Intelligence Approaches Based Direct Torque Control of Induction Motor

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Abstract. This paper presents a comparative study of two intelligent techniques to replace conventional comparators and selection table of direct torque control for induction machines, namely fuzzy logic and artificial neural network. The comparison with the conventional direct torque control proves that FL-DTC and NN-DTC reduces the electromagnetic torque ripple, stator flux, and stator current. Simulation results prove the effectiveness and the performances proposed strategies.

Keywords: artificial neural network, direct torque control, fuzzy logic, induction motor.

1 Introduction

A simplified variation of field orientation known as direct torque control (DTC) was developed by Takahashi [1]-[2] and Depenbrock [3]. In direct torque controlled induction motor drives, it is possible to control directly the stator flux linkage and the electromagnetic torque by the selection of an optimum inverter switching state. The selection of the switching state is made to restrict the flux and the torque errors within their respective hysteresis bands and to obtain the fastest torque response and highest efficiency at every instant [4]-[5]. DTC is simpler than field-oriented control and less dependent on the motor model, since the stator resistance value is the only machine parameter used to estimate the stator flux [6].

High torque ripple is one of the disadvantages of DTC [5]. Under constant load in steady state, an active switching state causes the torque to continue to increase past its reference value until the end of the switching period; then a zero voltage vector is applied for the next switching period causing the torque to continue to decrease below its reference value until the end of the switching period. That results in high torque ripple. A possible solution to reduce the torque ripple is to use a high switching frequency; however, that requires expensive processors and switching devices [7]-[8]. A less expensive solution is to use artificial intelligence control. In this article we propose two intelligent approaches namely fuzzy logic and artificial neural networks to replace conventional hysteresis comparators and selection table.

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An artificial neural network (ANN) is essentially a way to learn the relationship between a set of input data and the corresponding output data. That is, it can memorize data, generalize this information when given new input data, and adjust when the relationship changes. The training is normally done with input-output examples. After training, ANNs have the capability of generalization. That is, given previously unseen input data, they can interpolate from the previous training data [9]-[10]. Inspired by the functioning of biological neurons, ANN became popular in the research community when architectures were found to enable the learning of nonlinear functions and patterns [10]-[11].

The fuzzy reasoning approach can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis [12]-[13]. This approach provides an efficient way to cope with imperfect information and imprecise knowledge. It offers some kind of flexibility in decision making processes and is especially useful when a process can be controlled by a skilled human without knowledge of its underlying dynamics [12]-[14]-[15].

This paper is organized as follows: The principle of direct torque control is presented in the second part, the direct torque fuzzy control is developed in the third section, section four presents a direct torque neural control, and the fifth part is devoted to illustrate the simulation performance of this control strategy, a conclusion and reference list at the end.

Symbols:

R_s , R_r	stator and rotor resistance [Ω]
i_{sd} , i_{sq}	stator current dq axis [A]
v_{sd} , v_{sq}	stator voltage dq axis [V]
L_s , L_r	stator and rotor self inductance [H]
L_m	mutual inductance [H]
λ_{sd}, λ_{sq}	dq stator flux [Wb]
λ_{rd}, λ_{rq}	dq rotor flux [Wb]
T_e	electromagnetic torque [N.m]
E_{Te}	electromagnetic torque error [N.m]
$E_{\lambda s}$	stator flux error [Wb]
φ_s	stator flux angle [rad]
ω_r	rotor speed [rad/sec]
J	inertia moment [Kg.m^2]
p_p	pole pairs
σ	leakage coefficient
t_s	sampling period [sec]

2 Direct Torque Control

The principle of DTC is to directly select voltage vectors according to the difference between reference and actual value of electromagnetic torque and stator flux linkage.

Electromagnetic torque and stator flux errors are compared in hysteresis comparators. Depending on the comparators a voltage vector is selected from a table [16]-[17]. This can be explained by looking at the two following equations of the induction motor:

$$\begin{cases} \dfrac{d\lambda_s}{dt} = -\dfrac{R_s}{L_s}\lambda_s + \dfrac{R_s L_m}{\sigma L_s L_r}\lambda_r + v_s \\ \dfrac{d\lambda_r}{dt} = \dfrac{R_s L_m}{\sigma L_s L_r}\lambda_s + \left(jp_p\omega_r - \dfrac{R_r}{\sigma L_r}\right)\lambda_r \end{cases} \quad \text{with } \sigma = 1 - \frac{L_m^2}{L_s L_r} \tag{1}$$

