Adaptive PI Controller Based on RBF Neural Network for Speed Control of Induction Motor

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ABSTRACT

This paper presents an adaptive PI controller based on radial basis function (RBF) neural network for speed control of vector controlled induction motor. The structure of control scheme consists of RBF identifier, reference model and PI controller. The RBF identifier is used to online identify Jacobian value of the induction motor. Neural network parameters are online updated by using gradient descent method without prior training. The parameters of PI Controller are tuned online by using the RBF identified model. The proposed controller is tested under different operating conditions to demonstrate the reliability of the control technique. In this study, the results show that the proposed controller ensures good robustness and stability of the system under variable speed and load rather than the conventional PI controller.

Keywords: Radial basis function neural networks, adaptive PI control, indirect field oriented control, induction motor

1 INTRODUCTION

The induction motors have been widely used in many industrial and daily life applications such as pumps, fans and compressor due to its low cost, low maintenance, high robustness, simple construction and high efficiency [1-3]. Nowadays, the induction motor drives have been able to be used in variable speed applications with the rapid development of power electronics [4]. To obtain high dynamic performance in induction motor drives is based on vector control technique. The vector control method uses the dynamic mathematical model of induction motor and allows independent control of flux and torque which makes the induction motor deliver excellent dynamic performance [5-7].

PID control is the most common control algorithm used in the industrial process control. Although, it has simple algorithm and good robustness [8], the conventional fixed gain PID controllers in nonlinear system cannot achieve good output performance in all operating range [9]. The conventional PID control is a linear algorithm [10] and thus it becomes very difficult to achieve high dynamic performance in speed control of induction motors due to the nonlinear structure of the system and disturbance inputs. Many studies in recent years show that the benefits of using artificial intelligence-based control methods have been clearly demonstrated to increase the performance of induction motor drive systems [9, 11-14].

RBF neural network has been used extensively in the areas of pattern recognition, systems modeling and identification. RBF has shown its potential for online identification and control, and hence arouses much research interest [15-17].

Zhang and Li [18] designed a self-learning controller by using a single neuron PID model reference adaptive control based on RBF neural network online identification. Zhang et.al. [19] investigated an adaptive speed PID controller based on RBF neural network for permanent magnet synchronous motor system. Wei et.al. [20] proposed a novel approach based on single neuron PID adaptive control and repetitive control for repetitive periodic load control system. Xuemei and Jingdong [21] proposed adaptive PID control strategy based on RBF neural network for DC motor. Kim et.al [22] improved control performance for the PI controller parameters of a permanent magnet synchronous generator wind turbine by a tuning method. Kriauciunas et.al [8] proposed a hybrid fuzzy and PID controller to improve speed control of induction motor. The gains of PID are tuned by fuzzy logic controller.

In this study, an adaptive PI controller based on RBF neural network is developed in order to improve the efficiency and performance of vector controlled induction motor drive which has been implemented by using the MATLAB/Simulink environment. The indirect field oriented control (IFOC) technique, which is broadly used in high performance induction motor drives, has been preferred as drive method. The RBF neural network self-learning ability to online adjust the PI parameters was used to determine the best controller parameters. The performance of the induction motor drive has been analyzed by the variables of speed and load. The results show that the adaptive PI controller based on RBF neural network has adaptability, good dynamic performance and strong robustness in all operating conditions.

2 DYNAMIC MODEL OF INDUCTION MOTOR

Three phase induction motor mathematical model can be expressed by the five order nonlinear state equation in rotating d-q reference frame model as follows [23-25].

$$\frac{di_{sd}}{dt} = \frac{1}{\sigma L_s}\left[-R_E i_{sd} + \sigma L_s \omega_s i_{sq} + \frac{L_m R_r}{L_r^2}\psi_{rd} + \omega_r \frac{L_m}{L_r}\psi_{rq} + V_{sd} \right] \quad (1)$$

$$\frac{di_{sq}}{dt} = \frac{1}{\sigma L_s}\left[-R_E i_{sq} - \sigma L_s \omega_s i_{sd} + \frac{L_m R_r}{L_r^2}\psi_{rq} - \omega_r \frac{L_m}{L_r}\psi_{rd} + V_{sq} \right] \quad (2)$$

$$\frac{d\psi_{rd}}{dt} = \frac{R_r L_m}{L_r} i_{sd} - \frac{R_r}{L_r}\psi_{rd} + (\omega_s - \omega_r)\psi_{rq} \quad (3)$$

