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Simulation and Experimental Study of Vector Controlled Induction Motor Drive Based on RBFNN-MRAC Controller

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Abstract

Although induction motors have many structural advantages, they are difficult to control due to complicated and non-linear structures. In recent years, the control performance of induction motors has been improved by using intelligent control methods such as fuzzy control and artificial neural network control. This article presents implementation of model reference adaptive control (MRAC) based on radial basis function neural network (RBFNN) for vector controlled induction motor drive at real time. The complex calculations used in vector control of induction motors can be easily done with digital signal processors, powerful microprocessors. In this study, a dsPIC30F6010A microcontroller based speed control system was designed for an induction motor with three-phase squirrel cage. The system consists of control board based on dsPIC30F6010A device, power module, three phase induction motor and DC generator that acts as a proper load. The rotor flux vector required for the coordinate transformations is estimated using indirect field-oriented control technique. The results show that the proposed RBFNN based MRAC scheme has better tracking performance than traditional PI controller for different references and loading conditions. The success and superiority of the proposed RBFNN based MRAC controller over the traditional PI controller was demonstrated by simulation and experimental studies.

Keywords: Adaptive control, Neural networks, Induction motors, Speed control

1. Introduction

The induction motors have been commonly used in industrial applications such as pumps, fans, compressor, conveyors and hybrid vehicles due to their low cost, simple construction, high robustness and high efficiency. Parallel to the developments in power electronics, microelectronics, sensor technology and control theory; the reliability, efficiency and control accuracy of drive systems are increasing with each passing day [1]-[3]. Researchers focused on development of new control algorithms for high performance induction motor drives [4]-[7].

High performance induction motor drives can be implemented by vector control schemes based on the field oriented principle. The main objective of vector control techniques ensures that induction motor achieves dynamic performance similar to that of a separately excited DC motor [8]-[11].

The method of obtaining the flux yields two types of the field-oriented control (FOC): direct field-oriented control (DFOC) and indirect field-oriented control (IFOC). Direct field oriented control is based on direct measurement of the flux using various mechanisms. The rotor flux position can be measured using the sensor in air gap, but this method is difficult, expensive and unreliable. Instead, the rotor flux can be easily obtained from current, voltage and mechanical position. In IFOC, the mathematical model of the machine is used for slip calculation, when added to the rotor position yields the rotor flux angle [12]-[13]. Because of does not require flux sensor and has simple mathematics, good control stability, the IFOC technique is preferred in this study.

Artificial neural networks (ANN) have been successfully applied in nonlinear identification and control of nonlinear dynamical systems. ANN can be easily used in the synthesis of nonlinear adaptive controllers, thanks to the ability to learn from their experience to improve their performance and adapt to environmental changes. RBFNN has shown its potential for online identification and control, and hence arouses much research interest [14]-[15].

Adaptive control approaches can be described by

different methods. Those are gain scheduling, model reference adaptive control (MRAC), self-tuning regulators and dual control or stochastic model. MRAC is the important adaptive control techniques used for motor control and state estimation applications. The MRAC is used to solve the control problems in which the desired performance characteristics are given by a reference model that provides the ideal response of the system. This method is based on forcing the plant to track the reference model. The tracking error between the reference model output and the plant output is reduced by the adaptive controller using the adaptive mechanism. MRAC is a direct adaptive strategy with some adjustable controller parameters and an adjusting mechanism to adjust them. The performance of MRAC algorithm depends on the choice of a suitable reference model and the derivation of an appropriate learning mechanism [16]-[18].

In this study, RBFNN based MRAC scheme has been developed in order to increase the reliability, efficiency and control accuracy of induction motor drive system. The performance of the drive system has been analyzed for different reference speed and applied load. The vector controlled induction motor drive system has been implemented by simulation and experimental. In order to determine the success of proposed control system, the performances of RBFNN based MRAC controller and traditional PI controller were compared. The results show that the performance of RBFNN based MRAC controller is better than the performance of traditional PI controller under variable operating conditions.

2. Design of RBFNN Based Adaptive Controller

MRAC is an adaptive control method widely used in the control of complex nonlinear systems whose parameters are unknown or partly known. In MRAC; the desired system response is expressed by the reference model output. The controller parameters are adjusted to minimize the output error [19].

