Sensorless Speed Control System Using a Neural Network

Sung-Hoe Huh, Kyo-Beum Lee, Dong-Won Kim, Ick Choy, and Gwi-Tae Park

Abstract: A robust adaptive speed sensorless induction motor direct torque control (DTC) using a neural network (NN) is presented in this paper. The inherent lumped uncertainties of the induction motor DTC system such as parametric uncertainty, external load disturbance and unmodeled dynamics are approximated by the NN. An additional robust control term is introduced to compensate for the reconstruction error. A control law and adaptive laws for the weights in the NN, as well as the bounding constant of the lumped uncertainties are established so that the whole closed-loop system is stable in the sense of *Lyapunov*. The effect of the speed estimation error is analyzed, and the stability proof of the control system is also proved. Experimental results as well as computer simulations are presented to show the validity and efficiency of the proposed system.

Keywords: Neural network (NN), uncertainty observer, robust adaptive speed sensorless control, speed estimation error.

1. INTRODUCTION

One of the essential problems in the field of induction motor systems is the design of a robust stable speed controller against the unknown uncertainties such as parametric uncertainty, external load disturbances and unmodeled dynamics. Due to their strong nonlinearities, it is not easy to obtain their exact mathematical models, and until now, soft computing approaches using a recurrent fuzzy neural network (RFNN) [1] and fuzzy logic (FL) [2] have been persistently researched for replacing numerical methods. In [1], an RFNN observer for the unknown uncertainties was proposed, and showed superior performance results compared to the convectional approaches. However, complicated RFNN structure combined with numerous updated parameters brings on the computational burden, and design constants with trial and errors do not provide systematic transparency. In [2], the authors designed a simple static fuzzy controller for speed and torque regulation. However, its static mappings and structure do not have adaptive characteristics against variable system environment. As a result, neither robustness nor stability can be guaranteed, and moreover, because the fuzzy systems encode expert knowledge into linguistic manner directly, finite investigation on a controlled system is necessary.

Recently, the neural network (NN) is widely used as a universal approximator in the area of nonlinear mapping and uncertain nonlinear control problems [3]. The NN structure is to be implemented by input-output (nonlinear) mapping models and is constructed with input, output and hidden layers of sigmoid activation functions. Because the NN can be used for a universal approximator like fuzzy and neural systems [4], it has been introduced as a possible solution to the real multivariate interpolation problem. However, there must inevitably be a reconstruction error if the structure of the NN (the number of activation functions in the hidden layer) is not infinitely rich. These errors are introduced into the closed-loop system and deteriorate the stability. To compensate for the reconstruction error, a sliding-mode like compensating input term is widely used, and its input gain is closely concerned with the system uncertainties. Thus, it is used to being overestimated or obtained from the off-line learning phase.

In this paper, a speed controller using the NN uncertainty observer is proposed. The proposed controller is applied to a high power 3-level fed induction motor direct torque control (DTC) system. The inherent lumped uncertainties are approximated by the NN observer, and an additional robust control term is introduced to compensate for the reconstruction error. A control input and adaptive laws for the weights in the NN and the bounding constant

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are established so that the whole closed-loop system is stable in the sense of *Lyapunov*. In actual systems as well as in the analysis procedure, the speed estimation error is inevitable and is to be engaged in stability analysis, which has been out of account in many papers. In this paper, the stability analysis of the whole control system is presented considering the effect of the speed estimation error.

The contents of this paper are as follows. Firstly, a brief description of the NN as a universal approximator is presented. Secondly, the proposed speed control system using the NN uncertainty observer is described. Thirdly, simulation and experimental results are presented to verify the feasibility of the proposed system. Finally, in the last section, concluding comments are described.

2. NEURAL NETWORK AS A UNIVERSAL APPROXIMATOR

The universal approximators (UAs) such as NN, FL, and hybrid system of FL and NN have been successfully applied to many nonlinear control problems. The design objective of NN or FL is aimed at approximating some nonlinear mappings into idealistic approaches. This means that an arbitrary function $f : R^n \rightarrow R$ is to be approximated by NN or FL. It is well known that any continuous function

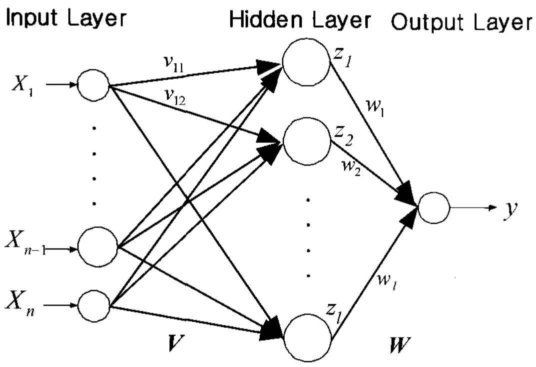


Fig. 1. Structure of the neural network.

