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Torque and Flux Ripple Reduction of Direct Torque Control for Induction Motor Using Intelligent Technique

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ABSTRACT:

The aim of this paper is reduction of torque and flux ripples in transient and steady state response of Direct Torque Control (DTC) for Induction Motor drive using intelligent technique. This proposed control to improve the torque, speed and flux response will be achieved with the Artificial Neural Network (ANN) DTC than the Conventional DTC (CDTC). In this paper DTC system using ANN is successfully implemented on three phase induction motor to optimize the flux and to improve the performance of fast stator flux response in transient state. To improve the performance of DTC with the modern technique using ANN approach is implemented, and performance of ANN DTC compared with CDTC is done, hence the ANN approach shows the better performance. The performance has been tested by using MATLAB/SIMULINK and NEURAL NETWORK toolbox.

Key words: Direct Torque Control (DTC), Artificial Neural Network (ANN), and Conventional DTC (CDTC).

1.0 INTRODUCTION

The induction motor is work horse in all industrial applications due to its well-known advantages of simple in construction, ruggedness and inexpensive and are available at all power ratings. In the field of power electronics enables the application of induction motors for high performance drives were traditionally replaced the DC motors were applied. The modern sophisticate control methods of induction motor drives offer the same control capabilities as high performance four quadrant DC drives. Induction motor drives controlled by Field Oriented Control (FOC) have been till now employed in high performance industrial applications, has achieved a quick torque response, and has been applied in various industrial applications instead of DC motors. It permits independent control of the torque and flux by decoupling the stator current into two orthogonal components FOC, however, is very sensitive to flux, which is mainly affected by parameter variations. It depends on accurate parameter identification to achieve the expected performance. During the last two decade a new control method called Direct Torque Control (DTC) has been developed for electrical machines. DTC principles were first introduced by Depenbrock and Takahashi. [1-3] In this method, stator voltage vectors is selected according to the differences between the reference and actual torque and stator flux linkage. The DTC method is characterized by its simple implementation and a fast dynamic response. Furthermore, the inverter is directly controlled by the algorithm, i.e., a modulation technique for the inverter is not needed. However if the control is implemented on a digital system, the actual values of flux and torque could cross their boundaries too far. The main advantages of DTC are absence of coordinate transformation and current regulator; absence of separate voltage modulation block. Common disadvantages of Conventional DTC are high torque ripple and slow transient response to the step changes in torque during start-up. For that reason the application of Intelligent Technique attracts the attention of many scientists from all over the world. The reason for this trend is the many advantages which the architectures of ANN have over traditional algorithmic of approximating non-linear functions, insensitivity to the distortion of the network, and inexact input data. In this paper we present the evaluation of flux and torque using the three stator currents is the voltage of input vector, and ANN has been devised having as inputs the torque error, the stator flux error and the position of the stator flux in which it lies, and as output the voltage vector to be generate by the inverter. The results are discussed and compared with CDTC.

2.0 MATHEMATICAL MODEL OF INDUCTION MOTOR

The mathematical model of induction motor by the analysis of dynamic d-q equivalent circuit. The dynamic behavior of asynchronous drive is complex to the coupling effect between the stator and rotor phases. The figure.1 below shows the dynamic d-q equivalent circuits of an asynchronous drive. The different parameters of asynchronous drive are also shown in the figure.1

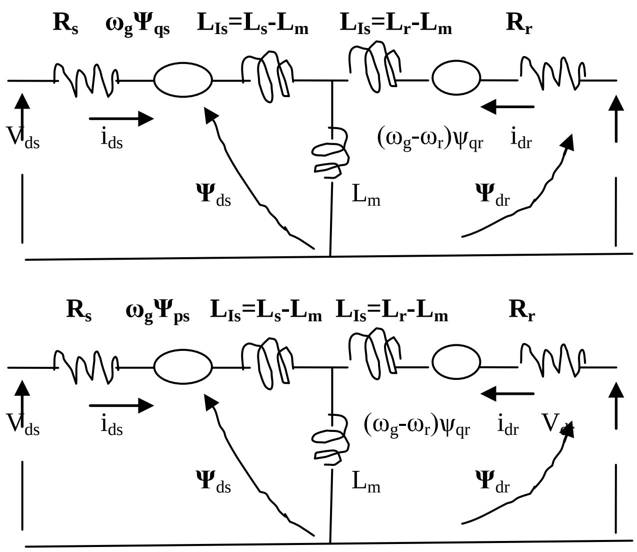

Figure.1 Dynamic d-q equivalent circuits of an asynchronous drive (a) d-axis, (b) q-axis

The flux linkage expressions in terms of the currents can be written from figure as follows:

