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Direct Torque Control of Induction Motor Based on Genetic Algorithm

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Abstract—Direct Torque Control (DTC) became the most popular controller for induction motor control in the last two decades. The popularity is due to its simple structure, and high response for torque requirements compared with the other types of controllers. However, some unavoidable drawbacks exist such as torque and flux ripples, especially at low speeds, at starting, and when transition from state to another. Therefore, an accurate estimation for flux and torque is required. In this paper, a proposed of Genetic Algorithm (GA) is used for stator resistance optimization which can improve the DTC performance, and then other input /output data are generated for a sixth neural network training.The input/output data of the trained neural networks are generated from simulation of mathematical model of DTC equations. A neuro-estimator for stator resistance is proposed based on stator current and frequency, it can estimate the stator winding temperature, and then the stator resistance estimation becomes straightforward. A test program is used for training successful test for all the proposed neural networks. For simulation and test purposes, MATLAB/Simulink model is built based on DTC and implemented to show the effect of sampling time and stator resistance variation on DTC performance. The results obtained from the work simplify the use of neural networks and genetic algorithms with DTC for producing the estimated and optimized output signals of torque, stator flux and flux angle with fast and high degree of response and computations of such control drive. Simulation programs and models are performed by using MATLAB package based IBM-PC.

Index Terms— Genetic Algorithm (GA), Induction Motor (I.M), Direct Torque Control (DTC).

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1. Introduction

The control of induction motor drives covers a wide and important subject, and the technology has further advanced in recent years. Induction motor drives with squirrel-cage motor have been the workhorses in industry for variable-speed applications in wide power range that covers from fractional horsepower to multi-megawatts. In addition to process of the control, the energy-saving aspect of variable-frequency drives is getting a lot of attention nowadays. The control of AC drives in general is considerably more complex than of DC drives; this complexity increases substantially if high performance is demanded. The main reasons for this complexity are the need for variable-frequency; harmonically optimum converter power supplies [1]. This scheme of control was introduced in commercial products by a major company and therefore created wide interest. This control scheme, as the name indicates, is the direct control of the torque and stator flux of a drive by inverter voltage space vector selection through a look-up table [1, 2]. A large number of papers appeared in literature to improve the direct torque control. This paper will focus deeply on this technique for controlling induction motors with brief review of other types of controllers.

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2. Direct Torque Control (DTC)

Direct Torque Control (DTC) has emerged over the last two decades to become one possible alternative to the well-known vector control of induction machines.

It became the most popular controller for controlling induction motors. Its main characteristics are the good performance, obtaining results as good the classical vector control, and it has some advantages based on its simpler structure and control diagram. It is one of the future ways of controlling the induction motor. It is possible to control directly the stator flux and the torque by selecting the appropriate inverter state. This method stil requires further research in order to improve the motor's performance, as well as achieve a better behavior environmental compatibility (Electro Magnetic Interference and Energy), that is desired for all industrial applications [1, 2]. Direct Torque control DTC Technique aims at controlling the flux directly rather than controlling the current as it's done in vector control technique [2]. Therefore, the basic idea of the DTC concept, whose block diagram is shown in figure (1), is to choose the best vector voltage, which makes the flux rotates and product the desired torque[3, 4]. During this rotation, the amplitude of the flux rests in predefined band.

DTC controls the electromagnetic torque and flux directly and independtly. This enables the machine to achieve an excellent dynamic performance as the rotor time constant is much larger in a larger cage induction machine, the rotor flux linkage can be assumed to be invariant in magnitude as well as in position, if it observed for a small time interval. The magnitude of the stator flux linkage can be changed, or it can be rotated in forward or backward direction, by applying appropriate voltage to the stator winding, so that the angle between the stator and rotor flux linkages can be increased or decreased, this modifies the electromagnetic torque and hence can be adjusted to meet the load requirements [3, 4, 5, 6]. With a three phase voltage source inverter, there are six non zero voltage vectors and two zero vectors as shown in Figure (2), which can be applied to the machine terminals.

