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TITLE

Neural Fault Diagnosis and Inverter Reconfiguration for a Neural Direct Torque Control of Induction Motor Drive

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Abbreviation and notification

ANN : Artificial Neural Network.

BNN : Biological Neural Network.

DTC : Direct Torque Control.

PWM : Pulse With Modulation.

AI: Artificial Intelligence.

FLC: Fuzzy Logic Control ,

ANFI: Adaptive Neuro - Fuzzy interference System.

AC : Alternative Current.

DC : Direct Current.

VSI: voltage-source inverter

ASM : asynchronous machine

S_a, S_b, S_c: inverter switches

ϵ_T:the hysteresis width of the electromagnetic torque comparator

ϵ_F:the hysteresis width of the flux comparator

F_s: stator flux

T_e:electromagnetic stator Torque

F_s*:reference stator flux

T_e*: reference electromagnetic stator torque

$\overline{V}_s$:The stator voltage vector

K_F:the flux amplitude of hysteresis flux comparator

K_T:the torque amplitude of hysteresis torque comparator

$\overline{\phi_s}$: The stator flux vector

$\overline{I_s}$:The stator currant vector

p: number of pole pair of induction motor

($\phi_{s\alpha}$,$\phi_{s\beta}$):the estimated flux magnitudes

(I_a,I_b ,I_c):currant in three dimension vector

($I_{s\alpha}$,$I_{s\beta}$):currant in two dimension vector

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الإهداء

إلى من لا يمكن للكلمات أن توفي حقهما

إلى من لا يمكن للأرقام أن تحصي فضائلهما

إلى والدي العزيزين أدامهما الله لي

إلى زوجتي و أخواتي

إلى الأصدقاء:

حسين وعلي

إلى اسماعيل بوعنان عائلته

إلى كل من عائلة تميسة و سلامي

إلى كل طلبة ماستر 2 تخصص الأنظمة المضمنة دفعة 2018

أهدي هذا العمل

GENERAL INTRODUCTION

Induction motors are the most widely used motors in the industry. These motors find applications in servo drives, heating, ventilation and air conditioning systems, motor driven pumps, fans, washing machines and other domestic appliances. The induction motors offer numerous distinct advantages over other motors. They are rugged, reliable, easy to maintain, cheap, highly efficient [1][2].

Without the use of power electronic converters and other sophisticated equipment, induction motors can operate in constant speed mode only. Original drive systems mostly depend on the use of DC motors. DC motors offer inherent decoupled flux and torque control with a simple control mechanism and fast torque response. The use of DC motors is limited mainly due to high maintenance requirements, and high voltages. DC drives are being replaced by AC drives due to the advent of advanced control techniques such as direct torque control offering precise position control and an extremely fast torque response [1].

Despite the fact that many Artificial intelligence (AI) techniques for control of induction motors have been developed, such as artificial neural networks (ANN), fuzzy logic control (FLC), and the adaptive neuro - fuzzy interference system (ANFIS). Human comportment and thinking (decision making, pattern recognition, associative memory etc.) form the basis of intelligent control techniques. By adopting techniques based on artificial-intelligence, the performance of motor control systems can be further improved [1][2] [3].

Neural networks are a class of statistical learning algorithms drawing inspiration from the functioning of the human nervous system. ANNs can be thought of as a system of interconnected neurons which compute values from inputs, and are capable of solving a wide range of problems. Similar to how a human brain remembers and learns, an ANN is trained to learn by associating patterns and mapping input/output data. The use of statistical and signal processing methods for use in software implementations of ANNs is increasing [1][2].

For variation speed of AC drives, there are several types of faults can possibly happen such as controller faults, motor faults, current sensor faults, switching device faults, and

DC bus faults. Switching devices are the weakest components. As a result, these components in a power conversion system are prone to be destroyed by faults.

For the voltage source inverter several faults are possible. In this work, two cases will be studied:

- Occurrence of one fault at a time. One class is dedicated to the healthy domain and the last six are to each faulty inverter switch.
- Occurrence of two faults simultaneously. One is dedicated to the healthy domain, fifteen are to each two faulty inverter switches, and the last six are to each faulty inverter switch.

The aim of this work is to make a simple feature extraction method to study the feasibility of fault detection, isolations, and reconfiguration using neural networks. And result Our work is divided in two chapters:

- In the first chapter, we describe the artificial neural networks (ANN), the basic direct torque control (DTC), and an artificial neural networks control of a system of asynchronous motor drive using a neural direct torque control. We end, by giving a simulation results in the case of one and two faults in inverter switch in classic and neural DTC mode.
- The second chapter will be dedicated to a theoretical study of switching defects of (Pulse with Modulation) PWM inverter in both cases (one and two fault occurrence). Also, we will make a feature extraction method to determine the signature of each defect based on the surface algebraic calculation of the three stator phase currents. A defect classifier based on artificial neural networks will be set to allow detection and localization of one or multiple faults in the PWM inverter. After detection and localization of faulty position, the diagnostic results will be generated to allow the replacement of the defective arm by a healthy auxiliary arm as a reconfiguration process for the PWM inverter.

Finally, we will terminate by a general conclusion where we give perspectives to this work.

1. CHAPTER ONE

1.1 INTRODUCTION

The asynchronous machine is currently the most used machine in industrial field and gradually replacing the DC machine. However, the asynchronous machine is a multivariate system. It is characterized by a nonlinear model, which makes the control very complicated. The Direct Torque Control (DTC) strategy is the most developed drive control technique of asynchronous machines. It is characterized by a fast dynamic response, simple implementation and robustness essentially to the rotor parameter variation. However, the direct torque control has the main disadvantages such as electromagnetic torque and stator flux ripples. Therefore, many methods are used to overcome these disadvantages for example replacing the hysteresis torque and flux controllers with neural block. The artificial neural networks are capable to explore multivariate correlations between the outputs and inputs variables without knowing the mathematical model of the system.

1.2 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a mathematical model that simulates the structure and functionalities of biological neural networks. A simple mathematical model has three sets of rules: multiplication, summation, and activation. At the entrance of artificial neuron are the inputs, each input has its own relative weight. Some inputs are made more important than others to have a greater effect; Weights are adaptive coefficients that determine the intensity of the input signal. In the middle section of artificial neuron is sum function that sums all weighted inputs and bias. At the exit of artificial neuron the sum of weighted, inputs and bias is passing through activation function that is also called transfer function (Fig. 1.1)[4].

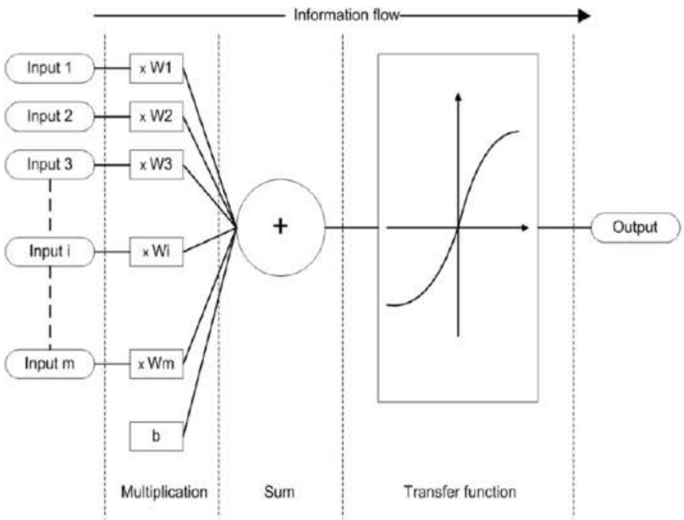

Fig. 1.1: Artificial neuron design[3].

For the above general model of artificial neural network, the output can be calculated As follows[3]:

$$y_(k) = F\left(\sum_{k=0}^{m} w_i(k)x_i(k) + b\right) \tag{1.1}$$

Where:

- $x_i(k)$ is input or pattern value in discrete time k
- $w_i(k)$ is weight value in discrete time k
- b is bias
- F is a transfer function

- y(k) is output value in discrete time k

The bias is much like a weight, except that it has a constant input of 1.However, if you do not want to have a bias in a particular neuron, it can be omitted. [5]

1.3 A Biological Neuron (BNN)

The connections between neurons are much more complex than those implemented in neural computing architectures. A typical neuron consists of the following four parts (Figure 1.2)[6][7]:

- ***Dendrites***: is responsible for receiving the information from other neurons.
- ***Soma***: It is the cell body of the neuron and is responsible for processing of information, they have received from dendrites.
- ***Axon***: It is just like a cable through which neurons send the information.
- ***Synapses***: It is the connection between the axon and other neuron dendrites.

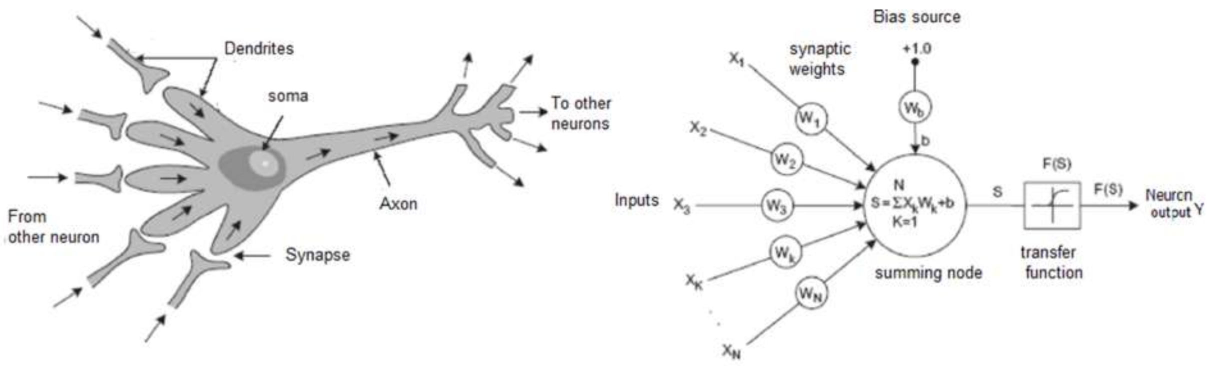

Fig. 1.2: Biological and artificial neuron design[7].

1.4 Network Topology

A network topology is the arrangement of a network along with its nodes and connecting lines. According to the topology, ANN can be classified as the following kinds[6][5]:

1.4.1 Feedforward Network

It is a non-recurrent network the signal can only flow in one direction, from input to output. It may be divided into the following two types:

- ***Single layer feedforward network:*** the input layer is fully connected to the output layer.

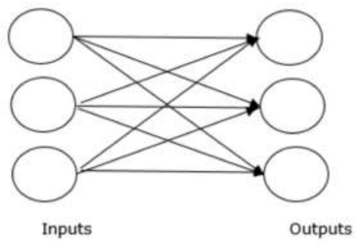

Fig. 1.3: Single layer feed forward network

- ***Multilayer feedforward network*:** this network has one or more layers between the input and the output layer, it is called hidden layers.

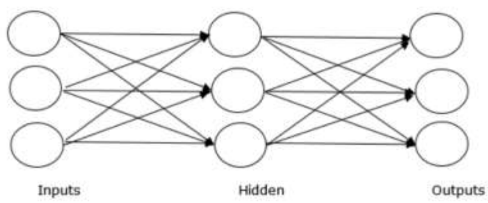

Fig. 1.4: Multilayer layer feed forward network

1.4.2 Feedback Network

A feedback network has feedback paths, which means the signal can flow in both directions using loops.

- ***Recurrent networks:***

They are feedback networks with closed loops. Having one or more hidden layers with at least one feedback loop is known as recurrent network as shown in Figure 1.5.

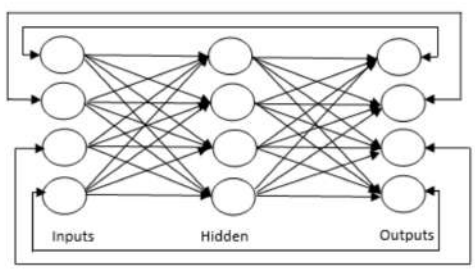

Fig. 1.5: Recurrent network

1.5 Learning or Training Artificial Neural Networks

When a network has been structured for a particular application, it is ready for training. At the beginning, the initial weights are chosen by chance and then the training or learning begins. There are three major learning models; supervised learning, unsupervised learning and reinforcement learning[4][6].

1.5.1 Supervised Learning

This type of learning is done under the supervision of a teacher. This learning process is dependent. During the training of ANN under supervised learning, the input vector is presented to the network, which will give an output vector. This output vector is compared with the desired output vector. An error signal is generated, if there is a difference between the actual output and the desired output vector. The weights are adjusted until the actual output is matched with the desired output[4][6]. .

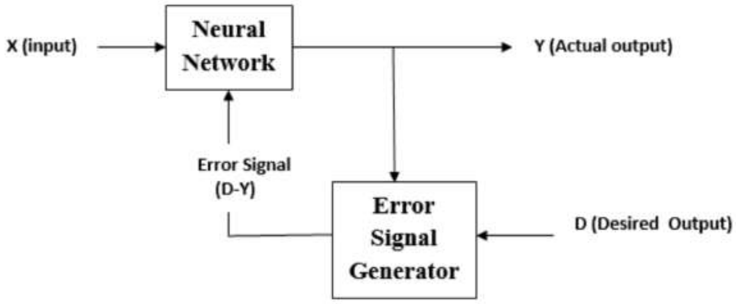

Fig. 1.6: Supervised learning block diagram

1.5.2 Unsupervised Learning

This type of learning is done without the supervision of a teacher, the network is provide with inputs but not with desired outputs. This is often referred to as self-organization or adaption. During the training of ANN under unsupervised learning, the input vectors of similar type are combined to form clusters. When a new input pattern is applied, then the neural network gives an output response indicating the class to which the input pattern belongs. There is no feedback from the environment to adjust their weights or what should be the desired output and if it is correct or incorrect. Hence, in this type of learning, the network itself must discover the patterns and features from the input data, and the relation for the input data over the output[6]. .

