Chapter 144
Direct Torque Control for Induction Motor Based on Fuzzy-Neural Network Space Vector Modulation

Cai Binjun, Ming XiaoBo and Li Chunju

Abstract In order to improve direct torque control (DTC) system dynamic performance and low-speed performance for space vector modulation (SVM) were analysed. The two PI controllers which were used to generate reference voltage vector in conventional SVM–DTC were analyzed. The parameters of PI controller are difficult to determine. A novel control strategy of DTC induction motor based on fuzzy-neural was proposed. The design process of the neural network controller which generates the flux reference voltage vector and fuzzy controller by applying the torque reference voltage vector was represented. Simulations and experiments were carried out to verify the proposed strategy, and the results were compared with conventional SVM–DTC. The simulation and experiment results verify whether the fuzzy-neural network SVM–DTC is capable of effectively improving the control performance, especially improving SVM–DTC system's low-speed performance.

Keywords Induction motors · Direct torque control · SVM · Fuzzy control · Neural-network control · Low-speed performance

A project supported by scientific research fund of Hunan Provincial Education Department (09C261/09C262).

C. Binjun (✉) · L. Chunju
Hunan Institute of Engineering, Xiangtan 411104, China
e-mail: Cbj12@163.com

M. XiaoBo
Department of Information Engineering, ShangRao Vocational Technical College, ShangRao 334109, China

Y. Yang and M. Ma (eds.), *Green Communications and Networks*,
Lecture Notes in Electrical Engineering 113, DOI: 10.1007/978-94-007-2169-2_144,

144.1 Introduction

Direct torque control (DTC) is a novel high-performance control strategy in the field of AC drives. Compared with complex coordinate transformation in vector control, DTC can be realized easily in digital with simple structure, while problems exist as well. Firstly, the switching frequency of voltage souse inverter is Non-Fixing. Non-Fixing switching frequency causes switching capability of the inverter not to be used fully [1, 2]. Secondly, there is sharp increase or decrease of torque because only one voltage vector works in a sampling period and the options of vector are limited [3].

Many scholars have put forward a lot of solutions for the inherent problem in DTC system. One of the methods is to apply algorithm of space vector modulation (SVM) in DTC system [4]. The key issue for SVM algorithm is how to obtain the reference voltage vector. In conventional SVM–DTC, two PI controllers are used to generate the two components of reference voltage vector. In theory, the reference voltage vector can accurately compensate error of Torque and flux. But in practice conventional SVM–DTC cannot achieve a precise control for two reasons. One is that the determination of the PI controller parameters is subject to repeated try. The other is that control performance of PI controller depends on exact observation on torque and flux [5]. The inaccurate observation occurred in motor controlling when motors work in a low speed.

Fuzzy logic control has manifested its robustness, and has been extensively researched and used as one of the intelligent control methods in control field [6, 7]. To further improve the performance of torque control and to enhance the system robustness, a novel SVM–DTC strategy of induction motors has been proposed. The new SVM–DTC strategy uses fuzzy-neural-network controller to substitute the original PI controller.

144.2 Theory of Direct Torque Control

Direct torque control system applies mathematical analysis about space vector, and is stator flux orientated. The flux–linkage equations of induction machines in the stator stationary reference frame as follows:

$$\psi_{\alpha s} = \int (v_{\alpha s} - R_s i_{\alpha s})\mathrm{d}t \tag{144.1}$$

$$\psi_{\beta s} = \int \left(v_{\beta s} - R_s i_{\beta s}\right)\mathrm{d}t \tag{144.2}$$

where $\psi_{\alpha s}$ and $\psi_{\beta s}$ are the α-axis and β-axis component of $\overrightarrow{\psi}_s$, respectively; $v_{\alpha s}$ and $v_{\beta s}$ are the α-axis and β-axis component of $\overrightarrow{v}_s$, respectively; $i_{\alpha s}$ and $i_{\beta s}$ are the α-axis and β-axis component of $\overrightarrow{i}_s$,respectively.

The electromagnetic torque can be expressed using the following equation:

$$T_e = \frac{3}{2} n_p (\vec{\psi}_s \times \vec{i}_s) = \frac{3}{2} n_p (\psi_{\alpha s} i_{\beta s} - \psi_{\beta s} i_{\alpha s}) \tag{144.3}$$

where T_e is electromagnetic torque and n_p is the number of rotor pole pairs.

