

# Neural Network Based Predictive DTC Algorithm for Induction Motors

N.Vahdatifar Ss.Mortazavi R.Kianinezhad

**Abstract**—In this paper, a Neural Network based predictive DTC algorithm is proposed. This approach is used as an alternative to classical approaches. An appropriate Feed - forward network is chosen and based on its value of derivative electromagnetic torque ; optimal stator voltage vector is determined to be applied to the induction motor (by inverter). Moreover, an appropriate torque and flux observer is proposed.

**Keywords**—Neural Networks, Predictive DTC

## I. INTRODUCTION

THE use of the induction motor in servo drives is limited by its complex highly coupled nonlinear structure. This complexity implies certain control related problems. However, due to its ruggedness, maintenance free operation and many other advantages, squirrel cage induction motor are still ideal actuators for industrial applications (in some cases).

The basic problem of the induction motor control is the lack of the inverse model. Inverse model could be applied to calculate the desired applied stator voltage from the desired values of torque and flux. Hence, the FOC and later DTC methods were developed [1-5]. However, none of these methods analytically connects applied stator voltages to the torque (although some work has been done in that area [6]). A popular approach is using torque and flux derivative functions for the presentation and execution of DTC [7]. However, in order to get an improved performance other factors like back - emf have to be taken into account. A substantial amount of work has been performed on this subject, and promising results have been obtained with use of predictive algorithms. Several predictive DTC approaches have been presented in last few years [9-13].

In most cases the PWM duty cycle is calculated to reduce the error of torque and flux from their desired values. In [14] the motivation was to use the Lyapunov stability function as a criteria function, which implies the inherent stability of control.

N.VAHDATIFAR is post graduate student of shahid chamran university of iran (corresponding author to provide phone: 0098-0611-3782722 e-mail: vahdatinaser@gmail.com)

SS.MORTAZAVI is now with the Department of Engineering, Shahid Chamran University (corresponding author to provide phone 0098-0611-61355 e-mail: mortazavi\_s@scu.ac.ir).

R.KIANINEZHAD is now with the Department of Engineering, Shahid Chamran University (corresponding author to provide phone 0098-0611-61355 e-mail: reza.kiani@scu.ir).

In this paper, a novel approach using Feedforward network is proposed. Torque and derivative functions are chosen as ANN inputs to calculate the optimal voltage vector.

## II. INDUCTION MOTOR MODEL

In smooth rotor and stator (i.e. with constant air gap), phase windings are symmetrical. Both neutrals of the star connected winding are isolated. The permeability of fully laminated stator and rotor iron is infinite. Saturation, iron losses, end - winding and slot-effects are ignored. Hence, model of a three - phase squirrel cage induction motor in the stator reference frame can be expressed as [1, 2, and 8]:

$$\frac{d\psi_s^s}{dt} = u_s^s - R_s i_s^s \quad (1)$$

$$\frac{d\psi_r^s}{dt} = \frac{L_m}{L_r} R_r i_s^s - R_r \psi_r^s + \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} p \omega_r \psi_r^s \quad (2)$$

$$\frac{di_s^s}{dt} = \frac{1}{\sigma L_s} \left( u_s^s - \left( R_s + R_r \left( \frac{L_m}{L_r} \right)^2 \right) i_s^s - \frac{L_m}{L_r} \frac{R_r}{L_r} \psi_r^s + \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} p \omega_r \frac{L_m}{L_r} \psi_r^s \right) = \frac{1}{\sigma L_s} (u_s^s - e_s^s) \quad (3)$$

$$e_s^s = R_s i_s^s + \left( \frac{L_m}{L_r} \right) \frac{d\psi_r^s}{dt}, \quad (4)$$