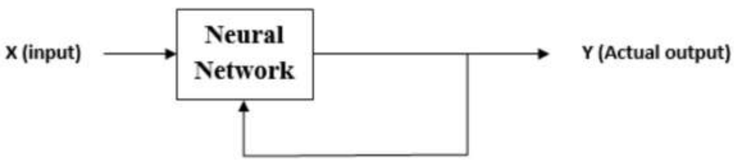

Fig. 1.7: Unsupervised learning block diagram

1.5.3 Reinforcement Learning

This type of learning is used to reinforce or strengthen the network over some critic information. This learning process is similar to supervised learning; however we might have very less information. During the training of network under reinforcement learning, the network receives some feedback from the environment. This makes it somewhat similar to supervised learning. However, the feedback obtained here is evaluative not instructive, which means there is no teacher as in supervised learning. After receiving the feedback, the network performs adjustments of the weights to get better critic information in future[4][6].

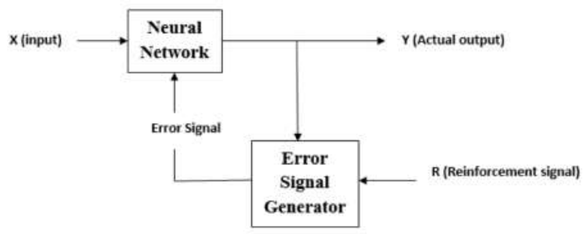

Fig. 1.8: Reinforcement learning block diagram

1.6 Transfer Functions

A particular transfer function is chosen to satisfy some specification of the problem that the neuron is trying to solve. Three of the most commonly used functions are in figure below[5].

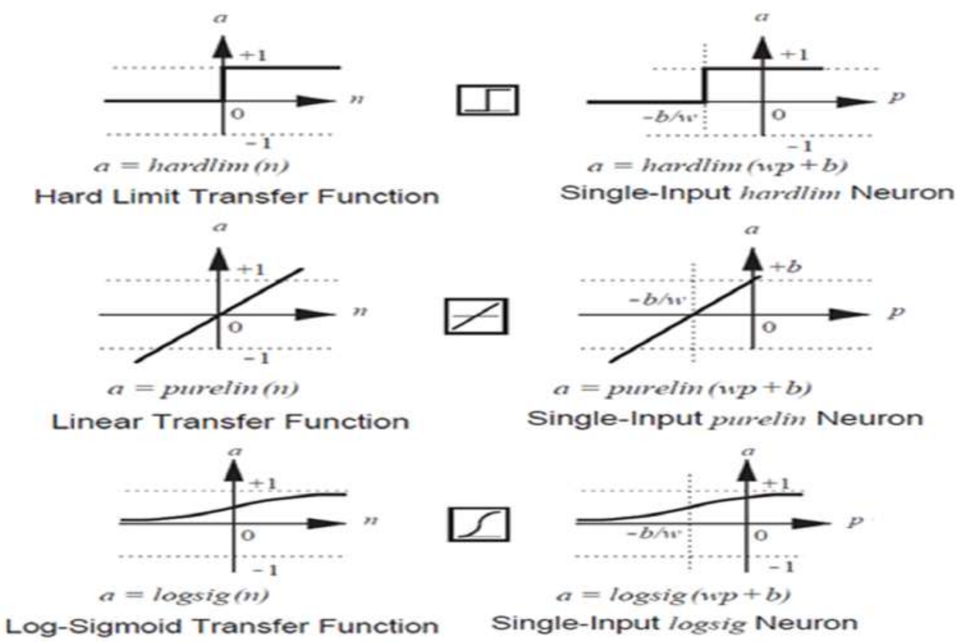

Fig. 1.9: Transfer function[5]

1.7 Network Architectures

1.7.1 Single-Input Neuron

A single-input neuron is shown in Figure 1.10.a

1.7.2 Multiple-Input Neuron

A neuron with multiple Inputs is shown in Figure 1.10.b

1.7.3 A Layer of Neurons

A single-layer network of S neurons is shown in Figure 1.10.c. Each of the P inputs is connected to each of the neurons. .

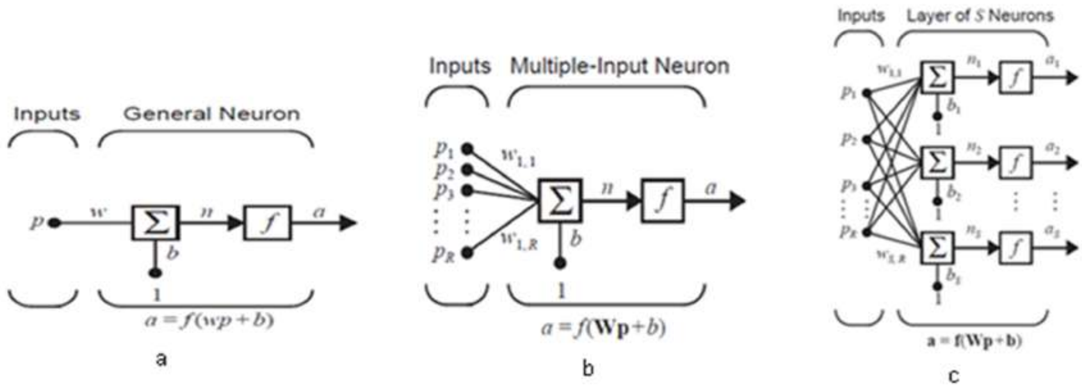

Fig. 1.10: a. Single-input neuron, b. Multiple-input neuron, c. Layer S neurons[5]

1.7.4 Multiple Layers of Neurons

A network with several layers is shown in Figure 1.11. .

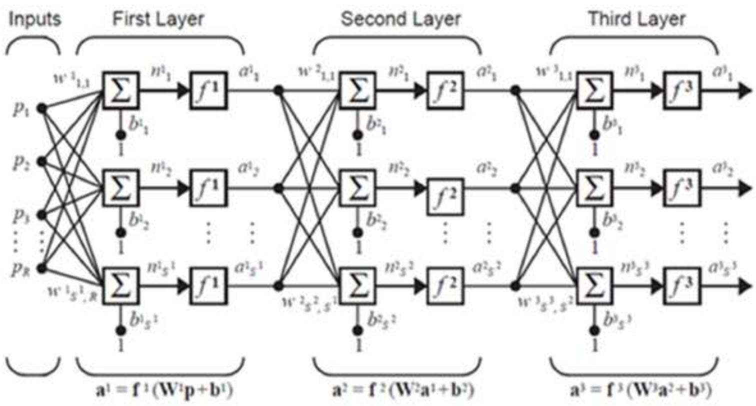

Fig. 1.11: Three-layer neurons[5]

1.8 Multiple Layer Perceptron (MLP) model

The most common NN model is the MLP Neural Network. It is a kind of supervised network which requires a desired output in order to learn; with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors [8]. The purpose of this network is to create a model that appropriately maps the input to the output using historical data so that the model can be used to produce the output when the desired output is unknown, it requires three or more layers, one or more hidden layer, and output layer as shown in Figure 1.12. The output signal should indicate the appropriate data of the input data. The weighted connections define the behavior of the network and are adjusted during training through a supervised training. In a feed forward network each input pattern vector is presented to input layer. For successive activation, the input to each term is the summation by their respective weight.

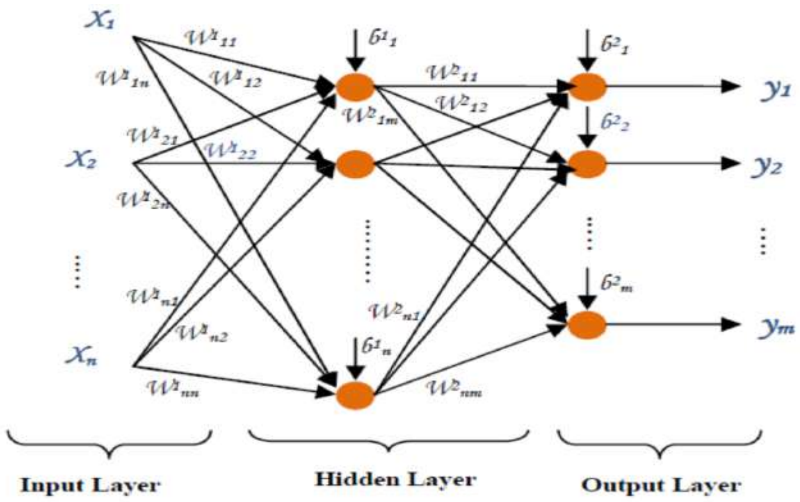

Fig. 1.12: Structure of perceptron network. [9]

1.9 Developing of Neural Network

The structure of the multilayer network is shown in Figure 1.13. Neural network has been employed to emulate space vector. The three inputs of the network are the flux error, torque error and the sector location. The three output signals are S_a, S_b, S_c. The neurons are represented by the circles and the interconnection between them is shown by links. Each link has a weight associated with it. The circle contains the summing node of the neuron with the activation function. Three layers of neurons exist in the network: input layer, hidden layer, and output layer. The network described is a 3-10-3 network with the number indicating the number of neurons in a layer. .

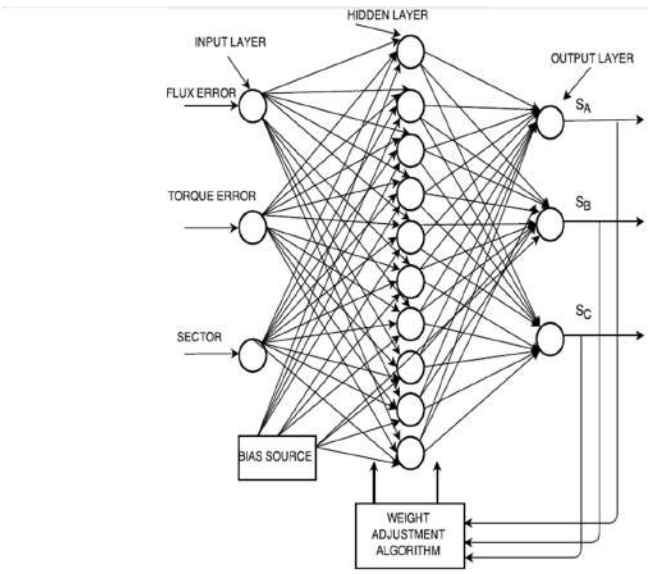

Fig. 1.13: The structure of the multilayer network[1]

1.9.1 Training Data

Network will be trained with normal and abnormal data, thus the size of the input matrix is three input data rows with 150000 columns for each pattern input (ϵ_T, ϵ_ϕ s). That gives 450000 for the training data set should also cover the operating region; thus, the test data sets are generated from simulation with various speed references. In our work 25% of input/output data are taken for validation and 25% for testing. We will make the training under the following conditions:

- The entries of the system are gathered in a matrix.
- The outputs of the system are gathered in a matrix.

The number of the off-line training epochs is 36 to reach the 0.03 imposed error (Figure 1.14). .

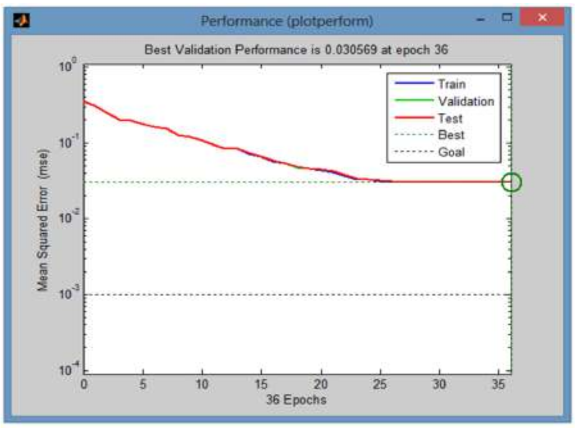

Fig. 1.14: Training, Validation, and Test Errors of the Developed Neuron Networks

1.10 Basic Principle DTC

Direct Torque Control is shown in figure 1.15. There are two different loops corresponding to the magnitudes of the stator flux and torque. The reference values for the stator flux ϕ_s* and the torque T_e* are compared with the actual values, and the resulting error values are fed into the two level and three level hysteresis block respectively. The outputs of the stator flux error and torque error hysteresis blocks, together with the position of the stator flux are used as inputs of the switching table. The inverter is switched on using these errors and position of stator flux over six region control in such a way that the inverter output voltage vector minimizes the flux and torque errors and defines the direction of the flux rotation. The outputs of these controllers are S_a, S_b and S_c where their values (0 or 1) are used to determine the inverter output voltage[9].