The developed electromagnetic torque in induction motors is the product of the magnitude of stator and rotor flux linkages and the angle between them [3].
The circular trajectory of the stator flux is divided into six symmetrical sectors referred to inverter voltage vectors. For each sector or section, a proper vector set is proposed. The certain vectors are applied to motor so that amplitude of the flux and torque remain constant. The three switches used in the inverter generate 2^3=8 possible switching states. Therefore, there are eight voltage vectors (Six none zero vectors in the 360^0 space, and two zero vectors) which can be applied to the machine terminals as shown in Figure 2 (the zero vectors are not shown).

In the DTC drive system the feedback signals can be calculated by using the following equations [1, 6]. The d-q components of stator voltage can be calculated as:

$$v_{ds} = \frac{Vdc}{3}\left(S_A - \frac{S_B + S_C}{2}\right) \qquad (1)$$

$$v_{qs} = \frac{Vdc}{\sqrt{3}}(S_B - S_C) \qquad (2)$$

Where *Vdc* is D.C link voltage of voltage source inverter, and *SA*, *SB*, and *SC* are the states of switching. The d-q components of stator currents can be calculated as:

$$i_{ds} = is_a \qquad (3)$$

$$i_{qs} = \frac{1}{\sqrt{3}}(is_a + 2 * is_b) \qquad (4)$$

Where *isa* and *isb* are stator current values of any two lines of the three power lines to which the motor is linked. Therefore, the d-q of stator flux can be calculated as:

$$\Psi_{ds} = \int (v_{ds} - R_s * i_{ds})dt \qquad (5)$$

$$\Psi_{qs} = \int (v_{qs} - R_s * i_{qs})dt \qquad (6)$$

Where Rs is the stator resistance. The flux linkage phase angle is given by:

$$\theta_s = tan^{-1}\left(\frac{\psi_{qs}}{\psi_{ds}}\right) \qquad (7)$$

and the developed electromagnetic torque is given by:

$$T_e = \frac{3}{2} * P * (i_{qs} * \psi_{ds} - i_{ds} * \psi_{qs}) \qquad (8)$$

Where P is the number of poles of the motor.

3. Genetic Algorithm

Genetic Algorithms (or simply called GAs) are one of the new generations of intelligent computing techniques which have entered the electrical and industrial applications. Genetic algorithm is a method mainly used to find the global optimization of complex system. Genetic algorithm works with coding of parameters. It searches from a set of possible solutions in parallel. It uses, the fitness function as a mean of discriminating among different sets of possible solutions and randomize operators instead of derivative information.
Genetic algorithm is based on generation of new possibly improving population among the previous population. The crossover and mutation ` (which will be dicussed and explained later) are the two tools for generation of the new solution. The crossover operation breaks the two chromosomes and swaps the two chromosome parts and form two new chromosomes (like bits) [7, 8].

GAs are highly parallel search methods applied to complex optimization problems. It has been found to overcome some of the problems of traditional search methods such as hill-climbing, the most notable problem being " getting stuck” at local optimum points, and therefore missing the global optimum (best solution)[8,9].
Genetic Algorithms are powerful and widely applicable stochastic search and optimization methods based on the concepts of natural selection and natural evaluations. GAs work on a population of individuals representing candidate solutions to the optimization problem. These individual consists of strings (called chromosomes) of genes. The genes are a practical allele (gene could be a bit, an integer number, a real value or an alphabet character,…, etc depending on the nature of the problem). GAs apply the principles of survival

of the fittest, selection, reproduction, crossover (recombining), and mutation on these individuals to get, hopefully, new better individuals (new solutions). GAs are applied to those problems which either cannot be formulated in exact and accurate mathematical forms and may contain noisy or irregular data or it takes so much time to solve or it is simply impossible to solve by the traditional computational methods. In other words, to apply a genetic algorithm to solve any practical problem, the user must [7, 10]:

1. Determine the representation scheme (how solutions are encoded as chromosomes).
2. Create the group of chromosomes (initial population of solutions) at the beginning of the evolution.
3. Determine the fitness measure (the metric for measuring the fitness of chromosome).
4. Determine the parameters and variables for controlling the algorithm (e.g population size, crossover rate, etc).
5. Apply genetic operators (e.g. three basic operators, selection, crossover and mutation) to produce new sets of individuals.
6. Determine a way of designating the result and a criterion for terminating a run.