$$\psi_s^s = \frac{L_m}{L_r} \psi_r^s + \sigma L_s i_s^s, \quad (5)$$

Where  $\psi_s^s = [\psi_{sa}^s \ \psi_{sb}^s]^T$  is stator flux,  $\psi_r^s = [\psi_{ra}^s \ \psi_{rb}^s]^T$  is rotor flux and  $u_s^s = [u_{sa}^s \ u_{sb}^s]^T$  is the stator voltage, and  $i_s^s = [i_{sa}^s \ i_{sb}^s]^T$  is the stator current,  $\omega_r$  is the rotor axis speed.  $\sigma$  is the total leakage factor ( $\sigma = 1 - L_m^2 / (L_r L_s)$ ) and  $p$  is number of pole pairs.  $R_s$  and  $R_r$  are stator and rotor resistance;  $L_s$  and  $L_r$  denote stator and rotor self - inductance, whereas  $L_m$  is mutual inductance.  $T_e$  the torque produced by the drive is calculated as:

$$T_e = \frac{3p}{2} (\psi_{sa}^s i_{sb}^s - \psi_{sb}^s i_{sa}^s) \quad (6)$$

The mechanism can be presented with the following equation:

$$J \frac{d\omega_r}{dt} = T_e - T_L \quad (7)$$

Where  $J$  is the inertia and  $T_L$  is the applied load torque including motor friction. However, the applied torque derivative can be calculated from (6):

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( \frac{d\psi_{ra}^s}{dt} \psi_{sb}^s + \frac{d\psi_{sb}^s}{dt} \psi_{ra}^s - \frac{d\psi_{rb}^s}{dt} \psi_{sa}^s - \frac{d\psi_{sa}^s}{dt} \psi_{rb}^s \right) \quad (8)$$

With the use of (1), (2) and (3), the equation can be rewritten as:

$$\begin{aligned} \frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} & \underbrace{(\psi_{ra}^s u_{sb}^s - \psi_{rb}^s u_{sa}^s)}_{\text{part1}} - \underbrace{\left( \frac{R_s}{\sigma L_s} + \frac{R_r}{\sigma L_r} \right)}_{\text{part2}} \\ & \underbrace{(\psi_{ra}^s \psi_{sb}^s - \psi_{rb}^s \psi_{sa}^s) - p\omega_r (\psi_{ra}^s \psi_{sa}^s + \psi_{rb}^s \psi_{sb}^s)}_{\text{part2}} \end{aligned} \quad (9)$$

Which result in:

$$\begin{aligned} \frac{dT_e}{dt} = - \left( \frac{R_s}{\sigma L_s} + \frac{R_r}{\sigma L_r} \right) T_e + \frac{3pL_m}{2\sigma L_s L_r} \\ \left( \psi_{ra}^s u_{sb}^s - \psi_{rb}^s u_{sa}^s - p\omega_r (\psi_{ra}^s \psi_{sa}^s + \psi_{rb}^s \psi_{sb}^s) \right) \end{aligned} \quad (10)$$

In a simpler form (10) can be rewritten with the use of (4) as:

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( (\psi_{ra}^s u_{sb}^s - \psi_{rb}^s u_{sa}^s) - (\psi_{ra}^s e_{sb}^s - \psi_{rb}^s e_{sa}^s) \right) \quad (11)$$

### III. DIRECT TORQUE CONTROL

The main idea of Direct Torque Control (DTC) is to directly control the torque and flux produced by the machine, without current control, as it is the case in FOC [4], [5]. Different approaches have been developed [12], [13]. However, in this paper only a basic approach and a new proposed algorithms will be presented.

Let us first present the basic conventional DTC control scheme, as described in [2], [3], [4]. The control scheme is presented in Fig. 2, where in the presentation of sectors of the stator flux angle is included also (Fig. 1). The applied switching table is presented in I. [14]

TABLE I SWITCHING TABLE-STATOR FLUX ORIENTED DTC ALGORITHM

| $\phi$     | $\tau$      | $\theta$ | $\theta(1)$ | $\theta(2)$ | $\theta(3)$ | $\theta(4)$ | $\theta(5)$ | $\theta(6)$ |
|------------|-------------|----------|-------------|-------------|-------------|-------------|-------------|-------------|
| $\phi = 0$ | $\tau = -1$ |          | V5          | V6          | V1          | V2          | V3          | V4          |
|            | $\tau = 0$  |          | V0          | V7          | V0          | V7          | V0          | V7          |
|            | $\tau = 1$  |          | V3          | V4          | V5          | V6          | V1          | V2          |
| $\phi = 1$ | $\tau = -1$ |          | V6          | V1          | V2          | V3          | V4          | V5          |
|            | $\tau = 0$  |          | V1          | V2          | V3          | V4          | V5          | V6          |
|            | $\tau = 1$  |          | V2          | V3          | V4          | V5          | V6          | V1          |

