować Wiarygodność naszego proponowanego podejścia, opracowano model symulacyjny układu MC z uszkodzonym łącznikiem energoelektronicznym zasilającym silnik asynchroniczny sterowany metodą DTC-SVM z róznymi wartościami momentu i prędkości obrotwej. Wyniki diagnostyczne pokazują wykonalność i skuteczność proponowanej metody. (**Metoda uczenia sieci neuronowej w diagnostyce przekształtników matrycowych**).*

Keywords: Matrix frequency converter, diagnosis, pattern recognition, convolutional neural networks, deep learning.
Słowa kluczowe: *Przekształtnik matrycowy*, diagnoza, rozpoznawanie wzorców, splotowe sieci neuronowe, głębokie uczenie się.

Introduction

Today, matrix frequency converters are more and more used in the drive systems of electric machines due to their following attractive characteristics [1, 2]

- Simple and compact circuit,
- A bidirectional power flow,
- Generation of controllable voltage in amplitude and frequency,
- Absorption and generation of sinusoidal currents,
- Possibility to control the power factor.

In addition, due to the absence of electrolytic capacitors, the MC can operate in high temperature environments [3].

Otherwise, Due to the large number of switching devices and associated control circuits, it is inevitable that a fault occurs during the operation of the converter. Thus, there is a great need to diagnose frequent faults which could occur in MC, such as short circuit and open circuit faults of switch. Diagnostic results can reduce the cost of downtime. Most importantly, the information about identified faulty switches can be used to start a fault tolerant strategy [3, 4]

The researchers proposed feasible methods in the field of fault diagnosis of electrical systems, notably those based on Bayesian networks, a Petri network, a neural network, etc [5, 6] The capacity for automatic modelling and updating of knowledge of Bayesian networks is still immature. The modelling of Petri network is complex and difficult. The neural networks work easily in the local optimum and have problems of gradient diffusion. However, improving the neural networks, has great advantages in the diagnosis of faults

The concept of deep learning is the result of research developpe mention artificial neural networks. Itis proposed by Hinton [8], in 2006. It is designed to manage large database by adding layers to the network. A deep learning model has the capacity to extract characteristics from data thanks to the multiple processing layers.

Deep learning has been applied to signal recognition, image identification and target recognition, but has just started in the area of electric system fault diagnosis [8–10] With the ability to automatically learn multiple complex features from the input data, deep learning algorithms have great potential to overcome the disadvantages of traditional machine learning. There are many deep learning models, such as the recurrent neural network (RNN), the deep belief network (DBN), the Deep Boltzmann machine (DBM), the stacked automatic encoder (SAE) and the convolutional neural network (CNN). In the family of DL algorithms, DBM and DBN are based on Restricted Boltzmann Machine (RBM), SAE is based on Auto-encoder (AE), all are unsupervised learning algorithms, while CNN is a supervised learning method [12].

Being motivated by this fact, in this article, we propose a CNN (alpha beta-CNN) model, to diagnose open circuit switch faults in MC using input and output current signals. a CNN will be used to locate the faulty switch thanks to the classification of the images of 2D transformed currents.

This paper is organized as follows. In the first section, analysis of the effect of open switch fault in matrix frequency converter on the performance of induction machine drive system controlled with DTC-SVM is presented. Then, description of the proposed fault detection and localization method proposed based on pattern recognition and CNN is presented. Finally, the results of simulation tests of the proposed method are presented and analysed.

Matrix frequency converter under open circuit fault

Figure 1 shows a matrix converter supplying a load via the electrical network. The three input phases of the network are interconnected to the three output phases via bidirectional power switches.

There are three types of the Bi-directional Switch arrangement: a diode bridge, a common emitter, and a common collector. In our work, we use a common emitter arrangement. It consists of two diodes and two IGBTs connected in anti-parallel.

An open circuit failure in the matrix converter can be results of [13]:

- IGBT Failure,
- diode failure,
- IGBT / Diode linking failure,

- Gate drive failure,
- Gate drive isolated power supply failure,
- Gate drive communication failure.

Before applying our approach of diagnosis, we analyzed the effect of an open circuit fault by simulation of induction machine drive system based on matrix frequency converter shown in figure 1 with the parameters shown in table1 in appendix. An open circuit fault in the 'S_{12}' switch is introduced at t = 0.65s.

