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Speed Sensorless Vector Control of Induction Motor Using Extended Kalman Filter

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Abstract—**A vector control of an induction motor by an estimated speed using an extended Kalman filter is proposed. With this method, the states are composed of stator current and rotor flux. The rotor speed is regarded as a parameter, and the composite states consist of the original states and the rotor speed. The extended Kalman filter is employed to identify the speed of an induction motor and rotor flux based on the measured quantities such as stator currents and dc link voltage. The estimated speed is used for vector control and overall speed control. Since the current control is performed at a synchronous rotating reference frame, the estimated speed information is also used for the reference frame transformation of the current controller. Computer simulations and experiments of the speed control have been carried out to test the usefulness of the speed estimation algorithm. The experimental results show that the performance of the speed estimation is very good.**

I. Introduction

IN MODERN control techniques for induction motor drives, speed transducers such as shaft-mounted tachogenerators, resolvers, or digital shaft position encoders are used to obtain speed information. These degrade the system's reliability, especially in defective environments, and reduce the advantage of an induction motor drive system. This has led to a speed sensorless vector control. The traditional approaches to speed sensorless vector control use the method of flux and slip estimation using stator currents and voltages [1], [2], but this has a large error in speed estimation, particularly in the low-speed range. MRAS (model reference adaptive system) techniques are also used to estimate the speed of an induction motor [3]. These also have a speed error in the low-speed range and settle to an incorrect steady-state value. In recent years, the Kalman filter algorithm has been used for the parameter estimation of an induction motor [4]–[6], or for the speed estimation of a synchronous and an induction motor [7], [8]. In the speed estimation of an induction motor using an extended Kalman filter algorithm [8], not only the angular speed of rotor, but also the angular frequency of rotor flux and the angle of rotor flux have to be augmented in the extended Kalman filter, because the state variables are only the stator currents and magnetizing current. In that case, the complete decoupling of d–q component fluxes is assumed. Also, the magnetizing current is assumed to be constant. This paper presents an alternative speed sensorless vector control algorithm that uses an extended Kalman filter to estimate the motor speed and rotor flux, and thereby established the vector control as well as the overall speed control. There is no assumption of decoupling of d–q component fluxes or constant magnetizing currents. In addition, in this system only the stator currents and dc link voltage are the measured quantities, instead of the stator currents and stator voltages. This new extended Kalman filter method has been implemented by a 32 b floating point TMS 320C30 DSP chip.

II. Induction Motor Model

A dynamic model for an induction motor in a stationary reference frame, by choosing the stator currents i_{ds}, i_{qs} and the rotor flux ϕ_{dr}, ϕ_{qr} as state variables, is as follows:

$$\frac{dX(t)}{dt} = A \cdot X(t) + B \cdot u(t) \tag{1}$$

and

$$Y(t) = C \cdot X(t) \tag{2}$$

where

$$X = [i_{ds}\, i_{qs}\, \phi_{dr}\, \phi_{qr}]^t$$

$$Y = [i_{ds}\, i_{qs}]^t$$

$$u = [v_{ds}\, v_{qs}]^t$$

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$$A = \begin{bmatrix} -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma\tau_r}\right) & 0 & \dfrac{L_m}{\sigma L_s L_r}\dfrac{1}{\tau_r} & \omega_r\dfrac{L_m}{\sigma L_s L_r} \\ 0 & -\left(\dfrac{R_s}{\sigma L_s} + \dfrac{1-\sigma}{\sigma\tau_r}\right) & -\omega_r\dfrac{L_m}{\sigma L_s L_r} & \dfrac{L_m}{\sigma L_s L_r}\dfrac{1}{\tau_r} \\ \dfrac{L_m}{\tau_r} & 0 & -\dfrac{1}{\tau_r} & -\omega_r \\ 0 & \dfrac{L_m}{\tau_r} & \omega_r & \dfrac{1}{\tau_r} \end{bmatrix}$$

$$B = \begin{bmatrix} \dfrac{1}{\sigma L_s} & 0 \\ 0 & \dfrac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}.$$

III. Extended Kalman Filter Algorithm

In the dynamic model of an induction motor, if the dimension of the state vector is increased by adding an angular speed of rotor, then the state model becomes nonlinear. Therefore, the extended Kalman filter has to be used to estimate the parameter. In this case, the angular speed of the rotor is considered as a state and a parameter. The extended Kalman filter algorithm should be calculated by using a microprocessor, and the system is to be expressed in a discrete-state model. The discrete-state model and the output model are given by (3) and (4):

$$\dot{x}(t) = f[x(t), u(t), t] + G(t)w(t) \tag{3}$$

and

$$z(t_i) = h[x(t_i), t_i] + v(t_i) \tag{4}$$

where

$G(t)$ = weighting matrix of noise
$w(t)$ = noise matrix of state model
$v(t)$ = noise matrix of output model.

