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Uncertainty Observer using the Radial Basis Function Networks for Induction Motor Control

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ABSTRACT

A stable adaptive sensorless speed controller for three-level inverter fed induction motor direct torque control (DTC) system using the radial-basis function network (RBFN) is presented in this paper. Torque ripple in the DTC system for high power induction motor could be drastically reduced with the foregoing researches of switching voltage selection and torque ripple reduction algorithms. However, speed control performance is still influenced by the inherent uncertainty of the system such as parametric uncertainty, external load disturbances and unmodeled dynamics, and its exact mathematical model is much difficult to be obtained due to their strong nonlinearity. In this paper, the inherent uncertainty is approximated on-line by the RBFN, and an additional robust control term is introduced to compensate for the reconstruction error of the RBFN instead of the rich number of rules and additional updated parameters. Control law for stabilizing the system and adaptive laws for updating both of weights in the RBFN and a bounding constant are established so that the whole closed-loop system is stable in the sense of *Lyapunov*, and the stability proof of the whole control system is presented. Computer simulations as well as experimental results are presented to show the validity and effectiveness of the proposed system.

Keywords : Sensorless speed control, direct torque control, RBFN, inherent uncertainty, Lyapunov

1. Introduction

DTC scheme has been widely used in the industrial application fields because of its several features such as quick torque response and robustness against the motor parameter variation[1-2]. In the basic DTC scheme, both of the torque and stator flux errors are directly induced with comparing between reference and estimated values, and the appropriate voltage vectors are produced by an off-line switching table. This simple mechanism allows a quick torque response to be achieved with increasing the robustness against the parameter variations. However, the torque ripple and stator flux demagnetization in the low DTC scheme shows some drawbacks such as large speed. region and switching frequency variation according to the changes of the motor parameters and the rotor speed. Because the inverter switching frequency is limited to the lower value for high power applications, the resulted torque ripples should be enlarged to undesired level.

Recently, many researches have been carried out to cope with these drawbacks[1-3], and especially for high power induction motor applications, the torque ripple mini

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mization and voltage selection algorithms for three-level inverter system could drastically reduce the torque ripple and remove the flux demagnetization phenomenon[2]. However, speed control performance is still influenced by the inherent uncertainty of the system such as parametric uncertainty, external load disturbances and unmodeled dynamics. Because the strong nonlinearity of the inherent uncertainty deteriorates obtaining the exact mathematical model of it, until now, many kinds of soft computing methods have been developed for identification and control of nonlinear dynamics such as adaptive fuzzy logic, fuzzy neural networks and recurrent fuzzy neural network[3-10,15]. Especially, in the fields of AC machine control, much intensive research on the design of a robust stable speed controller has been performed as applications of soft computing methods[3-6,8].

Among them, some efforts on the design of speed control for induction motor using recurrent fuzzy neural network (RFNN)[3], fuzzy logic approach[5-6] can be distinguished. The hybrid controller, proposed by R.J Wai[3], is based on the RFNN uncertainty observer for adaptation of the inherent uncertainty on line, and shows the better performance than that of IP control scheme. However, complicated RFNN structure and too many updated parameters design constants bring on the computational burden. In additional, there is difficulty that the system designer should find the bounding design constant from trials and errors, which needs a systematic insight.

In[5-6], the authors designed simple static fuzzy controllers for speed[5] and torque [6] regulation. However, because their static mappings do not hold adaptive characteristics against variations of system environment, the perfect robust ness cannot be guaranteed. Moreover, because fuzzy systems directly encoded expert knowledge to linguistic manner, finite investigation on controlled system is needed to determine the fuzzy rules for better performances.

The radial-basis function network (RBFN) is widely used as a universal approximator like fuzzy and neural systems[9-10]. The RBFN is the architecture of the instar-outstar model and constructed with input, output and hidden layers of normalized *Gaussian* activation functions. Due to its drastic performance despite of simple structure[1-3], it has been introduced as a possible solution to the real multivariate interpolation problem. However, there must be a reconstruction error if the structure of the RBFN (the number of activation functions in the hidden layer) is not infinitely rich, and this error is introduced into the closed-loop system and make the convergence time slow, and that, for the worst case, it can deteriorate the stability. To compensate for the reconstruction error, the method of additional sliding -mode like compensating input term is widely used[3,15], and its gain is computed with the information of the bounding constant of the system uncertainty. However, finding the bounding constant needs a systematic insight as mentioned early, thus, it can be easily overestimated or obtained from off-line learning phase.

In this paper, a speed controller using the RBFN observer is proposed. The inherent uncertainty of induction motor systems is approximated by the RBFN, and an additional robust control term is introduced to compensate for the reconstruction error instead of the rich number of rules and additional updated parameters. Control input, and adaptive laws for updating the weights in the RBFN and the bounding constant are established so that the whole closed-loop system is stable in the sense of *Lyapunov*. To achieve the speed sensorless process, speed estimation is completed by a conventional preferred method proposed by Kubota[11] in this paper. And to compare the characteristics of the proposed scheme, finely tuned integral plus proportional (IP) controller and a nominal controller from nominal dynamics without the RBFN observer are also designed. The contents of this paper are as follows. Firstly, a sensorless speed control using the conventional IP speed controller in the DTC system is described. Secondly, a brief description of the RBFN and the proposed speed controller using the RBFN observer are described. And next, based on the DTC for three-level inverter-fed induction motor system[2], simulation and experimental results are accomplished to verify the effectiveness and feasibility of the proposed system.