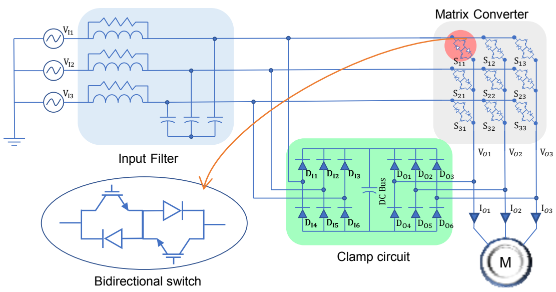


Fig.1. Induction machine drive-based matrix frequency converter

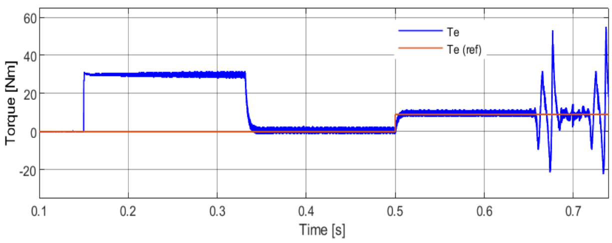


Fig.2. Torque response of induction motor controlled with DTC-SVM under healthy and faulty condition of MC.

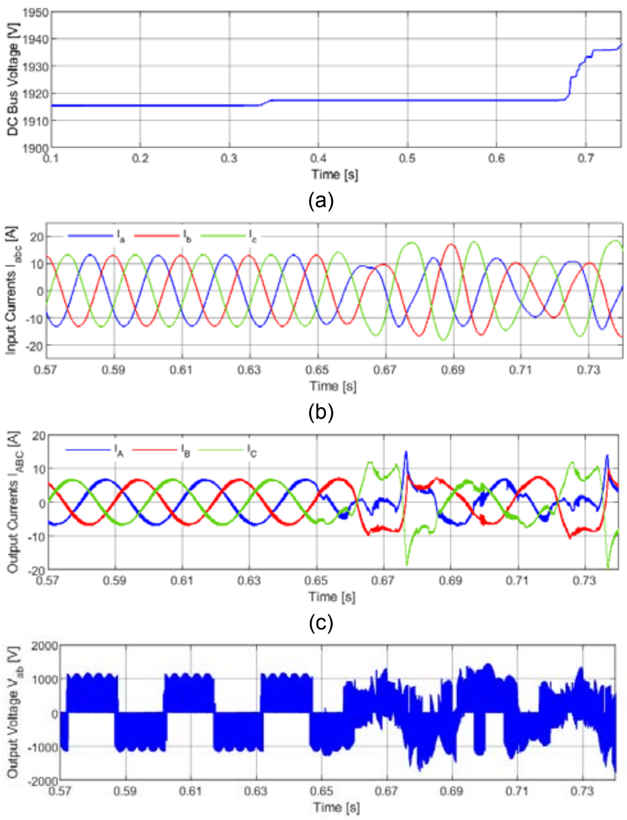


Fig.3. Currents and voltages in MC under healthy and faulty conditions (a) DC bus voltage of Clamp Circuit, (b) three-phase input currents, (c) three-phase output currents, and (d) line-to-line output voltages.

Figure 2 shows the behaviour of drive system-based matrix frequency converter when one switch is open circuit. At the moment when the open circuit fault occurs, A large disturbance in torque was noticed.

Figure 3 shows the behaviour of currents and voltages in matrix frequency converter when one switch is open circuit.

We noticed that:

- There is a sudden variation of more than 20 volts after a few milliseconds in the DC bus of clamp circuit. For that, we can take advantage of this variation to detect open circuit faults in MC switches.
- There are significant changes in the load currents, in particular the current of the faulty phase. Consequently, they cause also an overvoltage on the switches connected to the same output arm as the faulty switch. It may be also fail.

Proposed diagnosis method based deep learning

The proposed method for identifying the faulty switch uses a CNN based on pattern recognition. The Concordia frame's input and output currents are used for this purpose.

Figure 4 shows a diagram of the proposed method for the detection and localization of open circuit faults in a drive system based on a matrix frequency converter.