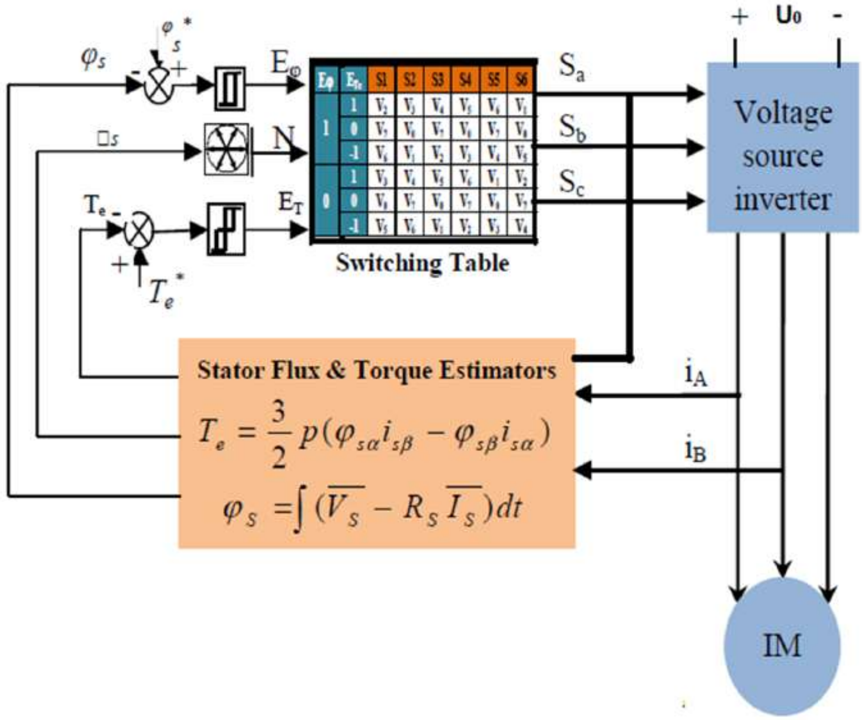

Fig. 1.15: Block diagram of basic DTC[9]

1.10.1 Voltage Source of Inverter

The figure 1.16 shows a voltage source inverter which is feeding a three phase asynchronous motor. The inverter converts the DC to AC through power electronic. The circuit is operated by switching S_a, S_b, S_c. The inverter uses two pairs of complementary controlled switches in each inverter phase or leg, as shown in figure 1.16. Considering that the two switches in each inverter phase or leg operate in a balancing pair in order to avoid short circuiting the DC source[10][11].

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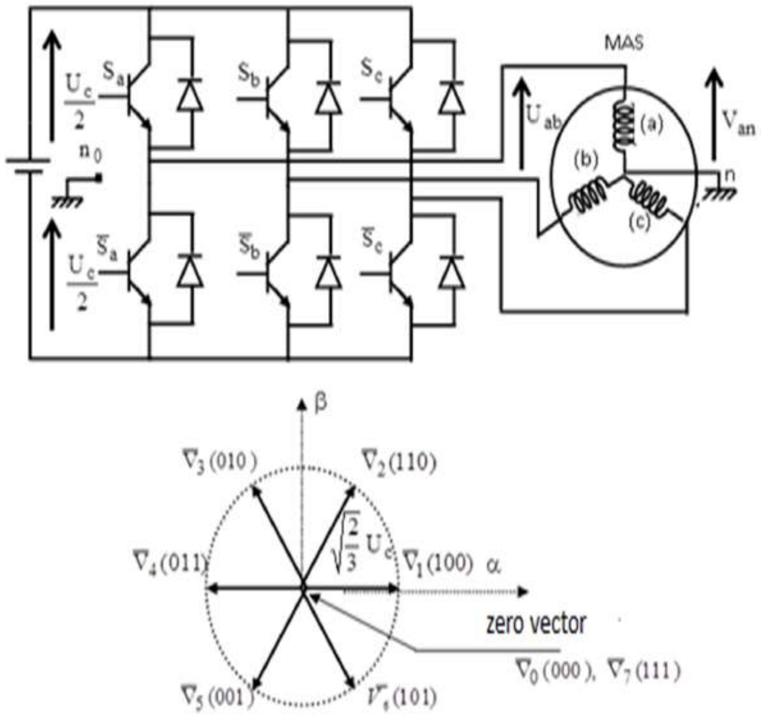

Fig. 1.16: Schematic of inverter voltage source[10]

The inverter is controlled from logic Boolean the state of the switches are $S_i = 1$ (i=a, b, c): $S_i = 1$: If the top switch is closed and the bottom open

$S_i = 0$: If the top switch is open and the bottom switch is closed

The vector V_s of the stator voltage can be written as[10]:

$$\overline{V}_s = \sqrt{\frac{2}{3}} U_0 \left[S_a + S_b \exp\left(i\frac{2\pi}{3} \right) + S_c \exp\left(i\frac{4\pi}{3} \right) \right] \quad (1.2)$$

The different combinations of the three values (S_a, S_b and S_c) are used to generate eight positions including two V_s vector corresponding to the zero vector. Where (S_a, S_b, S_c) represents the logical state of the 3 switches. So we seek to control the flux and torque via the selection voltage vector which will be by a switch configuration. As we have 3 switches, so there are 8 possibilities for vector V_s. Two vectors (V_o and V_7) is the zero vector $(S_a, S_b, S_c) = (0, 0, 0)$ and $(S_a, S_b, S_c) = (1, 1, 1)$.

1.10.2 Selection of stator voltage

The choice of vector V_s depends on the desired variation of the flux module, also the desired changes to its rotation speed and to the torque. The stator flux is controllable if a proper selection of the voltage vector is made. Figure 1.17 shows that the stator flux plane is divided into six sectors where each one has a set of voltages vectors[13]. .

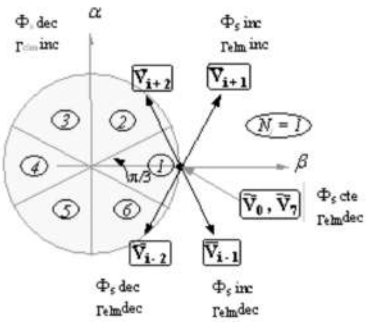

Fig. 1.17: Sectors detection[10]

When flux is in zone i, vector V_{i+1} or V_{i-1} is selected to increase the level of the flux, and V_{i+2} or V_{i-2} is selected to decrease it. At the same time, vector V_{i+1} or V_{i+2} is selected to increase the level of torque, and V_{i-1} or V_{i-2} is selected to decrease it. If V_0 or V_7 is selected, the rotation of flux is stopped and the torque decreases whereas the amplitude of flux remains unchanged[10]. .

Vector V_k	V_{i+1}	V_{i+2}	V_{i-1}	V_{i-2}
F_s	$\nearrow$	$\searrow$	$\nearrow$	$\searrow$
T_e	$\nearrow$	$\nearrow$	$\searrow$	$\searrow$

Tab. 1.1: Generalized tables for voltage vector selection

1.10.3 Switching source table

It's Depending on the determinate the phase of the estimated flux angle and the evolution of the magnitude of the flux as well as the evolution of the estimated torque. the voltage $V_s$can choose to be applied to respect the references flux, and torque . There are thus parameters who give the right selection of choosing the adequate voltage vector V_s As shown in table 1.2. and table 1.3.

$S_aS_bS_c$	000	100	110	010	011	001	101	111
V_i	V_0	V_1	V_2	V_3	V_4	V_5	V_6	V_7

Tab. 1.2: Values of the control signals [12][13][14]

1.10.4 Flux and Torque Estimator

The estimator calculates the stator flux and the electromagnetic torque. The inputs of the estimator are stator voltage and current space vectors. They are referred to a stationary reference frame; the voltage of the stator is given by[1][10]:

$$\overline{\phi_s} = \int_0^t (\overline{V_s} - R_s\overline{I_s})\, dt \tag{1.3}$$

The stator flux vector is calculated from two components of two-phase axes (α,β) is given[1][10]:

$$\overline{\phi_s} = \phi_{s\alpha} + i\phi_{s\beta} \tag{1.4}$$

$$\begin{cases} \phi_{s\alpha} = \int_0^t (V_{s\alpha} - R_s I_{s\alpha})\, dt \\ \phi_{s\beta} = \int_0^t (V_{s\beta} - R_s I_{s\beta})\, dt \end{cases} \tag{1.5}$$

The module of the stator flux is given by equation 1.6[1][10]:

$$\phi_s = \sqrt{\phi_{s\alpha}^2 + \phi_{s\beta}^2} \tag{1.6}$$

The angle ϕ_s is given by equation 1.7[1][10].

$$\theta_s = \arctan \frac{\phi_{s\beta}}{\phi_{s\alpha}} \tag{1.7}$$

We obtained the voltage $V_{s\alpha} V_{s\beta}$ by using the switching status (S_a, S_b and S_c) produced by the switching table, the stator voltages in the reference frame are determined as[10]:

$$\begin{cases} V_{s\alpha} = \sqrt{\frac{2}{3}} U_0 (S_a - \frac{1}{2}(S_b - S_c)) \\ V_{s\beta} = \frac{1}{\sqrt{2}} U_0 (S_b - S_c) \end{cases} \tag{1.8}$$

The electromagnetic torque can be estimated from the estimated flux magnitudes $\phi_{s\alpha}$,$\phi_{s\beta}$ and the calculated magnitudes of the current $I_{s\alpha}$,$I_{s\beta}$ It is evaluated by equation 1.9[8farid]

$$T_e = \frac{3}{2} p (I_{s\beta}\phi_{s\alpha} - I_{s\alpha}\phi_{s\beta}) \tag{1.9}$$

p: number of pole pair of induction motor

The measured currents (I_a,I_b ,I_c) can be transformed into two dimension vector ($I_{s\alpha}$,$I_{s\beta}$) by[10]:

$$\begin{cases} I_{s\alpha} = \frac{2}{3} I_{sa} - \frac{1}{3} I_{sb} - \frac{1}{3} I_{sb} \\ I_{s\beta} = \frac{1}{\sqrt{3}} \left(\frac{1}{3} I_{sb} - \frac{1}{3} I_{sb} \right) \end{cases} \tag{1.10}$$

.

1.10.5 The flux comparator

The purpose of this comparator is to keep the amplitude of the stator flux in a band .The output of the comparator must indicate the direction of evolution of the module of the flow. The control algorithm of this technique can be summarized as follows[10][12]:

$$\begin{cases} if \Delta F_s > \epsilon_\phi & \text{then } K_F = 1 \\ if - \epsilon_\phi \leq \Delta F_s \leq \epsilon_F and \dfrac{dF_s}{dt} > 0 & \text{then } K_F = -1 \\ \\ if - \epsilon_F \leq \Delta F_s \leq \epsilon_F and \dfrac{dF_s}{dt} < 0 & \text{then } K_F = 1 \\ if \Delta F_s < -\epsilon_F & \text{then } K_F = -1 \end{cases} \tag{1.11}$$

$K_F = -1$ signifies that the flow must be reduced

$K_F = 1$ Means to increase the flow.

$\Delta F_s = |F_s - F_s^*|$,With: (F_s^*) reference is a reference flux ,and ϵ_F is the hysteresis with of the comparator

1.10.6 Electromagnetic Torque Comparator

The torque comparator maintains the torque within the following limits:

$\Delta T = |T - T^*|$,With: (T^*) reference is a reference torque ,and ϵ_T is the hysteresis with of the comparator.

The comparator allows motor control in two directions of rotation, either for positive or negative torque. It indicates directly if the torque amplitude must be increased in absolute value ($K_t = 1$), for a positive order and ($K_t = -1$), for a negative order, or maintained ($K_t = 0$).

The control algorithm of this technique can be summarized as follows [12][13][14]:

$$\begin{cases} if \Delta T > \epsilon_T & \text{then } K_T = 1 \\ if 0 \leq \Delta T \leq \epsilon_t and \dfrac{dT}{dt} > 0 & \text{then } K_T = 0 \\ \\ if 0 \leq \Delta T \leq \epsilon_t and \dfrac{dT}{dt} < 0 & \text{then } K_T = 1 \\ \\ if - \epsilon_T \leq \Delta T \leq 0 and \dfrac{dT}{dt} > 0 & \text{then } K_T = -1 \\ \\ if - \epsilon_T \leq \Delta T \leq 0 and \dfrac{dT}{dt} < 0 & \text{then } K_T = 0 \\ if \Delta T < -\epsilon_T & \text{then } K_T = -1 \end{cases} \tag{1.12}$$

- $K_t = 1$ means that the torque is below the lower limit of the band and must be increased.
- $K_t = -1$ means that the torque is greater than the upper limit of the band and must be reduced
- $K_t = 0$ means that the torque is inside the band and must be maintained there

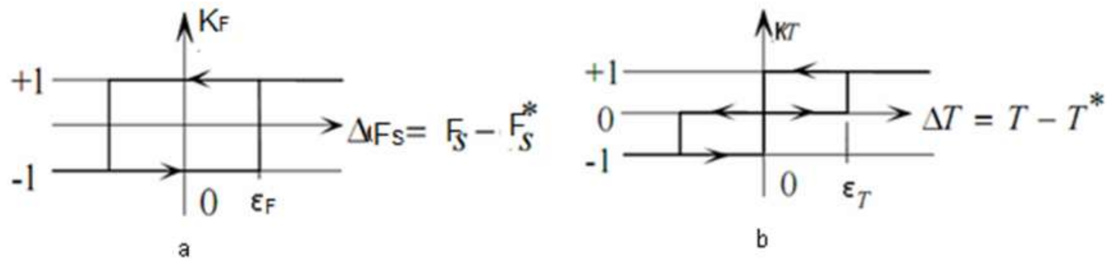

Fig. 1.18: a.Two levels hysteresis flux corrector, b.Three levels hysteresis torque corrector [12]

N_s		1	2	3	4	5	6
$K_\phi = 1$	$K_T = 1$	V_2	V_3	V_4	V_5	V_6	V_1
$K_\phi = 1$	$K_T = 0$	V_7	V_0	V_7	V_0	V_7	V_0
$K_\phi = 1$	$K_T = -1$	V_6	V_1	V_2	V_3	V_4	V_5
$K_\phi = -1$	$K_T = 1$	V_3	V_4	V_5	V_6	V_1	V_2
$K_\phi = -1$	$K_T = 0$	V_0	V_7	V_0	V_7	V_0	V_7
$K_\phi = -1$	$K_T = -1$	V_5	V_6	V_1	V_2	V_3	V_4

Tab. 1.3: Switching table for basic DTC[12][13][14]

1.11 Neural Structure Of DTC

In this approach, (Figure 1.19) we replaced the two hysteresis controllers and the switching table (basic DTC) by a neural network controller with torque errorϵ_T flux error ϵ_ϕ and number of sector S as inputs. The outputs of neural network controller are S_a, S_b and S_c where their values (0 or 1) are used to determine the inverter output voltage. .