$\Psi_{qs}= L_s i_{qs}+ L_m (i_{qs}+i_{qr})$ (2.1)
$\Psi_{qr}= L_r i_{qs}+ L_m (i_{qs}+i_{qr})$ (2.2)
$\Psi_{qm}= L_m (i_{qs}+i_{qr})$ (2.3)
$\Psi_{ds}= L_s i_{ds}+ L_m (i_{ds}+i_{dr})$ (2.4)
$\Psi_{dr}= L_r i_{ds}+L_m (i_{ds}+i_{dr})$ (2.5)
$\Psi_{dm}= L_m (i_{ds}+i_{dr})$ (2.6)

The electrical transient model in terms of voltages and currents can be given in matrix forms as

$$\begin{bmatrix} V_{qs} \\ V_{ds} \\ V_{qr} \\ V_{dr} \end{bmatrix} = \begin{bmatrix} R_s + SL_s & \omega_e L_s & SL_m & \omega_e L_m \\ -\omega_e L_s & R_s + SL_s & -\omega_e L_m & SL_m \\ SL_m & (\omega_e - \omega_r)L_m & R_r + SL_r & (\omega_e - \omega_r)L_r \\ -(\omega_e - \omega_r)L_m & SL_m & -(\omega_e - \omega_r)L_r & R_r + SL_r \end{bmatrix} \begin{bmatrix} I_{qs} \\ I_{ds} \\ I_{qr} \\ I_{dr} \end{bmatrix} \quad (2.7)$$

Where S is the Laplace operator, d/dt. The speed ω_r in the above equations is related to the torque by the following mechanical dynamic equation,

$T_e = T_L + J \frac{d\omega_m}{dt} = T_L + \frac{2}{P} J \frac{d\omega_r}{dt}$ (2.8)
n terms of stator and rotor currents, the torque can be written as:

$T_e = \frac{3}{2} \frac{P}{2} L_m (i_{rd}\, i_{sq} - i_{rq}\, i_{sd})$ (2.9)

2.1 Basic switching table and selection of voltage vectors

The basic working principle of switching table of DTC concept [7] is shown in figure.2. The reference stator flux Ψ_{sref}, and torque T_{eref} are compared with the actual value of Ψ_s and T_e in hysteresis flux and torque controller respectively. The hysteresis flux controller is a two-level comparator while the hysteresis torque controller is a three level comparator.

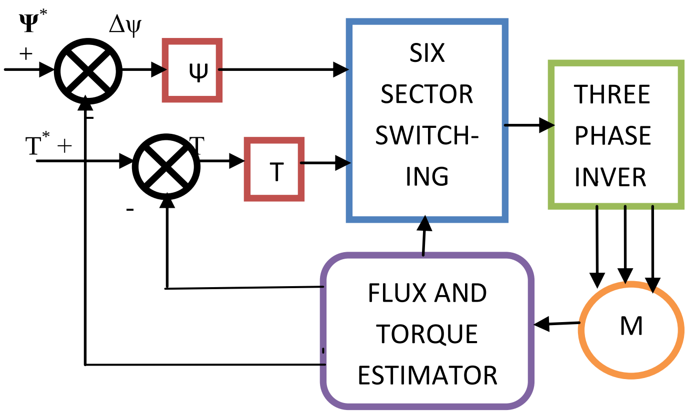

Figure 2 shows block diagram of DTC switching table concept

The output signal of hysteresis flux controller is define as given below

Ψ_{serr}=1, for $\Psi_s < \Psi_{sref} - H_\Psi$ (4.1)
Ψ_{serr}= -1, for $\Psi_s < \Psi_{sref} + H_\Psi$ (4.2)

and output signal of hysteresis torque controller are define as given below

$_{Teerr}$=1, for $T_e < T_{eref} - H_m$ (4.3)
$_{Teerr}$ = -1, for $T_e = T_{eref}$ (4.4)
$_{Teerr}$= -1, for $T_e < T_{eref} + H_m$ (4.5)

Where 2 H_Ψ is the flux tolerance band and 2 H_m is the torque tolerance band.On the basis of the torque and flux hysteresis status and stator flux switching sector which is indicated by

$$\alpha = \llcorner \varphi_s^s = \tan^{-1}(\varphi_{qs}^s / \varphi_{ds}^s) \quad (4.6)$$

Switching table output is a setting of switching devices of the inverter: hence DTC technique [8] selects the inverter voltage vector to apply the asynchronous machine. Figure 3 shows the relationship between the inverter voltage vector and stator flux switching sector in which six active switching vectors are:

V_1= [1 0 0], V_2= [1 1 0], V_3= [0 1 0],
V_4= [0 1 1], V_5 = [0 0 1], V_6= [1 0 1]
and two zero switching vectors are:

V_0= [0 0 0], V_7= [1 1 1] and also

-30° < α (1) < 30°, 30° < α (2) < 90°,
90° < α (3) < 150°, 150° < α (4) < 210°,
210° < α (5) < 270°, 270° < α (6) < 330°.