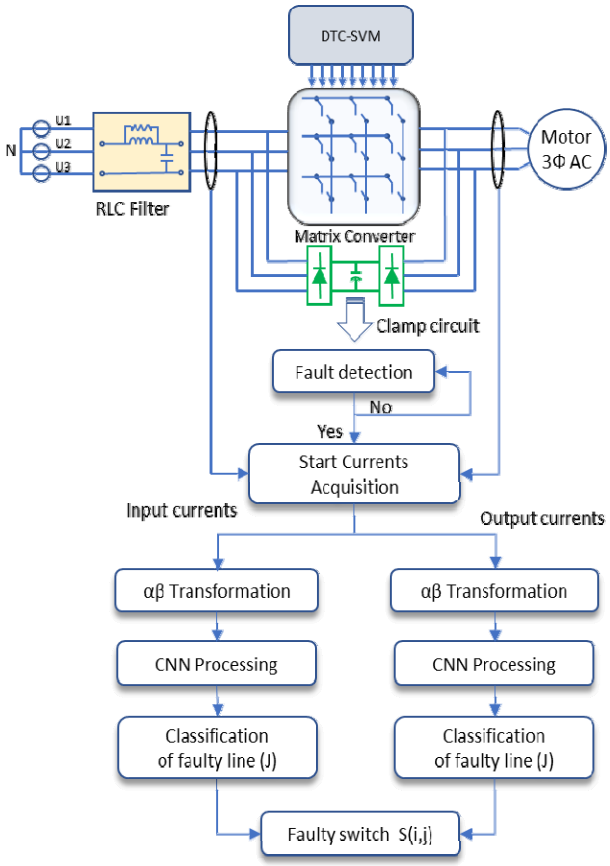


Fig.4. Proposed detection and localization method structure of a matrix frequency converter

a. Data preparation

The input and output currents in the Concordia αβ frame are given according to the three phase currents of the source (i_a, i_b, i_c) by [14]:

$$\left\{\begin{array}{l} i_\alpha = \frac{\sqrt{2}}{2} i_a - \frac{1}{\sqrt{6}} i_b - \frac{1}{\sqrt{6}} i_c \\ i_\beta = \frac{1}{\sqrt{2}} i_b - \frac{1}{\sqrt{2}} i_c \end{array}\right. \quad (1)$$

Figure below shows an example of the input currents in the Concordia frame when one switch is opened.

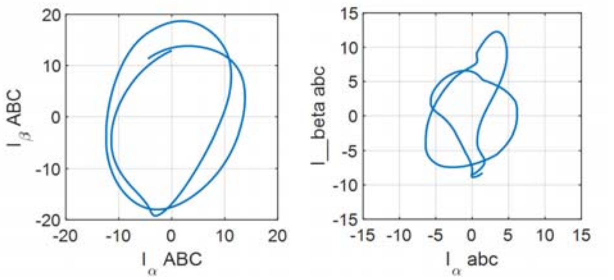


Fig.5. Input and output currents in Concordia frame with a faulty switch.

To be able to use these αβ currents in our approach, we must represent them in the form of an image of 100x100 pixels [9],[15] Each sample of αβ stator currents will be considered as a binary pixel belonging to the contour of the object with coordinates (I_x, I_y) given as follows:

$$\text{(2)} \qquad \begin{cases} I_x = \dfrac{[fix(i_\alpha - \min(I_\alpha))]}{K_x} + 1 \\ I_y = \dfrac{[fix(i_\beta - \min(I_\beta))]}{K_y} + 1 \end{cases}$$

$$\text{(3)} \qquad \begin{cases} K_x = \dfrac{(\max(I_\alpha) - \min(I_\alpha))}{L_x - 1} \\ K_y = \dfrac{(\max(I_\beta) - \min(I_\beta))}{L_y - 1} \end{cases}$$

with: i_α et i_β are the values of each element of the vectors I_α and I_β respectively
L_x and L_y are the pixel numbers in the (x) and (y) axis of the image. In our case $L_x = L_y = 100$.

