A Supervisory Fuzzy Neural Network Control System for Tracking Periodic Inputs

Faa-Jeng Lin, *Member, IEEE*, Wen-Jyi Hwang, *Member, IEEE*, and Rong-Jong Wai

***Abstract*—A supervisory fuzzy neural network (FNN) control system is designed to track periodic reference inputs in this study. The control system is composed of a permanent magnet (PM) synchronous servo motor drive with a supervisory FNN position controller. The supervisory FNN controller comprises a supervisory controller, which is designed to stabilize the system states around a defined bound region and an FNN sliding-mode controller, which combines the advantages of the sliding-mode control with robust characteristics and the FNN with on-line learning ability. The theoretical and stability analyses of the supervisory FNN controller are discussed in detail. Simulation and experimental results show that the proposed control system is robust with regard to plant parameter variations and external load disturbance. Moreover, the advantages of the proposed control system are indicated in comparison with the sliding-mode control system.**

***Index Terms*—Fuzzy neural network, periodic inputs, PM synchronous servo motor, supervisory control.**

I. Introduction

THERE are many control system applications where the tracking of periodic reference inputs are required, e.g., radar tracking and repetitive trajectories tracking of robots. Repetitive control systems with the application of internal model principle [1]–[3] have been shown to function well to track periodic reference inputs. However, a tradeoff between stability and accuracy is necessary for the performance of repetitive control systems [3]. The variable structure control strategy using the sliding mode can offer a number of attractive properties for the tracking of periodic reference inputs, such as insensitivity to parameter variations, external disturbance rejection, and fast dynamic responses [4], [5]. The motion of the sliding-mode control system can be described as two modes: reaching and sliding modes. The reaching mode is the control mode before the states of the system reaching the designed sliding surface and during which there is a control action toward the sliding surface. Once the states of the controlled system enter the sliding mode, the dynamics of the system are determined by the choice of sliding hyperplanes and are independent of uncertainties and external disturbances. On the other hand, the chattering phenomena in the sliding mode due to switching operation will influence the accuracy of tracking performance.

Recently, many research results have been accomplished by applying the fuzzy neural network (FNN) systems, which combine the capability of fuzzy reasoning in handling uncertain information [6]–[8] and the capability of neural networks in learning from processes [9]–[13], in the control fields to deal with nonlinearities and uncertainties of the control systems [8], [14]–[19]. For instance, in Wang [8, ch. 3], the adaptive fuzzy systems (or the FNN's) are introduced as identifiers for nonlinear dynamic systems based on backpropagation algorithm; Chen and Teng [15] proposed a model reference control structure using an FNN controller, which is trained on-line using an FNN identifier with adaptive learning rates; Zhang and Morris [16] described a technique for the modeling of nonlinear systems using an FNN topology; Jang and Sun [17] reviewed the fundamental and advanced developments in neuro-fuzzy synergisms for modeling and control based on adaptive network; in Lin *et al*. [19] a PM synchronous servo motor drive with integral-proportional (IP) position controller and an on-line trained FNN controller is introduced. Furthermore, to overcome the mentioned disadvantage of the sliding-mode controller, some techniques have used fuzzy or neural network control techniques [8], [20], [21] to alleviate the chattering phenomena and guarantee the system stability.

In this study, a field-oriented control [22], [23] permanent magnet (PM) synchronous servo motor drive [24] with a supervisory FNN controller is designed to track periodic reference inputs of rotor position with robust and accuracy tracking performance. The supervisory FNN controller comprises a supervisory controller [8], [25] and a FNN sliding-mode controller. The supervisory controller is designed so that the system states are stabilized around a defined bound region. The FNN sliding-mode controller combines the advantages of the sliding-mode control with robust characteristics and the FNN with on-line learning ability. The on-line learning algorithm for the FNN is derived according to the sliding condition, i.e., the parameters of the FNN are adjusted in the direction that minimizes the value of $S\dot{S}$ where S is the switching function. The main advantages of the specific FNN sliding-mode controller are: 1) the ability of on-line training according to sliding condition; (2) the alleviation of the chattering phenomena while maintaining sliding behavior with accurate tracking performance; 3) a structure fuzzy concepts that is easy to understand; and 4) a high degree of robustness and fault tolerance. The FNN sliding-mode controller is chosen to perform the main control action in the supervisory FNN control system. Moreover, the key in the proposed approach is to design the appended supervisory controller [8] to guarantee stability. Therefore, the supervisory controller is chosen to operate in the following supervisory fashion: if the FNN