Therefore, the genetic operators are used in GAs optimization procedure according to the flowchart, as shown in Figure (3).

4. Proposed Neuro-Genetic Simulation Model

The stator resistance (Rs) of induction motor is the main parameter in DTC performance, and its value affects the stator flux and torque ripples. Therefore, an optimized estimation of (Rs) leads to better performance in outputs of the motor according to electromagnetic torque, stator flux and flux angle. Therefore, the use of GA which has many advantages in prediction and optimization process leads to optimized output when it is used for stator resistance optimization to overcome the ripples problem.Neglecting the small amount of skin effect, winding resistance primarily varies with winding temperature, which is given by the known formula:

$$Rs=Rso + \alpha Rso\ (T-25^{\circ}) \qquad (9)$$

Where Rs is the resistance at stator winding temperature T in °C.
Rso is the nameplate resistance at 25 °C.
T is the stator winding temperature in °C.
α is the copper coefficient (11.21*10-3/ °C).

It can be seen from the above equation that the resistance is a direct measure of temperature since Rs variation is linearly proportional to T variation. Therefore, Rs based stator temperature (T) monitoring can provide an accurate estimation of Rs that is capable of responding to the change in the thermal characteristics of the motor. In order to optimize the stator resistance of the motor using genetic algorithm, fitness function is required and it is developed according to the thermal model represented in equation (9) which represents the effect of motor winding temperature variation on stator resistance value. Therefore, this equation can be adopted to be fitness function where:

$$F=1/(1+Rs) \qquad (10)$$

in order to obtain the optimum value of stator resistance.
The proposed model has been done and implemented by using MATLAB/ Genetic Algorithm toolbox. After running the toolbox, the result of optimum stator resistance obtained was (0.498Ω) at 37 °C, as shown in Figure (4). This obtained value represents the optimum value of stator resistance at specified range of stator winding temperature of (0-140 °C) according to the standard temperature rise data sheets and measurements of motors. It can be noted that the final value of the fitness function, when the algorithm is terminated, is very close to the actual value of stator resistance. This value can be adopted at the starting time of the motor for torque ripple reduction which may appear at the starting time (soft start). Also, this procedure of stator resistance determination can be represented as an unpowerd test at a certain temperature, for example at rated load temperature (off line test). This value is applied in the simulation model of DTC at sampling time (Ts) of (50 μs) and then obtaining new input/output data for neural network training.
The proposed design of neural network according to the optimized value of stator resistance is shown in Figure (5). The Mean Squared Error (MSE) as a function of the number of epochs is shown in Figure (6), and the accuracy performance of training between the actual and estimated output is shown in Figure (7). The parameters of the trained network can be summarized in Table (1). The parameters of the fitness function for stator resistance based on stator temperature can be summarized in Table (2).

5. Proposed Neuro-Estimator for Stator Resistance Based on Stator Winding Temperature.

The proposed stator resistance estimator is derived for neural networks based estimation of stator winding temperature which is defined as a function of stator current and frequency through an approximate thermal model of the motor. Figure (8) shows the block diagram of the proposed stator resistance estimation based on neural networks.
This estimator provides a compensation for correct estimation of torque and flux of induction motor drive. The estimator estimates the stator winding temperature rise:-

$$\Delta Tss=T-TA \qquad (11)$$

Where ΔTss is temperature rise above ambient.
T is stator winding temperature.
TA is the ambient temperature.
The ΔTss signal is defined by neuro estimator relation of rms of stator current (Is) and frequency (ωe). The estimator deals with the Is signal to represent the copper loss and the ωe signal to represent the core loss. Both of these signals are related non-linearly to compute the winding temperature rise (ΔTss) through the motor thermal resistance. Once the steady state