144.3 The Fuzzy-Neural Network SVM–DTC Scheme

144.3.1 Theory of Voltage Space Vector Modulation

Voltage space vector modulation can synthesize reference voltage vector with arbitrary size and direction by using adjacent basic voltage space vector

$$\vec{U}_s = \frac{t_1}{T_0} \vec{U}_1 + \frac{t_2}{T_0} \vec{U}_2 + \frac{t_3}{T_0} \vec{U}_0 \tag{144.4}$$

where $\vec{U}_1$ and $\vec{U}_2$ are the basic voltage vectors; $\vec{U}_0$ is the zero vector; and $\vec{U}_s$ is the reference voltage vector. $T_0 = t_1 + t_2 + t_3$, T_0 is a control cycle.

Formula (144.4) is transferred to two-phase static coordinate system as follows:

$$u_{\alpha s} = \frac{t_1}{T_0} u_1 \cos\theta_1 + \frac{t_2}{T_0} u_2 \cos\theta_2 \tag{144.5}$$

$$u_{\beta s} = \frac{t_1}{T_0} u_1 \sin\theta_1 + \frac{t_2}{T_0} u_2 \sin\theta_2 \tag{144.6}$$

where θ_1 is the angle between vector $\vec{U}_1$ and the positive direction of α-axis. θ_2 is the angle between vector $\vec{U}_2$ and the positive direction of α-axis. $u_{\alpha s}$ and $u_{\beta s}$ are the α-axis and β-axis component of $\vec{U}_s$, respectively.

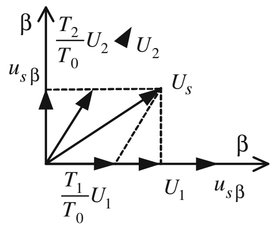
The effect time of basic voltage vector is answered by (144.5) and (144.6). The example of applying basic voltage vector $\vec{U}_1$ and $\vec{U}_2$ to synthesize reference voltage vector $\vec{U}_s$ is illustrated in Fig. 144.1. Substituting $\theta_1 = 0°$ and $\theta_2 = 60°$ in (144.5) and (144.6) yields

$$t_1 = \frac{(3u_{\alpha s} - \sqrt{3}u_{\beta s})T_0}{3u_4} \tag{144.7}$$

$$t_2 = \frac{2\sqrt{3}T_0 u_{\beta s}}{3u_6} \tag{144.8}$$

$$t_3 = T_0 - t_1 - t_2 \tag{144.9}$$

Fig. 144.1 Systhesize reference voltage vector



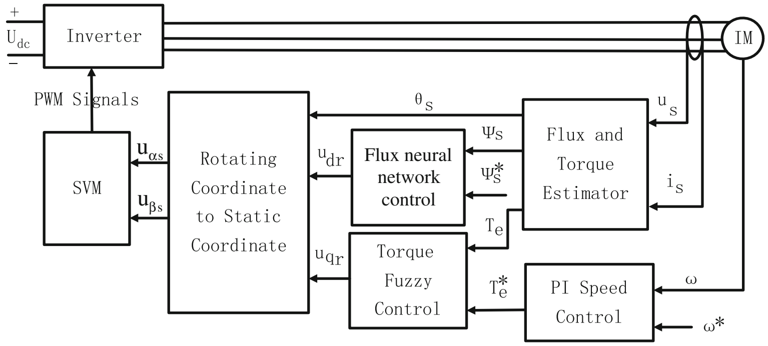


Fig. 144.2 Fuzzy-neural network SVM–DTC system block diagram

144.3.2 Fuzzy-Neural Network SVM–DTC Scheme

The voltage vector can compensate the flux linkage error and torque error is named reference voltage vector. The core issue of SVM–DTC algorithm is how to obtain the reference voltage vector. Figure 144.2 is principle block diagram of improved SVM–DTC.

In Fig. 144.2, the d-axis component of reference voltage vector in the rotor frame is generated by using flux neural-network controller to tackle the flux error, and the q-axis component of reference voltage vector in the rotor frame is generated by using torque fuzzy controller to tackle the torque error.