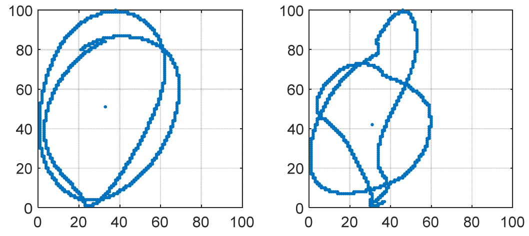


Fig.6. Input and output currents after segmentation

In a binary image, we consider an object with each pixel (xi, yi), the pixels belonging to the objects that we want to recognize being transferred to the foreground pixels (object pixels) I (xi, yi) = 1, the other pixels are transferred to the background pixels I (xi, yi) = 0.

b. Database structuration

The training database is created by the acquisition of input and output current signal at each frequency applied to the motor, this signal is transformed into αβ then into binary image, therefore this database is structured as a three-dimensional array of instance with image width and height. For a multilayer perceptron model, we need to reduce the images to a vector of pixels. In this case, the 100 × 100 size images will have an input value of 10000 pixels with values of 0 or 1. The output variables are also a binary from 0 to 1.

c. Learning network architecture

The network used for pattern recognition is a convolutional network (CNN). Fig. 7 shows the architecture of the CNN network with an input layer, convolutional layers and an output layer of the SoftMax type [16, 17].

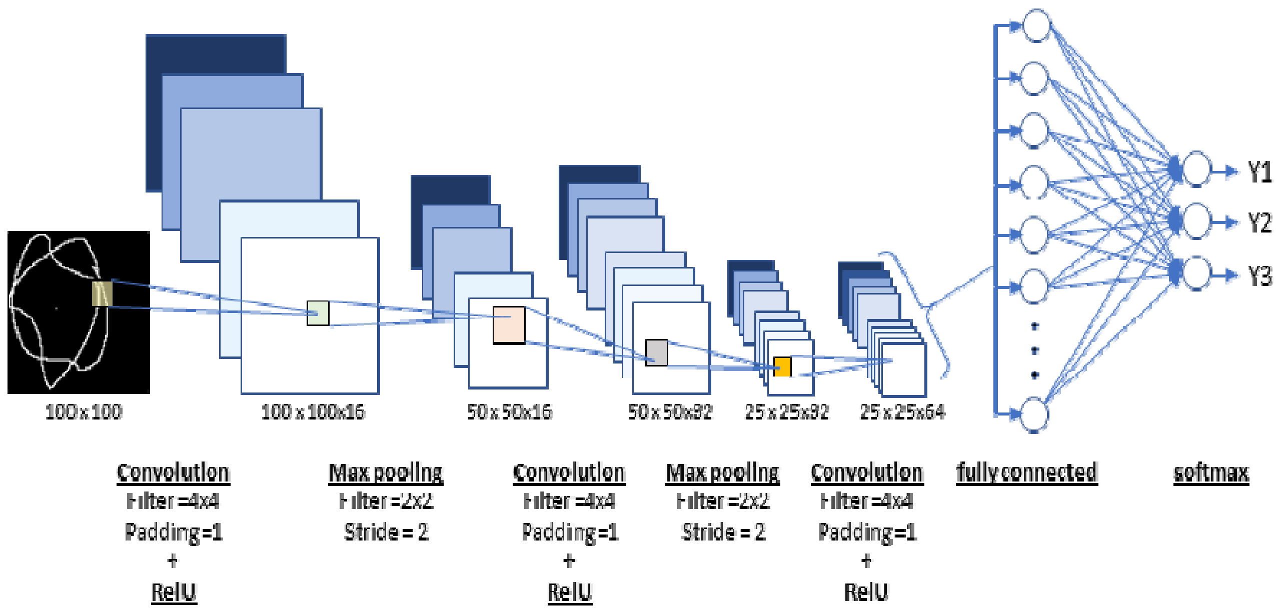


Fig.7. CNN architecture includes an input layer, convolutional layers and a softmax-type output layer.

d.Input layer

The input layer contains grayscale images of size 100x100x1. Each image pixel is characterized by its position and weight.

e. Convolutional layer

Zero fill to grab image borders vertically and horizontally has been applied. For each region of the input image, we apply a filter that moves along the image vertically and horizontally, repeating the same calculation for each region. In our case, the size of the filter is 4 x 4.