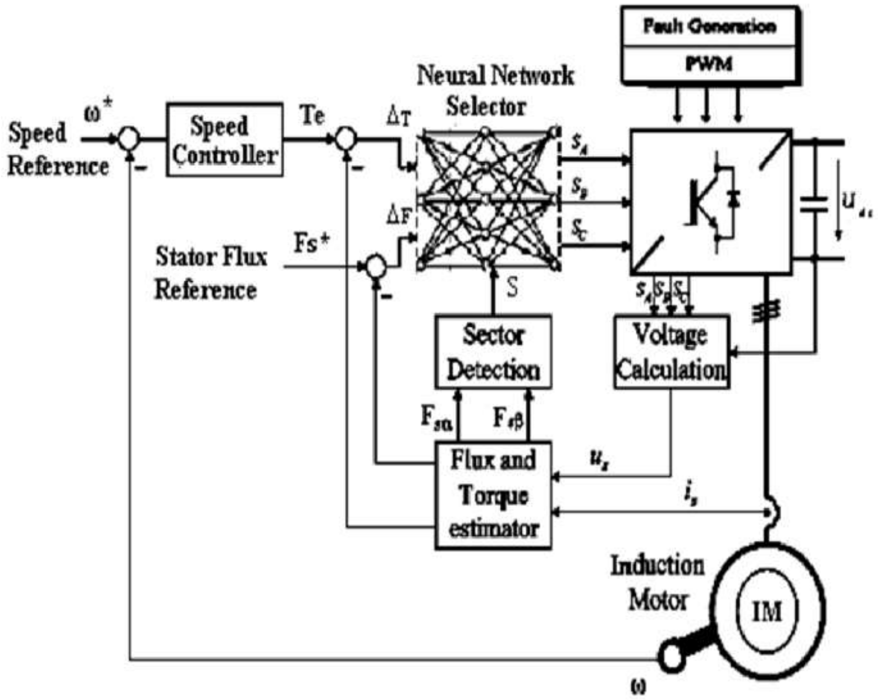

Fig. 1.19: Induction motor direct torque control block diagram (Neural network DTC)[13].

1.11.1 Voltage Source Inverter Model

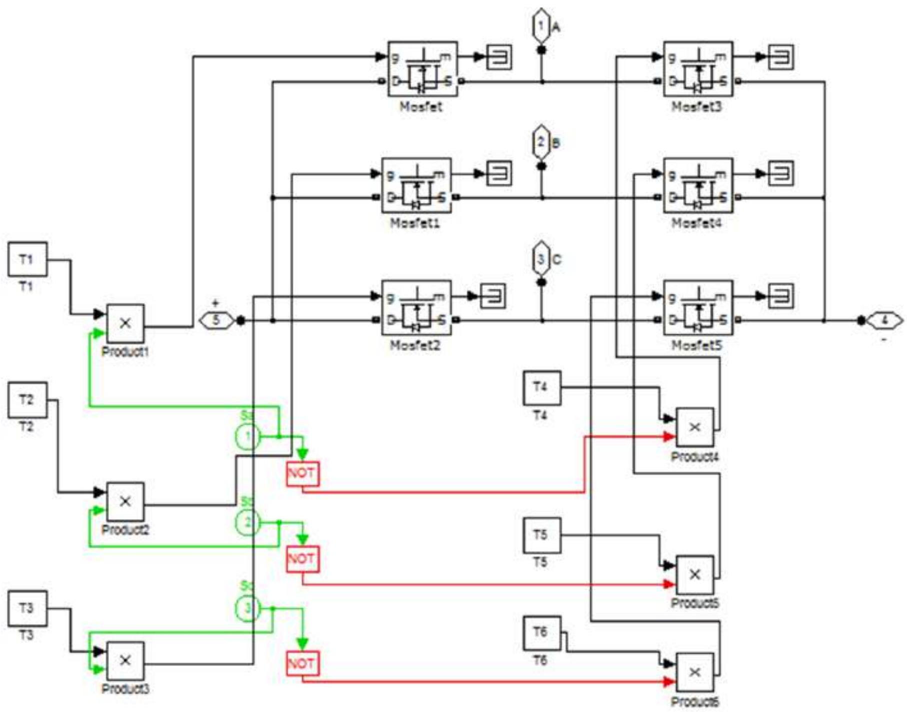

Fig. 1.20: Voltage source inverter model

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1.11.2 PI Speed Control Model

PI control has been widely used as a cascaded form of control in variable-speed motor drives. Typical anti-windup methods are experimentally applied to the speed control of a vector-controlled induction motor driven by a pulse width modulated (PWM) voltage-source inverter (VSI). In the speed control mode, a PID controller is used, the input of which is the error between the reference speed and the actual speed of the motor. In the scheme discussed in this study (Figure 1.21), a PID controller with anti-wind up gain is used. The anti-windup is in function when saturation occurred[15][16].

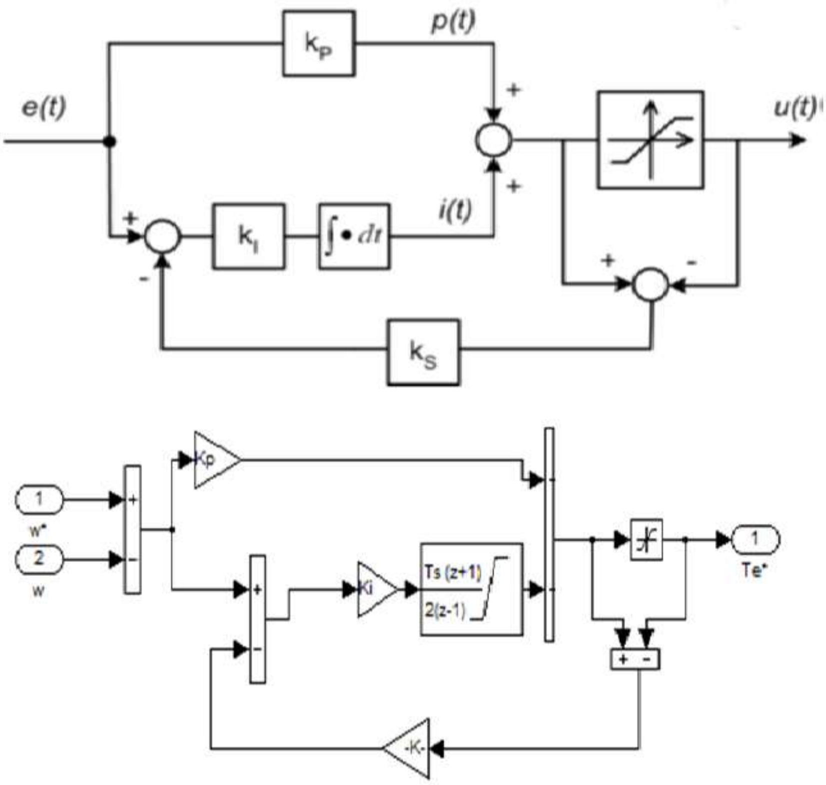

Fig. 1.21: PI speed control model[17][18]

$$
\begin{cases}
K_p = \dfrac{J}{\tau} = 5 \\[2ex]
K_i = \dfrac{f}{\tau} = 1 \\[2ex]
F_s = \dfrac{1}{k_i} = 1
\end{cases}
\tag{1.13}
$$

F(Hz)	P(kw)	P	$V(v)$	$R_s(\Omega)$	$R_r(\Omega)$	$L_s(H) = L_r(H)$	M(H)	$J(kgm^2)$
50	1.5	2	280	0.5	1	0.05	0.1	0.02

Tab. 1.4: Characteristics of the induction motor

1.12 Simulation and Discussion of Results

The simulation results of basic DTC are presented according to:

- Basic and neural DTC Simulation for a speed and flux variation.
- Basic and neural DTC Simulation for all cases in a single fault defect.
- Basic and neural DTC Simulation for all cases in a double faults defect.

1.12.1 Basic DTC Simulation for a Speed and Flux Variation

We will perform a reference speed to 90 rad/s, and a reference flow to 1 Wb.T.

After half a second (0.5s) of operation, the reference speed is varied into 30rad/s, and the reference flux at 0.5 Wb.T.

After(1s) we made a fault in switch one (T1).

The simulation results are illustrated on the Figure 1.22.

1.12.2 Basic DTC Simulation for all Cases in a Single Fault Defect

We will make all the switches in faulty from T1 to T6.

The results are presented in the alpha-beta stator currents which are illustrated in Figure 1.23.

It can be noted that the path drawn is a semicircle for all cases of defects.

1.12.3 Basic DTC Simulation for all Cases in a Double Faults Defect

Here, we will make two faulty switches in all possible situations with a fifteen (15) cases.

The results are presented in alpha-beta stator currents which are illustrated in Figure 1.24.

It can be noted that the path drawn is a portion shape of circle for all cases of defects.

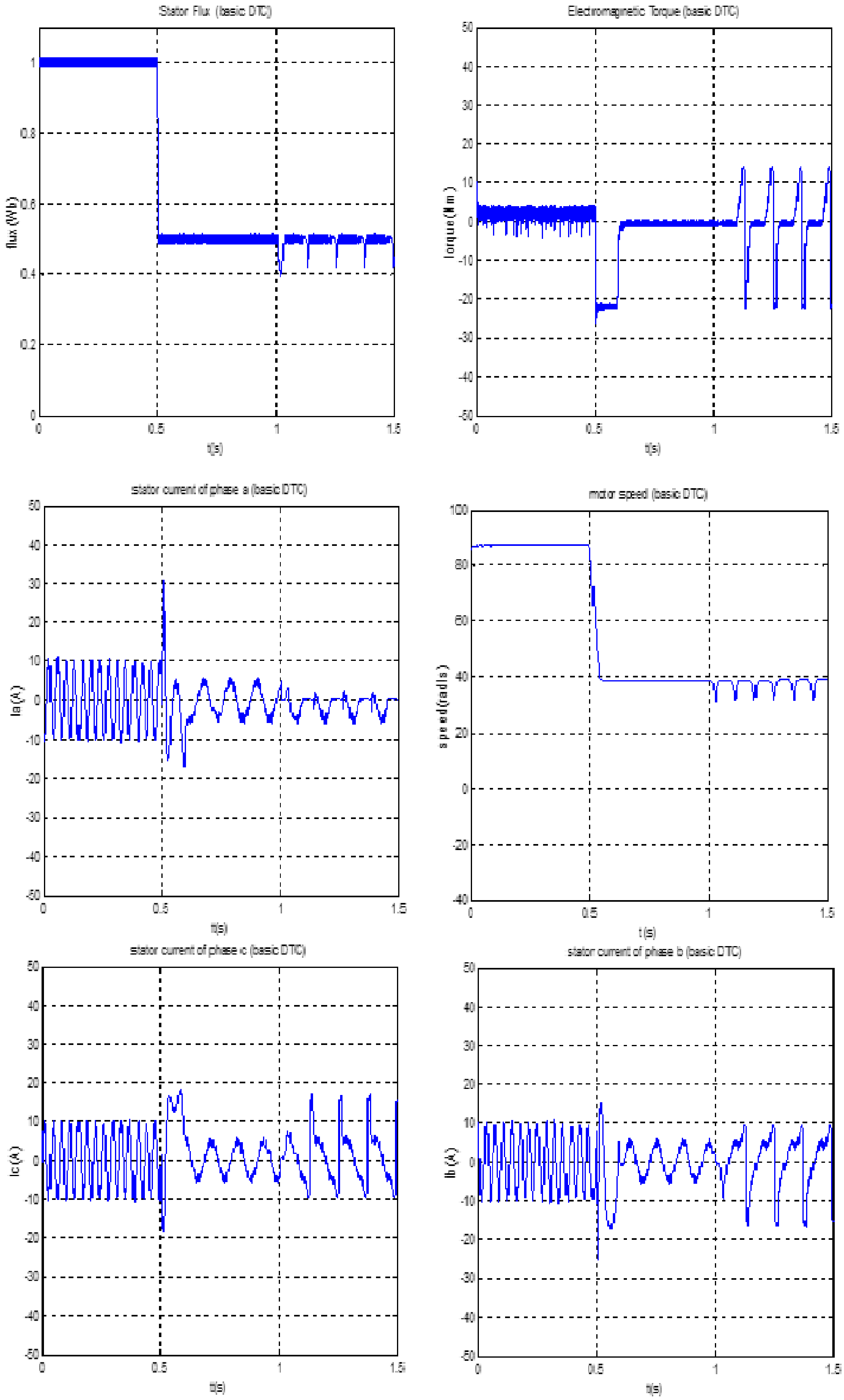

Fig. 1.22: Basic DTC simulation in permanent state for a speed and flux variation