$$\frac{d\psi_{rq}}{dt} = \frac{R_r L_m}{L_r} i_{sq} - \frac{R_r}{L_r}\psi_{rq} - (\omega_s - \omega_r)\psi_{rd} \quad (4)$$

$$\frac{d\omega_r}{dt} = \frac{3}{2}\frac{pL_m}{JL_r}(i_{sq}\psi_{rd} - \psi_{rq} i_{sd}) - \frac{B}{J}\omega_r - \frac{T_L}{J} \quad (5)$$

where, ω_s and ω_r are the electrical synchronous stator and rotor speed, respectively; V_{sd}, V_{sq}, i_{sd}, i_{sq}, ψ_{rd} and ψ_{rq} are d-q axis stator voltages, d-q axis stator currents and d-q axis rotor fluxes, respectively; R_s and R_r are the stator and rotor resistances per phase, respectively; L_s, L_r and L_m are stator and rotor main inductances and the mutual inductance, respectively; p is the number of motor poles, J is the rotor inertia, B is the viscous friction coefficient, T_L is the load torque, R_E is the equivalent resistance, σ is the leakage coefficient.

3 RBF NEURAL NETWORK

RBF neural network is a kind of neural network that uses radial basis functions as activation function. Due to the good generalization capabilities and a simple network structure, RBF neural network has recently attracted much attention [26]. The RBF neural network is used to identify the system online. RBF neural network has three layers: the input layer, the hidden layer, and the output layer. We supposed that RBF neural network was provided with 3 inputs, 6 hidden layer nodes and one output node. The structure of network is shown in Figure1.

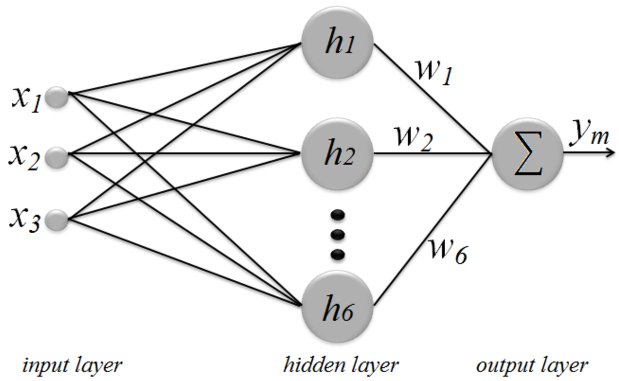

Figure1. RBF neural network structure

The output of hidden layer can be defined as follows:

$$h_j(x) = \exp\left[\frac{-\left\|X - C_j\right\|^2}{2b_j^{\ 2}}\right] \tag{6}$$

where h_j denotes the output of the j_{th} node in hidden layer, X is the input vector, $C_{ij}=[c_{1j}, c_{2j}, \ldots c_{ij}, \ldots c_{nj}]^T$ is center vector, b_j is the basis width parameter of the j_{th} node. c_j and b_j must be chosen according to the scope of the input value. The output of network is given as:

$$y_m(k) = \sum_{j=1}^{J} w_j h_j(x) \tag{7}$$

where w_j is weights of the RBF neural network. The performance index function can be presented as:

$$E(t) = \frac{1}{2}[y(k) - y_m(k)]^2 \tag{8}$$

where $y(k)$ is ideal output. Based on the gradient descent method, the RBF neural network parameters can be updated as follow:

$$w_j(k+1)=w_j(k)+\eta[y(k)-y_m(k)]h_j+\alpha[w_j(k)+w_j(k-1)] \tag{9}$$

$$c_{ij}(k+1)=c_{ij}(k)+\eta[y(k)-y_m(k)]h_j w_j \frac{(x_i-c_{ij})}{b_j^2}+\alpha[c_{ij}(k)+c_{ij}(k-1)] \tag{10}$$

$$b_j(k+1)=b_j(k)+\eta[y(k)-y_m(k)]h_j w_j \frac{\left\|x-c_j\right\|^2}{b_j^3}+\alpha[b_j(k)+b_j(k-1)] \tag{11}$$

where, $\eta \in (0,1)$ is a learning rate and $\alpha \in (0,1)$ is momentum factor. The Jacobian matrix algorithm is as follows [18-20]:

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)}=\sum_{j=1}^{m} w_j h_j \frac{c_{1j}-x_1}{b_j^2} \tag{12}$$

where $x_1=u(k)$. The PI controller parameters are adjusted by Jacobian matrix of control plant that is obtained by RBF neural network identificiation.