In this model $f[X(t), t]$ is the nonlinear part of the state model. The extended Kalman filter relinearizes the nonlinear-state model for each new estimate as it becomes available. From the above dynamic model the rotor speed can be estimated by the following extended Kalman filter algorithm.

1) Prediction of State:

$$\hat{x}(k+1|k) = \hat{x}(k|k) + \int_{t_k}^{t_{k+1}} f[\hat{x}(t|t_k), u(t), t)]dt. \tag{5}$$

2) Estimation of Error Covariance Matrix:

$$P(k+1|k) = \Phi(k+1, k)P(k|k)\Phi^t(k+1, k) + Q_d(k) \tag{6}$$

where

$$\Phi(k+1, k) = \exp(F(k) \cdot T_s)$$
$$T_s = \text{sampling time}$$
$$Q_d = \int \Phi(t_{k+1}, \tau)G(\tau)Q(\tau)G^t(\tau)\Phi^t(t_{k+1}, \tau)d\tau$$
$$F[k] = \left.\frac{\partial f[x(t), u(t), t]}{\partial x}\right|_{x=\hat{x}(k|k)}.$$

3) Computation of Kalman Filter Gain:

$$\begin{aligned} K(k+1) = {} & P(k+1|k)H^t(k+1) \\ & \times [H(k+1)P(k+1|)H^t(k+1) \\ & + R(k+1)]^{-1} \end{aligned} \tag{7}$$

where

$$H[k+1] = \left.\frac{\partial h[x(t), t]}{\partial x}\right|_{x=\hat{x}(k+1|k)}.$$

4) Update of the Error Covariance Matrix:

$$P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k). \tag{8}$$

5) State Estimation:

$$\begin{aligned} \hat{x}(k+1|k+1) = {} & \hat{x}(k+1|k) + K(k+1) \\ & \times \{z(k+1) - h[\hat{x}(k+1|k), k+1]\}. \end{aligned} \tag{9}$$

IV. Estimation of Rotor Speed by Extended Kalman Filter Algorithm

Let the state variables be defined as follows:

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix} = \begin{bmatrix} i_{ds}(t) \\ i_{qs}(t) \\ \phi_{dr}(t) \\ \phi_{qr}(t) \\ \omega_r(t) \end{bmatrix}.$$

Then, the same model of the induction motor is described by (10):

$$\dot{x}(t) = f[x(t), u(t), t] + G(t)w(t) \tag{10}$$

where

$$f[x(t),u(t),t)] = [f_1(t), f_2(t), f_3(t), f_4(t), f_5(t)]^t$$

$$= \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right)x_1+\frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r}x_3+\frac{L_m}{\sigma L_s L_r}x_4x_5+\frac{1}{\sigma L_s}V_{dsf} \\ -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right)x_2-\frac{L_m}{\sigma L_s L_r}x_2x_5+\frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r}x_4x_5+\frac{1}{\sigma L_s}V_{qsf} \\ \frac{L_m}{\tau_r}x_1-\frac{1}{\tau_r}x_3-x_4x_5 \\ \frac{L_m}{\tau_r}x_2+x_3x_5-\frac{1}{\tau_r}x_4 \\ 0 \end{bmatrix}$$

$$\sigma = 1-\frac{L_m^2}{L_sL_r}$$

$$G(t) = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\sigma} \end{bmatrix}$$

$$w(t) = \begin{bmatrix} w_1(t) \\ w_2(t) \\ n(t) \end{bmatrix}.$$

In addition, the output matrix is as follows:

$$z(t_i) = h[x(t_i), t_i] + v(t_i) \tag{11}$$

where

$$z(t_i) = \begin{bmatrix} i_{ds}(t) \\ i_{qs}(t) \end{bmatrix}$$

$$h[x(t_i), t_i)] = \begin{bmatrix} i_{ds}(t_i) \\ i_{qs}(t_i) \end{bmatrix}$$

$x(t_0)$ is the initial condition with mean x_0 and covariance P_0, $u(t)$ is deterministic input, $w(t)$ is a zero-mean white Gaussian noise that is independent of $x(t_0)$ with covariance $Q(t)$, and $v(t)$ is zero-mean white Gaussian noise that is independent of $x(t_0)$ and $w(t)$ with covariance $R(t_i)$.