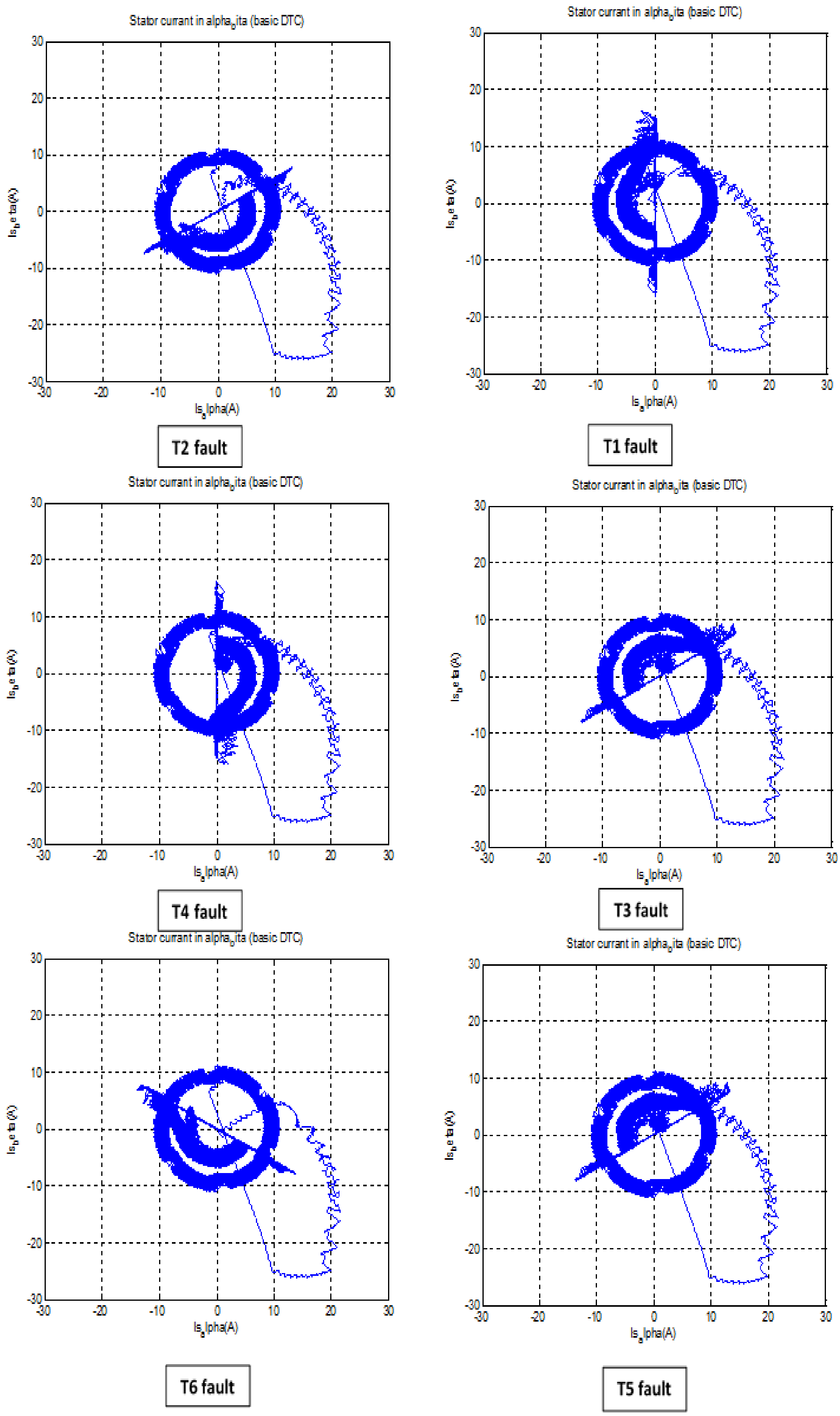

Fig. 1.23: Basic DTC simulation for all cases in a single fault defect

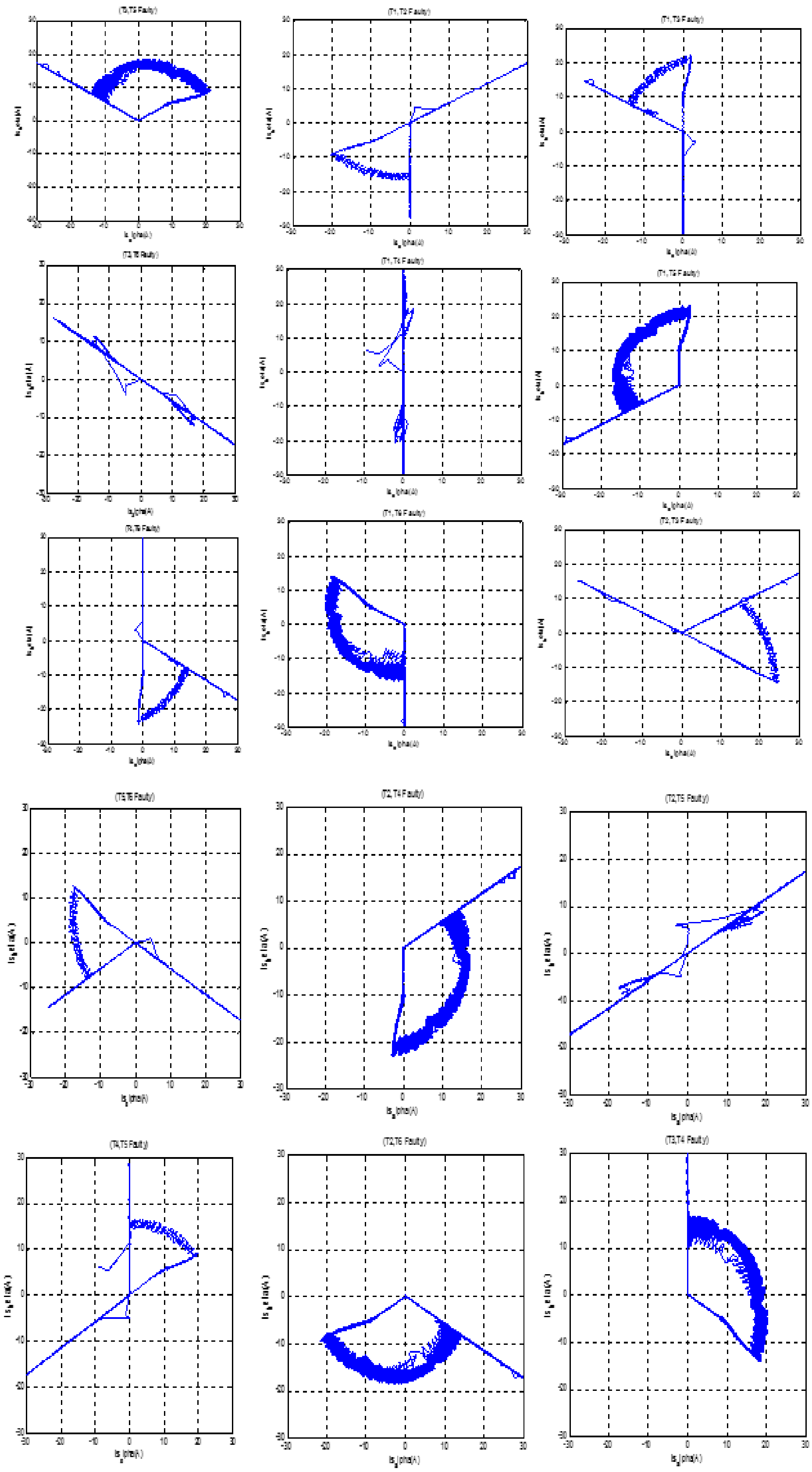

Fig. 1.24: Basic DTC simulation for all cases in a double faults defect

.

1.12.4 Neural DTC Simulation for a Speed and Flux Variation

We will perform a reference speed to 90rad/s, and a reference flux to 1Wb.T. After half a second (0.5s) of operation, the reference speed is varied into 40rad/s, and the reference flux at 0.5 Wb.T. After also half a second tow (0.5s) we made a fault in first switch (T1). The simulation results are illustrated on the Figure 1.25.

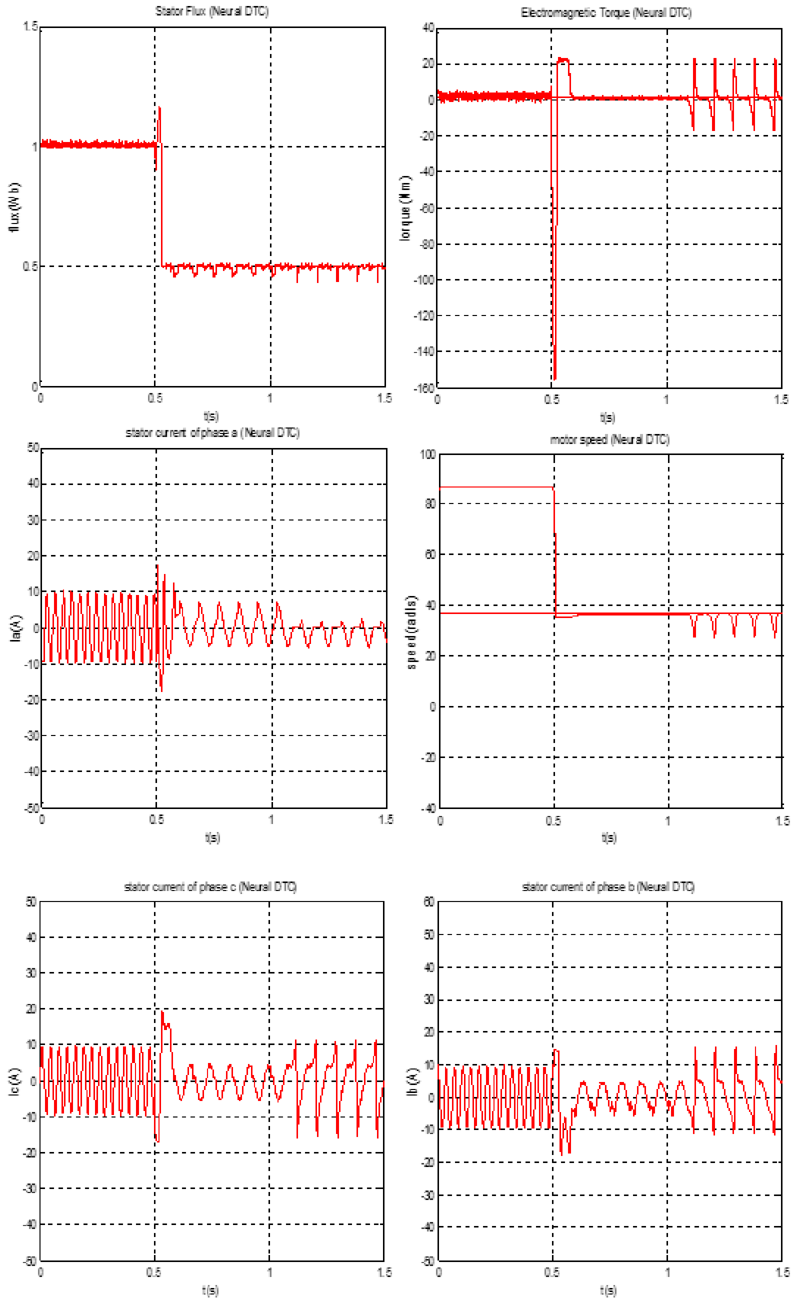

Fig. 1.25: Neural DTC simulation in permanent state for speed and flux variation

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1.12.5 Neural DTC Simulation for all Cases in a Single Fault Defect .

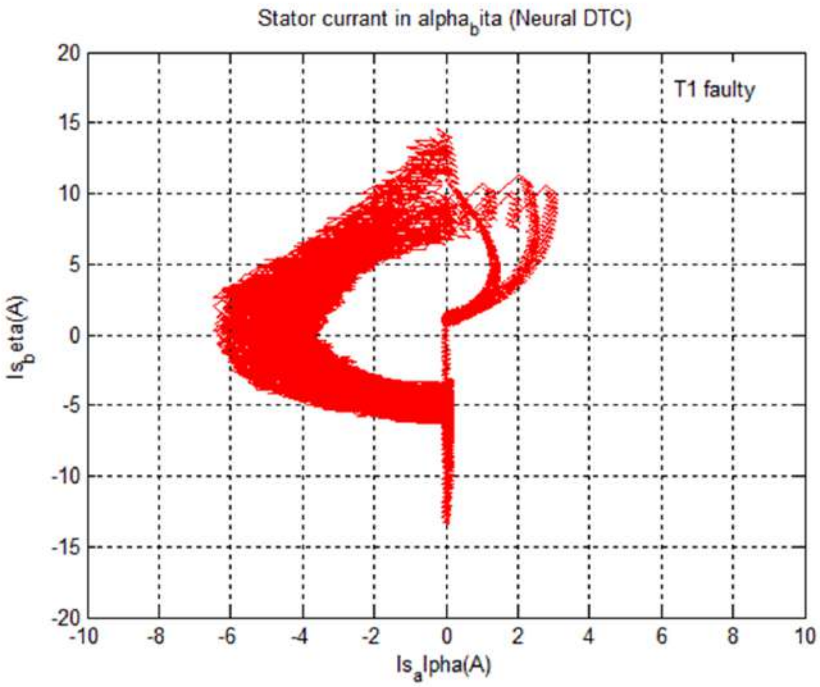

Fig. 1.26: Neural DTC simulation for a T1 switch defect

- **Note**

We can obtain the same results in neural network DTC as in basic DTC by replacing switching table, torque and flux controllers by a neural network block. Figure 1.26 illustrates an example of T1 faulty switch.