$f : [a,b] \rightarrow R$ defined on a compact set can be uniformly approximated by polynomials for any degree of accuracy, and polynomial $p(x)$ on $[a,b]$ makes $\sup_{x\in[a,b]} |p(x) - f(x)| < \varepsilon$ for a given ε. That is the Weierstrass theorem, and the extended form of the Stone-Weierstrass theorem provides the general framework for designing function approximators [6].

The NN is composed of input, output and hidden layers, and because it satisfies the Stone-Weierstrass conditions, it can be used for an universal approximator. A schematic diagram of its general form consisting of n-input, single-output and single hidden layer is shown in Fig. 1, and output of the NN is as shown in the following equation (1).

$$y(X,V,W) = \mathbf{W}^T \mathbf{Z}(V^T X) = [w_1\ w_2\ \ldots\ w_l][z_1\ z_2\ \ldots\ z_l]^T, \tag{1}$$

where $\mathbf{x}$ is the input vector, w_i's, $i = 1,\cdots,l$ are the weights between the i th node and the output, and $\mathbf{W} \in R^n$ is the vector of w_i's.

3. ROBUST STABLE SENSORLESS SPEED CONTROLLER IN DTC SYSTEM USING A NEURAL NETWORK

3.1. Integration and Proportion (IP) control approach

In the field of speed control systems, IP speed control is a generally used scheme because it has several advantages such as negligible overshoot in its step tracking response, good regulation characteristics compared to proportion and integration (PI) control scheme and zero steady state error [6]. The IP controller is to be designed to stabilize the speed control loop, and its parameters *Ki*, *Kp* are derived to show the desired response. A block diagram of the basic induction motor DTC system including the IP speed controller, torque and flux comparators fed switching logic generator, adaptive observer and 3-level inverter system is presented in Fig. 2. Now, if

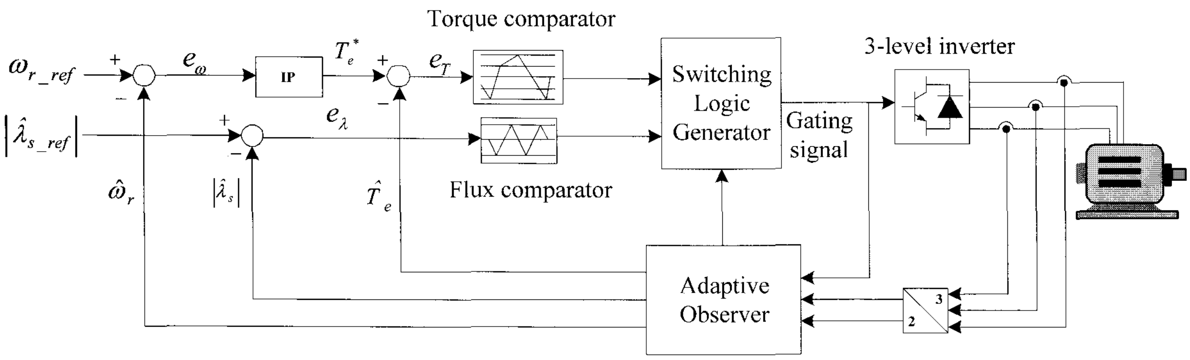


Fig. 2. Block diagram of the basic DTC for 3-level inverter system.

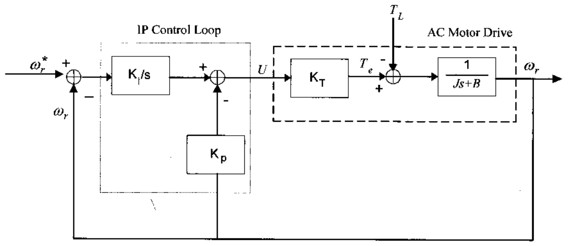


Fig. 3. Simplified DTC system.

some reasonable assumptions are adopted into nominal model dynamics such as rotor speed, then flux and torque estimations and regulations are stably worked, and the DTC system can be further simplified as indicated in Fig. 3.

For the speed control loop on Fig. 3, the transfer function $G_{IP}(s)$ for the reference signal ω_r^* is to be derived as follows:

$$G_{IP}(s) = \frac{\omega_r(s)}{\omega_r^*(s)} = \frac{K_T K_I}{Js^2 + (B + K_T K_P)s + K_T K_I}. \quad (2)$$

For the unit step reference signal, speed response can be derived as follows:

$$\omega_r(s) = \frac{K_T K_I / J}{s^2 + (B + K_T K_P / J)s + (K_T K_I / J)} \cdot \frac{1}{s}. \quad (3)$$

And the following equation is true.

$$\omega_r(s) = \frac{\omega_n^2}{s\left(s^2 + 2\varsigma s + \omega_n^2\right)}, \quad (4)$$

where $\varsigma = \frac{B + K_T K_P}{2\sqrt{JK_T K_I}}$ and $\omega_n = \sqrt{K_T K_I / J}$. In (4), the speed function has no differential term in the numerator, and the speed signal from the IP control scheme has more stable transient response compared to the PI approach, which has a differential term in the numerator. IP gains can be derived from (4) as in the following equation.