In the following a digital control is considered with sampling period t_s very short with respect to the motor time constants. In a generic $(k+1)t_s$ instant the stator and rotor flux space-vectors can be evaluated by means of the simplified expressions:

$$\begin{cases} \lambda_{s,k+1} = \lambda_{s,k} + \dfrac{d\lambda_{s,k}}{dt}t_s = \lambda_{s,k} + \left(-\dfrac{R_s}{L_s}\lambda_{s,k} + \dfrac{R_s L_m}{\sigma L_r L_s}\lambda_{s,k} + v_{s,k}\right)t_s \\ \lambda_{r,k+1} = \lambda_{r,k} + \dfrac{d\lambda_{r,k}}{dt}t_s = \lambda_{r,k} + \left(\dfrac{R_s L_m}{\sigma L_r L_s}\lambda_{s,k} + \left(jp_p\omega_r - \dfrac{R_r}{\sigma L_r}\right)\lambda_{r,k}\right)t_s \end{cases} \tag{2}$$

In terms of stator and rotor flux the electromagnetic torque is:

$$T_{e,k} = \frac{3}{2}p_p \frac{L_m}{\sigma L_s L_r}\operatorname{Im}\left\{\lambda_{s,k}\lambda_{r,k}\right\} \tag{3}$$

where Im [ ] represents the imaginary part of the expression in brackets.
The electromagnetic torque variation $\Delta T_{e,k}$ in each sampling interval:

$$\Delta T_{e,k} = T_{e,k+1} - T_{e,k} \tag{4}$$

Can be evaluated by introducing Eq. (2) in (3) and neglecting the terms containing the square of t_s:

$$\Delta T_{e,k} = -T_{e,k}\left(\frac{R_s}{L_s} + \frac{R_r}{L_r}\right)t_s + \frac{3}{2}p_p \frac{L_m}{\sigma L_s L_r} I_m\left\{\left(v_{s,k}\lambda_{r,k}\right) - jp_p\omega_{r,k}\left(\lambda_{s,k}\lambda_{r,k}\right)\right\}t_s \tag{5}$$

A discrete from of stator flux in a generic sampling instant can be obtained:

$$\lambda_{s,k+1} = \lambda_{s,k} + \left(v_{s,k} - R_s i_{s,k}\right)t_s \tag{6}$$

From Eq. (9) the variations of the stator flux magnitude:

$$\Delta\lambda_{s,k} = \left|\lambda_{s,k+1}\right| - \left|\lambda_{s,k}\right| \tag{7}$$

can be easily evaluated as a function of the applied voltage. By a proper analysis of Eqs. (5) and (7), useful information can be yield about the influence both on stator flux and torque of a generic inverter voltage space vector, in correspondence of a fixed operating condition. The DTC optimum switching table is shown in Table 1.

Table 1. Switching table for conventional direct torque control

$E_{\lambda s}$	E_{Te}	n_1	n_2	n_3	n_4	n_5	n_6
1	1	V_2	V_3	V_4	V_5	V_6	V_1
	0	V_7	V_0	V_7	V_0	V_7	V_0
	-1	V_6	V_1	V_2	V_3	V_4	V_5
0	1	V_3	V_4	V_5	V_6	V_1	V_1
	0	V_0	V_7	V_0	V_7	V_0	V_7
	-1	V_5	V_6	V_1	V_2	V_3	V_4

3 Fuzzy Logic Based Direct Torque Control

The structure of the switching table can be translated in the form of vague rules. Therefore, we can replace the switching table and hysteresis comparators by a fuzzy system whose inputs are the errors on the flux and torque denoted $E_{\lambda s}$ and E_{Te} and the argument φ of the flux. The output being the command signals of the voltage inverter n. The fuzziness character of this system allows flexibility in the choice of fuzzy sets of inputs and the capacity to introduce knowledge of the human expert.

The i^{th} rule R_i can be expressed as:

$$R_i\text{: if } E_{Te} \text{ is } A_i,\ E_{\lambda s} \text{ is } B_i, \text{ and } \varphi \text{ is } E_i, \text{ then } n \text{ is } N_i \tag{8}$$

where A_i, B_i and C_i denote the fuzzy subsets and N_i is a fuzzy singleton set.