The extended Kalman filter prediction equation is given by (12):

$$\hat{x}(k+1|k) = \hat{x}(k|k) + \int_{t_k}^{t_{k+1}} f[\hat{x}(t|t_k), u(t), t)]dt. \tag{12}$$

In this case $u(t)$ is assumed to be constant between t_k and t_{k+1}.

The covariance is as follows:

$$P(k+1,k) = \Phi(k+1,k)P(k|k)\Phi^t(k+1,k) + Q_d(k) \tag{13}$$

where

$$\Phi(k+1,k) = \exp(F(k)\cdot T_s)$$

$$T_s = \text{sampling time}$$

$$Q_d = \int \Phi(t_{k+1},\tau)G(\tau)Q(\tau)G^t(\tau)\Phi^t(t_{k+1},\tau)d\tau$$

$$F[k] = \left.\frac{\partial f[x(t),u(t),t]}{\partial x}\right|_{x=\hat{x}(k|k)}$$

$$= \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) & 0 & \frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r} & \frac{L_m}{\sigma L_s L_r}x_5 & \frac{L_m}{\sigma L_s L_r}x_4 \\ 0 & -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) & -\frac{L_m}{\sigma L_s L_r}x_5 & \frac{L_m}{\sigma L_s L_r}\frac{1}{\tau_r} & \frac{L_m}{\sigma L_s L_r}x_2 \\ \frac{L_m}{\tau_r} & 0 & -\frac{1}{\tau_r} & -x_5 & -x_4 \\ 0 & \frac{L_m}{\tau_r} & x_5 & -\frac{1}{\tau_r}x_4 & -x_3 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}.$$

The Kalman gain is given by (14):

$$K(k+1) = P(k+1|k)H^t(k+1)[H(k+1)P(k+1|k) \cdot H^t(k+1) + R(k+1)]^{-1} \tag{14}$$

where

$$H[k+1] = \left.\frac{\partial h[x(t),t]}{\partial x}\right|_{x=\hat{x}(k+1|k)} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}.$$

The updated covariance is given by (15):

$$P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k). \tag{15}$$

The extended Kalman filter correction equation is described by (16):

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K(k+1)\{z(k+1) - h[\hat{x}(k+1|k), k+1]\}. \tag{16}$$

V. Current Control

In the vector control of an induction motor, the current controller is also very important to achieve desirable performance. In this work, the current control is performed at a synchronous rotating reference frame. Therefore, the steady-state error and phase delay are minimized [9]. The rotor flux angle for the transformation between a stationary reference frame and a synchronous rotating reference frame is obtained by the Kalman filter. As a PWM technique, the voltage-space vector method [10] is used to obtain constant switching frequency. Therefore, the reference voltages V_{ds}^*, V_{qs}^* are achieved by applying a weighted average of three inverter voltage vectors, V_r, V_1, and V_0, in sampling time T_s. Each inverter voltage vector is applied for a portion of the sampling period. The durations of the voltage vectors are given by the following:

$$T_r = \sqrt{3}\, T_s \frac{|V^*|}{|V_{dc}|} \sin(2\pi/3 - \alpha). \tag{17}$$

$$T_1 = \sqrt{3}\, T_s \frac{|V^*|}{|V_{\mathrm{dc}}|} \sin(\alpha). \tag{18}$$

$$T_0 = T_s - (T_r + T_1). \tag{19}$$

The reference voltages V_{ds}^* and V_{qs}^* are used in the Kalman filter algorithm as stator voltages without measurement since in this current control method the reference voltages are about the same voltages with the actual voltages under the assumption of dead time compensation. Thus, in this system, the stator voltages are not to be measured; only the stator currents and dc link voltage are measured.