2. Sorless Speed Control for Induction Motor DTC System

A block diagram of the basic induction motor DTC system is shown in Fig. 1 including speed control scheme, torque and flux comparators fed switching logic generator, adaptive observer and 3-level inverter system. Our main control object in this paper is on improving speed control performance. In this section, two types of speed controllers as conventional schemes are to be discussed before the proposed approach.

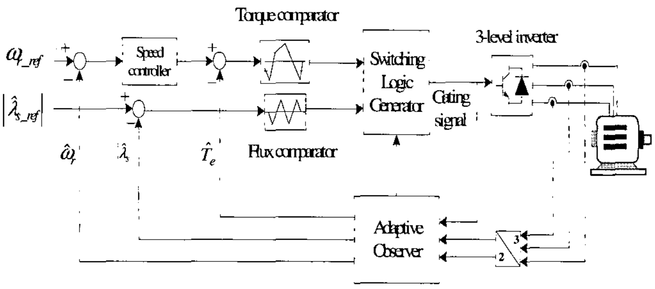


Fig. . Block Diagram of the Basic DTC for Three-level Inverter System.

2 1 IP Control Scheme

IP control has a few advantages of negligible overshoot in its step tracking response, good regulation characteristics as against the PI control, and zero steady state error [4]. The IP controller is to be designed to stabilize the speed control loop, and its parameters, *Ki*, *Kp*, can be derived to obtain the desired control performance. If some reasonable assumptions are adopted into nominal model dynamics such as flux. torque estimations and their regulation are perfectly performed, then the block diagram of the DTC system can be further simplified as Fig. 2. Now to design the IP controller, the following transfer function can be derived from Fig. 2 where the external load torque, T_L, is zero.

$$\left.\frac{\omega_r}{\omega_r^*}\right|_{T_L=0} = \frac{K_T K_I}{Js^2 + (B + K_T K_P)s + K_T K_I} \tag{1}$$

In (1), the unit step response of the rotor speed is derived as follows:

$$\omega_r(s) = \frac{\omega_n^2}{s\left(s^2 + 2\zeta\omega_n s + \omega_n^2\right)} \tag{2}$$

where $\zeta = \dfrac{B + K_T K_P}{2\sqrt{JK_T K_I}}$ and $\omega_n = \sqrt{\dfrac{K_T K_I}{J}}$.

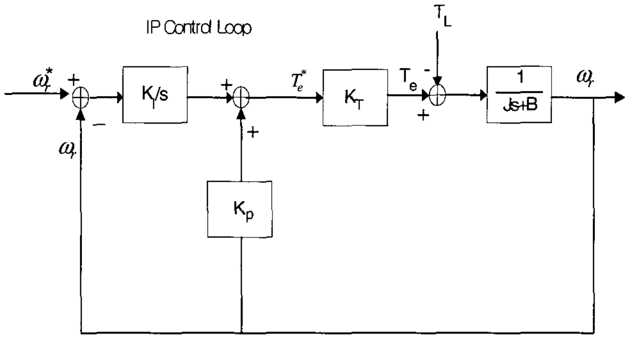


Fig. 2. Simplified IP Speed Control in DTC System.

Therefore, IP gains are decided as the following forms, and because the function(1) has no zeros so that the undesired overshoot can be avoided.

$$K_I = \frac{\omega_n^2}{K_T} J, \quad K_P = \frac{2\zeta\omega_n J - B}{K_T} \tag{3}$$

2.2 Nominal control scheme

The control object is to force ω_r to follow a given bounded reference speed ω_r^* under the inherent uncertainty with the constraint that all signals in the closed loop system must be bounded. From Fig. 2, the following state equation is obtained using the estimated speed $\hat{\omega}_r$ instead of sensored one, ω_r :

$$\dot{X}_n = A_n X_n + B_n U_m + C_n T_L \tag{4}$$

where $X_n = \hat{\omega}_r$, $A_n = -B/J$, $B_n = k_T/J$, $U_m = T_e^*$, $C_n = 1/J$.

The above equation (4) is expressed by nominal values, but in most practical cases, inherent uncertainty in the induction motor model should exist. Therefore, it is reasonable that the inherent uncertainty is engaged, and the following equation is obtained.

$$\dot{X}_q = A_n X_q + B_n U_n + \varepsilon \tag{5}$$

where ΔA_n, ΔB_n are modeling errors of A_n, B_n, $X_q = \hat{\omega}_r$, U_n is control input, $\varepsilon = (\Delta A_n X_q + \Delta B_n U_n + C_n T_L + \rho)$ and ρ is the unmodeled uncertainty. In equation (5), if we know exactly the inherent uncertainty, ε, then the perfect control input for the closed loop system to be asymptotically stable is computed as the following form.

$$U_n = B_n^{-1}[\dot{X}_d - A_n X_q - \varepsilon + K_x e_x] \tag{6}$$

where $e_x = X_d - X_q$, and K_x is a design constant to stabilize the system. Now, substituting (6) into (5), the following error dynamics is obtained,

$$\dot{e}_x + K_x e_x = 0 \tag{7}$$

which implies that the control input (6) leads the whole closed loop system to be stable, $\lim_{t\to\infty} e_x(t) = 0$, with an appropriate design constant, K_x.