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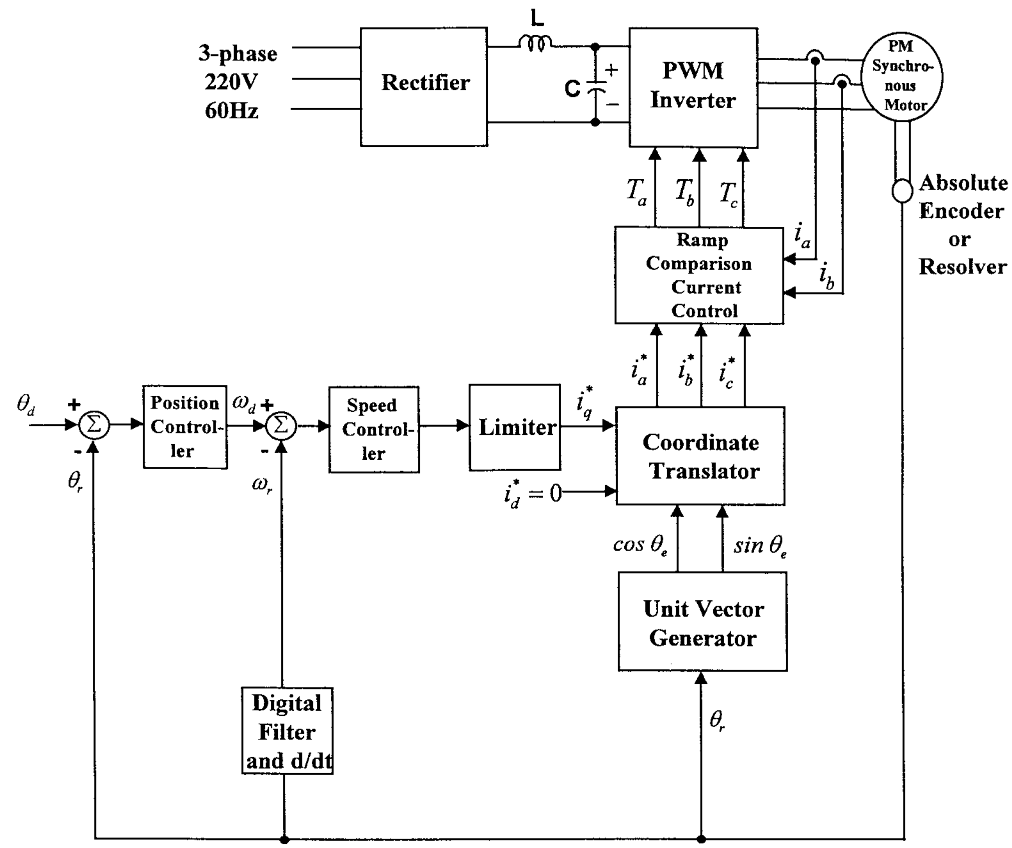


Fig. 1. System configuration of field-oriented synchronous servo motor drive.

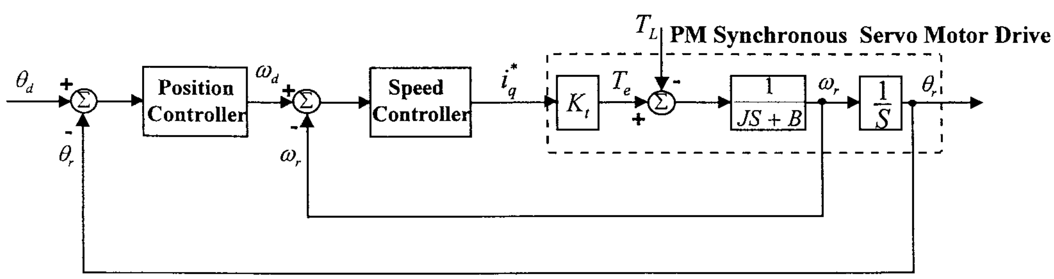


Fig. 2. Simplified control system block diagram.

sliding-mode controller works well, the supervisory controller is idle; if the pure FNN control system tends to be unstable, the supervisory controller starts to work to guarantee stability.