The synthesized voltage vector n denoted by its three components is the output of the controller.

The inference method used in this paper is Mamdani's [18] procedure based on min-max decision [19]. The firing strength η_i, for i^{th} rule is given by:

$$\eta_i = \min\left(\mu_{A_i}(E_{T_e}), \mu_{B_i}(E_{\lambda_s}), \mu_{C_i}(\varphi)\right) \tag{9}$$

By fuzzy reasoning, Mamdani's minimum procedure gives:

$$\mu'_{N_i}(n) = \min\left(\eta_i, \mu_{N_i}(n)\right) \tag{10}$$

where μ_A, μ_B, μ_C, and μ_N are membership functions of sets A, B, C and N of the variables E_{Te}, $E_{\lambda s}$, φ and n, respectively.

Thus, the membership function μ_N of the output n is given by:

$$\mu_N(n) = \max_{i=1}^{72}\left(\mu'_{N_i}(n)\right) \tag{11}$$

We chose to share the universe of discourse of the stator flux error into two fuzzy sets, that of electromagnetic torque error in five and finally for the flux argument into seven fuzzy sets. This choice was based on Table 1. However the number of membership functions (fuzzy set) for each variable can be increased and therefore the accuracy is improved. All the membership functions of fuzzy controller are given in Fig. 1.

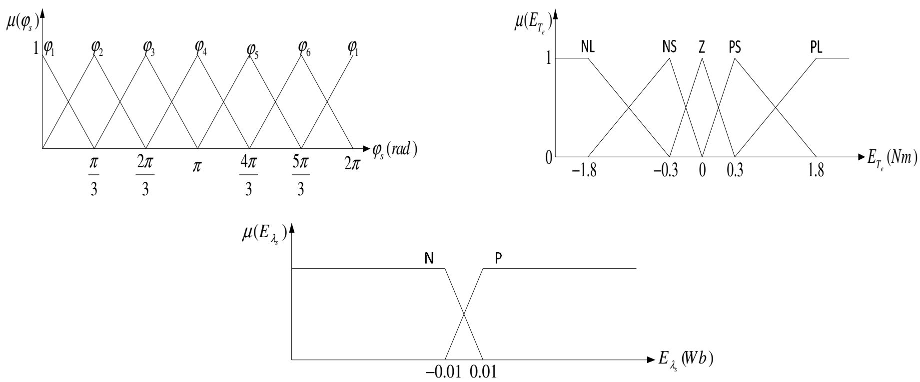


Fig. 1. Membership functions for fuzzy logic controller

Table 2. Fuzzy rules

		φ					
$E_{\lambda s}$	E_{Te}	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6
	P	V_6	V_2	V_3	V_1	V_5	V_4
PL	Z	V_4	V_6	V_2	V_3	V_1	V_5
	N	V_5	V_4	V_6	V_2	V_3	V_1
	P	V_6	V_2	V_3	V_1	V_5	V_4
PS	Z	V_7	V_0	V_7	V_0	V_0	V_0
	N	V_5	V_4	V_6	V_2	V_3	V_1
	P	V_2	V_3	V_1	V_5	V_4	V_6
NS	Z	V_0	V_7	V_0	V_7	V_0	V_7
	N	V_1	V_5	V_4	V_6	V_2	V_3
	P	V_2	V_3	V_1	V_5	V_4	V_6
NL	Z	V_3	V_1	V_5	V_4	V_6	V_2
	N	V_1	V_5	V_4	V_6	V_2	V_3

4 Neural Network Based Direct Torque Control

This section presents the outline of neural networks to emulate the table of inverter switching states of DTC. The input signals of the table are the errors of electromagnetic torque, stator flux and the position vector of flux. The output signals are the inverter switching states n_a, n_b and n_c. As the switching table depends only on the electromagnetic torque error, stator flux angle and sector where the flux is located, and induction motor parameters, this neural network can be trained independently of the set. With the changes in the switching table reduces the training patterns and increases the execution speed of training process. This has been achieved by reducing the table to convert input analog signals to a digital bit for the flux error, two bits for the torque error and three bits for the flux position, which has a total of six inputs and three outputs, and only sixty-four training patterns. With these modifications, the network used to simulate has the advantage that it is independent of parameter variation of induction motor. This allows applying to any induction motor irrespective of its power.