3. Stable Adaptive Speed-Sensorless Induction Motor DTC System

In this paper, the unknown inherent total uncertainty is modeled by the RBFN observer The proposed scheme is detailed described in this section. At first, structure of the RBFN is shortly outlined, and a control law and parameter update laws are derived. And next, additional update laws to prevent the RBFN uncertainty observer from being divergence are derived using the parameter projection algorithm. And the last part in this section, asymptotic stability of the whole control system including parameter projection algorithm is to be presented.

3.1 Brief Description of the RBFN

The RBFN is the architecture of the instar-outstar model and constructed with input, output and hidden layers of normalized *Gaussian* activation functions. The RBFN is based on the concept of the locally tuned and overlapping receptive field structure. A schematic diagram of a simple type of the RBFN is shown in Fig. 3, which consists of one input, one output and single hidden layer. In general, the hidden nodes in the RBFN have normalized *Gaussian* activation function as follows[12].

$$z_q = \xi_q(\mathbf{x}) \triangleq \frac{\phi_q(\mathbf{x})}{\sum_k \phi_k(\mathbf{x})} = \frac{\exp\left[-\left|\mathbf{x}-\mathbf{m}_q\right|^2/2\sigma_q^2\right]}{\sum_k \exp\left[-\left|\mathbf{x}-\mathbf{m}_q\right|^2/2\sigma_k^2\right]} \tag{8}$$

where $\mathbf{x}$ is the input vector, $\mathbf{m}_q$ is the center, and σ_q is the width of qth *Gaussian* function. For each qth hidden node, its receptive field, $\phi_q(\mathbf{x})$, is a region centered on $\mathbf{m}_q$, and σ_q is the variance of the qth *Gaussian* function. Therefore, hidden node q gives a large response value to input vectors as close to $\mathbf{m}_q$.

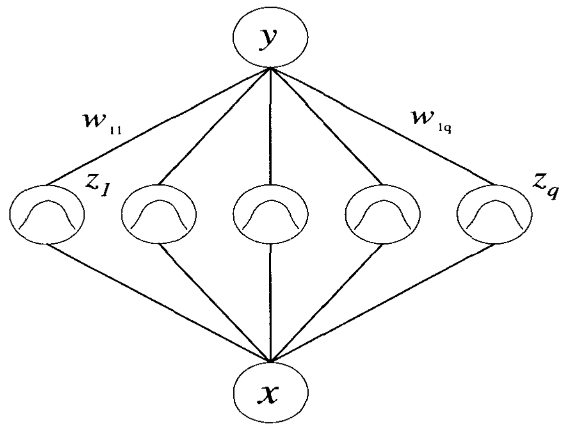


Fig. 3. Structure of the RBFN.

The output of the RBFN is simply the weighted sum of the hidden node output. In this paper, the RBFN output has a simple form of a linear combination of the output of the hidden layer:

$$\begin{aligned} y &= \sum_{q=1}^{l} w_q \cdot z_q \\ &= [w_1\ w_2\ \ldots\ w_l][z_1\ z_2\ \ldots\ z_l]^T = W^T \cdot Z \end{aligned} \tag{9}$$

where w_i, $(i = 1, \cdots, l)$ are the weights between the ith node and the RBFN output, $W \in R^n$ is the vector of w_i's. The RBFN has been introduced as one possible solution of the real multivariate interpolation problem[9,12]. Some theorems reflect that the three-layered RBFN is a universal approximator like fuzzy and neural systems if the activation function used in the hidden layer is infinitely differentiable and not a polynomial[9-10].

4. Robust Stable Speed Controller Using the RBFN Observer

Using the output of the RBFN, $\hat{\varepsilon}$, instead of ε, the equation (5) is rewritten as follows:

$$\dot{X}_q = A_n X_q + B_n U_q + \hat{\varepsilon} \tag{10}$$

where, U_q is the overall control input. The control input for inverse dynamics of (10) can be written as the following form.

$$U_o = B_n^{-1}\left[\dot{X}_d - A_n X_q - \hat{\varepsilon} + K e_x\right] \tag{11}$$

In (11), if the universal approximator perfectly identifies the unknown uncertainty, i.e. $\hat{\varepsilon}(t) = \varepsilon(t)$, $(\forall t \geq 0)$, then the control input(11) makes the overall system to be asymptotically stable. However, in practical cases, the reconstruction error is inevitable, and thus an additional compensating control is required. To describe some theorems, the following assumption and definition of constraint set are required.

Assumption 1. The following inequality holds

$$\left|\zeta(t)\right| \leq \overline{\zeta}^* \tag{12}$$

where $\zeta(t) = \varepsilon^* - \varepsilon$, ε^* is the optimized modeled inherent total uncertainty, and $\overline{\zeta}^* > 0$ is a small finite constant.

Definition 1.

$$\mathbf{W}^* = \arg\min_{\mathbf{W}\in\Omega_W}\left[\sup_{e_x\in \mathbf{U}_C}\left|\hat{\varepsilon}(e_x / \mathbf{W}) - \varepsilon\right|\right],$$
$$\Omega_W = \{\mathbf{W} : \|\mathbf{W}\| \leq M_W\}$$

where Ω_W is a constraint set for $\mathbf{W}$, M_W is a positive constant specified by a designer, and $\mathbf{U}_C$ is a certain controllability region such as $\mathbf{U}_C \subset R^n$.