ΔTss is estimated by neuro estimator, it is added to ambient temperature TA to derive the actual stator temperature T, and then the derivation of Rs by equation (9) becomes straightforward. Therefore, the proposed design of neural network based proposed model of stator resistance estimator can be represented as two input neurons (stator current Is (A), and frequency ωe (rad/s)) and one output neuron (stator temperature T). The hidden layer neurons are chosen by the same procedure of the previous networks proposed, as shown in Figure (9). The input/output data of the proposed trained network are obtained for a wide range of stator currents and speeds. It can be seen that this proposed estimator can be used for thermal protection and monitoring purposes.
The Mean Squared Error (MSE) as a function of the number of epochs is shown in Figure (10), and the accuracy performance of training between the actual and estimated output is shown in Figure (11). The parameters of the trained network can be summarized in Table (3). The input/output data that are used for neural network training of the proposed estimator can be plotted as shown in Figure (12).

6. Simulink Model of DTC for Three-Phase Induction Motor

Direct Torque Control (DTC) for three-phase induction motor has been built and simulated using Simulink package.
The model was built and implemented for the test of performance of the motor under different conditions such as sampling time interval (Ts) and stator resistance variation (Rs). Figure (13) shows the DTC system for induction motor based MATLAB/Simulink. The high level schematic of DTC consists of six main blocks; Induction motor, the three phase inverter based on IGBT device, the three phase diode rectifier, speed controller, braking chopper and DTC controller. Figure (14) shows these blocks.

7. Conclusions

Direct Torque Control (DTC) is very effective technique for driving and controlling any induction motor. Its main principles have been introduced and explained deeply. A demonstration of independent and decoupled control of motor orque and motor stator flux is performed in this work. Compared with other control approaches, DTC has the ability for achieving good response with the absence of speed or position feedback sensors. In other words, it is the best sensorless control approach. The proposed model of DTC is based on the use of the updated simpower systems included in MATLAB/Simulink.
The main concluding remarks can be summarized as follows:

1) Direct torque control is sensitive to the sampling interval and it has the best performance when the sampling interval is very short, but a further reduction in sampling interval means a very high switching frequency of the inverter and this is not suitable for practical applications especially at high power ratings.
2) Genetic Algorithms (GAs), which are based on the laws of natural selection and survival of the fittest, have been used successfully to optimize the stator resistance (Rs) to reduce the torque and flux ripples.
Because GAs quickly reach the region of optimal solutions and its accuracy for the following reasons:
a) GAs avoid local minima by searching in several regions to arrive at global minima.
b) The only information they need is some performance value that determines how good stator resistance value is.
The results show that the optimum stator resistance value improves the stator flux, electromagnetic torque which means better performance.
The advantage of obtaining an optimized stator resistance is to get an optimum setting of motor and drive system for optimum performance, especially in specific industrial applications which require a certain setting for an efficient and accurate performance.
As the obtained optimized resistance seems to be rather larger than the nominal value, but its value is very effective on stator flux and electromagnetic torque.

4) A neuro-estimator for stator resistance of induction motor is proposed based on stator resistance winding temperature with respect to stator current and frequency data. This estimator can be used for thermal protection and monitoring purposes.