In this study, RBFNN based MRAC algorithm is used as speed controller. The aim of RBFNN is to compensate the parts that are difficult to control due to the induction motor nonlinearity. The structure of the RBFNN based MRAC controller applied to the system is shown in Figure 1.

The electromagnetic torque of the motor to the *d-q* reference frame as given by:

$$T_e = \frac{3}{4}\frac{pL_m}{L_r}(i_{sq}\psi_{rd} - \psi_{rq}i_{sd}) \tag{1}$$

where i_{sd} , i_{sq} , ψ_{rd} and ψ_{rq} are *d-q* axes stator currents and rotor fluxes respectively; p is number of motor poles, L_r is rotor main inductance, L_m is mutual inductance between stator and rotor.

At IFOC, the *q*-axis rotor flux (ψ_{rq}=0) is zero in the synchronous reference frame and the electromagnetic torque of the induction motor can be expressed as:

$$T_e = \frac{3}{4}\frac{pL_m}{L_r}i_{sq}\psi_{rd} = K_t i_{sq} \tag{2}$$

The electromechanical dynamic of the induction motor can be modeled as:

$$J\frac{d\omega_m}{dt} + B\omega_m + T_L = T_e = K_t i_{sq} \tag{3}$$

where ω_m is mechanical speed, J is the moment of inertia of the motor and load; B is viscous friction coefficient of the motor; T_L is load torque.

Thus, the motor model can be expressed by the following first-order dynamic equation:

$$\frac{d\omega_m}{dt} + f(\omega_m) = i_{sq} \tag{4}$$

The plant and reference model can be described by differential equation:

$$\dot{\omega}_m(t) + f\left[\omega_m(t)\right] = i^*_{sq}(t) \tag{5}$$

$$\dot{\omega}_{rm}(t) + k_1\omega_{rm}(t) = k_2\omega_{ref}(t) \tag{6}$$

where $\omega_{ref}(t)$, $\omega_m(t)$ and $\omega_{rm}(t)$ are the reference speed, plant output and reference model output, respectively; $i^*_{sq}(t)$ is the control signal and $f(.)$ is unknown nonlinear function; k_1 and k_2 real positive coefficients [20].

The aim of the MRAC system is to design a controller that forces the process to track the model output. To design the controller, the proposed control law is as following:

$$i^*_{sq}(t) = -k_2\omega_m(t) + k_1\omega_{ref}(t) + N_f\left[\omega_m(t), w(t)\right] \tag{7}$$

where N_f is the output of RBFNN; w is weight vector of the RBFNN. The N_f can be presented as:

$$N_f\left[\omega_m(t), w(t)\right] = \sum_{j=1}^{J} w_j(t)\exp\left[\frac{\left\|\omega_m(t) - c_j\right\|^2}{2\sigma^2}\right]$$

Equations (5)-(7) can be considered together and can be re-written as follow:

$$\left[\dot{\omega}_m(t)-\dot{\omega}_{rm}(t)\right]+k_2\left[\omega_m(t)-\omega_{rm}(t)\right] = N_f\left[\omega_m(t),w(t)\right]-f\left[\omega_m(t)\right] \quad (8)$$

When N_f approaches asymptotically $f(.)$, the current tracking error $e(t)$ tends to zero.