VI. Simulation Results

To verify the speed estimation method, digital simulations were carried out. The parameters used in this simulation study are given in the Appendix. The Kalman filter is useful in the system that has system noise and measurement noise. Therefore, the effect of noise is included in this simulation. The included noises of voltage and current are 0.5 [V] and 0.5 [A], respectively. Also, in the Kalman filter, the noise covariances are the same values with those noises. Fig. 1 shows the real speed and the estimated speed when the speed reference is 1500 rpm. The estimated speed means the speed that is estimated using an extended Kalman filter. We know the real speed from the simulation variable because it is the simulation. The speed error between the real speed and the estimated speed is within a few revolutions per minute. At $t = 1.25$ s, load torque is increased to its rated value. The speed control is performed by the estimated speed, and the speed has reached the reference speed very well. Fig. 2 shows the real and the estimated speed when the speed reference is 60 rpm. The speed control starts at $t = 0.1$ s. Also in this case, the speed error is within a several revolutions per minute. Fig. 3 shows the real and the estimated speed when the speed reference is 20 rpm. The speed error is within a few revolutions per minute even at the low-speed range, about 20 rpm.

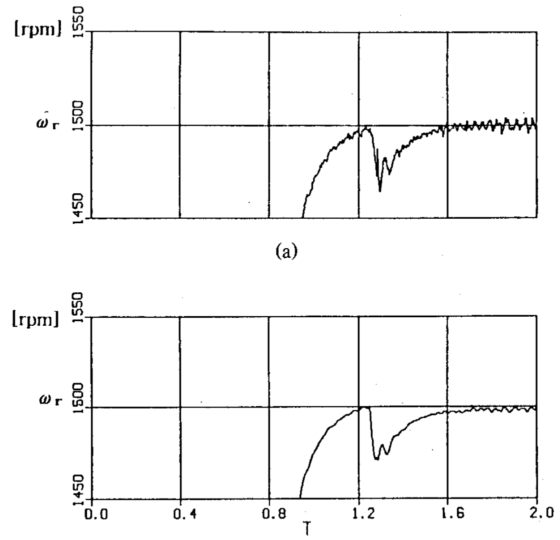
VII. On-Line Estimation

A. Experimental Setup

The block diagram of the complete speed control system is shown in Fig. 4. The part within the dashed line is implemented by a 32 b, 33 MHz, floating-point TMS 320C30 DSP chip. The current control is performed at the synchronous rotating reference frame, executed every 100 μs, which gives about a 5 kHz switching frequency of the IGBT inverter. The current control and vector control algorithm could be calculated within 22 μs, including A/D conversion time, and the remaining time is used for the extended Kalman filter algorithm. The execution time of the extended Kalman filter algorithm itself is about 150 μs. Also, the extended Kalman filter is updated every 200 μs. Within this time span the rotor speed is regarded as almost constant, and therefore the extended Kalman filter is useful.

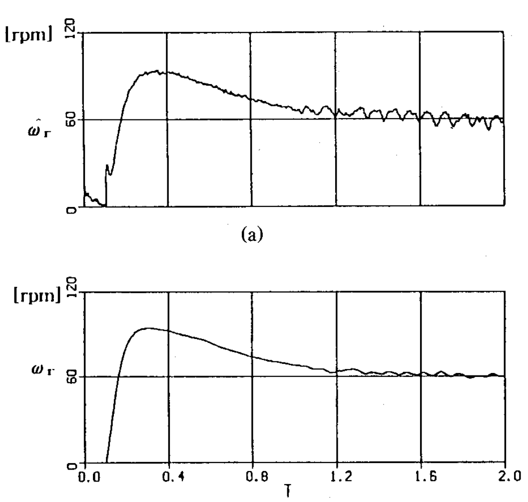
B. Experimental Results

Fig. 5 shows the speed reference and real speed when the speed control is performed by the estimated speed. The real speed means the speed that is measured by the



(b)

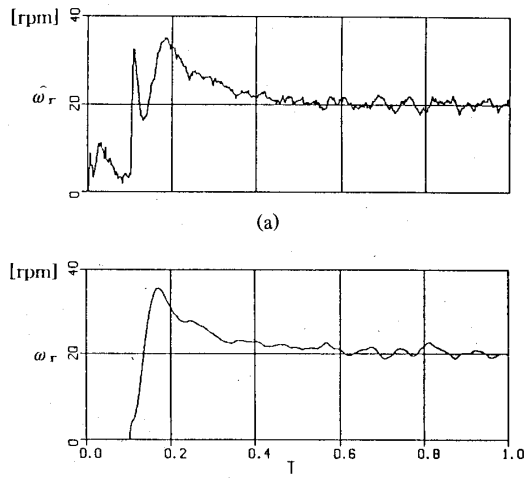
Fig. 1. Real speed and its estimated value ($\omega_{m\text{ref}} = 1500$ rpm). (a) Estimated speed and (b) real speed.