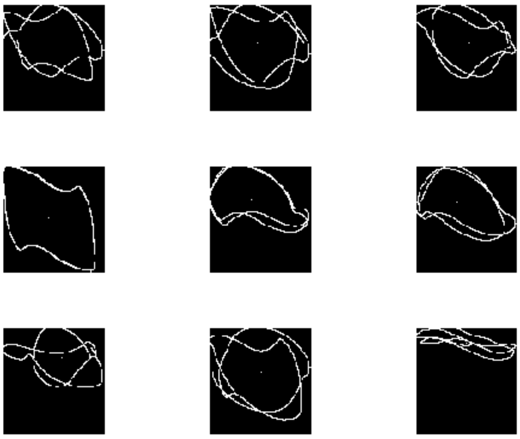


Fig.8. Example of nine inputs images for Training

f. Batch Normalization layer

Batch normalization layers between the convolutional layers and the non-linearities such as the ReLU layers are used to accelerate network formation and reduce the sensitivity to network initialization.

g. ReLU layer

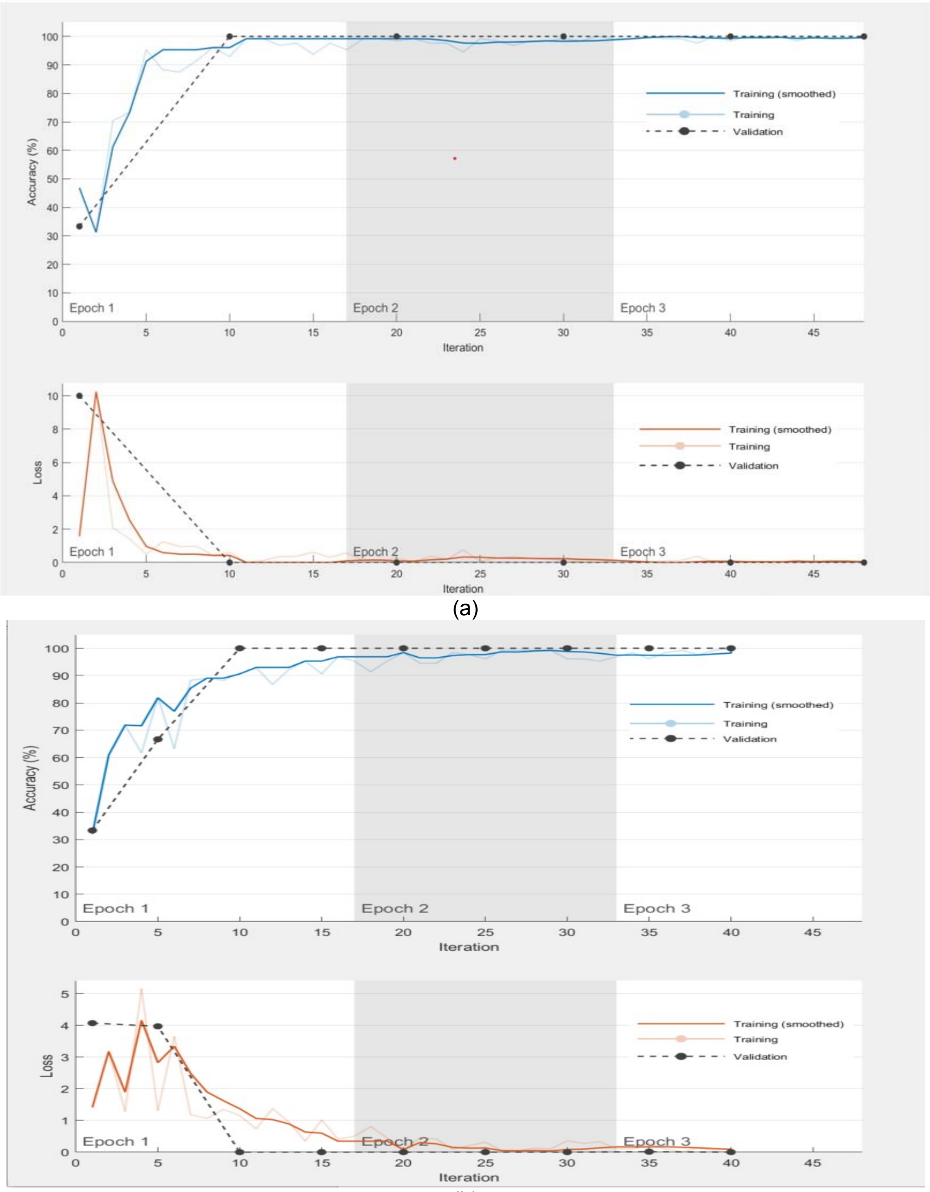
The convolutional and normalization layers are generally followed by a non-linear activation function such as a rectified linear unit (ReLU).

h. Max- Pooling layers

Convolutional layers (with activation functions) are followed by a sub-sampling operation which reduces the spatial size of the feature map and removes redundant spatial information. Subsampling increases the number of filters in deeper convolutional layers without increasing the amount of computation required per layer.

i. Output layer

The convolutional and sub-sampled layers are followed by one fully connected layers. As the name suggests, a fully connected layer is a layer in which neurons connect to all neurons in the previous layer. For classification issues, the last fully connected layer combines functionality to classify images. A softmax layer and then a classification layer must follow the fully connected final layer.