4 DESIGN OF ADAPTIVE PI CONTROLLER BASED ON RBF NEURAL NETWORK

The adaptive PI controller based on RBF neural network identification is proposed in this paper for speed control of induction motor. The proposed control system structure is as shown in Figure 2.

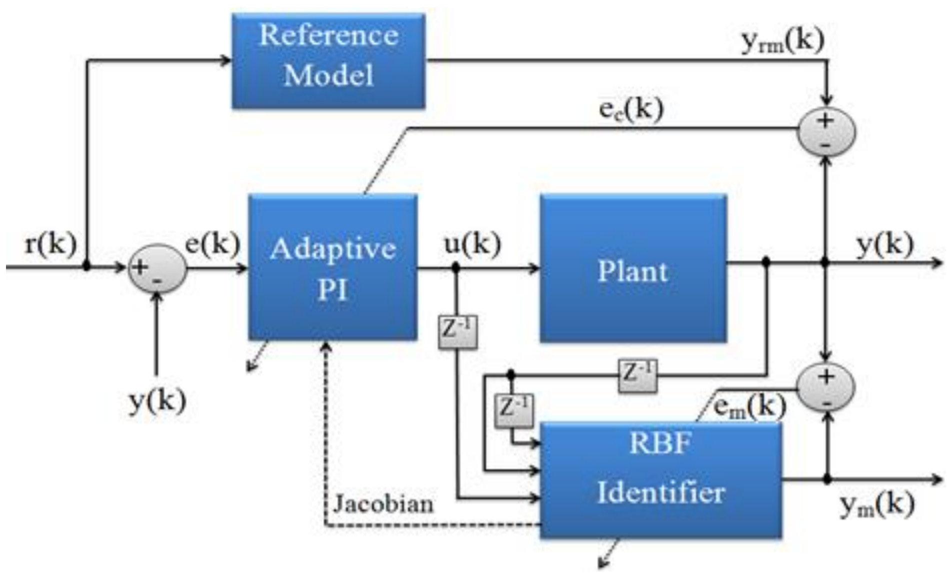

Figure 2. Adaptive PI Controller based on RBF neural network

In Figure 2, $r(k)$ is the reference input, $y(k)$ is the output of plant, $y_{rm}(k)$ is the output of reference model, $y_m(k)$ is the output of RBF identifier, $u(k)$ is the control signal, $e(k)$ is the plant error, $e_c(k)$ is the control error, $e_m(k)$ is identification error.

$$e(k)=r(k)-y(k) \tag{13}$$

$$e_c(k) = y_{rm}(k) - y(k) \tag{14}$$

$$e_m(k) = y(k) - y_m(k) \tag{15}$$

The two inputs of PI controller are given following as:

$$x_c(1) = e(k) - e(k-1) \tag{16}$$

$$x_c(2) = e(k) \tag{17}$$

The gradient descent method is used for adjustment of proportion parameter K_p and integral parameter K_i.

$$K_p(k+1) = K_p(k) + \eta e_c(k) \frac{\partial y(k)}{\partial u(k)} x_c(1) \tag{18}$$

$$K_i(k+1) = K_i(k) + \eta e_c(k) \frac{\partial y(k)}{\partial u(k)} x_c(2) \tag{19}$$

where, the $\frac{\partial y(k)}{\partial u(k)}$ can be obtained by identification of RBF neural network. The output of adaptive PI controller is given as:

$$u(k) = K_p x_c(1) + K_i x_c(2) \tag{20}$$

5 SIMULATION RESULTS

The computer simulation of vector controlled induction motor drive is simulated by using MATLAB/Simulink environment. IFOC and space vector pulse width modulation have been used in the drive system of induction motor. The performance comparisons between the proposed adaptive PI controller based on RBF neural network and the conventional PI controller scheme are shown in Figures 4-7. For both types of controller, the performance of induction motor drive is presented during starting, step change in speed and step change in load. The block diagram of simulation system is shown in Figure 3. The parameters of the induction motor used in simulation research are as in appendix.

The conventional PI controller parameters which are tuning by trial-and-error method have been considered with proper coefficients. These parameters are K_p=1.5, K_i=100 for speed controller, K_p=150, K_i=500 for torque controller and K_p=25, K_i=1000 for flux controller. The inverter switching frequency is selected to be 5 kHz and a nominal DC link voltage of 550 V is chosen. The sample interval time T_s =0.02 ms was used in the simulation.