From the flux space vectors λ_{ds} and λ_{qs} we can calculate the flux angle φ and flux magnitude λ_s. The coding of the flux angle is given by ξ_1, ξ_2 and ξ_3 according to following equations:

$$\lambda_s = \sqrt{\lambda_{ds}^2 + \lambda_{qs}^2}\ ,\ \varphi_s = \tan^{-1}\frac{\lambda_{ds}}{\lambda_{qs}},\ \xi_1\xi_2\xi_3 = encoder(\varphi_s) \tag{12}$$

$$\xi_1 = \begin{cases} 1 & \lambda_{qs} \ge 0 \\ 0 & otherwise \end{cases} \tag{13}$$

$$\xi_2 = \begin{cases} 1 & \left(\frac{\lambda_{qs}}{\lambda_{ds}} \ge -\tan(\frac{\pi}{3}) \quad and \quad \lambda_{ds} \prec 0\right) or \left(\frac{\lambda_{qs}}{\lambda_{ds}} \prec -\tan(\frac{\pi}{3}) \quad and \quad \lambda_{qs} \prec 0\right) \\ 0 & otherwise \end{cases} \tag{14}$$

$$\xi_3 = \begin{cases} 1 & \left(\frac{\lambda_{qs}}{\lambda_{ds}} \prec \tan(\frac{\pi}{3}) \quad and \quad \lambda_{ds} \ge 0\right) or \left(\frac{\lambda_{qs}}{\lambda_{ds}} \ge \tan(\frac{\pi}{3}) \quad and \quad \lambda_{qs} \prec 0\right) \\ 0 & otherwise \end{cases} \tag{15}$$

The network structure used, as shown in Fig. 2 has an input layer with five neurons, a first hidden layer with six neurons, a second hidden layer with five neurons and an output layer with three neurons. After training satisfactory, taking the weights and thresholds calculated and placed into the neural network prototype replacing the switching table. This network is incorporated as a part of the DTC.

5 Simulation Results

To compare and verify the proposed techniques in this paper, a digital simulation based on Matlab/Simulink program with a Neural Network Toolbox and Fuzzy Logic Toolbox is used to simulate the NN-DTC and FL-DTC, as shown in Fig. 4. The block diagram of a C-DTC/FL-DTC/NN-DTC controlled induction motor drive fed by a 2-level inverter is shown in Fig. 3. The induction motor used for the simulation studies has the following parameters:

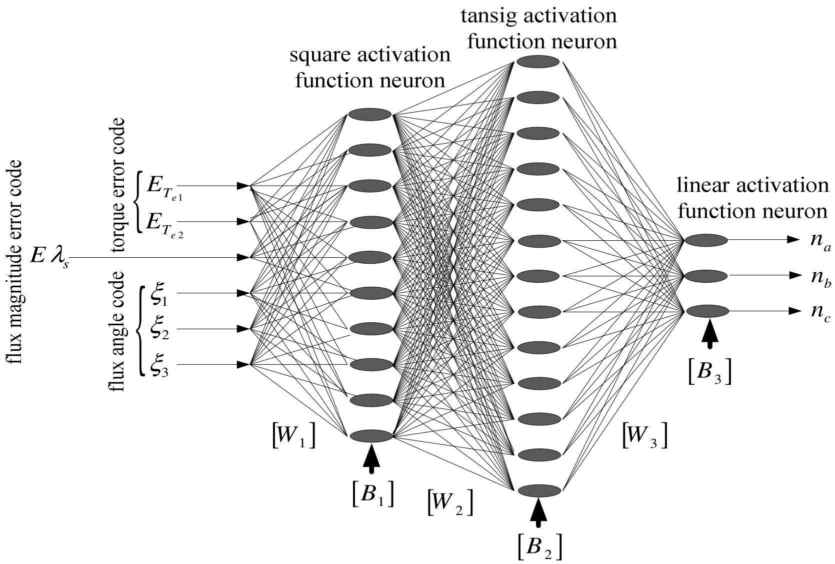


Fig. 2. Neural-network implementation of DTC

Rated power = 7.5kW, Rated voltage = 220V, Rated frequency = 60Hz, R_r = 0.17Ω, R_s = 0.15Ω, L_r = 0.035H, L_s = 0.035H, L_m = 0.0338H, J = 0.14kg.m^2.