$$K_P = \frac{2\varsigma\omega_n J\text{-}B}{K_T}, \quad K_I = \frac{\omega_n^2}{K_T} J \quad (5)$$

3.2. Robust stable approach using NN

The control object is to force ω_r to follow a given bounded reference speed ω_r^* under the inherent uncertainties with the constraint that all signals in the closed loop system must be bounded. From Fig. 3, an open loop mechanical model is obtained:

$$\dot{\omega}_r = -\frac{B}{J}\omega_r + \frac{k_T}{J} T_e^* - \frac{1}{J} T_L. \quad (6)$$

And the equation (6) can be rewritten as the state variable form:

$$\dot{x}_n = A_n x_n + B_n u_m + C_n T_L, \quad (7)$$

where $x_n = \omega_r$, $A_n = -B/J$, $B_n = K_T/J$, $u_m = T_e^*$ and $C_n = -1/J$.

The above equation (7) is expressed by nominal values, but in most practical cases, the inherent uncertainties in the induction motor system should exist. Besides, for the speed sensorless control, the estimated rotor speed instead of the sensed value is to be fed back for generating a control signal based on the assumption that the estimated rotor speed is perfectly identical to the real one. However, in any real system, estimation error is inevitable even though it is negligible, and thus, the influence of the error must be analyzed on feedback control systems.

Now, considering the inherent uncertainties with the estimated speed, equation (7) is further expressed as in the following state variable form:

$$\dot{\hat{x}}_q = A_n x_q + B_n u_o + \varepsilon, \quad (8)$$

where $\varepsilon = (\Delta A_n \hat{x}_q + \Delta B_n u_o + C_n T_L + \rho)$, $\hat{x}_q = \hat{\omega}_r$, $A_n = -B/J$, $B_n = k_T/J$, $C_n = -1/J$, u_o is control input, ρ is the unmodeled uncertainties, and ΔA_n, ΔB_n are modeling errors of A_n, B_n.

Let the two variables, $\hat{e}_x$ and e_x, be defined as

$$\hat{e}_x = \omega_r^* - \hat{\omega}_r \text{ and } e_x = \omega_r^* - \omega_r, \quad (9)$$

where $\omega_r = \hat{\omega}_r + \varphi$ and φ is an exponentially decaying estimation error.

Assumption 1: The following inequalities hold

$$|\varphi| \le \bar{\varphi} \text{ and } |\zeta(t)| \le \bar{\zeta}, \quad (10)$$

where $\bar{\varphi} > 0$ is a positive finite constant, $\zeta(t) = \varepsilon^* - \varepsilon$, ε^* represents the optimally modeled total uncertainties, and $\bar{\zeta} > 0$ is a positive finite constant.

If we know the inherent uncertainties exactly, the perfect control input for the overall system (8) to be asymptotically stable can be computed as follows:

$$u_o = B_n^{-1}[\dot{x}_d - A_n \hat{x}_q - \varepsilon + K\hat{e}_x], \quad (11)$$

where $x_d = \omega_r^*$. In this paper, the unknown uncertainties are modeled by the NN model.

Denoting the output of the NN as $\hat{\varepsilon}$, the equation (11) is rewritten in the following form.

$$u_r = B_n^{-1}[\dot{x}_d - A_n \hat{x}_q - \hat{\varepsilon} + K\hat{e}_x]. \quad (12)$$

If the universal approximator exactly identifies the unknown uncertainties, i.e. $\hat{\varepsilon}(t)=\varepsilon(t)$ for $\forall t \geq 0$, then the control input (12) makes the overall system to be asymptotically stable. However, in most practical cases, the reconstruction error is inevitable, and thus, an additional compensating control is required.

Thoerem 1: Let the overall control input u_q as

$$u_q = u_r + u_p, \quad u_P = B_n^{-1}\xi \,\mathrm{sgn}(\hat{e}_x), \tag{13}$$

where u_r is determined as (12) and u_p is an additional control input for compensating reconstruction error. We also determine the update laws for the NN weight $\mathbf{W}$ and the estimation of the constant $\xi^* \triangleq \left(|A_n|\bar{\varphi}+K\bar{\varphi}+\bar{\zeta}\right)$ as

$$\dot{\mathbf{W}} = -\gamma_W(\hat{e}_x\mathbf{Z}+\sigma_1\mathbf{W}), \quad \dot{\xi} = \gamma_\xi(|\hat{e}_x| - \sigma_1\xi). \tag{14}$$

Then, the tracking error as well as other signals involved in the closed-loop system are unified ultimately bounded (UUB).

Proof: For deriving the adaptive laws for unknown constant limit, ξ, and compensating control input, $\mathbf{u}_p$, we define *Lyapunov* function as in the following form.