Theorem 1. Let the overall control input U_q including U_o be

$$U_q = U_0 + U_p$$
$$U_p = B_n^{-1}\overline{\zeta}\,\mathrm{sgn}(e_x) \tag{13}$$

where U_o is determined as (11), U_p is an additional control for compensating reconstruction error of the RBFN and $\mathrm{sgn}(\cdot)$ is the sign function. We also determine the update laws for the RBFN weight, $\mathbf{W}$, and the estimation of the constant as

$$\dot{\mathbf{W}} = -\gamma_W e_x \mathbf{Z}$$
$$\dot{\overline{\zeta}} = \gamma_\zeta \left|e_x\right| \tag{14}$$

Then, the speed control system (5) is asymptotically stable, i.e.,

$$e_x \to 0 \text{ for } \forall t \to \infty.$$

Proof. For deriving the adaptive laws for bounding constant, $\overline{\zeta}$, the weights of the RBFN, $\mathbf{W}$, and compensating control input, U_p, we define a *Lyapunov* candidate function as follows:

$$V_e(t) = \frac{1}{2}e_x^2 + \frac{1}{2\gamma_W}(\mathbf{W} - \mathbf{W}^*)^T(\mathbf{W} - \mathbf{W}^*) + \frac{1}{2\gamma_\xi}(\overline{\zeta} - \overline{\zeta}^*)^2 \tag{15}$$

where ζ^* is an optimal value of $\overline{\zeta}$. Now, let the overall control input (13) be engaged into (5) instead of U_n, then the time derivative of the error equation is

$$\begin{aligned}\dot{e}_x &= \dot{X}_d - \dot{X}_q = \dot{X}_d - \left\{ A_n X_q + B_n \left(U_o + U_p \right) + \varepsilon \right\} \\ &= \dot{X}_d - \left[A_n X_q + B_n \left\{ B_n^{-1} \left(\dot{X}_d - A_n X_q - \hat{\varepsilon} + K e_x \right) + U_p \right\} + \varepsilon \right] \\ &= -K e_x - B_n U_p + \hat{\varepsilon} - \varepsilon^* + \zeta = -K e_x - B_n U_p + \left(\mathbf{W} - \mathbf{W}^* \right) \mathbf{Z} + \zeta \end{aligned} \quad (16)$$

Take the time derivative of the *Lyapunov* equation (15), then

$$\begin{aligned}\dot{V}_e(t) &= e_x \left\{ -K e_x - B_n U_p + \left(\mathbf{W} - \mathbf{W}^* \right)^T \mathbf{Z} + \zeta \right\} + \frac{1}{\gamma_W} \left(\mathbf{W} - \mathbf{W}^* \right)^T \dot{\mathbf{W}} + \frac{1}{\gamma_\xi} \left(\bar{\zeta} - \bar{\zeta}^* \right) \dot{\bar{\zeta}} \\ &= -K e_x^2 - e_x B_n U_p + e_x \left(\mathbf{W} - \mathbf{W}^* \right)^T \mathbf{Z} + \frac{1}{\gamma_W} \left(\mathbf{W} - \mathbf{W}^* \right)^T \dot{\mathbf{W}} + e_x \zeta + \frac{1}{\gamma_\xi} \left(\bar{\zeta} - \bar{\zeta}^* \right) \dot{\bar{\zeta}} \\ &\leq -K e_x^2 - e_x B_n U_p + e_x \left(\mathbf{W} - \mathbf{W}^* \right)^T \mathbf{Z} + \frac{1}{\gamma_W} \left(\mathbf{W} - \mathbf{W}^* \right)^T \dot{\mathbf{W}} + |e_x| \bar{\zeta}^* + \frac{1}{\gamma_\xi} \left(\bar{\zeta} - \bar{\zeta}^* \right) \dot{\bar{\zeta}} \end{aligned} \quad (17)$$

Substituting (13) and (14) into (17), it is easily observed that the *Lyapunov* equation is to be a negative value as

$$\dot{V}_e(t) \leq -K e_x^2 \leq 0 \quad (18)$$

The inequality (18) shows that all variables in (15), e_x, $\left(\mathbf{W} - \mathbf{W}^* \right)$ and $\left(\bar{\zeta} - \bar{\zeta}^* \right)$, are finitely bounded.

To show the fact that the speed control system is asymptotically stable, i.e., $e_x \to 0$ for $\forall t \to \infty$, let a function be defined as $\Lambda = K e_x^2 \leq -\dot{V}_e(t)$.

Integration of the function with respect to time is as follows:

$$\int_0^t \Lambda(\tau) d\tau = V_e(0) - V_e(t) \quad (19)$$

Because V_e is bounded from (17), so that $\lim_{t \to \infty} \int_0^t \Lambda(\tau) d\tau$ exists and is finite. Moreover, because $\dot{\Lambda} = 2K e_x \dot{e}_x$ is also bounded, the function Λ is uniformly continuous from the finite difference theorem [13]. From the *Babalat*'s lemma [14] the following result is true,

$$\Lambda \to 0 \quad \text{for} \quad \forall t \to \infty \quad (20)$$

which shows that the system is asymptotically stable, i.e. $e_x \to 0$ for $\forall t \to \infty$. This is the end of the proof.

4.1 Stability analysis of the RBFN observer

Because the RBFN is the functional network composed of their design parameters, the convergence of these parameters leads to the stable characteristic of the RBFN [3, 12]. In this paper, parameter projection[15] is used to derive it.