The parameters of adaptive PI controller are adjusted by using the control error between the output of the plant and the output of the reference model which is selected as a first order system.

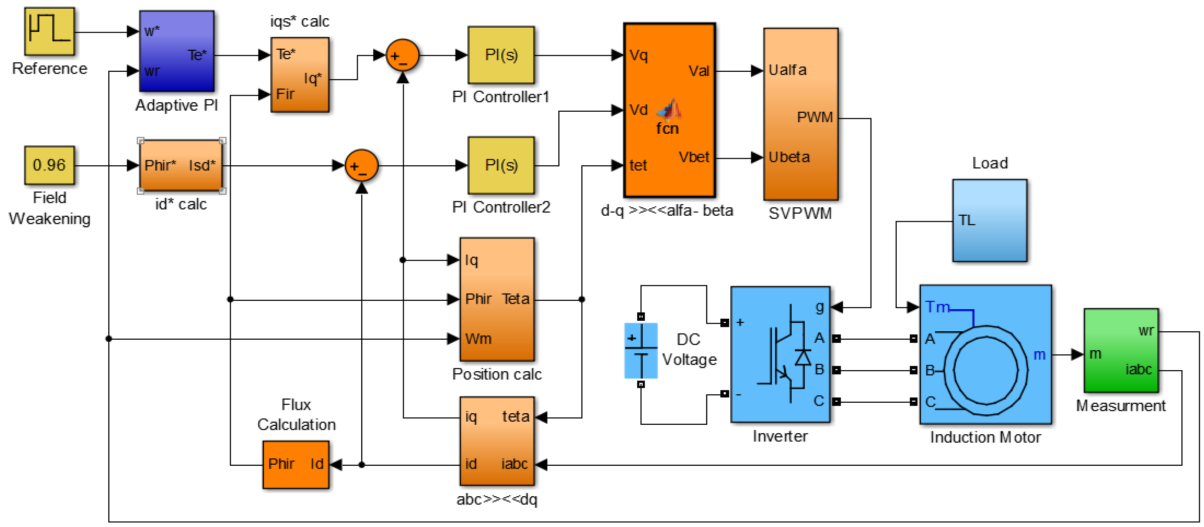

Figure 3. Simulink model for vector controlled induction motor drive system

The induction motor is started with a load of 5 Nm. The Figure 4 shows comparison of induction motor speed response between adaptive PI controller based on RBF neural network and PI controllers for step increase and step decrease in reference. The reference speed is increased from 400 rpm to 800 rpm at t=0.5 sec and from 800 rpm to 1200 rpm at and t=1.0 sec. The reference speed is decreased from 1200 rpm to 800 rpm at t=1.5 sec.

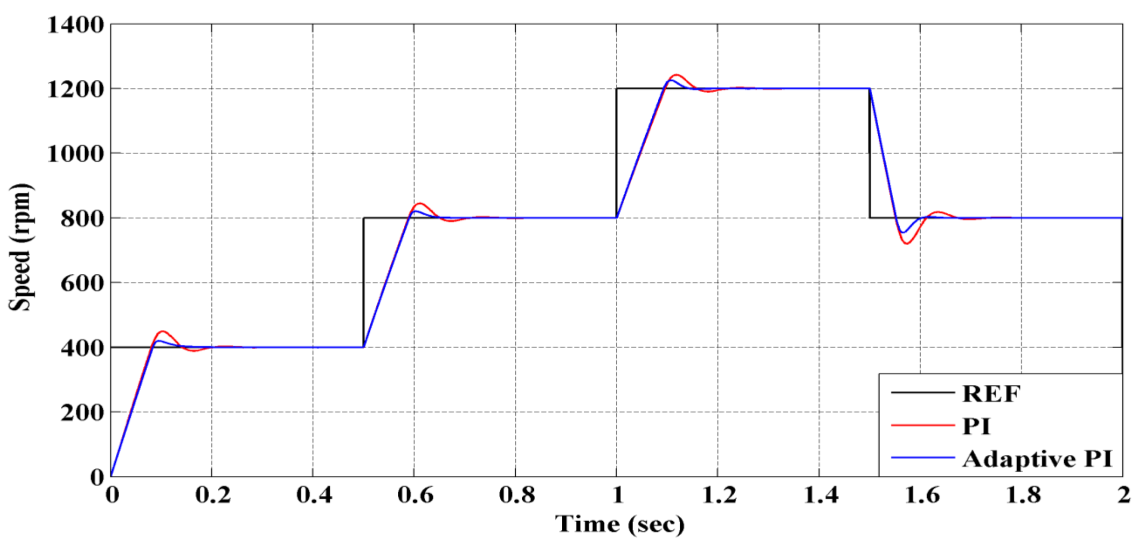

Figure 4. Speed response for step change reference speed

It can be seen that from Figure 4, the response of the induction motor drive system based on proposed adaptive PI control method has smaller overshoot and steady-state error than conventional PI control method at step change in reference speed. The proposed controller has not have a demonstrable effect on the rise time.