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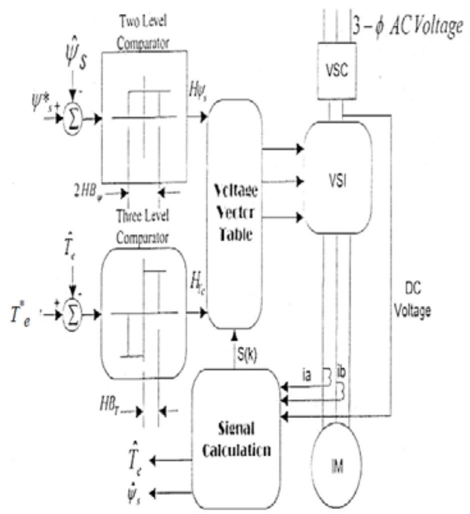

Figure (1) Direct torque and flux control block diagram.

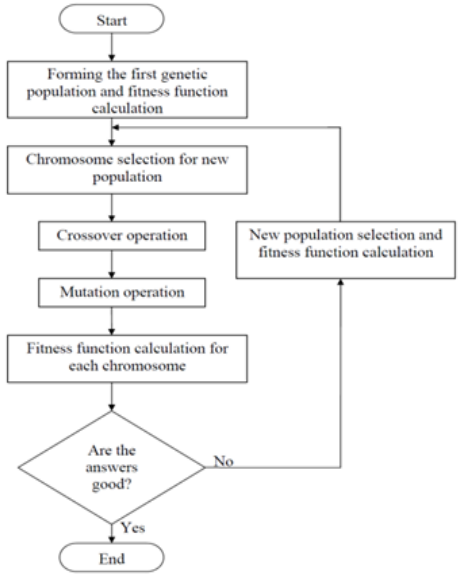

Figure (3) Flowchart for general structure of GAs.

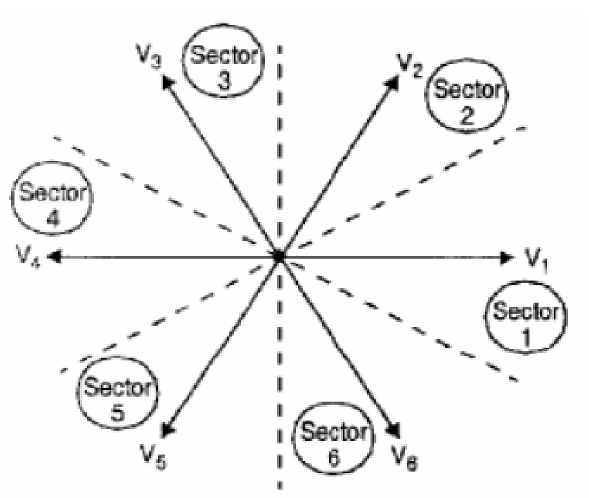

Figure (2) Voltage source inverter vector.

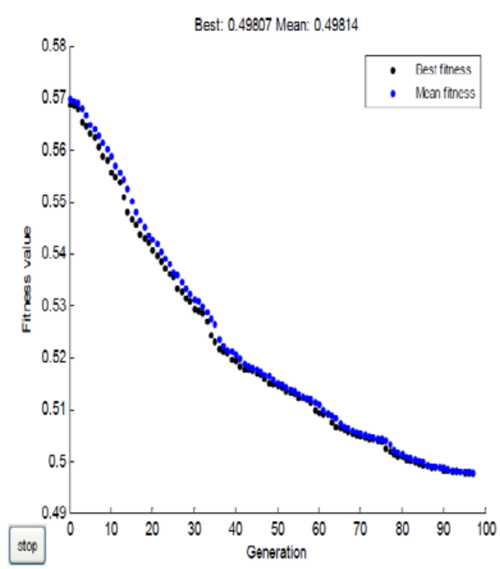

Figure (4) Optimum value resistance based on genetic toolbox.