Theorem 2. Let we determine the update laws with (13) and (14) for the RBFN weight, **W**, as follows:

$$\dot{\mathbf{W}} = -\gamma_W e_x \mathbf{Z}, \quad \text{if } |\mathbf{W}| < M_W \quad (\text{or } |\mathbf{W}| = M_W \text{ and } e_x \mathbf{W}^T \mathbf{Z} \geq 0),$$

$$\dot{\mathbf{W}} = -\gamma_W e_x \mathbf{Z} + \gamma_W e_x \frac{\mathbf{W}\mathbf{W}^T \mathbf{Z}}{|\mathbf{W}|^2}, \quad \text{if } |\mathbf{W}| = M_W \text{ and } e_x \mathbf{W}^T \mathbf{Z} < 0. \quad (21)$$

Then, the RBFN observer is stable, i.e., $\mathbf{W} \in \Omega_W$, $\forall t \geq 0$.

Proof Let a *Lyapunov* equation be

$$V_W = \frac{1}{2} \mathbf{W} \mathbf{W}^T,$$

and its time derivative be $\dot{V}_W = \mathbf{W}\dot{\mathbf{W}}^T$. In the first case of (21), if the condition is true, then

$$\dot{V}_W = \mathbf{W}\dot{\mathbf{W}}^T = -\gamma_W e_x \mathbf{W}^T \mathbf{Z} \leq 0 \quad (22)$$

This means that the weight vector of the RBFN is bounded (i.e., $|\mathbf{W}| \leq M_W$, $\forall t \geq 0$).

If the second condition of (21) is true, then the following equation is right.

$$\dot{V}_W = \mathbf{W}\dot{\mathbf{W}}^T = \mathbf{W} \left[-\gamma_W e_x \mathbf{Z} + \gamma_W e_x \frac{\mathbf{W}\mathbf{W}^T \mathbf{Z}}{|\mathbf{W}|^2} \right] = 0 \quad (23)$$

This means that $|\mathbf{W}| \leq M_W$ ($\forall t \geq 0$) is true because of $|\mathbf{W}(0)| < M_W$.

The above two cases with (22) and (23) completely show the stable characteristics of the RBFN observer.

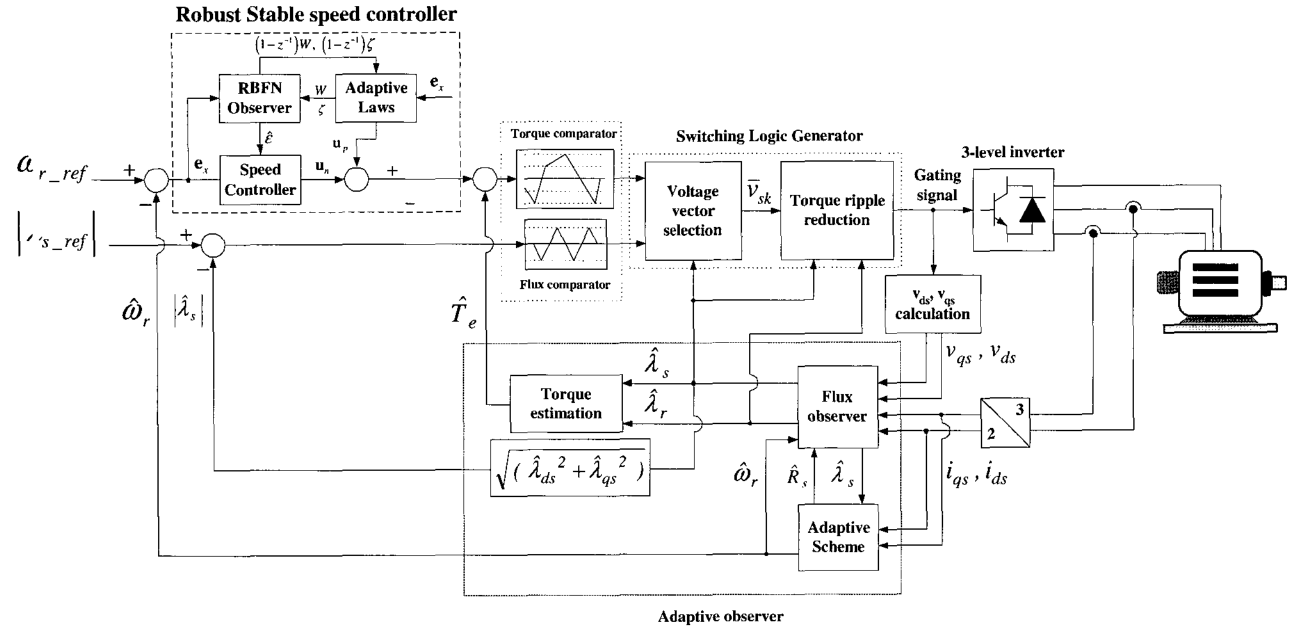


Fig. 4. Schematic diagram of the proposed DTC control system.

4.2 Stability analysis of the whole control system

To prove the asymptotic stability of the whole control system including parameter projection, consider the *Lyapunov* equation (14). Now, applying the parameter projection of the second line of (21) to (14) with the computed control input and update laws, (13), (14), respectively, then the following result is obtained.

$$\dot V(t) \le -Ke_x^2 - e_x B_n U_p + e_x(\mathbf{W}-\mathbf{W}^*)^T \mathbf{Z} + \frac{1}{\gamma_W}(\mathbf{W}-\mathbf{W}^*)^T \dot{\mathbf{W}} + |e_x|\zeta^* + \frac{1}{\gamma_\zeta}(\zeta-\zeta^*)\dot\zeta = -Ke_x^2 + e_x \mathbf{W}^T\mathbf{Z}\left[\frac{(\mathbf{W}-\mathbf{W}^*)^T\mathbf{W}}{|\mathbf{W}|^2}\right] \quad (24)$$

Because the last term in (24) is a negative value (i.e., $e_x \mathbf{V}'^T \mathbf{Z} < 0$ and $|\mathbf{W}| = M_W > |\mathbf{W}^*|$), the time derivative of the *Liapunov* function is negative semi definite, $\dot V_e \le 0$ for $\forall t \ge 0$. From the *Babalat*'s lemma [14] which is the same as *Theorem 1*, it is true that the whole closed loop system with the parameter projection is asymptotically stable. The overall block diagram of the proposed control system is shown in Fig. 4.