(b)

Fig. 2. Real speed and its estimated value ($\omega_{m\text{ref}} = 60$ rpm). (a) Estimated speed and (b) real speed.

pulse encoder. The estimated speed is the speed that is estimated using an extended Kalman filter. In Fig. 5 (a), the speed references are 0, 10, and 20 rpm. During the operation of an induction motor, the temperature of the motor increases. Also, the rotor time constant varies with the increase of the temperature. Therefore, the case when the rotor time constant varies about ±20 percent is also illustrated. In Fig. 5 (b) the speed references are 100, 600, 1000, and 1500 rpm. The speed error is within 5 rpm, which is about 0.3 percent of the rated speed. When the



(b)

Fig. 3. Real speed and its estimated value ($\omega_{m\text{ref}} = 20$ rpm). (a) Estimated speed and (b) real speed.

parameter varies about 20 percent, the error increases to about 10 rpm or more in the low-speed range. So it is important to compensate the parameter variation to estimate the speed more accurately. Fig. 6 shows acceleration characteristics when the speed reference is varied from −1500 to 1500 rpm. In Fig. 7 it is varied from −20 ro 20 rpm. In this case the speed response is about the same as in the case when the speed control is performed by the real speed, and the speed error is within a few revolutions per minute. Therefore, the extended Kalman filter could be used in the system where the variable speed control is needed except very-high-performance applications. But a few revolutions per minute error is tolerable in almost all industrial applications. Fig. 8 shows the real speed and torque command at 0 rpm with the increase of the load torque. The real speed means the speed error at 0 rpm. In this case, the torque command increases with the load torque and the speed error is within 10 rpm.

VIII. CONCLUSIONS

The extended Kalman filter has been used for the speed sensorless vector control of an induction motor. The speed estimation method is implemented by a TMS 320C30 DSP chip. The speed control and the vector control by the estimated speed produce a desirable performance over the entire speed-control range. The estimation error of speed is within a few revolutions per minute, even at extremely low speeds. The speed response is good enough to use in a variable speed control. The parameter dependency of the speed estimation error is also studied. The speed error increases when the parameter variation increases. Therefore, the compensation of the parameter variation with the increase of temperature is needed, and further study will be required.