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

where $\mathbf{W}^*$ is an optimal value of $\mathbf{W}$. In the equation (15), because e_x is an unknown value, the following equality should be required.

$$e_x = x_d - x_q = x_d - \left(\hat{x}_q+\varphi\right) = \hat{e}_x - \varphi. \tag{16}$$

The time derivative of (16) is

$$\begin{aligned}\dot{e}_x &= \dot{x}_d - \dot{x}_q = \dot{x}_d - (A_n x_q + B_n(u_r+u_p)+\varepsilon)\\ &= -A_n\varphi - K\hat{e}_x - B_n u_p + \left(\mathbf{W}-\mathbf{W}^*\right)^T\mathbf{Z}+\zeta.\end{aligned} \tag{17}$$

Let $\tilde{\mathbf{W}} = \mathbf{W}-\mathbf{W}^*$, $\tilde{\xi} \triangleq \xi - \xi^*$ and take the time derivative of the *Lyapunov* equation, then

$$\begin{aligned}\dot{V}_e(t) =& -K\hat{e}_x^2 + B_n u_P(\varphi-\hat{e}_x) - A_n\hat{e}_x\varphi \\ &+ A_n\varphi^2 + K\hat{e}_x\varphi - \varphi\zeta + \tilde{\mathbf{W}}^T\mathbf{Z}(\hat{e}_x-\varphi) \\ &+ \frac{1}{\gamma_W}\tilde{\mathbf{W}}^T\dot{\mathbf{W}} + \frac{1}{\gamma_\xi}\tilde{\xi}^T\dot{\xi} + \hat{e}_x\zeta \\ \leq& -K\hat{e}_x^2 + A_n\varphi^2 + B_n u_P(\varphi-\hat{e}_x) - \varphi\zeta \\ &+ \tilde{\mathbf{W}}^T\mathbf{Z}(\hat{e}_x-\varphi) + \frac{1}{\gamma_W}\tilde{\mathbf{W}}^T\dot{\mathbf{W}} \\ &+ \frac{1}{\gamma_\xi}\tilde{\xi}^T\dot{\xi} + |\hat{e}_x|\left(|A_n|\bar{\varphi}+K\bar{\varphi}+\bar{\zeta}\right).\end{aligned} \tag{18}$$

From (17), (18) and the following inequalities

$$\begin{aligned}\sigma_1\tilde{\mathbf{W}}^T\mathbf{W} &= \frac{\sigma_1}{2}|\tilde{\mathbf{W}}|^2 + \frac{\sigma_1}{2}|\mathbf{W}|^2 - \frac{\sigma_1}{2}|\mathbf{W}^*|^2 \\ &\geq \frac{\sigma_1}{2}|\tilde{\mathbf{W}}|^2 - \frac{\sigma_1}{2}|\mathbf{W}^*|^2, \\ \sigma_2\tilde{\xi}\xi &= \frac{\sigma_2}{2}|\tilde{\xi}|^2 + \frac{\sigma_2}{2}|\xi|^2 - \frac{\sigma_2}{2}|\xi^*|^2 \\ &\geq \frac{\sigma_2}{2}|\xi|^2 - \frac{\sigma_2}{2}|\xi^*|^2.\end{aligned} \tag{19}$$

The time derivative of V_e can be further written as

$$\begin{aligned}\dot{V}_e(t) \leq& -K\hat{e}_x^2 + A_n\varphi^2 + B_n u_P\varphi - \varphi\zeta \\ &- \tilde{\mathbf{W}}^T\mathbf{Z}\varphi - \sigma_1\tilde{\mathbf{W}}^T\mathbf{W} - \sigma_2\tilde{\xi}^T\xi \\ =& -\frac{\sigma_1}{2}\left(|\tilde{\mathbf{W}}| - \frac{\bar{z}\bar{\varphi}}{\sigma_1}\right)^2 - \frac{\sigma_2}{2}\left(|\xi| - \frac{\bar{\varphi}}{\sigma_2}\right)^2 \\ &- K\hat{e}_x^2 + \lambda,\end{aligned} \tag{20}$$

where the constants $\bar{z}$ and λ are defined as

$$\bar{z} = \sup_z |\mathbf{Z}|,$$

$$\lambda = \frac{(\bar{z}\bar{\varphi})^2}{2\sigma_1} + \frac{\bar{\varphi}^2}{2\sigma_2} + |A_n|\bar{\varphi}^2 + \bar{\varphi}\bar{\zeta} + \frac{\sigma_1}{2}|\mathbf{W}^*|^2 + \frac{\sigma_2}{2}|\xi^*|^2$$