In this figure, torque ripple reduction and voltage selection algorithms for three-level inverter system [2] are included, and flux observer for speed estimation, which is com pleted by a conventional preferred method is also contained.

5. Simulation and Experimental Results

5.1 Simulation Results

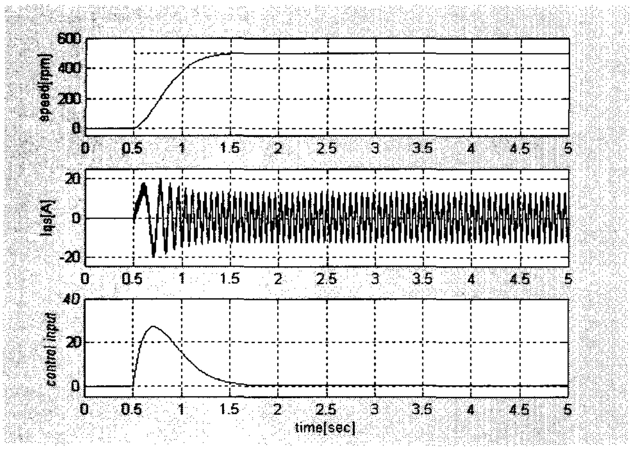
Some simulation results are shown to confirm the validity of the proposed control algorithm. The overall control system consists of the basic DTC, the torque ripple reduction algorithm, the adaptive observation of the stator flux and the stator resistance estimation and the proposed speed regulator blocks. The induction motor used in this paper reads a nameplate of 3-phase 220Vac, 10hp, and the rated speed of 1740rpm. In this paper, two test conditions as follows are provided.

CASE1: ΔJ=ΔB=0, Tl = 0

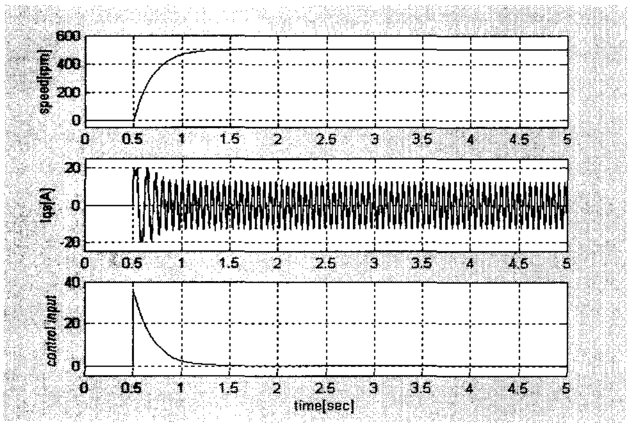
CASE2: ΔJ= 0.4 x J, ΔB= 0.4 x B, Tl=8

In the above conditions, "J" is inertia constant, "B" is friction constant, and "Tl" means external load torque. IP gain is computed as is in the reference paper [4] and the speed estimation is completed by a conventional preferred method proposed by Kubota [11].

At first, Fig.5 shows the comparative results of rotor speed, phase current and control input in the CASE1 at 500rpm of desired rotor speed. Because there is no uncertainty in this case, simulated results with all of controllers have satisfactory tracking performances. Secondly, Fig. 6 shows the simulation results of CASE2



(a) Conventional IP control (CASE1)



(b) Proposed control (CASE1)

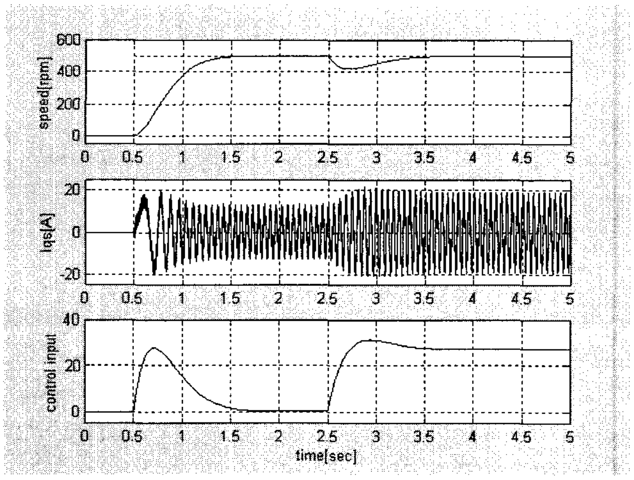
Fig. 5. Simulation results of CASE 1: speed, phase current and control input.

when the parameter variations and external disturbance are abruptly occurred at 2.5s. For IP control, about 1.5s is taken to overcome the affection and for the tracking error to be zero. However, for the RBFN control, it takes about 0.2s for tracking error to be zero.