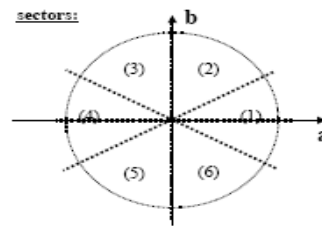


Fig. 1. Sectors which table 1 is configured

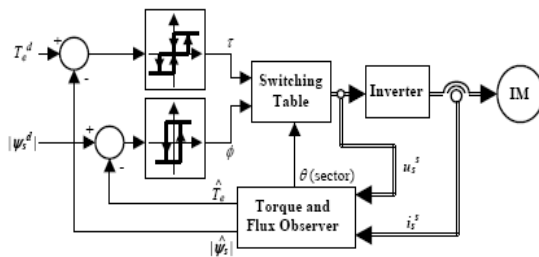


Fig. 2. DTC control scheme - stator flux oriented DTC algorithm

### IV. BASIC PRINCIPLE OF ARTIFICIAL NEURAL NETWORK USED FOR TRAINING

Neural networks have self-adapting compatibilities which makes them well suited to handle non-linearities, uncertainty and parameter variations. A multilayered feed forward neural network constructs a global approximation to non-linear input-output mapping [15]. Neural networks are capable of generalization in regions of the input space, where little or no training data are available. The structure of the proposed neural network used in this paper, is shown in Fig. 3

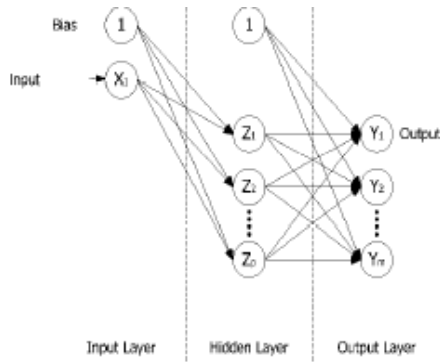


Fig. 3. Structure of proposed artificial neural networks

The proposed neural networks have three layers, i.e. input layer, hidden layer and the output layer. Input layer has 10 neurons, output layer has only one neuron and hidden layer has 15 neurons. Momentum coefficient, learning rate and final error is 0.9, 0.09 and 1e-6 respectively. Neural network based predictive control scheme is present in Fig.4.

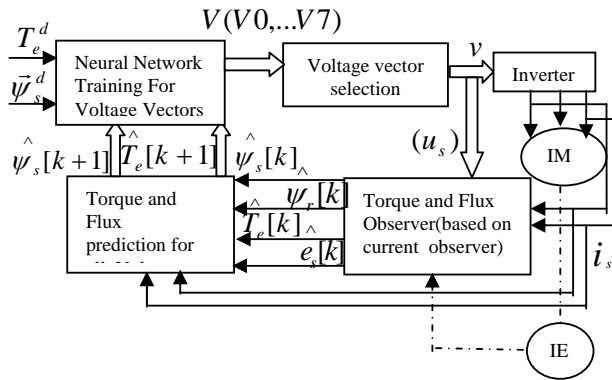


Fig. 4. Neural network based predictive control scheme.