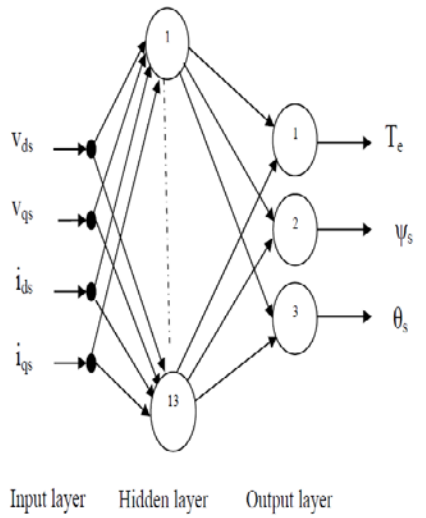

Figure (5) Training of (4-13-3) network at Ts= 50 μs, Rs=Roptimum.

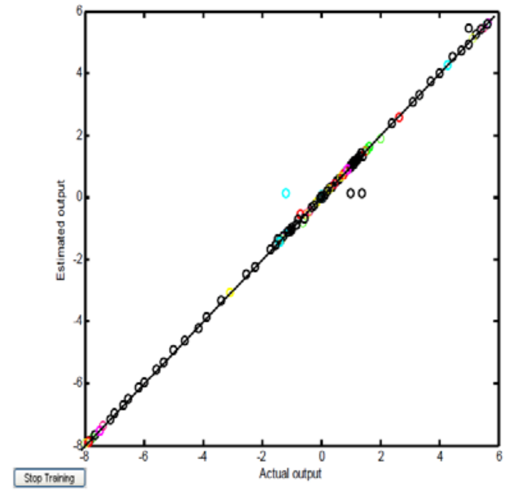

Figure (7) Accuracy performance of training between the actual and estimated output.

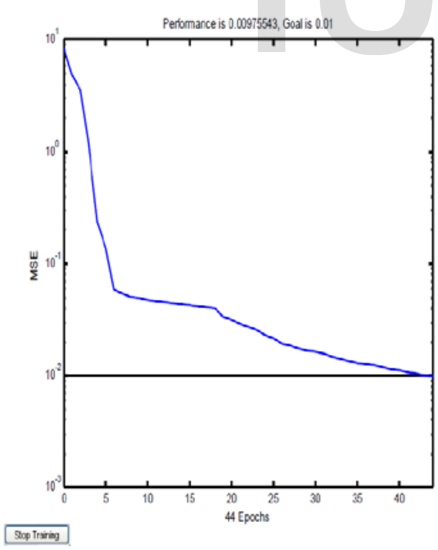

Figure (6) MSE as a function of the number of epoch.

Table (1) Parameters of the trained neural network.

Input	v_{ds}, v_{qs}, i_{ds}, i_{qs} (p.u)
Output	T_e, ψ_s, θ_s (p.u)
Maximum input value	$v_{ds\,(max.)}$=3.80 (p.u), $v_{qs\,(max.)}$=5.38 (p.u) $i_{ds\,(max.)}$=1.56 (p.u), $i_{qs\,(max.)}$=2.22 (p.u)
Minimum input value	$v_{ds\,(min.)}$=-3.80 (p.u), $v_{qs\,(min.)}$=-5.38 (p.u) $i_{ds\,(min.)}$= -1.56 (p.u), $i_{qs\,(min.)}$= -2.22 (p.u)
Maximum output value	$T_{e\,(max.)}$=1.5(p.u), $\psi_{s\,(max.)}$=1(p.u), $\theta_{s\,(max.)}$=1(p.u)
Minimum output value	$T_{e\,(min.)}$= -1.5(p.u),$\psi_{s\,(min.)}$=0(p.u), $\theta_{s\,(min.)}$= -1(p.u)
Functions	Tansigmoidal
Hidden nodes	13
Number of epochs	44
Learning rate (η)	0.1
Momentum coefficient (β)	0.3
Mean squared error (MSE)	$1*10^{-2}$

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Table (2) Parameters of fitness function.