$$e(t)=\omega(t)-\omega_m(t) \quad (9)$$

$$\dot{e}(t)+a_m e(t)\approx 0 \quad (10)$$

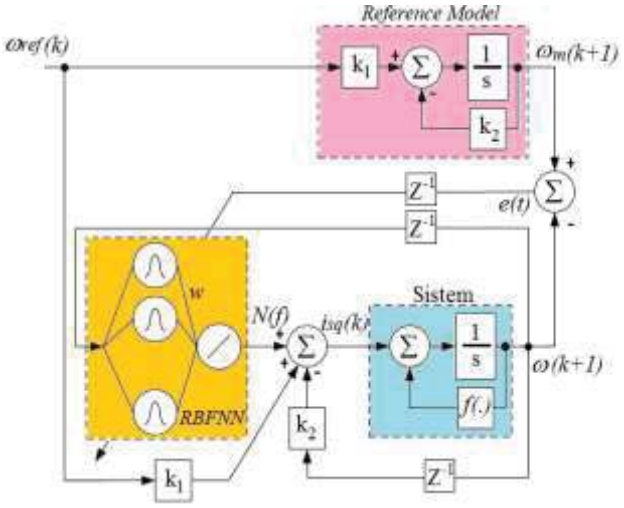


Figure 1. RBFNN based MRAC strategy structure

RBFNN is a kind of neural network that uses radial basis functions as activation function. Because of the good generalization capabilities and a simple network structure, RBFNN has recently attracted much attention [21-23].

The structure of RBFNN is shown in Figure 2. The RBFNN has three layers. The input layer consists of the source nodes; the hidden layer is composed of nonlinear units; the output layer is a linear.

Training of RBFNN includes process of determining of adaptive parameters that are network center (c_j), width of basis function (σ_j) and output layer weights (w_{kj}). c_j and σ_j must be chosen according to the scope of the input value.

The back-propagation algorithm is used to update parameters of RBFNN. The output of each hidden unit can be calculated as:

$$\phi_j(x)=\exp\left[\frac{-\left\|x-c_j\right\|^2}{\sigma_j^{\,2}}\right] \quad (11)$$

where ϕ_j denotes the output of the j_{th} node in hidden layer, x is the input vector, $||x\text{-}c_j||$ is Euclidian distance function, c_j is center of the j_{th} gaussian function, σ_j is the width of the gaussian function of the j_{th} node and j denotes the number of hidden layer nodes. The transformation to hidden layer to output layer is a linear and it can be computed as following:

$$o_k=\sum_{j=1}^{J} w_{kj}\phi_j(x) \quad (12)$$

where w_{kj} is weights of the RBFNN.

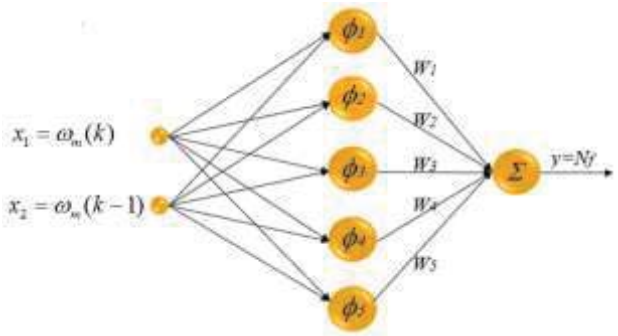


Figure 2. Structure of RBFNN

The adjustable parameters of RBFNN that are weights, network center and width of basis function, are online updated by using back-propagation training algorithm and tracking error. where $\eta \in (0,1)$ is learning rate.

$$w_{kj}(t+1)=w_{kj}(t)+\eta e(t)\phi_j \quad (13)$$

$$c_j(t+1)=c_j(t)+\eta e(t)\phi_j w_j\frac{(x-c_j)}{\sigma^2} \quad (14)$$

$$\sigma_j(t+1)=\sigma_j(t)+\eta e(t)\phi_j w_j\frac{\left\|x-c_j\right\|}{\sigma^3} \quad (15)$$

3. Simulation and Experimental Results

The experimental setup is designed for realization of speed control of induction motor. The experimental system consists of motor control development board based on dsPIC30F6010A microcontroller, 1 kW rectifier and inverter module, 0.25kW three phase induction motor and a shunt wound DC generator. The block diagram of experimental setup is shown in Figure 3 and the experimental setup is shown in Figure 4.

The IFOC technique is the most suitable control technique for vector controlled induction motor. By using SVPWM technique, the pulse width modulation signals are generated. These signals control the inverter output. Three are three control loops controlling the rotor speed, the rotor flux and the rotor torque. In proposed control method, the RBFNN based MRAC is designed to replace the PI speed controller. The flux and torque control loop

executes every 100 µsec and the speed control loop executes every 10 msec. The inverter switching frequency as selected is 10 kHz and the dead time as selected is 2 µsec. The performance of induction motor drive is presented at the start, step change in speed command reference and applied sudden load. The parameters of induction motor are shown in Table 1.