1.13 Conclusion

In this chapter, we presented a basic control system based on DTC applied to an induction motor fed by a PWM three phase voltage inverter.

Also, we presented an artificial neural network and we developed a neural networks method from a classic DTC in order to be able to improving performances of basic DTC.

2. CHAPTER TOW

2.1 INTRODUCTION

The asynchronous machine(ASM) is the most robust machine. This machine is widely used in most of electric systems in several industrial fields. However, the asynchronous machines are exposed to breakdowns due to different faults such as electrical or mechanical defects in the stator, or rotor, or both simultaneously which, leads to financial losses as well as wastage of time, which affects productivity in industries. Therefore, early detection of a fault is recommended to repair in the shortest delay and minimize these consequences. This pushed the majority of manufacturers to use in their production lines sophisticated systems of fault detection and isolation.

There are many research focused on early fault detection. In the last decades, several artificial intelligence techniques have been developed and applied in monitoring and diagnostic of systems, such as, Artificial Neural Networks and Fuzzy Logic [8].

In this work, a robust ANN-based approach is proposed to detect and isolate faults in case of asynchronous machines. A proposed model system is simulated using MATLAB/SIMULINK We will study the detection and the diagnosis of opening faults of the PWM inverter switch occurrence for one and two faults simultaneously. Different patterns of faults (single and two faulty switches) are simulated but the proposed diagnosis system; is done only for single faulty switch cases. A reconfiguration of the PWM inverter is done before a faulty case to allow the control system to continue operating when a fault occurs and a transistor switch is open.

2.2 Current patterns mode

The current pattern which indicates the location of the faulty switch can be distinguished into six-patterns. Figure 2.1. shows the shape of the current pattern in a healthy condition as a circle. If an open switch fault has occurred, the phase current where the fault occurred has only a positive or a negative value. A semicircle shape, therefore, Figure 2.2 and Figure 2.3 represents an open fault condition.

2.2.1 Current patterns in healthy mode

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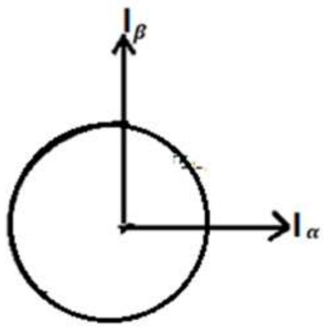

Fig. 2.1: Healthy mode

2.2.2 Current patterns in faulty modes

- **One Fault Occurrence at a Time**

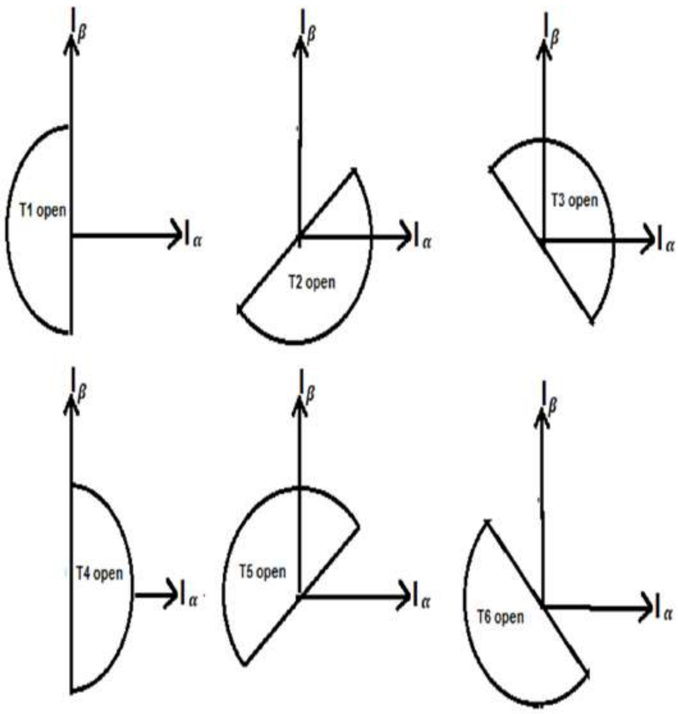

Fig. 2.2: Single faulty modes

- **Two faults occurrence simultaneously**

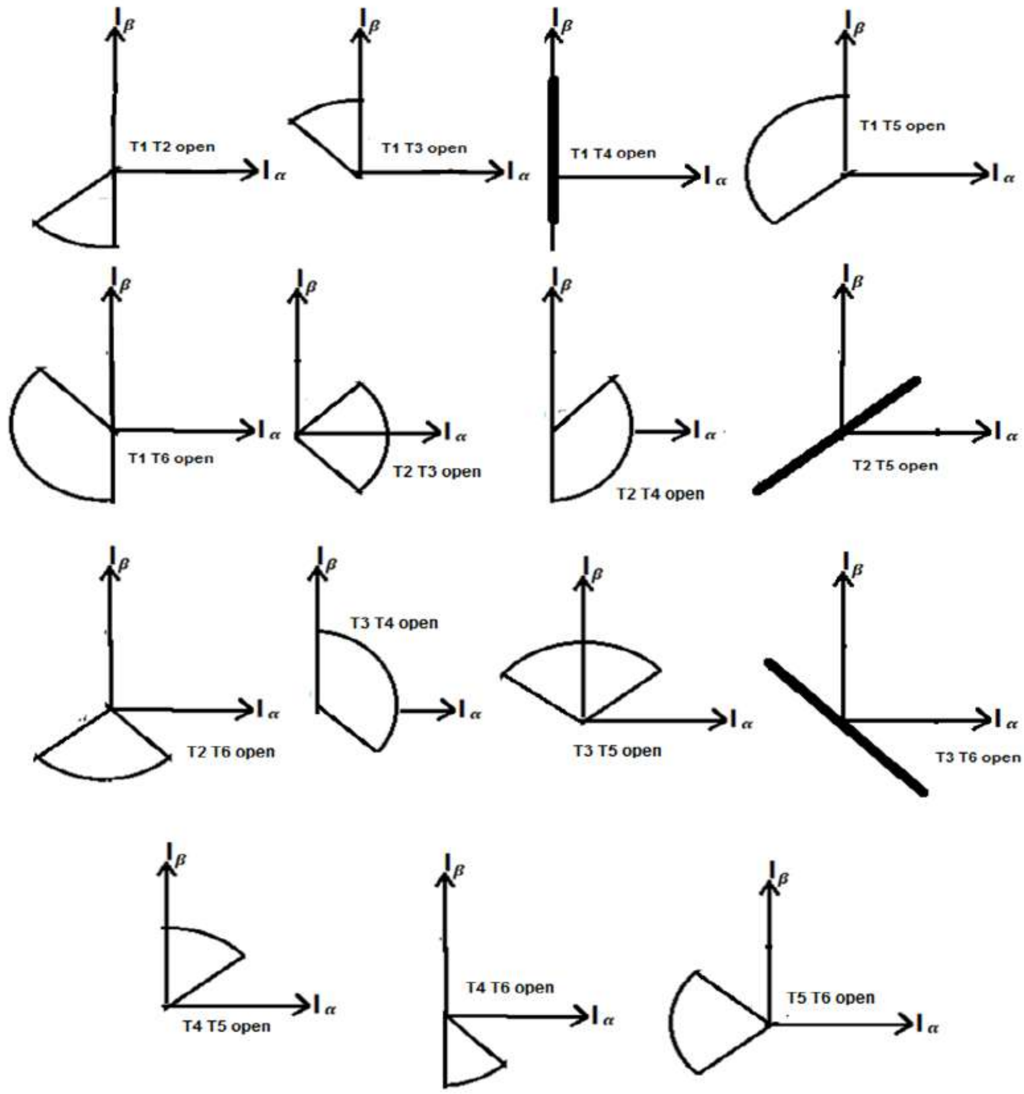

Fig. 2.3: Two faulty modes

2.3 Feature Extraction System

Feature extraction is a process which can provide neural network enough significant information in the pattern set to achieve the highest accuracy in neural network performance. Feature extraction system should be universal for different speed references by normalized functions. A feature is extracted to be used as input of neural network. Because is playing a vital role in fault detection and localization to make the system more accurate and effective by differentiating single and multiple faults. Block diagram of the proposed extraction and diagnosis Technique is shown in Figure 2.4. To get the feature in the

SIMULINK environment, this feature is explained using the follow equation[13][19]:

$$S_{\alpha,\beta} = \frac{\sum_{i=1}^{N} I_{s_{\alpha,\beta}}(i)}{lengh(I_{s_{\alpha,\beta}}) * max(I_{s_{\alpha,\beta}})} \tag{2.1}$$

N: define the number of samples contained in $I_{s_{\alpha,\beta}}$.
The choice of N depends on diagnosis decision time.

Faults are generated manually to obtain the features in faulty condition. This process

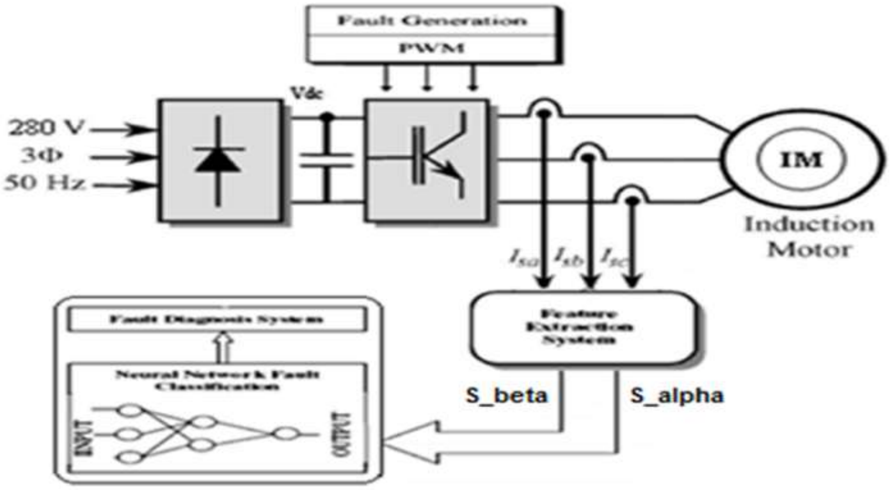

Fig. 2.4: Proposed fault diagnosis system[12][19]

is repeated several times for every possible change in data due to noise and other unpredicted in a real-time environment. Also, for better neural network training, features data entrance limit is determined in each faulty condition based on data collected previously (Figure 2.5.). The neural network is further trained with this organized data set. .

2.4 Structure of Fault Diagnosis System

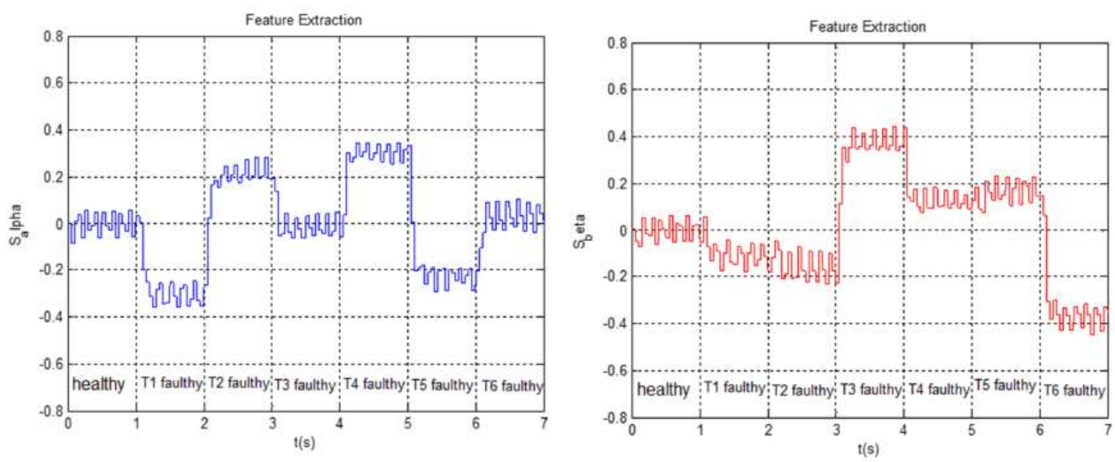

Fig. 2.5: Feature extraction functions in α_β plane

The diagnostic method can be summarized by the flowchart shown in Figure 2.6.

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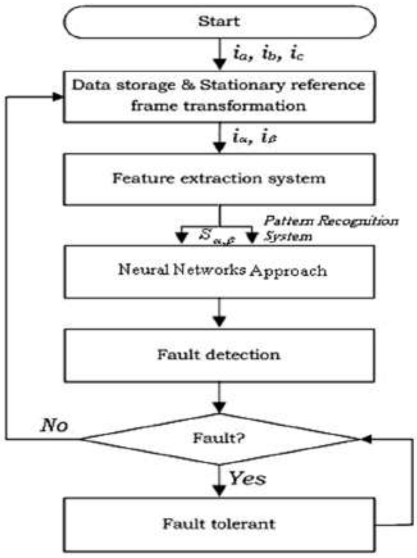

Fig. 2.6: Flow chart of fault diagnostic system

2.5 Neural Network Fault Classification

The architecture of the proposed fault diagnostic neural network is multilayer feed forward networks (MLP). The network has different hidden layers with two inputs corresponding to the normalized algebraic sum of $S_{\aleph}$,S_β and three outputs describing the state of three legs of PWM inverter. For each output, three levels are expected. 0 for a healthy leg,-1 for an upper faulty switch, and $+1$ for a downer faulty switch.