In order to reach the best convergence behavior, the voltage vector is selected from the existing 8 (actually 7) choices. The equation 9 has two parts. Part 2 is independent of voltage vector. Values of the inputs of neural network are divided to 7 vectors according to 7 switching states. However, the following formulas are calculated (estimated values are denoted by ^):

$$\frac{dT_e}{dt}[k] = \frac{3pL_m}{2\sigma L_s L_r} \begin{pmatrix} \begin{pmatrix} \hat{\psi}_{ra}^s[k]u_{sb}^s[k] - \hat{\psi}_{rb}^s[k]u_{sa}^s[k] \\ \hat{\psi}_{ra}^s[k]e_{sb}^s[k] - \hat{\psi}_{rb}^s[k]e_{sa}^s[k] \end{pmatrix} \end{pmatrix} \quad (12)$$

$$\frac{d\hat{i}_s}{dt} = \frac{1}{\sigma L_s}(u_s^s - \hat{e}_s^s) \quad (13)$$

$$\hat{T}_e[k+1] = \hat{T}_e[k] + T \frac{d\hat{T}_e}{dt}[k], \quad (14)$$

$$\hat{\psi}_s^s[k+1] = \hat{\psi}_s^s[k] + T \frac{d\hat{\psi}_s^s}{dt}[k], \quad (15)$$

## V . TORQUE AND FLUX OBSERVOR

Torque and flux observer (Fig. 5) is based on (3), which is rewritten in following form [14]:

$$\frac{d\hat{\psi}_s^s}{dt} = u_s^s[k] - R_s \hat{i}_s^s[k], \quad (16)$$

Where

$$\hat{e}_s^s = R_s \hat{i}_s^s + \left( \frac{L_m}{L_r} \right) \left( \frac{d\hat{\psi}_r^s}{dt} + k(\hat{i}_s^s - i_s^s) \right) \quad (17)$$

and

$$\frac{d\hat{\psi}_r^s}{dt} = \frac{L_m}{L_r} R_r \hat{i}_s^s - \frac{R_r}{L_r} \hat{\psi}_r^s + k(\hat{i}_s^s - i_s^s). \quad (18)$$

Stator flux is calculated with (5), whereas torque calculation is performed with (6).

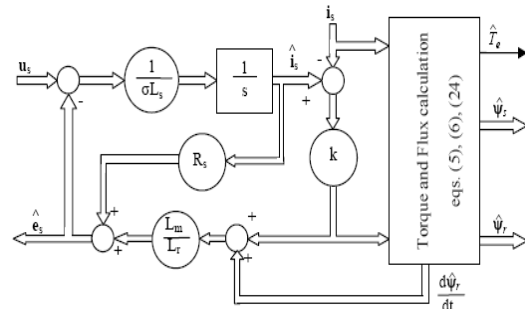


Fig. 5 Torque and Flux observer based on the current observer.

## VI . SIMULATION RESULTS

Simulation results for the presented algorithm are shown in Fig 5 – 12. Excellent torque and flux tracking can be observed, torque ripple is reduced for a considerable rate and stator current is sinusoidal. Fig.5 shows the seven group data which train with back propagation algorithm. The quadrature axis is different state switching which is normalized. The . and denote to output without training and with training respectively. Fig.7 shows difference between target and output of neural network in different outputs. Stator voltages are presented in Fig.11.