(a)

(b)

Fig.9. Learning process of CNN. (a): Input currents. (b); Output currents

Test and Validation

The CNN learning processes with input and output current signals are shown in Fig 9. Initially, 4212 samples of input and output current signals are transformed in images and used to form two CNNs. These images have been constructed from simulations of drive system-based MC for different operating point (load frequencies and torque). Then, each CNN formed was evaluated by tests with 52 samples from the test set. Very high accuracy and a satisfactory result have obtained.

To validate the proposed strategy, simulation tests of the open switch fault with frequencies and load torques different from those appearing in the database was carried out. Nine cases are presented. Each case corresponds to the mode of operation of the drive system different to the other. The results of the simulation are shown in the fig.10.

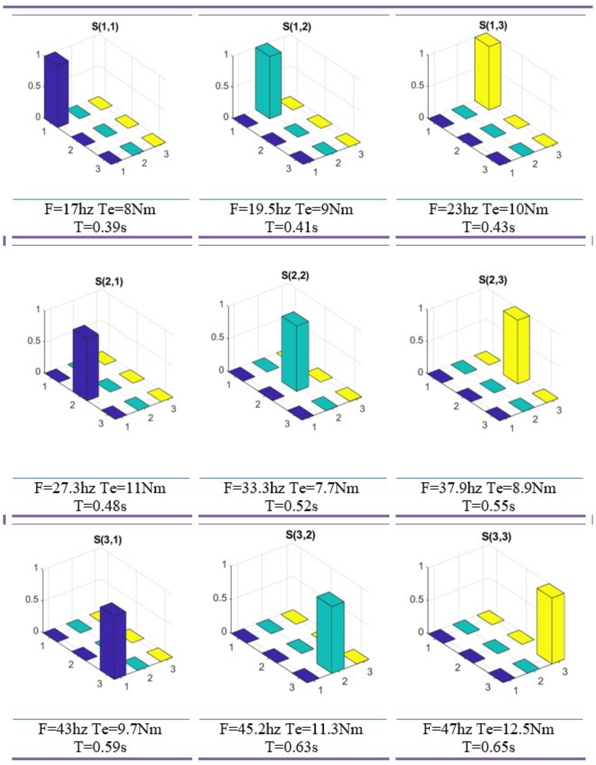


Fig .10. Test results for nine switch faults with different operation modes.

Conclusions

In this article, the CNN method is proposed to detect and locate an open circuit fault in a switch among the nine matrix frequency converter switches. This proposed strategy is based on the analysis of Concordia vectors of input and output currents of MC. The current forms obtained are used as digital images. An image database associated with faulty switch identification has been formed by simulating of MC-based drive system in different operation modes. Afterwards, a learning process using CNN is carried out.

The performance of the proposed decision system is tested and validated using other operating modes (outside the trained database).

The results obtained prove the effectiveness of the proposed approach in terms of speed, precision and robustness:

- The speed of detection is linked to the sensitivity of the DC bus voltage sensor and the speed of location is linked to the time for storing and processing current signals, which is short in our case.

- The accuracy of the identification of the faulty switch is proven by the exact identity of the switch concerned given for all the tests carried out.

- The robustness of the proposed strategy is proven by giving a precise result whatever the load and the speed of the engine.

Appendix

Table 1. Parameters of the simulation setup

Parameters	Values
Source phase voltage (V_{rms})	400 V
Source voltage frequency (f_{in})	50 Hz
Input filter inductor (L_f)	8 mH
Input filter capacitor (C_f)	10μF
Input filter resistance (R_f)	0.01 Ω
Clamp circuit capacitor (C_c)	180 μF
Stator resistance R_s	1.405 Ω
Stator inductance L_{ls}	5.839 mH
Rotor resistance R_r	1.395 Ω
Rotor inductance L_{lr}	5.839 mH
Mutual inductance L_m	172.2 mH
pole pairs:	2

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