2.6 Training Data

The network will be trained with normal and abnormal data, thus the size of the input matrix is two inputs data rows with 500 columns for each pattern inputs. That gives 500 for healthy pattern, 500*6=3000 for one fault occurrence. The target output corresponding with classification data is represented for different speed references. The training data set should also cover the operating region; thus, the test data sets are generated from simulation with various speed references. In our work 25% of inputs/outputs data are taken for validation and 25% for testing. .

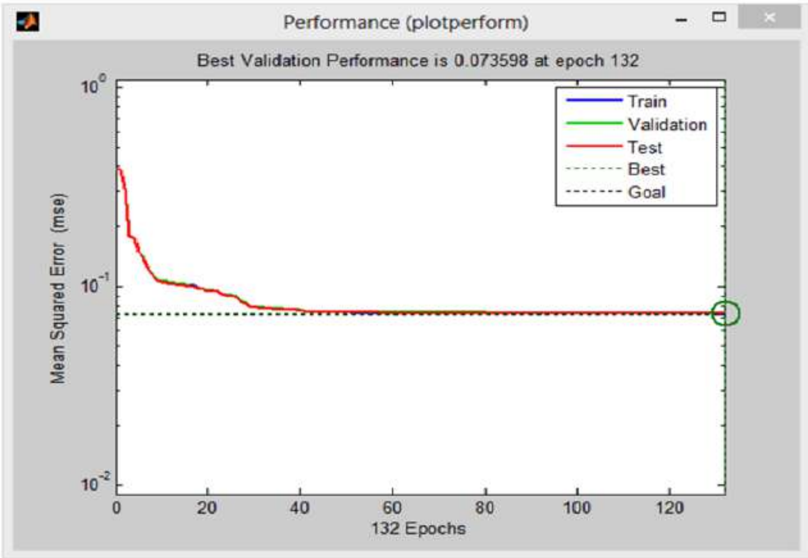

Fig. 2.7: Training Validation and Test errors of the developed neuron networks

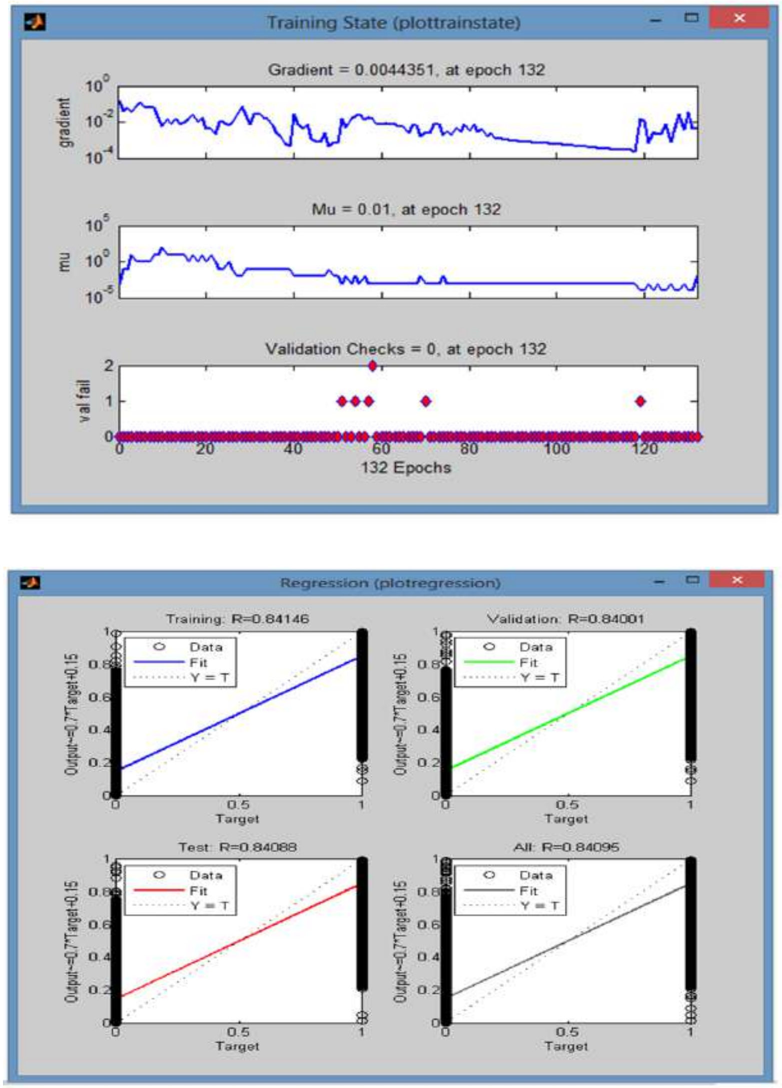

Fig. 2.8: Regression, and Training States of the proposed neuron networks

2.7 Simulation Results

2.7.1 Current Patterns without a Fault Switch

Figure 2.9 represents the healthy state, it takes the form of a circle.

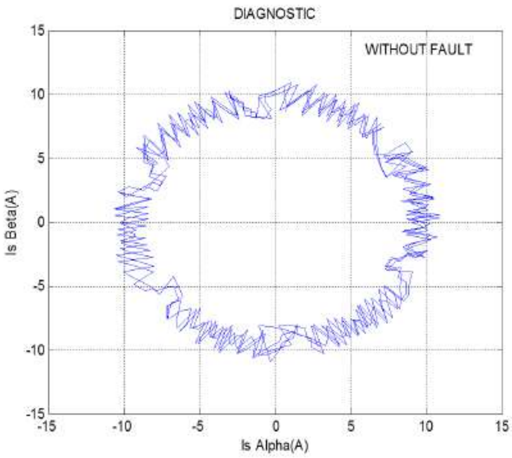

Fig. 2.9: α_β Stator currents simulation and diagnosis result in healthy mode

2.7.2 Current Pattern in Single Fault Switches

The figures 2.10 shows various forms of defects for different faulty switches. The semicircle corresponds to the location of the defective switch (T1, T2, T3, T4, T5, and T6). .

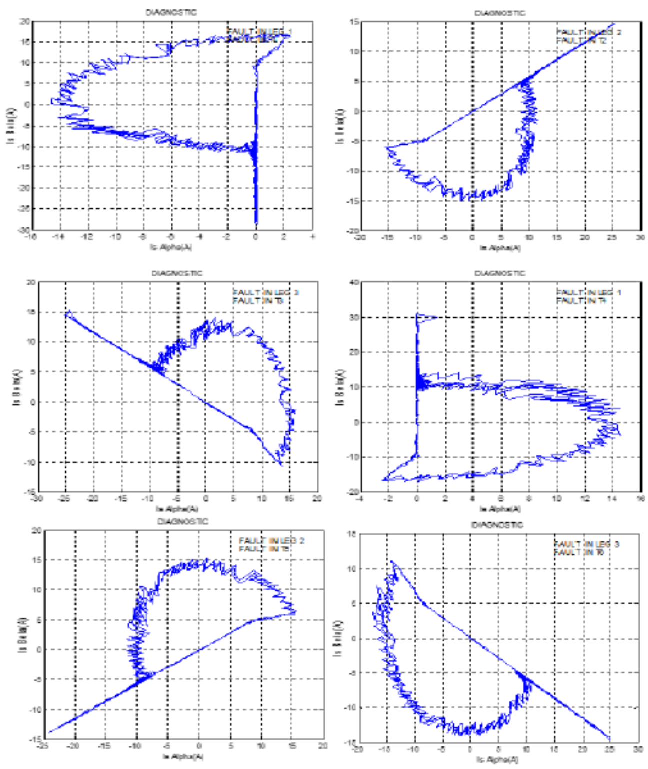

Fig. 2.10: α_β Stator currents simulation and diagnosis result for single faulty Mode

2.8 Reconfiguration of the inverter at the faults occurrence

We add three auxiliary legs to be placed in operation with the three main legs of the inverter. Each auxiliary leg is connected in parallel with the main leg. When a fault switch occurs the auxiliary leg will be activated by a reconfiguration signal and the main leg that carried the fault switch turned off by the same reconfiguration signal. Figure 2.11 present the structure of the proposed three-phase inverter; this structure consists of six symmetrical arms, each arm has two switches in series, the center of each auxiliary arm connected with the output of the asynchronous motor and the other arms linked with a reconfigurable switch.

Three reconfiguration signals are generated as inputs C1, C2, C3 automatically by the

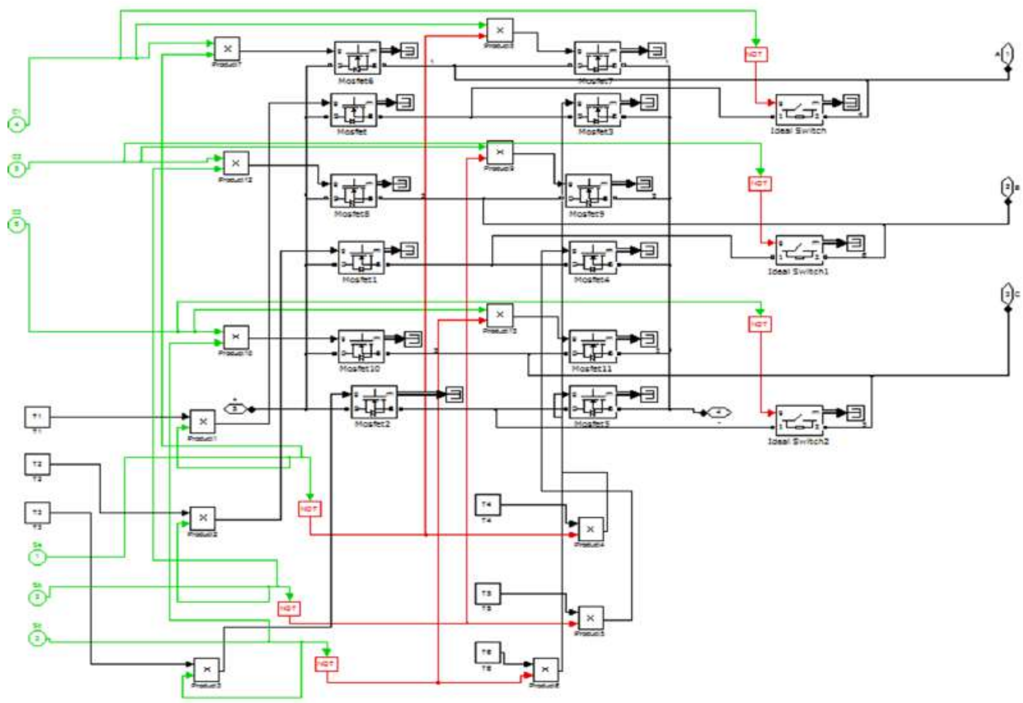

Fig. 2.11: SIMULINK Model of PWM Inverter with reconfiguration

diagnostic system, these signals are expected to disable or enable the inverter arms, and they change the reconfiguration each time with respect to the type of fault. When there is a fault, the main arm is disconnected by the switch lock and the auxiliary arm is connected.

The following figure shows how to reconfigure PWM inverter faults controlled by DTC.

2.8.1 Diagnosis Results for a Sequence of Faulty Transistor The simulation is done like the following:

- We made half a second (0.5s) for healthy mode.