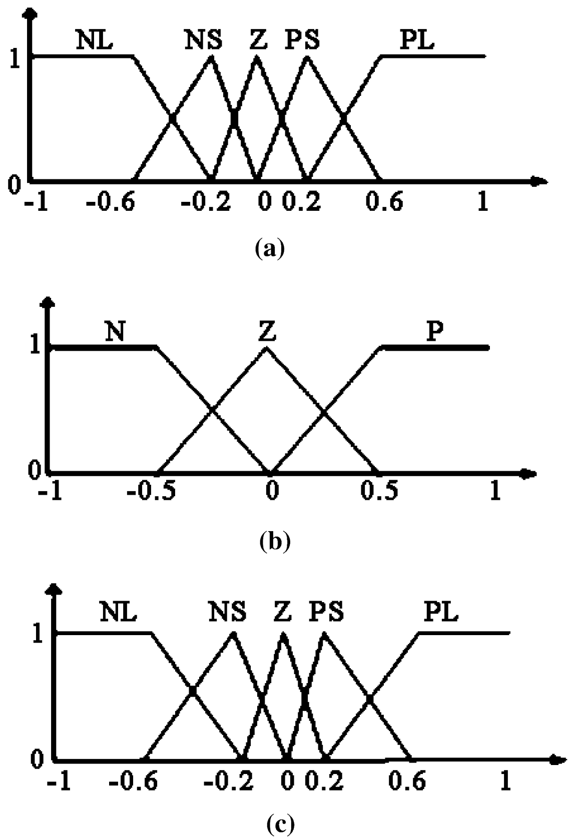
The two components of reference voltage vector in the stationary frame are input into SVM module and generate PWM signal controlling switch state of the inverter.

144.4 Design Fuzzy Controller of Torque

144.4.1 Fuzzy Variables and Membership Functions

The torque fuzzy controller also has two input variables and one output variable. Input variables: torque error E_T and change rate of torque error ΔE_T. Output variable: q-axis component of reference voltage vector u_{qr}. E_T has five fuzzy

Fig. 144.3 The fuzzy membership functions of torque controller **a** Torque error. **b** Change rate of torque error. **c** Q-axis component of reference voltage vector



subsets: PL, PS, Z, NS, and NL. ΔE_T has three fuzzy subsets: P, Z, and N. u_{qr} has five fuzzy subsets: PL, PS, Z, NS, and NL (Fig. 144.3).

144.4.2 Fuzzy Control Rules

Fuzzy control rules apply IF–THEN form. The rule of torque fuzzy controller R_i can be written as R_i : If $E_T = A_i$ and $\Delta E_T = B_j$ then $u_{\mathrm{qr}} = C_{\mathrm{ij}}$; where: $A_i, B_j, C_{\mathrm{ij}}$ is some fuzzy subset of $E_T, \Delta E_T$ and u_{qr}, respectively.

The total number of rules of torque fuzzy controller is 15 as shown in Table 144.1.

Table 144.1 Fuzzy control rules of torque

u_{qr}	E_T				
$\triangle E_T$	*NL*	*NS*	*Z*	*PS*	*PL*
N	PL	PL	PS	Z	Z
Z	PL	PS	Z	NS	NL
P	Z	Z	NS	NL	NL

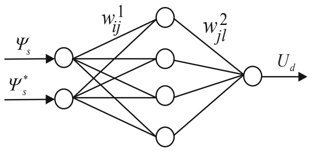


Fig. 144.4 Neural-network structure of stator flux

144.4.3 Fuzzy Reasoning and De-Fuzzy

The reasoning method is mamdani's procedure based on min–max decision. The firing strength of the rule of torque fuzzy controller $\mu_{R_{ij}}(u_{qr})$ can be obtained by considering

$$\mu_{R_{ij}}(u_{qr}) = \mu_{A_i}(E_T) \wedge \mu_{B_j}(\Delta E_T) \wedge \mu_{C_{ij}}(u_{qr}) \tag{144.10}$$

Fuzzy quantity must de-fuzzy before being sent to control object, and use the center of gravity method for defuzzification.

144.5 Design Neural-Network Controller of Torque

144.5.1 The Neural-Network Structure of Flux

The flux reference voltage vector U_{dr} was realized by BP neural network. Its structure is show in Fig. 144.4.