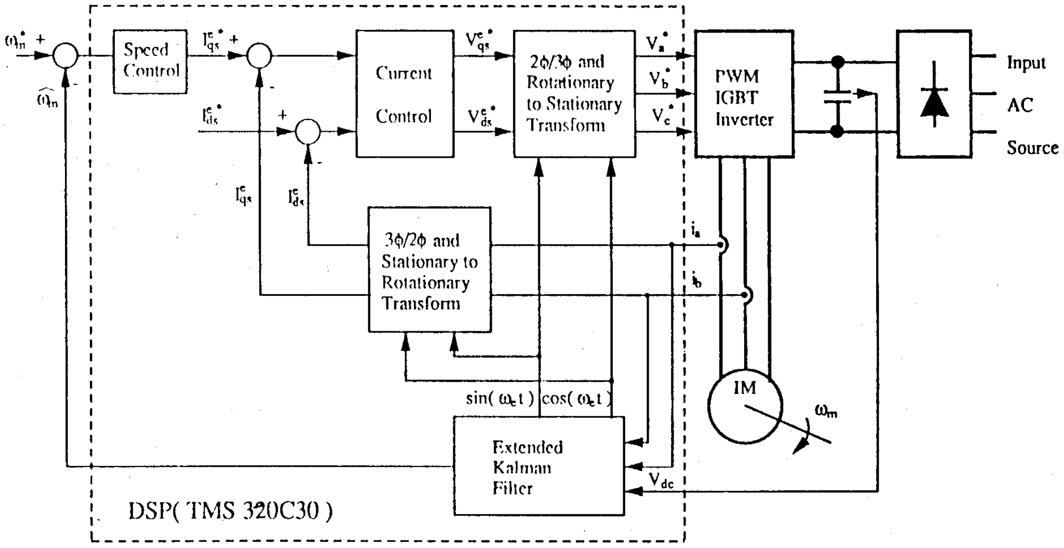
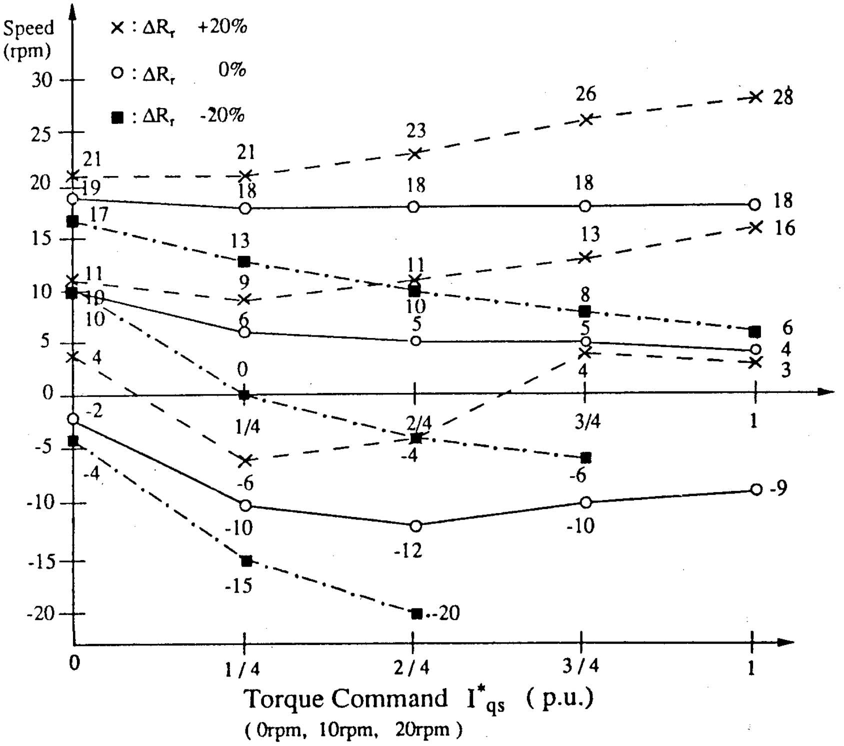
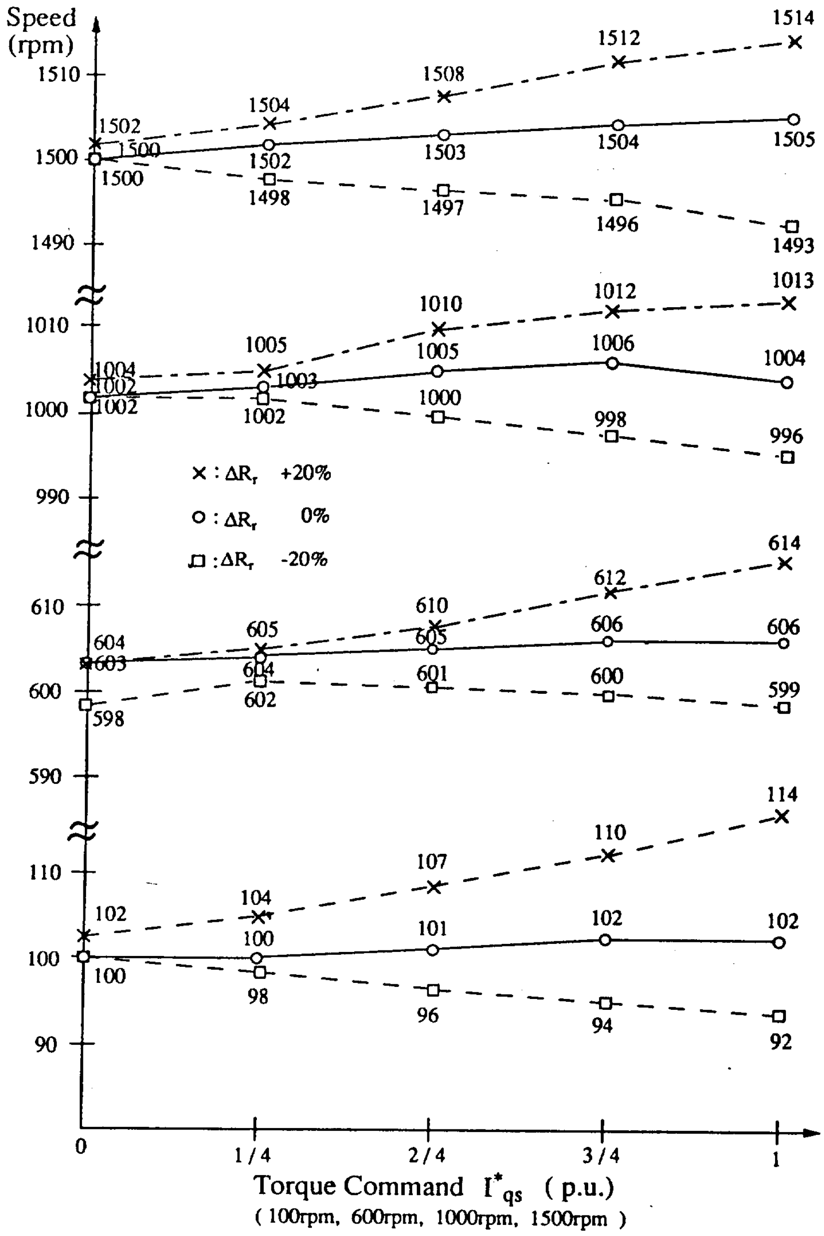