From (20) and the *Lyapunov*'s direct method, it is easily observed that the upper bounds for $|\hat{e}_x|$, $|\tilde{\mathbf{W}}|$, and $|\xi|$ are

$$|\hat{e}_x| \leq \frac{\lambda}{K}, \quad |\tilde{\mathbf{W}}| \leq \frac{\bar{z}\bar{\varphi}}{\sigma_1} + \sqrt{\frac{2\lambda}{\sigma_1}}, \quad |\xi| \leq \frac{\bar{\varphi}}{\sigma_2} + \sqrt{\frac{2\lambda}{\sigma_2}}, \tag{21}$$

which shows the UUB of the signals. □

An update law for the weight vector V can be easily derived by using the gradient decent rule with back propagation algorithm. Let the activation (sigmoid) function be $T(I) = \left(1+e^{-\alpha I}\right)^{-1}$, and its derivative is to be $\partial T/\partial I = \alpha(1-T)T$. Now, using the gradient decent rule, we can find the following equation.

$$\Delta v_{1k} = -\eta_v \frac{\partial \hat{e}^2}{\partial v_{1k}} = \eta_v x_1 \sum_{m=1}^{l} \delta_{1k}, \tag{22}$$

where $\eta_v > 0$, $\delta_{1k} = 2\hat{e}\frac{\partial y}{\partial I_z}w_{k1}\frac{\partial z_k}{\partial I_{xk}} = \delta_{k1}w_{k1}\frac{\partial z_k}{\partial I_{xk}}$,

$I_z = \sum_{q=1}^{l} w_q \cdot z_q$, and $I_{xk} = \sum_{m=1}^{n} v_{1m} \cdot x_m$.

Finally, the following update rule is to be computed.

$$v_{1k}(1+K) = v_{1k}(K) + \eta_v x_1 \sum_{m=1}^{l} \delta_{1k}. \tag{23}$$

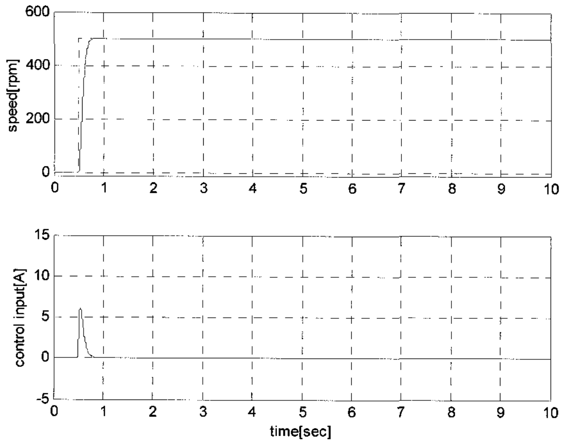
4. SIMULATION AND EXPERIMENTAL RESULTS

4.1. Simulation results

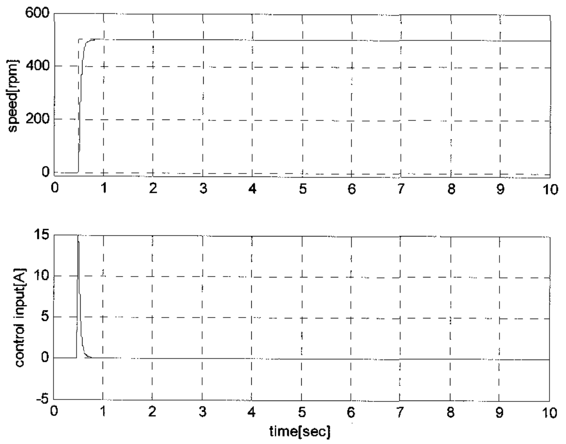
Some simulation results are shown to confirm the validity of the proposed control algorithm. The induction motor used in this paper reads a nameplate of 3-phase 220Vac, with rated speed of 1740rpm. In this paper, to demonstrate the comparative results of the proposed approach, an abnormal condition is provided including external load change. For convenience, two test conditions are presented as

i. CASE1: Δ J= Δ B=0, Tl = 0

ii.CASE2: $\Delta J = 4 \times J$, $\Delta B = 4 \times B$, $Tl = 5 \times \sin\omega t$



(a) Conventional IP control (CASE 1)



(b) Proposed control (CASE 1)

Fig. 4. Simulation results of CASE 1.

In the above conditions, "J" is inertia coefficient, "B" is viscous friction coefficient and "Tl" means external load torque. To show the effectiveness of the proposed controller, a comparative result with finely tuned IP control from (4) and (5) without the NN observer is demonstrated. IP gains are computed to have the same response time for the proposed scheme, 1.27s. The speed estimation is completed by a conventionally preferred method proposed by Kubota [7]. At first, Fig. 4 shows the comparative results in CASE 1. In this figure, rotor speed, phase current and control input are presented, and the desired rotor speed is set to 500rpm. Because no uncertainties are engaged in this case, simulated results with two controllers demonstrate satisfactory tracking performances. However, the second case in which the parameter variations abruptly occurred at 5s shows different results.

Refer to Fig. 5. For IP control, in Fig. 5(a), engaged uncertainty which is shown in lower part deteriorates speed control performance, and the robust characteristics can not be obtained. However, the proposed controller has improved speed response for the same uncertainties as indicated in Fig. 5(b), because IP gains are derived based on a nominally mechanical model and it usually takes extensive time to catch the unmodeled uncertainties that deteriorate feedback control response.