Figure 5 shows electromagnetic torque response for step change in reference speed. It is seen from figure that the adaptive PI control scheme has the fast torque response and low torque ripple compared with the conventional PI controller.

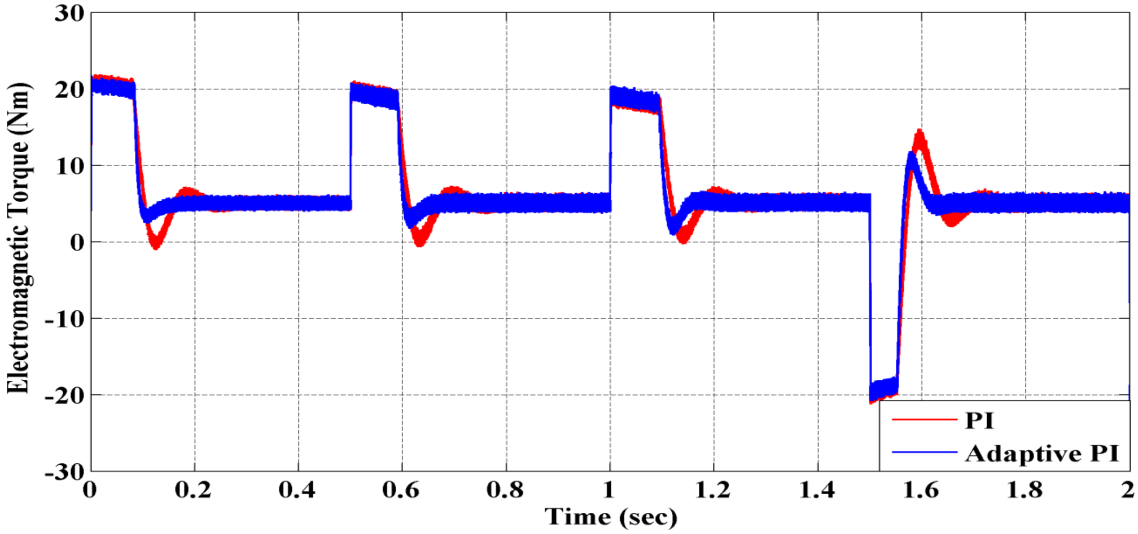

Figure 5. Electromagnetic torque response for step change reference speed

Figure 6 shows speed response of motor at step change in load torque at steady state speed of 1400 rpm. When the load torque step change 5 Nm to 10 Nm at t=1.0 sec, in the conventional PI control, the speed drops to 1385 rpm and takes 0.18 sec to recover the speed to rated value and in the proposed control, the speed drops to 1395 rpm and takes 0.04 sec to recover the speed to rated value. When the load torque step change 10 Nm to 19Nm at t=1.5 sec, in the conventional PI control, the speed drops to 1376 rpm and takes 0.22 sec to recover the speed to rated value and in the proposed control, the speed drops to 1391 rpm and takes 0.07 sec to recover the speed to rated value.