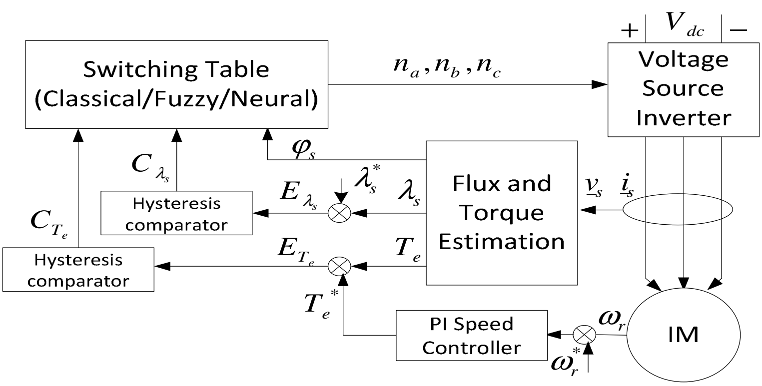
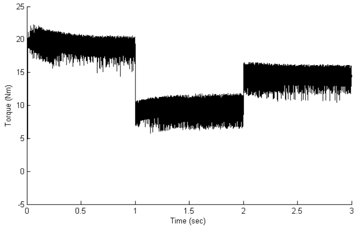
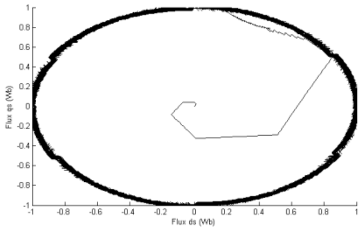


Fig. 3. General configuration of C-DTC/FL-DTC/NN-DTC scheme

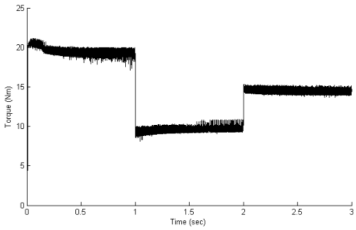
Figs. 4(a), 4(b) and 4(c) show the torque response of the C-DTC, FL-DTC and NN-DTC respectively with a torque reference of [20-10-15] Nm. While Figs. 4(a'), 4(b') and 4(c') show the flux response of the C-DTC, FL-DTC and NN-DTC respectively with a stator flux reference of 1Wb.



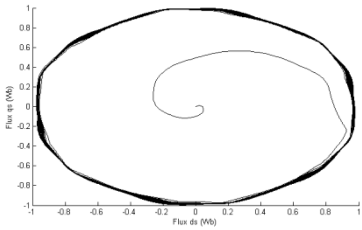
a



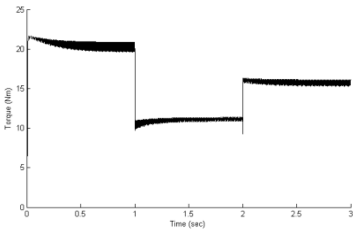
a'



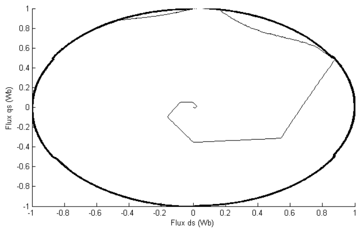
b



b'



c



c'

Fig. 4. (a), (b) and (c) torque response of C-DTC, FL-DTC and NN-DTC respectively, (a'), (b') and (c') Stator flux trajectory response of C-DTC, FL-DTC and NN-DTC respectively

Table 3 represents the comparative results in both stator flux and torque ripples percentage for C-DTC, FL-DTC and NN-DTC. The steady state response for the torque in NN-DTC is faster and provided more accuracy compared to other control strategies presented in this paper.

Table 3. Comparative study of C-DTC, FL-DTC and NN-DTC

Control strategies	Torque ripple (%)	Flux ripple (%)	Rise time (sec)	Setting time (sec)
C-DTC	10.6	2.3	0.009	0.01
FL-DTC	3.9	2.1	0.007	0.0085
NN-DTC	2.9	1.6	0.006	0.0082

6 Conclusions

A comparative study of C-DTC, FL-DTC and NN-DTC for an inverter fed induction motor drive was proposed in this paper. A better precision in the torque and flux responses was achieved with the NN-DTC method with greatly reduces the execution time of the controller; hence the steady-state control error is almost eliminated. The application of neural network techniques simplifies hardware implementation of direct torque control and it is envisaged that NN-DTC induction motor drives will gain wider acceptance in future.

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