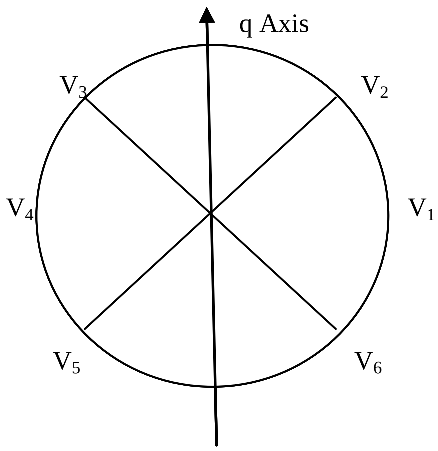

Figure 3 shows switching vectors

3.0 NEURAL NETWORKS DTC CONTROLLER

The principle of Artificial Neural Networks (ANN) is the one of the most important features for control the asynchronous drives. Neural Networks [12] have a self adapting capability which makes them well suited to handle the non-linear ties, uncertainness and parameter variations. In this section we discussed a multilayered feed forward neural networks constructs a global approximations to non-linear input, output mapping.

The basic element of an Artificial Neural Networks (ANN) is as shown in figure 4.

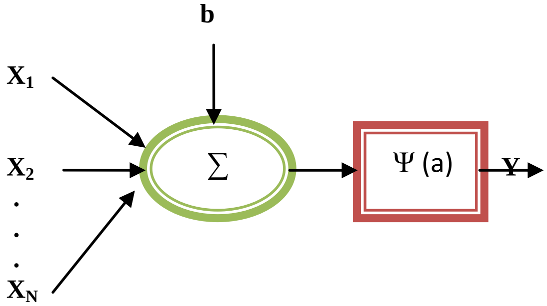

Figure 4 Basic elements of ANN

The mathematical model of a neuron is given by the formula is

$$\mathbf{y = \Psi \left(\sum_{i=1}^{N} w_i * x_i + b\right)} \qquad \mathbf{(6.1)}$$

where x_1, x_2,…x_N are the input signals of neuron, w_1,w_2,…w_N are their corresponding weights and b a bias parameter and Ψ is a tangent sigmoid function and y is the output signal of the neuron. It is simply shown in the above figure 4. The above can be trained learning algorithm which performs the adaptation of weight of the network. The error between target vectors and the output of the ANN is less than a predefined threshold values. The output results depends on the following factors are: network architecture, initial parameter values, the details of input and output mapping, selected training data set and the learning rate constant.

3.1 Learning algorithm in ANNs

The levenberg-marquardt back propagation techniques have been used to train the ANN. generalization in regions of the input space where little or no training data are available. The most popular supervised learning algorithm is back propagation which consists of forward and backward action. In ANN the forward step, the free parameters of the network are fixed and the input signals are propagated throughout the network from the first layer. In this forward phase, we compute a mean square error

$$\mathbf{E\ (k)} = \frac{1}{N} \sum_{i=1}^{N} (d_i\,(k) - y_i\,(k)^2\,) \quad \mathbf{(6.2)}$$

Where, d_i is the desired response, y_i is the actual output produced by the network response to the input x_i, k is the iteration member and N is the number of input-output training data.

In second step of the backward phase the error signal E (k) is propagated to entire network, to perform adjustments upon the free parameters of the network in order to decrease the error E (k). The weights associated with output layer of the network, its formula is

$$w_{ji}\,(k+1) = w_{ji}\,(k) - \Psi \frac{\partial E(k)}{\partial w_{ji}\ (k)} \quad \mathbf{(6.3)}$$

In this learning method, the value of ƞ has to be chosen carefully to avoid instability because, the large value of ƞ may accelerate the ANN learning and consequently faster convergence, but may cause oscillation in the network output, whereas low values will cause slow convergence. To ensure fast convergence, we change the formula of equation as rewrite, where α is a positive constant called momentum constant.

$$w_{ji}\,(k+1) = w_{ji}\,(k) - \Psi \frac{\partial E(k)}{\partial w_{ji}\ (k)} + \alpha\ \Delta\ w_{ji}\,(k) \quad \mathbf{(6.4)}$$

The flowchart shows the back propagation [13] training process of an ANN is trained properly; it must be adequately tested using data which is different from the training set in order to test the validity of the model.