Parameter	Value
Rated Power [P]	0.25 kW
Rated Speed [n]	3000 rpm
Rated Stator Voltage [U]	220 V
Rated Stator Current [I]	1.4 A
Rated Frequency [f]	50 Hz

Table 1.Parameters of induction motor.

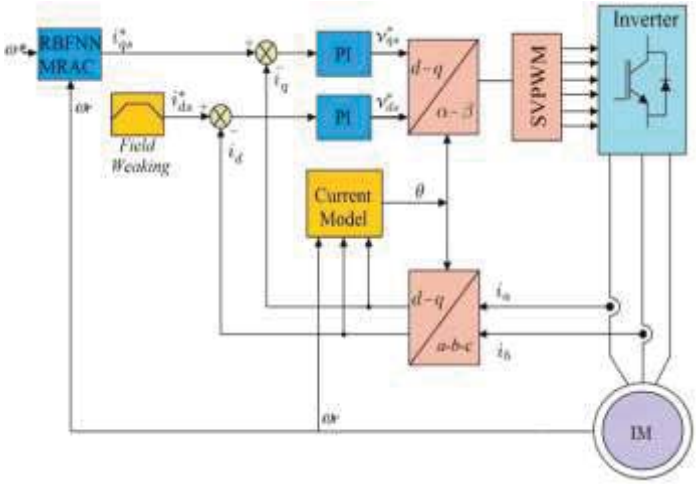


Figure 3. Block diagram of induction motor

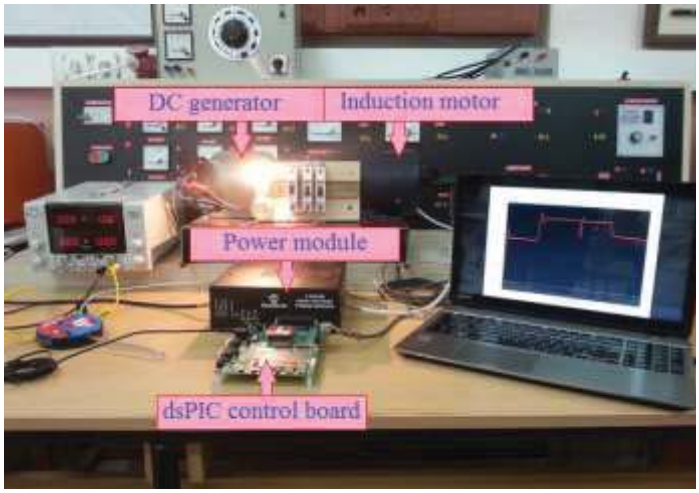


Figure 4. Experimental setup

The results of proposed controller have been compared with that of PI controller's. The experimental and simulation results are shown in Figure 5. The speed response is shown in Figure 5.a and 5.e. The motor is started without load. The reference speed is 1000 rpm. The reference speed was increased from 1000 rpm to 1500 rpm at t=5 sec. It is observed that the proposed controller has shorter settling time and smaller overshoot than PI controller. When the motor speed is steady-state the load is suddenly applied at t=10 sec. The motor speed is slowdown due to loading, but then it is compensated by the controller. The proposed RBFNN based MRAC controller has good performance compared to PI controller for the speed remains regulated at 1500 rpm. The reference speed has been reduced to 1200 rpm at t=15 sec.

Figure 5.b and 5.f show that the control output signals. It is evident from figure the output signal of the proposed RBFNN based MRAC controller has a non-linear waveform. Figure 5.c-d and 5.g-h show that the *dq-axis* current response. The proposed controller shows smoother response than traditional PI controller.