144.5.2 The Neural-Network Learning Algorithm of Flux

The neural network can signify arbitrary nonlinear function. Three layer BP neural network contains input layer, hide layer and output. The relationship among three layer is as follows:

$$v_j^1(n) = \sum \omega_{ij}^1(n) u_i(n) \tag{144.11}$$

$$v_k^2(n+1) = \sum \omega_{jk}^2(n) v_j^1(n) \tag{144.12}$$

$$y_k(n+1) = f\left(v_k^2(n+1)\right) \tag{144.13}$$

where k is the output layer variable; j is the hide layer variable; v is the neural-network unit; y is the neural-network output; $\omega_{\mathrm{ij}}(n)$ is the neuron weight from i to j; and f is the activate function. Suppose $d(n)$ is the expectation output of neural output, then transient error vector can expressed as:

$$e(n) = d(n) - y(n) \tag{144.14}$$

The target function can be defined as:

$$E(n) = \frac{1}{2} e(n)^T e(n) \tag{144.15}$$

According to the shortest down rules we can obtain the amendment quantity $\omega_{\mathrm{lm}}(n)$

$$\Delta\omega_{\mathrm{lm}}(n) = -\eta \frac{\partial E(n)}{\partial \omega_{\mathrm{lm}}(n)} \tag{144.16}$$

In order to keep the stability of the algorithm, momentum factor α is quoted in the weight:

$$\Delta\omega_{\mathrm{lm}}(n) = -\eta \frac{\partial E(n)}{\partial \omega_{\mathrm{lm}}(n)} + \alpha\Delta\omega_{\mathrm{lm}}(n-1) \tag{144.17}$$

Theoretical analysis verifies this network structure, and mapping arbitrary nonlinearity function only hide layer quantity is enough. The input parameter is flux given value ψ_s^* and flux calculated value, the output variable is the reference voltage vector U_d. Activated function adopts to tansig. Hide layer unit is 4, according to learning rate and target error adjust the quantity of hide layer. The training result shows that the target error can receive less than 0.01 when hide layer quantity is 4, learning rate is 0.2 and training frequency.

144.6 System Simulation Results

144.6.1 Simulation and Results

In this section, the software Matlab/Simulink is used to simulate the whole DTC system to examine the performance of the novel SVM–DTC system. The parameters of the induction machine used in the simulation experiment are:

$$P_n = 2.2\,\mathrm{k}, U_n = 380\,\mathrm{V}, R_s = 4.35\,\Omega, R_r = 0.43\,\Omega,$$
$$L_s = 2\,\mathrm{mH}, L_r = 2\,\mathrm{mH}, L_m = 69.31\,\mathrm{mH}, J = 0.089\,\mathrm{kg}\cdot\mathrm{m}^2, P = 2.$$

The simulation conditions are given as: speed is 50r/min; simulation time is 0.8 s.

As shown in Figs. 144.5a, c, and e are simulation results of conventional SVM–DTC system at low speed, flux is basically round, but the ripple of flux is large;