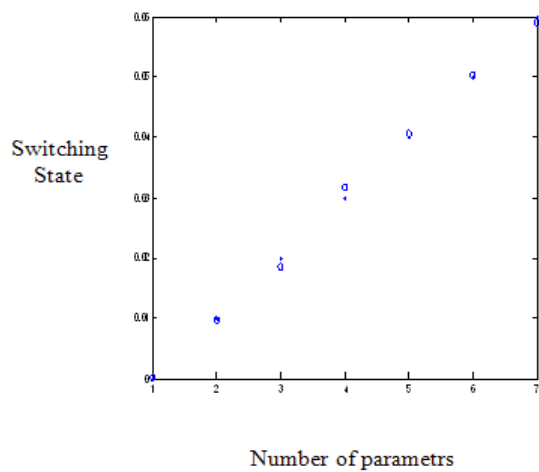


Fig. 6. Output after training network

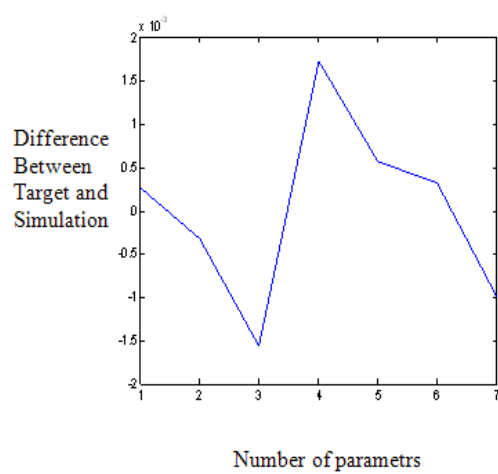


Fig.7. Difference between target and simulation result

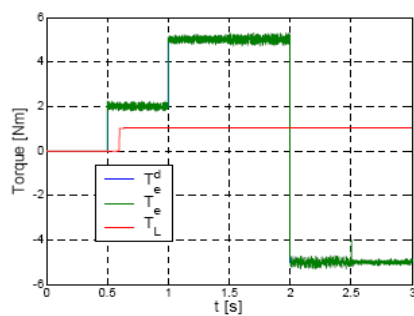
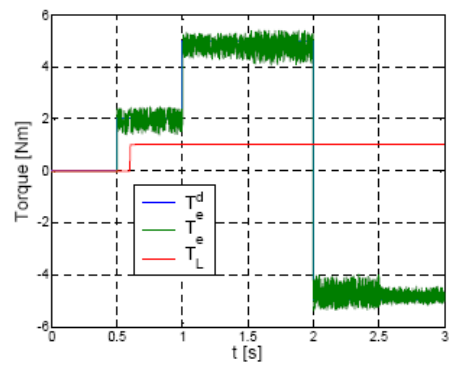
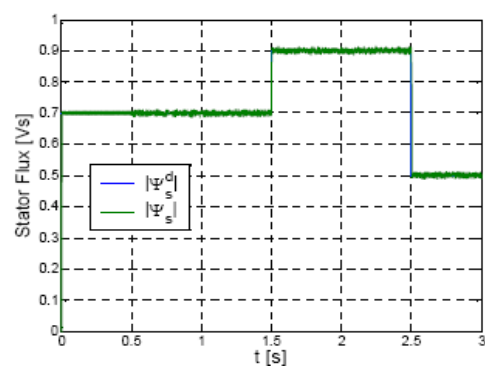
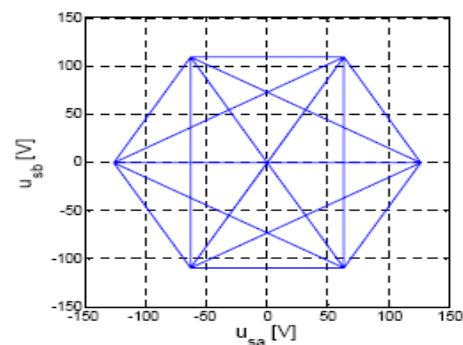

Fig. 8. Simulation results – Neural network based DTC Applied torque ( $T_e$ ), its desired value ( $T_d$ ) and applied load torque ( $T_L$ ).

Fig. 9. Simulation result- classic DTC – Applied torque ( $T_e$ ), its desired value ( $T_d$ ) and applied load torque ( $T_L$ ).

Fig. 10. Simulation results – Neural network based DTC - Stator flux ( $|\psi_s|$ ) and its desired value ( $|\psi_s^d|$ )


Fig. 11. Simulation results – Neural network based DTC - Stator voltage

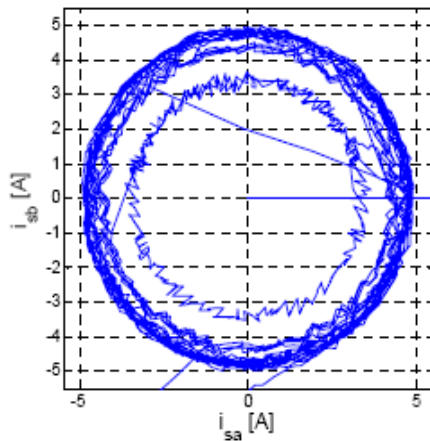


Fig. 12. Simulation results Neural network based DTC - Stator current

## VII. CONCLUSION

A neural network based predictive DTC for induction motors is presented in this paper. To control the motor, an appropriate torque and flux observer is proposed also. Torque and its derivative are chosen as ANN inputs to calculate the optimal voltage vector. It is shown in simulation results, that under identical conditions the results obtained by the use of proposed method, are improved compared to classical DTC, which is especially true for the torque ripple. Torque ripple is reduced by a considerable ratio due to soft interpolation property of ANN. A comprehensive simulation study in MATLAB shows satisfactory results.