Fig. 4. Block diagram of the speed-control system.



(a)

Fig. 5. Speed estimation characteristics. (a) $\omega_{m\text{ref}} = 0$, 10, and 20 rpm. (b) $\omega_{m\text{ref}} = 100$, 600, 1000, and 1500 rpm.

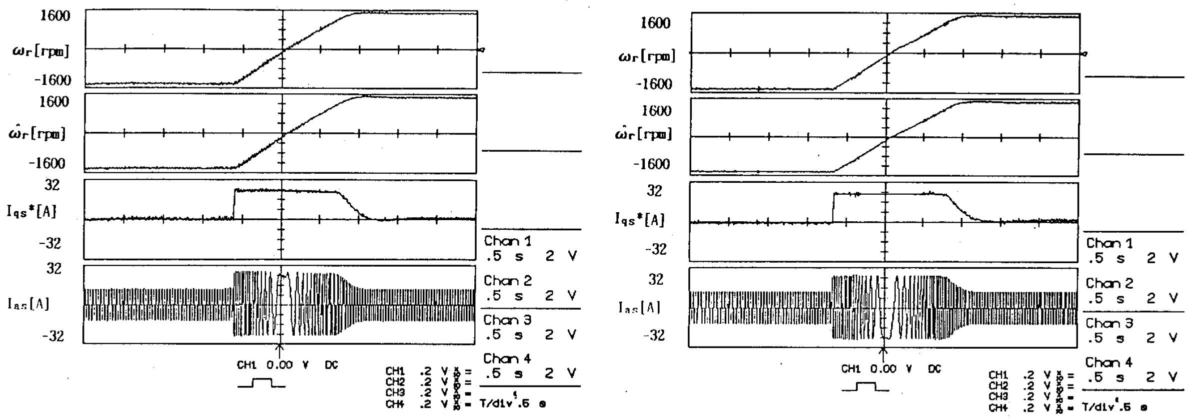


(b)

Fig. 5. (*Continued*)