However, the NN observer approximates the uncertainties to minimize the rotor speed error, and the compensated control input is applied for reconstruction error by the feedforward manner. Only under 0.15s is taken for the speed error to be zero, and as a result, the tracking performance can be drastically improved despite abrupt uncertainties. The lowest part in Fig. 5(b) shows its identification ability.

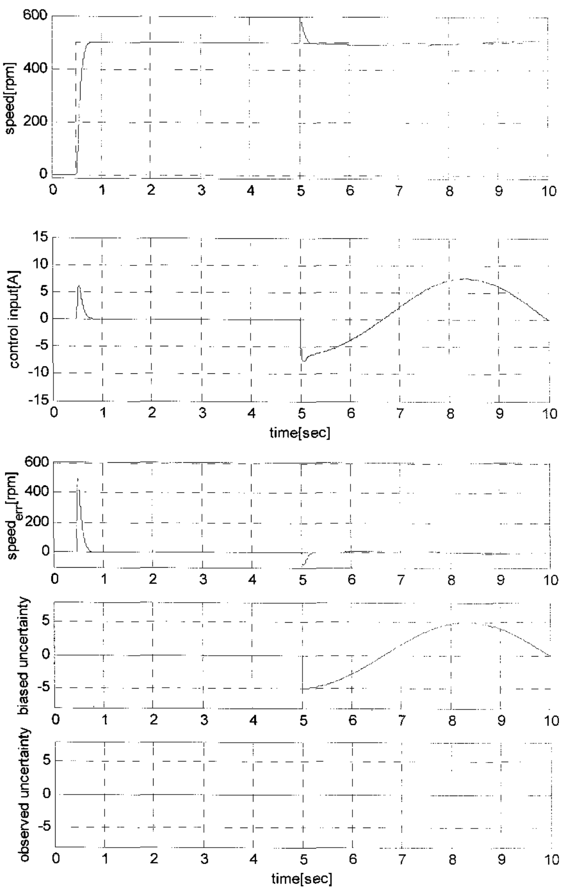
4.2. Experimental setup

To confirm the feasibility of the proposed system, experimental verification is accomplished with the following conditions.

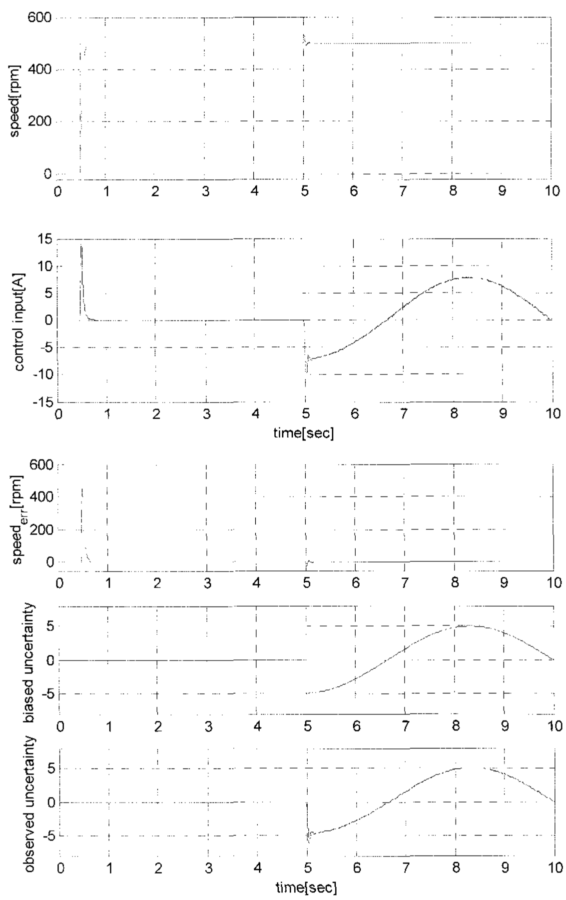
i. CASE1: Δ J= Δ B=0, Tl = 0,

ii.CASE2: $\Delta J = 4 \times J$, $\Delta B = 4 \times B$, Tl=8 .

The experimental setup is implemented based on the main control board of DS1003 which includes speed control algorithm with the flux observer and DTC scheme shown in Fig. 6. For high power induction motor applications, the torque ripple can be drastically reduced by using the three-level inverter DTC approach [8] even though speed control performance is still unstable. The sampling time of the control cycle is set at 200 μs for the torque ripple reduction and the proposed algorithms. Because the experimental setup is for a high power induction motor DTC system, the switching frequency remains in the region of 500 Hz – 1.0 kHz. Fig. 7 shows the comparatively experimental results of CASE 1 at 500rpm of the desired rotor speed. In this case, both controllers have



(a) Conventional IP control (CASE 2)



(b) Proposed controller (CASE 2)

Fig. 5. Simulation results of CASE 2.