## REFERENCES

- [1] W. Leonhard, Control of Electric Drives, Springer Verlag, Berlin, Germany, 3rd edition, 2001.
- [2] P. Vas, Vector Control of AC Machines, Clarendon press, Oxford, 1990.
- [3] J. H. Nash, "Direct Torque Control, Induction Motor Vector Control Without an Encoder", IEEE Transactions on Industry Applications, vol. 33, no. 2, March/April 1986, pp. 333-341.
- [4] I. Takahashi, T. Noguchi, "A New Quick Response and High-Efficiency Control Strategy of an Induction Motor", IEEE Transactions on Industry Applications, vol. IA-22, no. 5, September/October 1986, pp. 820-827.
- [5] I. Boldea, Direct Torque and Flux Control (DTFC) of A.C. Drives: A Review, in Proceedings of EPEPEMC'2000, Vol. 1, Kosice, Slovakia, 2000, pp. 88-97.
- [6] C.A. Martins, T.A. Meynard, X. Roboam, A.S. Carvalho, "A predictive sampling scale model for direct torque control of the induction machine fed by multilevel voltage-source inverter", The European Physical Journal. Applied Physics 5, 1999, pp. 51-61.
- [7] T.G. Habetler, F. Profumo, M. Pastorelli, L.M. Tolbert, "Direct torque control of induction machines using space vector modulation", IEEE Transactions on Industry Applications, Volume 28, Issue 5, Sept.- Oct. 1992 pp. 1045 – 1053.
- [8] J. Holtz, "The Representation of AC Machine Dynamics by Complex Signal Flow Graphs," IEEE Transactions on Industrial Electronics, vol. 42, no. 3, June 1995, pp. 263-271.
- [9] J. Kley, G. Papafotiou, K. Papadopoulos, P. Bohren, M. Morari, Performance evaluation of model predictive direct torque control, in Proceedings of Power Electronics Specialists Conference, 2008, PESC 2008, Rhodes, Greece, June 2008, pp. 4737-4744.
- [10] S. Kaboli M. R. Zolghadr, D. Roye, J. Guiraud, J.-C. Crebier, Design and Implementation of a Predictive Controller for Reducing the Torque Ripple in Direct Torque Control Based Induction Motor Drives, in Proceedings of 35th Annual IEEE Power Electronics Specialist's Conference, Aachen, Germany, 2004, pp. 476–481.
- [11] G. Papafotiou, T. Geyer and M. Morari, Optimal Direct Torque Control of Three-Phase Symmetric Induction Motors, 43rd IEEE Conference on Decision and Control, in Proceedings of, Atlantis, Paradise Island, Bahamas, December 2004, pp. 1860–1865.
- [12] M. Pacas, J. Weber, "Predictive Direct Torque Control for the PM Synchronous Machine", IEEE Transactions on Industrial Electronics, Vol. 52, No. 5, October 2005, pp. 1350 – 1356.
- [13] G. Gatto, I. Marongiu, A. Serpi, A. Perfetto, A Predictive Direct Torque Control of Induction Machines, in Proceedings of SPEEDAM 2008, June 2008, Ischia, Italy, pp. 1103-1108.
- [14] Rodic, M. Jezernik, K. "Lyapunov Based Predictive Dtc Algorithm For Induction Motors", Power Electronics And Applications, 2009, EPE, 09.13<sup>th</sup> European Conference On 8-10 Sept. 2009.
- [15] S. Panta, S. Premrudeepreechacharn, S. Nuchprayoon, C. Dechthummarong, S. Janjornmanit and S. Yachiangkam, Optimal Economic Dispatch For Power Generation Using Artificial Neural Network, The 8<sup>th</sup> International Power Engineering Conference (IPEC2007).