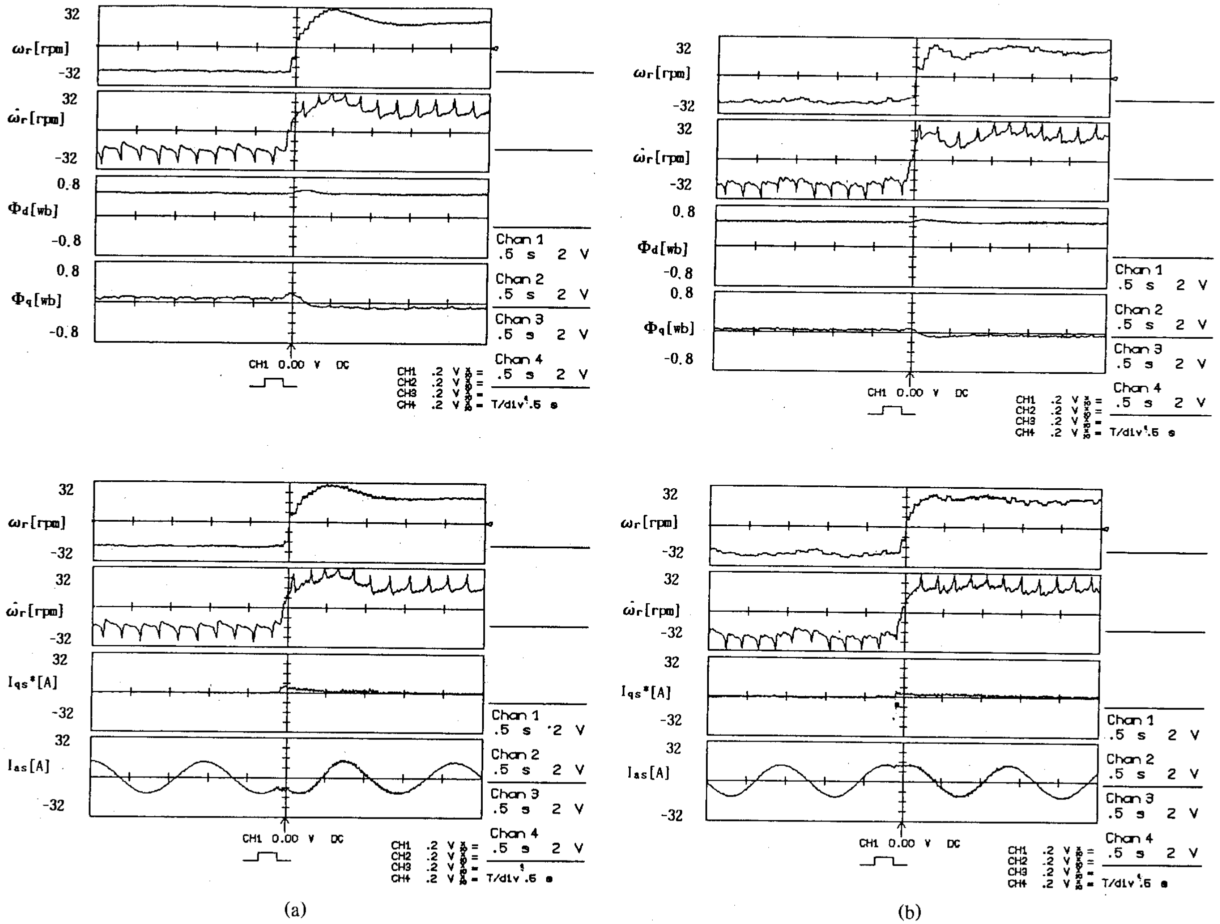
NOMENCLATURE

i_{ds}	d axis component of stator current in stationary reference frame
i_{qs}	q axis component of stator current in stationary reference frame
ϕ_{dr}	d axis component of rotor flux in stationary reference frame
ϕ_{qr}	q axis component of rotor flux in stationary reference frame
v_{ds}	d axis component of stator voltage in stationary reference frame
v_{qs}	q axis component of stator voltage in stationary reference frame
v_{dsf}	fundamental d axis component of stator voltage in stationary reference frame
v_{qsf}	fundamental q axis component of stator voltage in stationary reference frame
V_{dc}	dc link voltage
L_m	mutual inductance



(a) (b)

Fig. 6. Dynamic response of speed estimation (high-speed range) (a) in the case of real speed feedback and (b) in the case of estimated speed feedback.



(a) (b)

Fig. 7. Dynamic response of speed estimation (low-speed range) (a) in the case of real speed feedback and (b) in the case of estimated speed feedback.

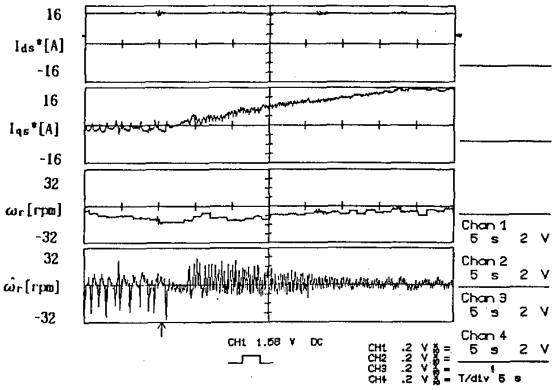


Fig. 8. Torque response at 0 rpm.

L_s	stator self inductance
σ	leakage coefficient factor
τ_r	rotor time constant

APPENDIX
RATING AND PARAMETERS OF INDUCTION MOTOR USED FOR SIMULATION

5HP, 220V, 4poles, 60Hz			
R_s	: 0.2417Ω	R_r	: 0.2849Ω
L_s	: 37.3 mH	L_r	: 37.3 mH
L_m	: 36 mH	σ	: 0.06849

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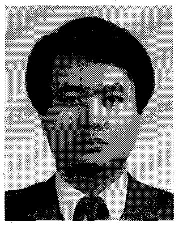

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Dr. Park is the former President of the Korean Institute of Electrical Engineers, and the former Chairman of IEEE Korean Section.