Population type	Double Vector
Population size	20
Creation function	Uniform
Scaling function	Rank
Selection function	Roulette Wheel
Crossover fraction	0.7
Crossover function	Heuristic
Mutation fraction	0.06
Generation	100
Stall generation	50

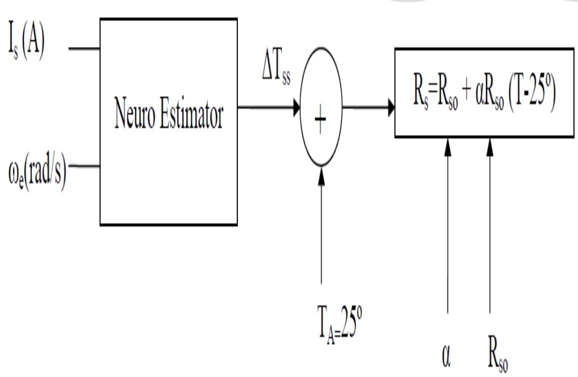

Figure (8) Block diagram of neuro- estimator for stator rsistance.

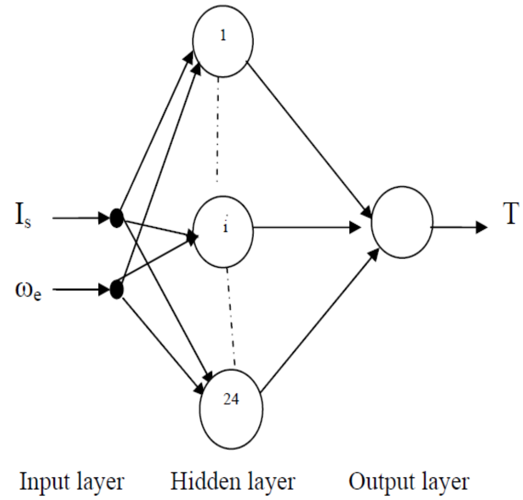

Figure (9) Proposed neural network for neuro-estimator based on stator winding temperature estimation.

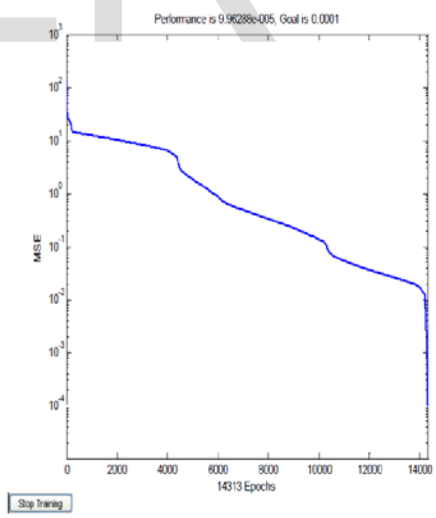

Figure (10) MSE as a function of the number of epoch.

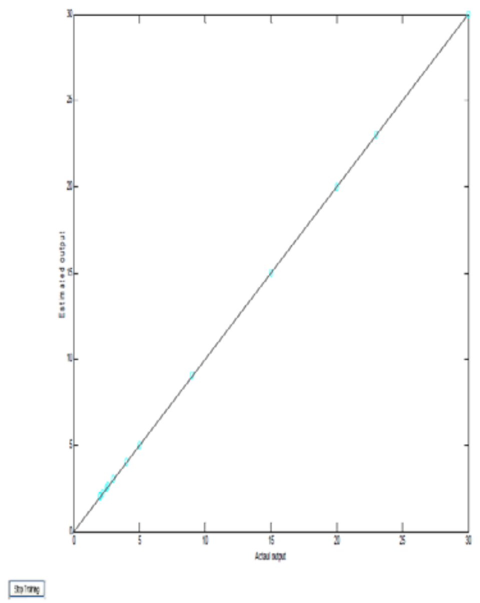

Figure (11) Accuracy performance of training between the actual and estimated output.