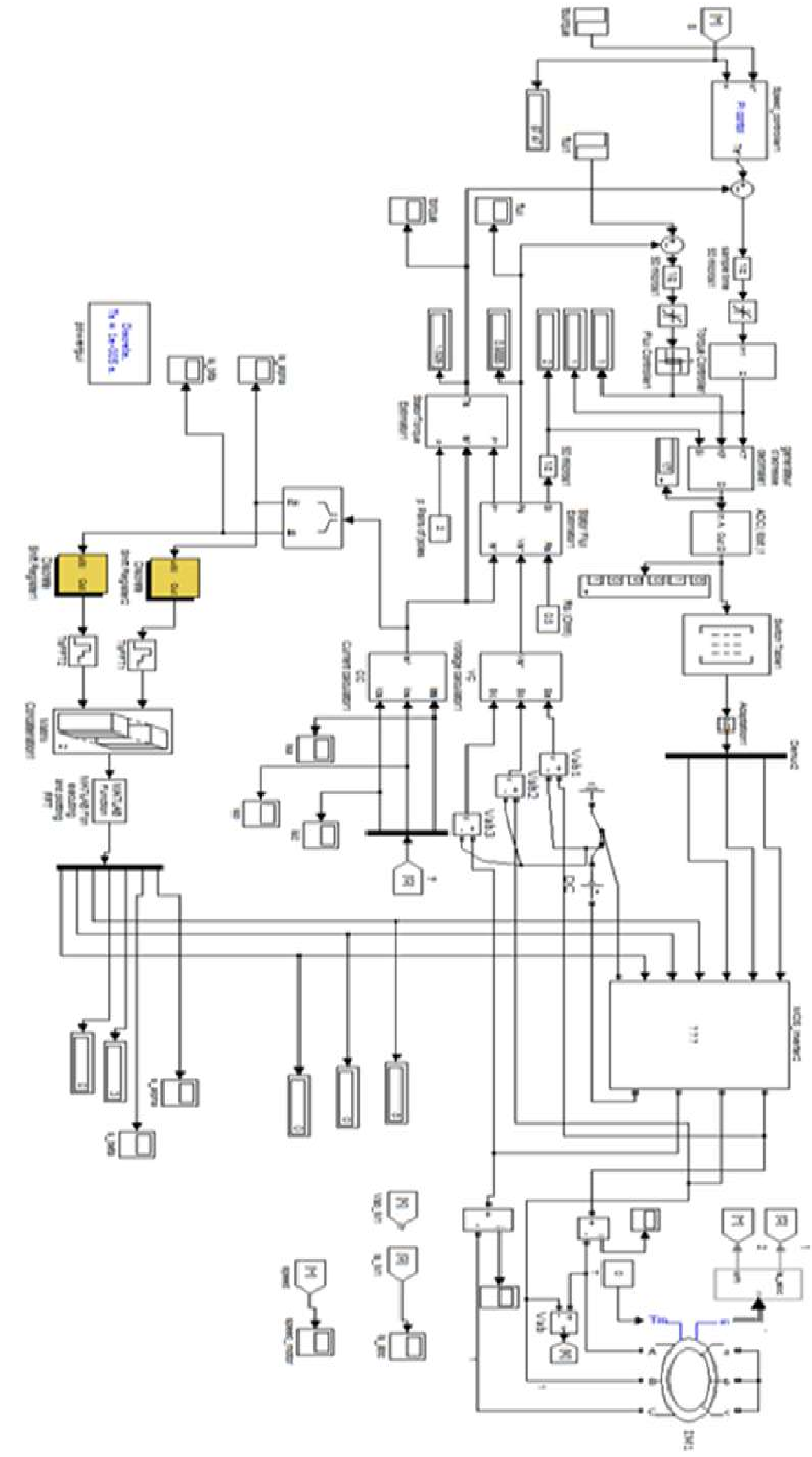

Fig. 2.12: Matlab/Simulink block diagram of reconfigurable PWM inverter controlled by DTC

- After each half a second (0.5s) we made a fault corresponding to the six faults switches (T1, T2, T3, T4, T5 and T6). A total time is three second and half (3.5s) the result of diagnosis is shown down. flux, torque, motor speed and three stator currents for each phase feeding the induction motor.
- Speed reference is 90 (rad/s), flux is 1(wb).

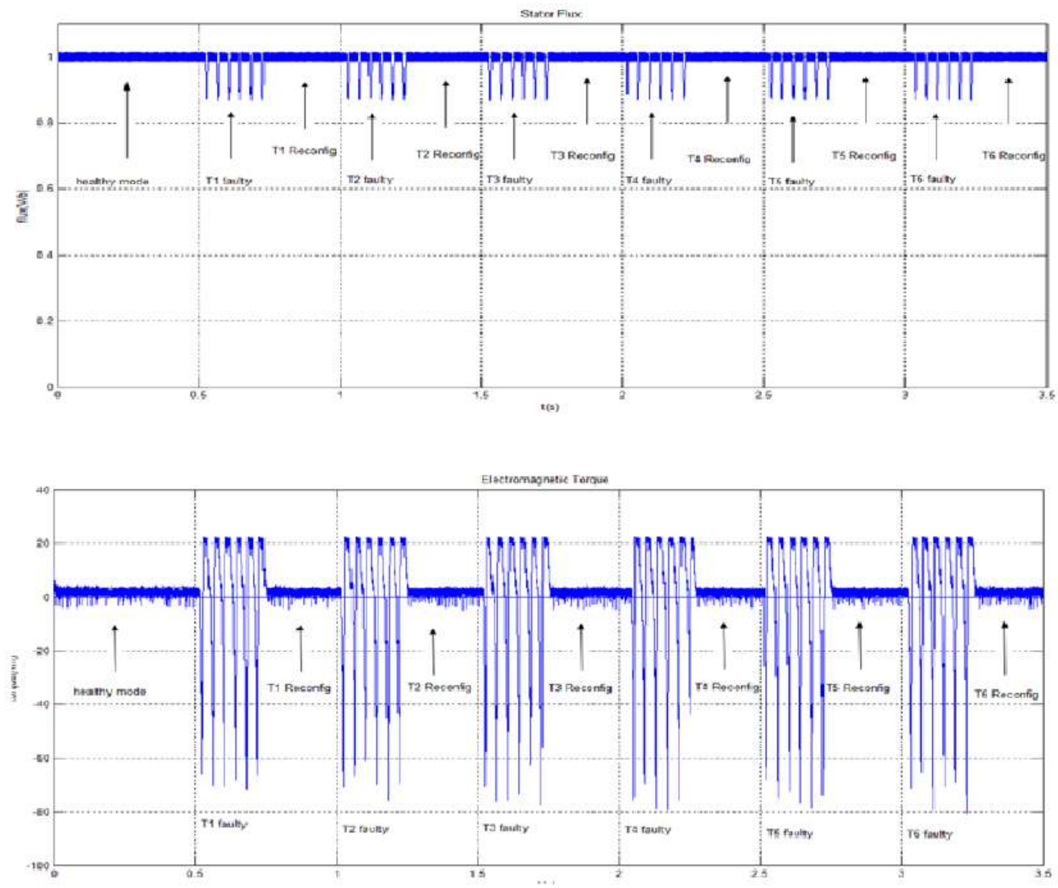

Fig. 2.13: Flux and Torque Simulation for a Sequence of Faulty Transistor

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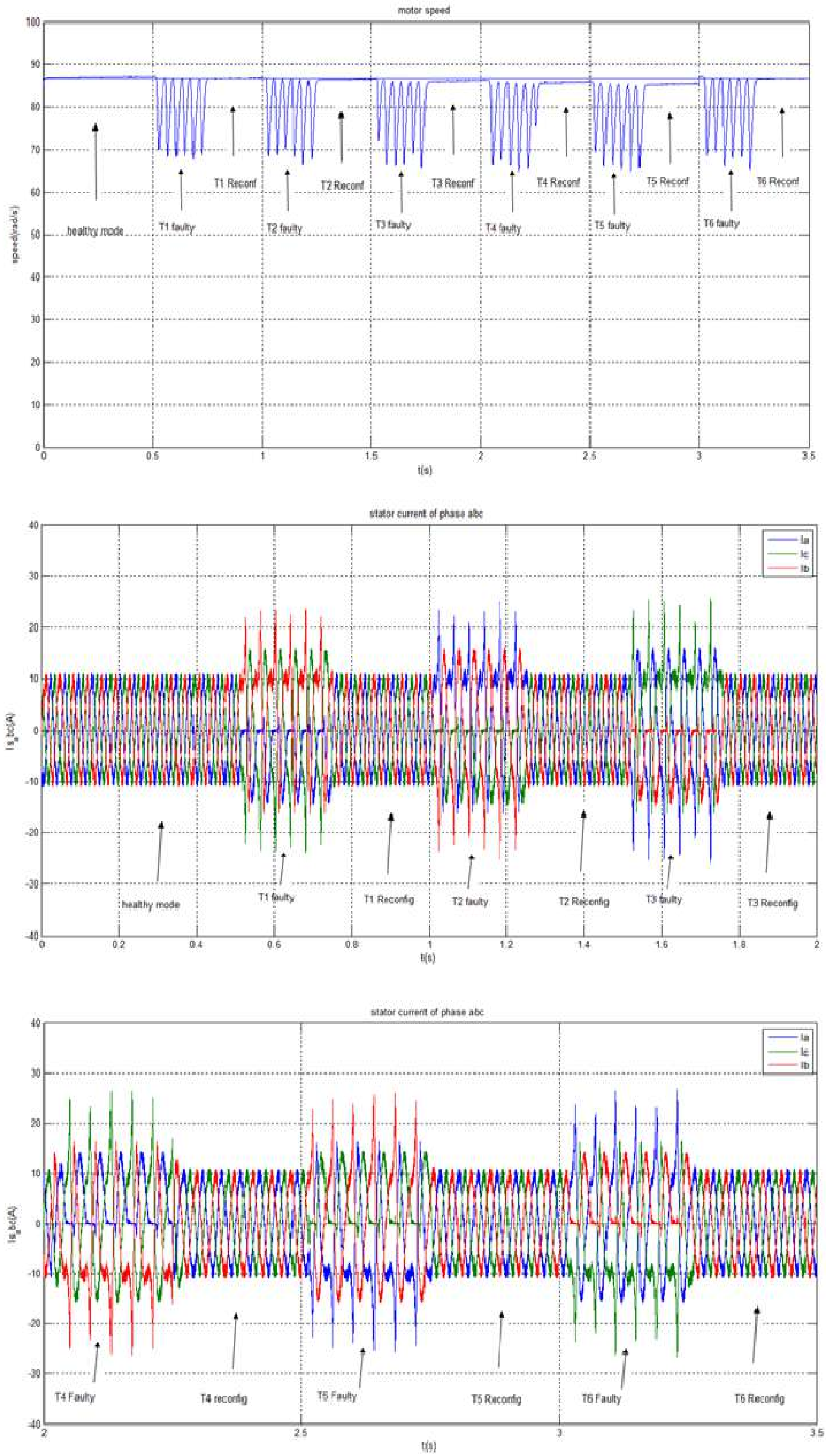

Fig. 2.14: Speed and α_β Stator Currents Simulation for a Sequence of Faulty Transistor

- **Discussion of results**

For a beginning all the signals are good for a healthy mode after each half a second (0.5s) there is a ripple signals just for (0.25s) after the ripple signals are removed by an automatic reconfiguration action making returning the drive motor in healthy state.

2.9 Conclusion

In this chapter, various inverter faults are done using MATLAB/SIMULINK to simulate different situations. A simple feature extraction of current patterns method has been proposed. In this chapter we made a neural network diagnosis system of a DTC motor drive method able to detect switching inverter faults with a reconfiguration to allow the motor drive to continue to operate in safely state.

GENERAL CONCLUSION

In this project, the work was aimed in fault diagnosis and reconfiguration of a PWM inverter with an induction motor drive controlled by an artificial neural networks direct torque control (ANN_DTC).

A model of ANN_DTC of induction motor drive feeding a PWM three-phase inverter has been presented. This control technique appears as a simple and effective way to control an induction motor drive; therefore, it provides a promising solution to robustness problems. Also in this project, we presented the simulation results of a speed regulation of induction motor using a basic and neural direct torque control.

The proposed model system is developed using the SIMULINK tool from MATLAB. The simulation results show the interest of the anti-windup regulator to solve the problem of saturation and to limit the peaks of the currents during the variation or the inversion of the speed of rotation.

We have studied the detection and diagnosis of an open inverter switching faults; where, we have simulated the different modes of defects for the six switches using an artificial intelligence technique. These diagnostic results are used to make a reconfiguration of the inverter to deflect the appearance of faults making the neural networks direct torque control system able to operate with any stability guarantee.

As perspective to this work, we propose to use other intelligent techniques to increase the recognition rate and improving diagnostic for occurrence of two or three faults.

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ملخص

في الوقت الحالي، تقترن المحركات الكهربائية بشكل عام بالعاكس وآلة التحريض. لذلك ، يجب أخذ هذين العنصرين في الاعتبار من أجل توفير تشخيص لهذه الأنظمة الكهربائية. من المهم اكتشاف الفشل المبكر ومنع حدوثه. إن الهدف من هذه المذكرة هو دراسة جدوى الكشف عن الأخطاء والتشخيص في محرك تحريضي لا تزامني يتغذى من طرف عاكس ثلاثي الأطوار. وتحقيقا لهذه الغاية، نقدم من خلال هذه العمل نتائج المحاكاة بالاعتماد على نظام تحكم مباشر للعزم لمحرك لا تزامني باستعمال الشبكات العصبية الاصطناعية، مع نظام كشف للأعطال وإعادة هيكلة للعاكس وذلك باستعمال الذكاء الاصطناعي من خلال تقنية الشبكات العصبية الاصطناعية حيث قدمنا وصفا مفصلا للأعطال الأحادية والثنائية الممكن حدوثها في العاكس مع استعمال طريقة بسيطة لاستخراج الخصائص بغرض كشف، تشخيص، وتحديد هذه العيوب وفي نفس الوقت محاولة إعادة هيكلة العاكس لتفادي هذه العيوب والأعطال فور حدوثها.

كلمات مفتاحيه: التحكم المباشر للعزم ، المحرك التحريضي اللاتزامني ، التحكم بالشبكات العصبية الاصطناعية ، تشخيص الأعطال، إعادة هيكلة العاكس.

Abstract

At the present time, electrical drives generally associate inverter and induction machine. Therefore, these two elements must be taken into account in order to provide a relevant diagnosis of these electrical systems. So it is important to detect early different defects that can occur in these systems in order to find ways to allow us to monitor the operation and preventive action to avoid frequent breakdowns. The aim of this work is to study the feasibility of fault detection and diagnosis in a three-phase inverter feeding an induction motor. We present the simulation results of a neural network direct torque control of induction motor with a fault diagnosis and reconfiguration system using an artificial intelligence technique. we gave a detailed description of one or multiple inverter switching faults with a simple method for extraction of characteristics to study the feasibility of detection and diagnosis of these defects, and at the same time trying to made a reconfiguration of the inverter to surround faults when they occurs.

Keywords: Direct Torque Control, Induction Motor, Neural Network Control, Fault Diagnosis, Inverter Reconfiguration.

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