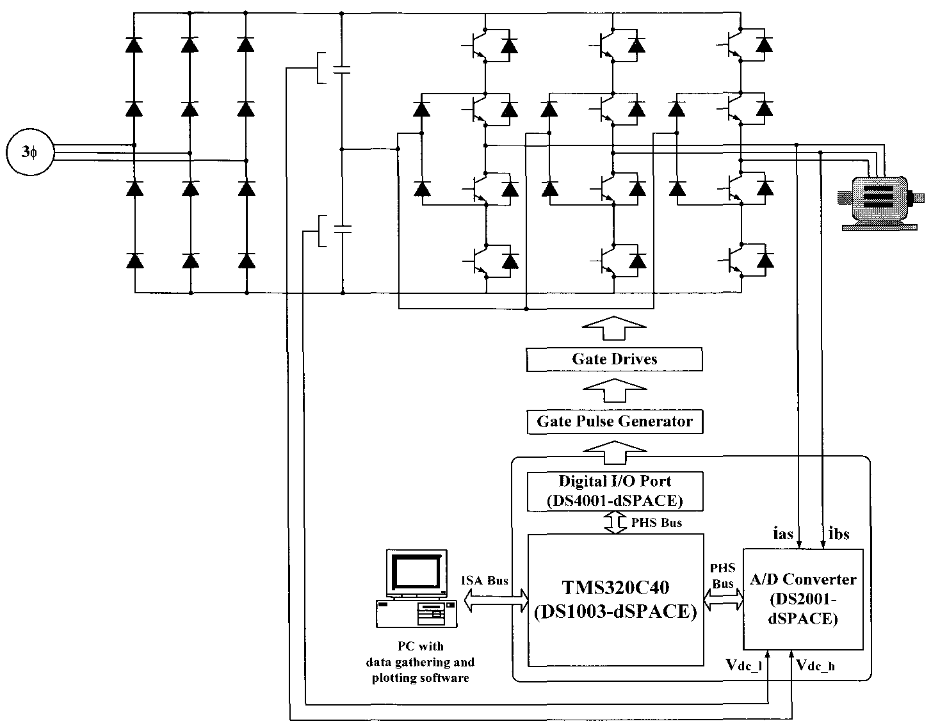
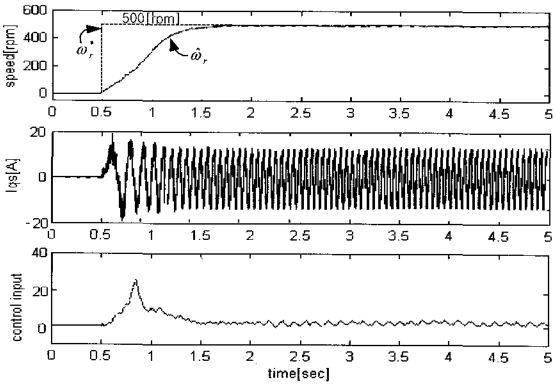
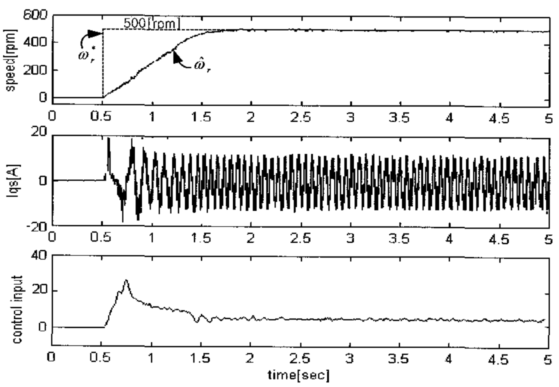


Fig. 6. Schematic diagram of the experimental setup.

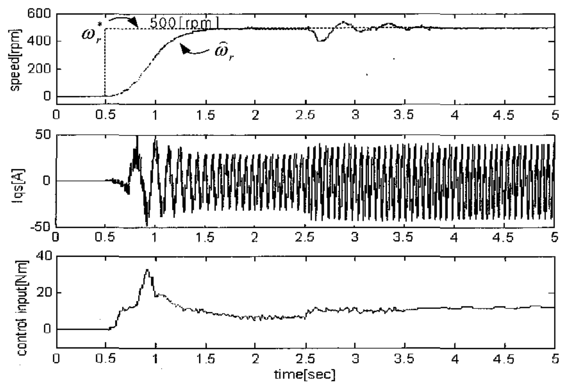


(a) Conventional IP control (CASE 1).