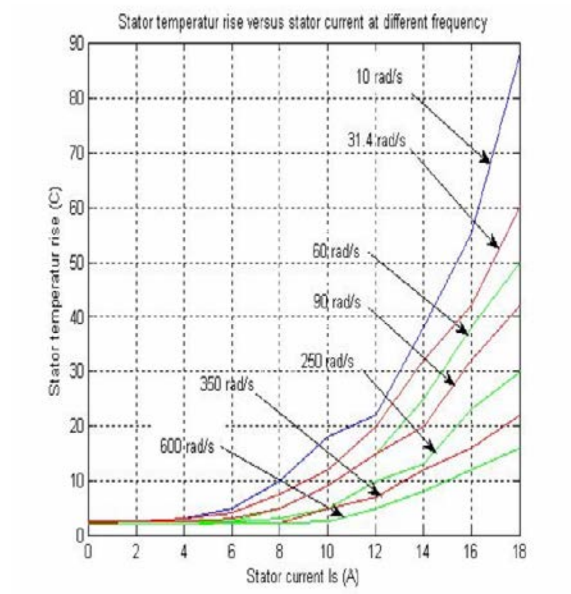

Figure (12) Input/output data of the trained neuro- estimator network.

Table (3) Parameters of the trained neural network.

Input	I_s(A), ω_e(rad/s)
Output	T(°C)
Maximum input value Minimum input value	$I_{s\,(max.)}$=18, $\omega_{e\,(max.)}$=600 $I_{s\,(min.)}$=0, $\omega_{e\,(min.)}$=10
Maximum output value	$T_{(max.)}$=88
Minimum output value	$T_{(min.)}$=2
Functions	Tansigmoidal
Hidden nodes	24
Number of epochs	14313
Learning rate (η)	0.6
Momentum coefficient (α)	0.3
Mean squared error (MSE)	$1*10^{-4}$

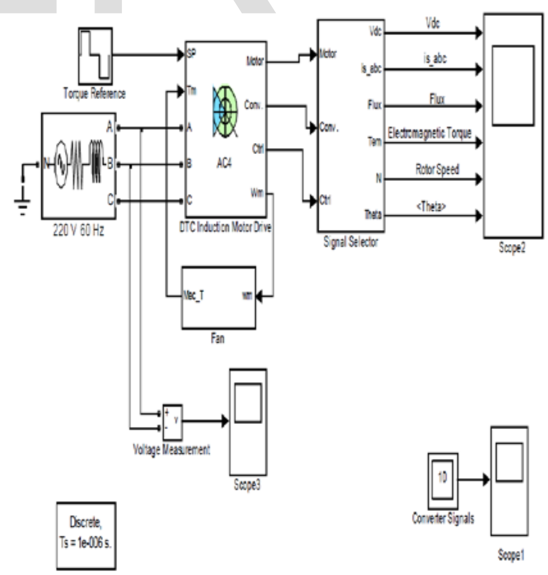

Figure (13) Simulink Model of DTC Induction Motor.

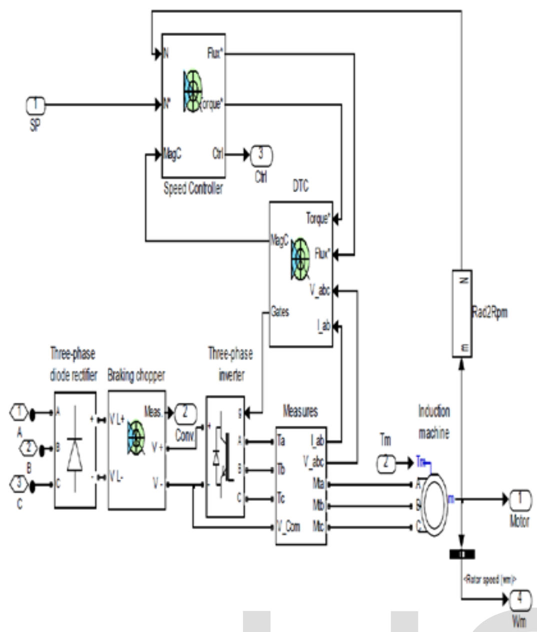

Figure (14) Schematic of DTC based Simulink.