3.2 **Structure of ANN for DTC**

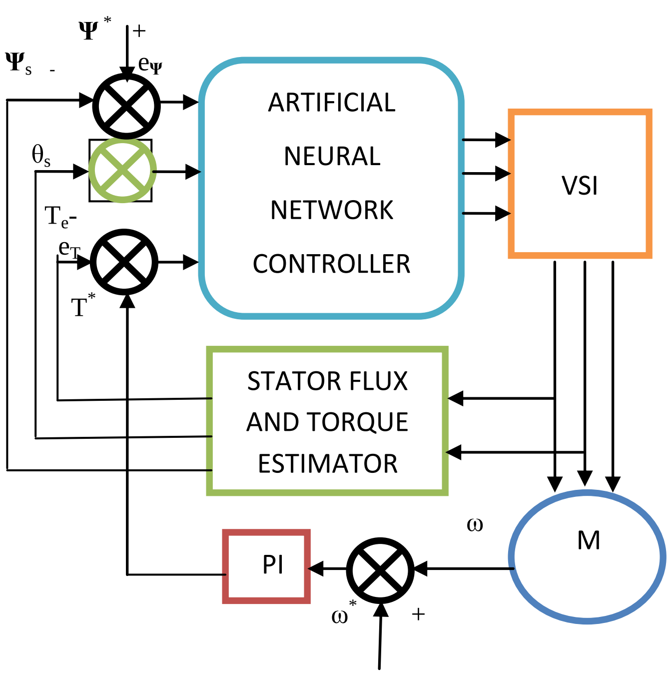

Figure 5 shows the structure of ANN

The basic concept and structure of DTNNC method for asynchronous drive is shown in the figure 5. The ANN replaces the switching table selector block [14,16,20] and the two hysteresis controllers. The figure 6 shows the proposed neural networks have three layers, i.e., input layer, hidden layer and the output layer. The input layer has N neurons, output layer has only one neuron and hidden layer has depends on the input layer and the purpose of control. The ANN inputs are the error between the estimated flux value and its reference value, the difference between the estimated electromagnetic torque and the torque reference and the position of flux stator vector represented by the number of corresponding sector. The output layer is depends upon the inputs and weights of ANN.

3.3 **Simulation results of ANN**

The simulation results of ANN is excellent torque and flux tracking [15-20] can be observed torque ripple is reduced for a considerable rate and stator current is sinusoidal this is shown in figures. The group data which train with back propagation algorithm. The q axis is different state switching which is normalized and denote the output without training and with training respectively.

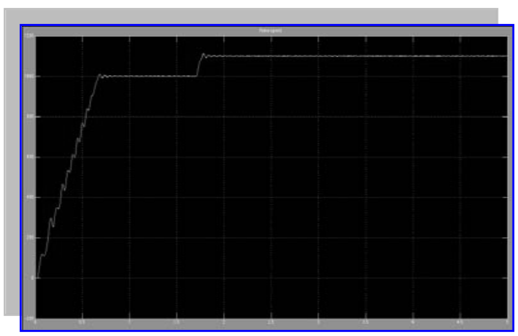

Figure 6 shows the speed response of motor

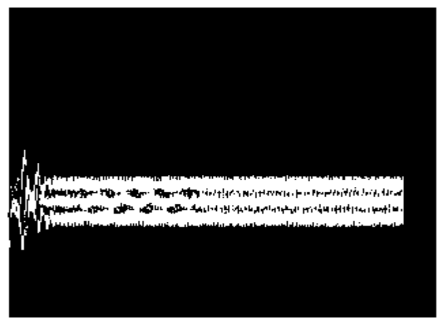

Figure 7 shows the stator current response

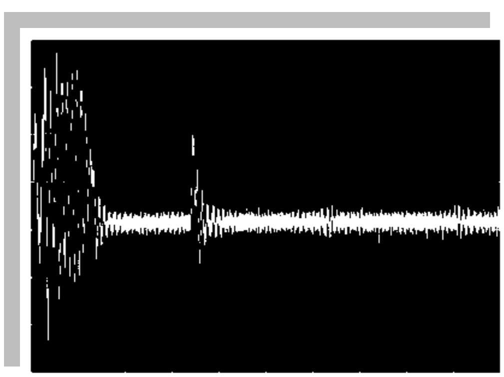

Figure 8 show the electromagnetic torque response

4.0 CONCLUSION AND FUTURE WORK

In this work an improves torque, speed and flux response was achieved with the ANNDTC than the CDTC. The performance has been rested by simulation using MATLAB/SIMULINK. The results show a reasonable improvement by flux optimization, the main improvements are as follows:

- Fast stator flux response in transient state
- Reduction of torque, flux and current ripples in transient and steady state response
- No flux drooping caused by the sector changes circular trajectory
- Reduction of speed ripples in transient and steady state response
- Implementation made easy, because simple algorithm to implemented in ANNDTC.

The future work to improve the performance of rotor speed, torque and flux ripple reduction carried out by using combined intelligent techniques.

5.0 Acknowledgment

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