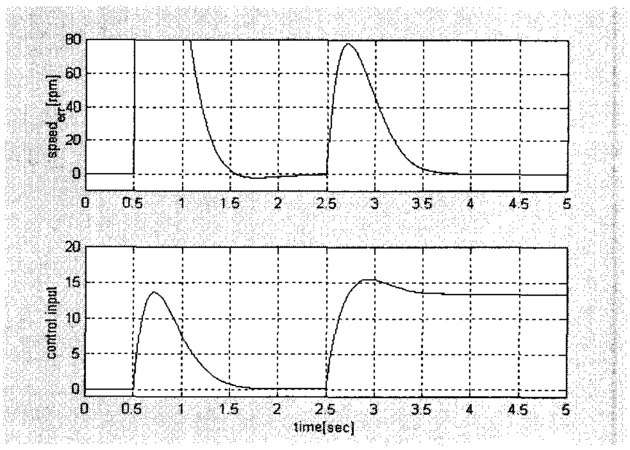
The tracking error performance in the case of proposed scheme is preferred because the RBFN observer approximates the uncertainty minimizing the rotor speed error. The theoretical value of the inherent uncertainty is about −180, and Fig. 6(d) shows the estimated value by using the RBFN observer. Because the compensated control input is applied for compensating reconstruction error, tracking performance can be improved despite of slower observation of the uncertainty. From these simulation results, the better speed control characteristic of the proposed scheme in the DTC system when the inherent uncertainty exists is observed.

5.2 Experimental Setup

To confirm the feasibility of the proposed system, experiment is accomplished as the same conditions those



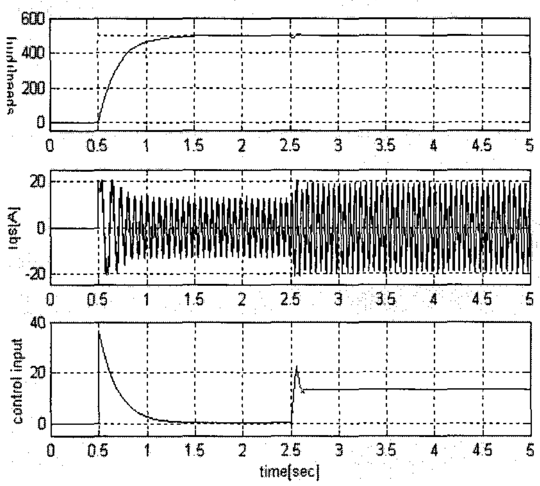
(a) Conventional IP controller (1) (CASE2)



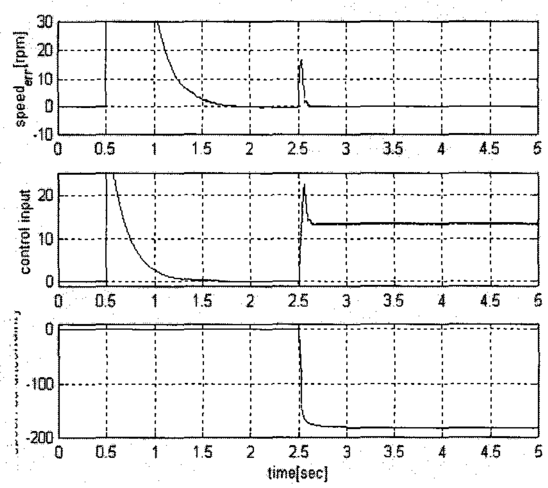
(b) Conventional IP controller(2) (CASE2)

of simulation process. The experimental set-up is implemented based on the main control board of DS10 03.Fig.

7sl ows the schematic diagram of the experimental eqı .ipments includidng 3-level inverter system and main coı .trol board for speed control with speed estimation and DTC scheme. The sampling time of control cycle is set at2)0 *us* for the torque ripple reduction algorithm and the prc posed speed regulator. The switching frequency of the prc posed DTC system remains in the region of 500 Hz – 1.C kHz, maximized line to line voltage is 380 (V) and de: d time compensator is not used.Fig. 8 shows the exj erimental results of CASE1 at 500rpm of the desired rot)r speed.



(c) Proposed controller (1) (CASE2)



(d) Proposed controller (2) (CASE2)

Fig. 6. Simulation results of CASE 2: speed, speed error, phase current, control input and observed uncertainty.