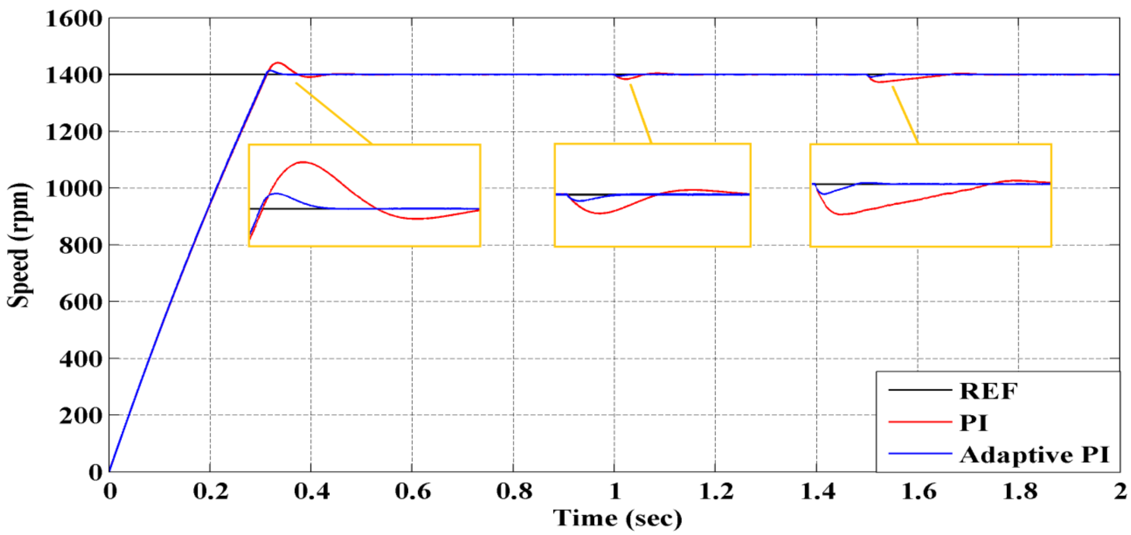

Figure 6. Speed response for step change in load torque

Figure 7 shows electromagnetic torque response for step change in load torque. It is concluded that the adaptive PI control based on RBF neural network has fast torque response and low torque ripple compared with the conventional PI controller.

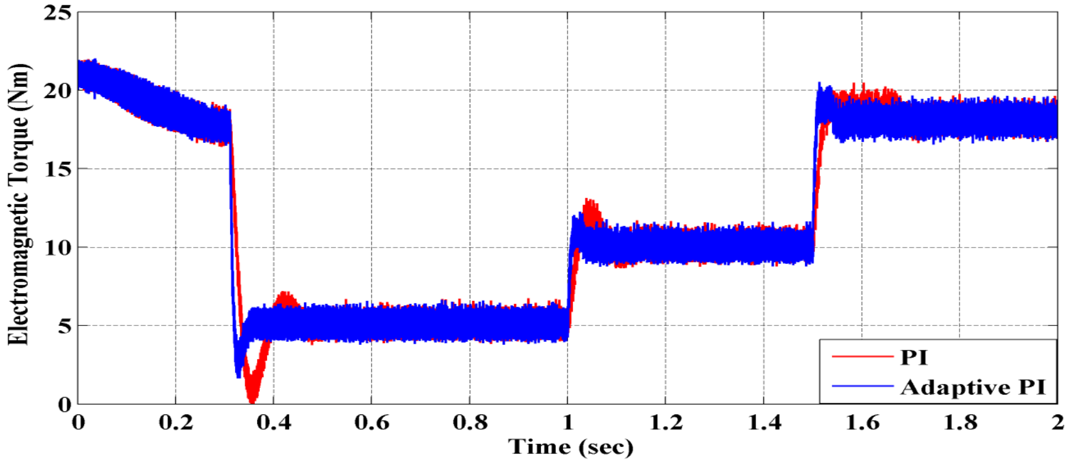

Figure 7. Electromagnetic torque response for step change in load torque

6 CONCLUSION

A RBF neural network based adaptive PI control strategy for speed control of induction motor is proposed in this paper. The parameters of proposed controller are adjusted online to get desired performance of controller. In order to prove the superiority of the proposed controller, a performance comparison has been made with conventional PI controller.

The results show that the proposed controller has adaptability, strong robustness and good performance as compared with the conventional PI controller. This study have shown clearly the adaptive PI control algorithm based on RBF neural network is improved the performance of induction motor drive system which are overshoot, settling time and steady-state error. In subsequent studies, the effect of rise time can be improved by developing the proposed controller and it can be used in the motor applications when high dynamic performance, wide speed range and low torque ripple are required.

APPENDIX

Table 1. Parameters of induction motor

Parameter	Value
Rated Power [P]	3 kW
Rated Speed [n]	1430 d/d
Rated Stator Voltage [U]	380 V
Rated Stator Current [I]	6.7 A
Rated Shaft Load Torque [M]	19 Nm
Number of Poles [p]	2
Rated Frequency [f]	50 Hz
Rotor Resistance [R_r]	1.93Ω
Stator Resistance [R_s]	1.45Ω
Mutual Inductance [L_m]	188 mH
Stator Inductance [L_s]	200 mH
Rotor Inductance [L_r]	200 mH
Moment of Inertia of Rotor [J]	0.03 $kg.m^2$
Coefficient of Friction [B]	0.01 Nm.s/rad

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