The organization of this paper is as follows. First, the field-oriented control PM synchronous servo motor drive is introduced. Next, the theoretical and stability analyses of the supervisory FNN position control system are described in detail. The supervisory FNN position controller is then implemented in a computer controlled PM synchronous servo motor drive. Finally, the effectiveness of the proposed controller is demonstrated by some simulation and experimental results.

II. The Field-Oriented PM Synchronous Servo-Motor Drive

The configuration of a field-oriented PM synchronous servo-motor drive is shown in Fig. 1 [24], which consists of a PM synchronous servo motor (loaded with a PM dc machine), a ramp comparison current-controlled pulse-width modulation (PWM) voltage source inverter (VSI), a field-orientation mechanism, including the coordinate translator and unit vector ($\cos\theta_e + j\sin\theta_e$ where θ_e is the rotating angle of the rotor flux) generator, a speed-control loop and a position-control loop. The PM synchronous servo motor used in this drive system is a three-phase four-pole 750 W 3.47 A 3000 rpm type. For the position control system, the PM dc machine is operated as a motor and is driven by a current source drive to provide constant disturbance torque. An inertia varying mechanism is also coupled to the rotor of the synchronous servo motor.

With the implementation of field-oriented control [22], [23], the PM synchronous servo motor drive can be simplified to a control system block diagram as shown in Fig. 2 [24] in which

$$T_e = K_t i_q^* \tag{1}$$

$$K_t = 3pL_{md}I_{fd}/2 \tag{2}$$

$$H_p(s) = \frac{1}{Js+B} = \frac{b}{s+a} \tag{3}$$

where T_e is the electric torque, K_t is the torque constant, i_q^* is the torque current command, p is the number of pole pairs, L_{md} is the d-axis mutual inductance, I_{fd} is the equivalent d-axis magnetizing current, J is the moment of inertia, and B is the damping coefficient. Moreover, in Fig. 2, T_L is the external load disturbance, θ_r and ω_r are the rotor position and speed, and θ_d and ω_d are the desired position and speed of the rotor.

Curve-fitting technique based on step response of the rotor position is applied to find the model of the drive system in the nominal condition [24] ($T_L = 0$ Nm without parameter variations). For the convenience of the controller design, the position and speed signals in the control loop are set at 1 V $= 50$ rad and 1 V $= 50$ rad/sec. The results are

$$\begin{aligned}\bar{K}_t &= 0.6732 \text{ Nm/A}, \quad a = 4.4, \quad b = 15.2\\ \bar{J} &= 1.32 \times 10^{-3} \text{ Nms}^2 = 0.066 \text{ Nmsrad/V}.\\ \bar{B} &= 5.78 \times 10^{-3} \text{ Nms/rad} = 0.289 \text{ Nm/V}\end{aligned} \tag{4}$$

The "$^-$" symbol represents the system parameter in the nominal condition.

III. Supervisory FNN Controller

The PM synchronous servo-motor drive system can be represented in the following state-space form:

$$\begin{bmatrix}\dot{x}_1(t)\\ \dot{x}_2(t)\end{bmatrix} = \begin{bmatrix}0 & 1\\ 0 & -B/J\end{bmatrix}\begin{bmatrix}x_1(t)\\ x_2(t)\end{bmatrix} + \begin{bmatrix}0\\ K_t/J\end{bmatrix} i_q^*(t) + \begin{bmatrix}0\\ -1/J\end{bmatrix} T_L \tag{5}$$

where $[x_1(t) \;\; x_2(t)]^T = [\theta_r \;\; \omega_r]$. Define the tracking error vector as follows:

$$\mathbf{E} = [\theta_d - \theta_r \quad \omega_d - \omega_r]^T = [e \quad \dot{e}]^T. \tag{6}$$