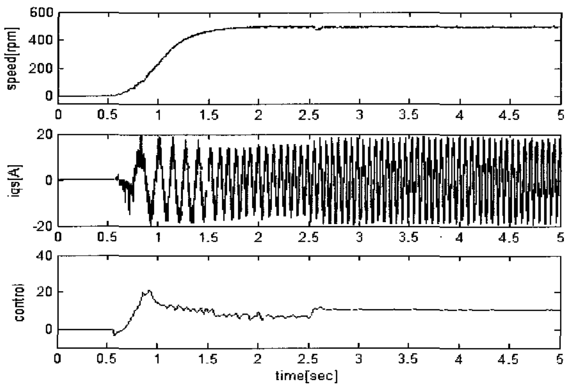


(b) Proposed control (CASE 1).

Fig. 7. Experimental results of CASE 1.



(a) Conventional IP control (CASE 2).



(b) Proposed control (CASE 2).

Fig. 8. Experimental results of CASE 2.

effective tracking performances as gathered from the simulated results. IP gains are derived by (4) and (5) as in the simulation processes. Even though a modeling error from the simplified mechanical model used for experimental test exists, the IP control shows robust response by the integrating operation. The overall DTC system including 3-level inverter is approximated by a simple mechanical model as shown in Fig. 3, and the approximation error and unmodeled dynamics are not serious enough to deteriorate the speed regulation. However, for CASE 2, concerning the keener disturbances in which the parameter variations and abrupt external disturbance are engaged at 2.5s, the distinctions between the two approaches are obviously displayed. As shown in Fig. 8, the proposed control scheme shows advanced robust performance comparing the IP scheme. When the test condition is engaged, for the proposed control (Fig. 8(b)), it takes about 0.1s for tracking error to be zero, but IP control (Fig. 8(a)) needs 1.5s for the recovery process, with a greater degree of tracking error and fluctuation. IP control is based on the nominal model and is not effective for the serious disturbances of CASE 2. It takes a great deal of time to melt the effects of unmodeled uncertainties that deteriorate feedback response. However, using the NN observer and the compensated control input, speed response can be drastically improved. A simple NN structure quickly approximates the uncertainties, and the additional compensating control input engaged to control the input. As a result, tracking performance can be drastically improved under serious disturbances. With these experimental results, the feasibility and robustly stable characteristics are established. The proposed control scheme shows relatively small tracking error compared to conventional IP control schemes even when a definite inherent uncertainty is abruptly engaged.

5. CONCLUSION

In this research, a robustly stable speed controller for the induction motor system using the NN observer is presented. To cope with the inherent uncertainties such as parametric uncertainty, external disturbance and unmodeled dynamics, the NN is used as an uncertainty observer approximates the inherent uncertainties. Moreover, the stability analysis of the whole control system considering the effect of the speed estimation error is presented. A control law for stabilizing the system and adaptive laws for updating both the weights in the NN and a bounding constant 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. Moreover, various kinds of control or motor systems such as vector control and PM synchronous motors can be applied with this approach. In this research, as one of the application examples, a high power 3-level fed induction motor direct torque control system is presented. To achieve the speed sensorless process, speed estimation is completed by a conventionally preferred method. The effectiveness and validity of the proposed system are shown in simulation and experimental results.

REFERENCES

[1] R. J. Wai, "Hybrid control for speed sensorless induction motor drive," *IEEE Trans. on Fuzzy Systems*, vol. 9, no. 1, pp. 116-138, 2001.

[2] B. Heber and L. Xu, "Fuzzy logic enhanced speed control of an indirect field-oriented induction machine drive," *IEEE Trans. on Power Electronics*, vol. 12, no. 5, pp. 772-778, September, 1997.

[3] P. Vas, *Sensorless Vector Control and Direct Torque Control*, Oxford Univ. Press, 1998.

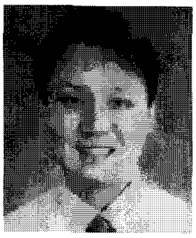
[4] Z. Uykan, C. Guzelis, M. Celebi, and H. Koivo, "Analysis of input-output clustering for determining centers of RBFN," *IEEE Trans. on Neural Networks*, vol. 11, no. 4, pp. 851-858, 2000.

[5] W. Rudin, *Principle of Mathematical Analysis*, McGraw-Hill, New York, 1976.

[6] S. H. Kim, T. S. Park, J. Y. Yoo, and G. T. Park, "Speed-sensorless vector control of an induction motor using neural network speed estimation," *IEEE Trans. on Power Electronics*, vol. 48, no. 3, pp. 609-614, September 2001.

[7] H. Kubota, K. Matsuse, and T. Nakano, "DSP-based speed adaptive flux observer of induction motor," *IEEE Trans. on Industry Applications*, vol. 29, no. 2, pp. 344-348, 1993.

[8] K.-B. Lee, J.-H. Song, I. Choy, and J.-Y. Yoo, "Torque ripple reduction in DTC of induction motor driven by three-level inverter with low switching frequency," *IEEE Trans. on Power Electronics*, vol. 17, no. 2, pp. 255-264, March 2002.



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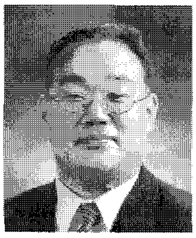

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