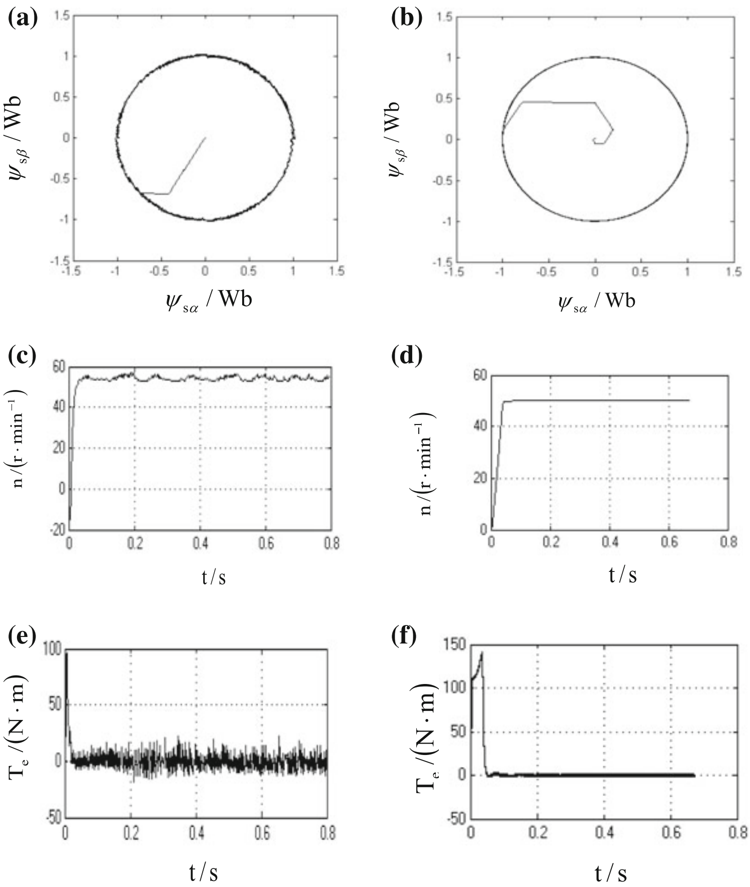


Fig. 144.5 Waveform graphs of simulation. **a** Conventional SVM–DTC flux. **b** Fuzzy-neural SVM–DTC flux. **c** conventional SVM–DTC speed.**d** fuzzy-neural SVM–DTC speed.**e** Conventional SVM–DTC torque. **f** fuzzy-neural SVM–DTC torque

speed response is slow and large overshoot is existed; there is large torque ripple at different jumping change time. Figures. 144.5b, d, and f are simulation results of fuzzy-neural network SVM–DTC system at low speed, waveform of flux is a standard round; speed response is fast and speed ripple decreased sharply; torque can achieve stability quickly and without ripple.

144.6.2 Experiment and Results

In order to verify the correctness of new strategy, the experiments were carried out in DSP2812 experiment platform. The parameters were same as to simulation. The experiment results are follows:

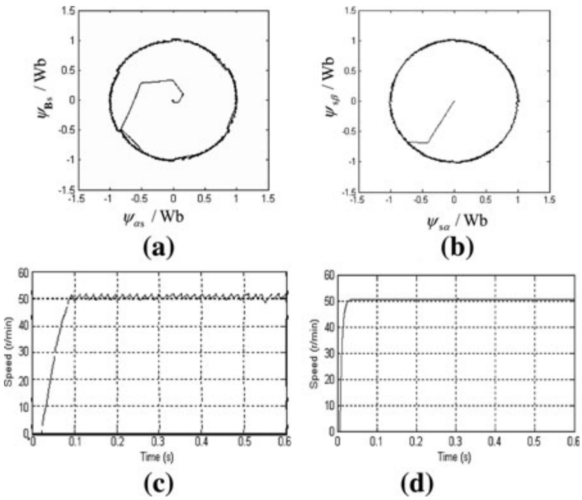


Fig. 144.6 Waveform graphs of experiment. **a** Conventional SVM–DTC flux. **b** Fuzzy-neural SVM–DTC flux. **c** Conventional SVM–DTC speed. **d** Fuzzy-neural SVM–DTC speed

It can be seen from Fig. 144.6 that the experiments results are similar to the simulation results. The new strategy has better torque and speed characteristic compared to the conventional VM–DTC. It can improve the control system's low-speed performance and the new method's validity is verified.

144.7 Conclusion

To resolve the problem in conventional SVM–DTC system of induction motors, a new strategy of direct torque control based on fuzzy-neural network space vector modulation is proposed and applied in induction motor speed control system. By system simulation and experiment, the results illustrate that the new strategy can sharply reduce torque, flux and speed ripple of SVM–DTC system and the system has a better dynamic and steady performance in low-speed.

References

1. Casadei D, Profumo F, Tani A (2002) FOC and DTC: two viable schemes for induction motors torque control. IEEE Trans Power Electron 17(5):779–787
2. Buja GS, Kazmierkowski MP (2004) Direct torque control of PWM inverter-fed AC motors—a survey. IEEE Trans Indus Electron 51(4):744–758

3. Wei X, Chen D, Zhao Chunyu (2005) A new direct torque control strategy of induction motors based on duty ratio control technique. Proc Chin Soc Electr Eng 25(5):93–97
4. Habetler TG, Profumo F, Pastorelli M, Tolbert LM (1992) Direct torque control of induction motor using space vector modulation. IEEE Trans Ind Appl 28:1045–1053
5. Xu Z, Rahman MF (2005) An improved stator flux estimation for a variable structure direct torque controlled IPM synchronous motor drive using a sliding observer. IEEE Trans Ind Appl 38(1):2484–2490
6. Mir S, Elbuluk ME (1995) Precision torque control in Inverter-Fed induction machines using fuzzy logic. Proc 26th IEEE Power Electr Specialists Conf (PESC) 1:396–401
7. Ding X, Liu Q, Ma X, He X, Hu Q (2007) The fuzzy torque control of induction motor based on space vector modulation. Third international conference on natural computation