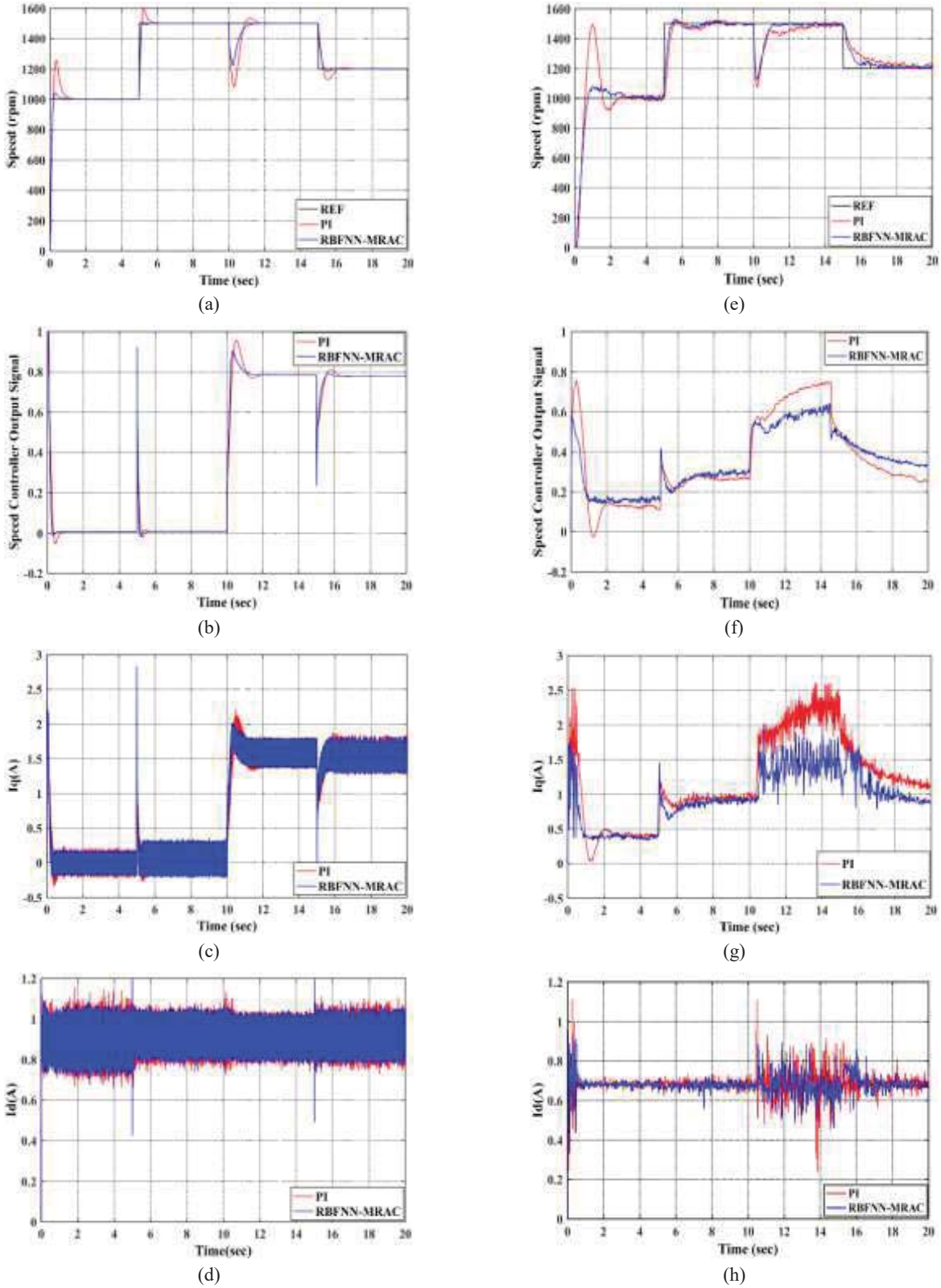


Figure 5. Simulation Results (a-d) and Experimental (e-h) Results

3. Conclusions

In this study, a dsPIC30F6010A microcontroller based

induction motor speed control system has been realized by using a PI controller and RBFNN based MRAC controller. The PI controller is replaced by RBFNN based MRAC controller for speed controller in IFOC scheme. In order to determine the superiority of the RBFNN based MRAC controller, the experimental and simulation results have been presented and compared to PI controller at different operation conditions. The obtained results have shown the proposed controller has shorter settling time and smaller overshoot than PI controller. The results show that the developed RBFNN based MRAC method is more robust during the sudden change in speed and load.

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