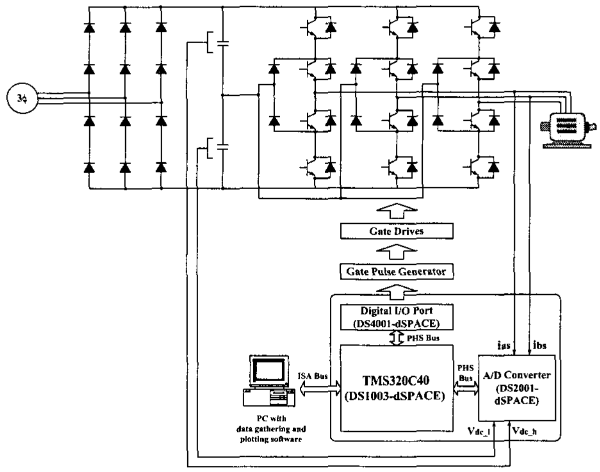
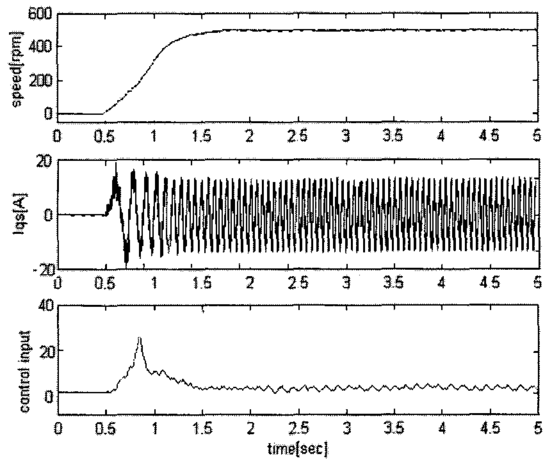
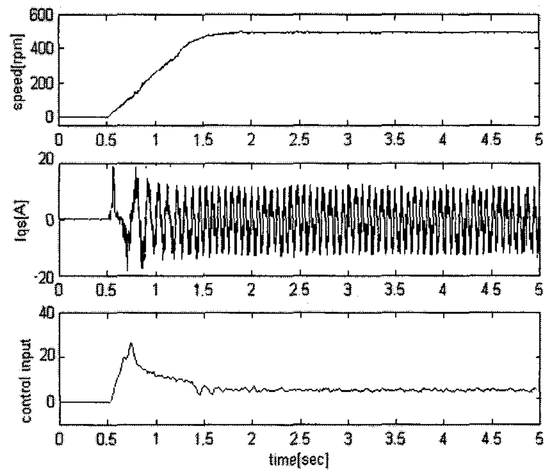


Fig. 7. Schematic diagram of the experimental setup.



(a) Conventional IP control (CASE1)



(b) Proposed control (CASE1)

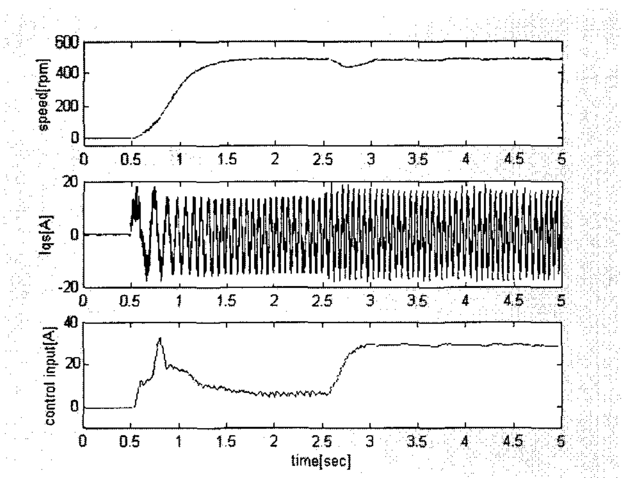
Fig. 8. Experimental results of CASE 1: speed, phase current, and control input.

In CASE1, both controllers have an effective tracking performance. However, for CASE2, the proposed RBFN observer scheme shows more robust performance compare -d the IP control. For the RBFN control (Fig. 9(b)), it takes about 0.3s for tracking error to be zero, but IP control (Fig. 9(a)) is about 1s. Moreover, IP control shows more lager tracking error than that of the RBFN scheme.

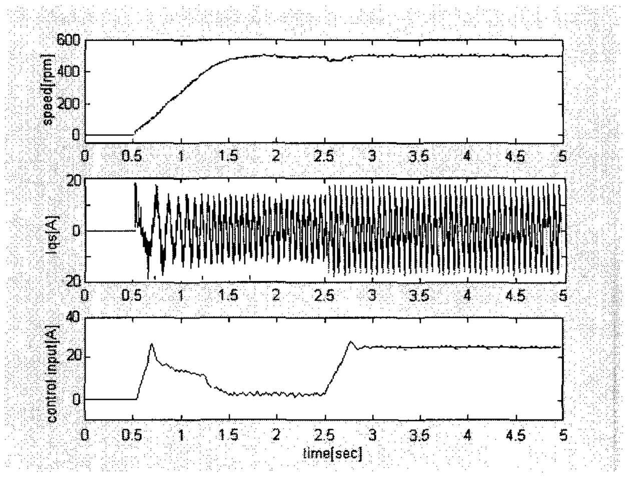
The experimental results are similar to the respective simulation results. From these experimental results, it can be said that the proposed robust stable speed control scheme shows relatively small tracking error compared to conventional IP control scheme even when a certain inherent uncertainty is abruptly engaged.

6. Conclusions

A speed control scheme for sensorless induction motor DTC systems is presented to achieve the robust stable control characteristics against the inherent uncertainty such as parametric uncertainty and external load distur bances and unmodeled uncertainty. The inherent total uncertainty is approximated by the RBFN, and its information is fed to the speed control block. The proposed algorithm is applied to the DTC system for three-level inverter fed induction motor control. A Control law and adaptive laws for the bounding constant and weights in the output layer of the RBFN are established so that the whole closed loop system is stable in the sense of Lyapunov. The proposed control algorithm is relatively simple and requires no restrictive conditions on the design constants for the stability. The effectiveness and validity of the proposed system is shown through simulation and experimental results.



(a) Conventional IP control (CASE2)



(b) Proposed control (CASE2)

Fig. 9. Experimental results of CASE 2: speed, speed error, phase current, and control input.

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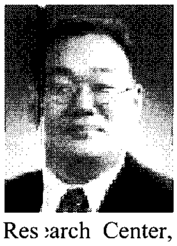

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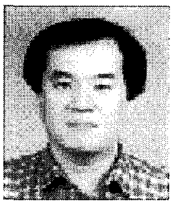

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