Now, a designed signal $\hat{\omega}_r$ is generated by the following:

$$\dot{\hat{\omega}}_r = A_u(\ddot{\theta}_d, \mathbf{E}) \tag{7}$$

in which

$$A_u(\ddot{\theta}_d, \mathbf{E}) = \ddot{\theta}_d + k_1\dot{e} + k_2 e \tag{8}$$

where k_1 and k_2 are positive constants. Then a switching function is defined as

$$S(t) = \omega_r - \hat{\omega}_r. \tag{9}$$

If the sliding mode occurs, i.e., $S = 0$, then

$$\omega_r = \hat{\omega}_r. \tag{10}$$

Substituting (10) into (7) and using (8), it can be obtained

$$\ddot{e} + k_1\dot{e} + k_2 e = 0 \tag{11}$$

which implies that $\lim_{t\to\infty} e(t) = 0$.

The control law is assumed to take the following form:

$$i_q^* = U_{\text{FNN}} + U_S \tag{12}$$

where U_{FNN} is an FNN control, and U_S is a supervisory control [8], [25]. The FNN control U_{FNN} is the main tracking controller and the supervisory control U_S is designed so that the states of the control system are stabilized around a predetermined bound region.

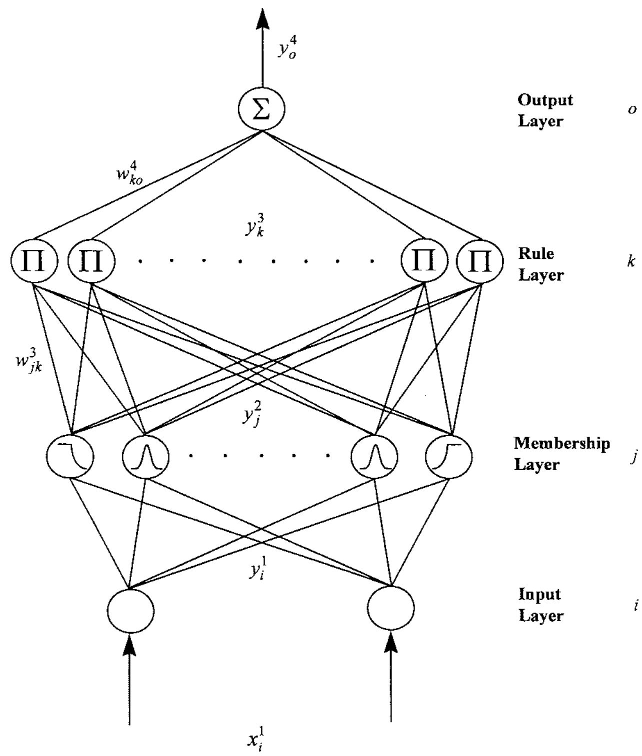


Fig. 3. Structure of four-layer FNN.

A. Description of the FNN

A four-layer FNN [16], as shown in Fig. 3, which is comprised by the input (the i layer), membership (the j layer), rule (the k layer), and output layer (the o layer), is adopted to implement the FNN sliding-mode controller in this study. In the sliding-mode control, the sliding condition that ensure the hitting and existence of a sliding mode is derived from the Lyapunov stability theory by selecting a Lyapunov function $V = 0.5S^2$. Then, the sliding condition is as follows:

$$\dot{V} = S\dot{S} < 0. \tag{13}$$

The sliding condition (13) guarantees that $S \to 0$ as $t \to \infty$. In order to train the FNN according to the minimization of the value of $S\dot{S}$ using the gradient search algorithm, the $S(t)$ and $\dot{S}(t)$ are taken as the inputs of the FNN. The signal propagation and the basic function in each layer of the FNN is introduced in the following.

Layer 1: input layer. For every node i in this layer, the net input and the net output are represented as

$$\text{net}_i^1 = x_i^1, \quad y_i^1 = f_i^1(\text{net}_i^1) = \text{net}_i^1, \quad i = 1, 2 \tag{14}$$

where $x_1^1 = S(t)$ and $x_2^1 = \dot{S}(t)$.

Layer 2: membership layer. In this layer, each node performs a membership function. The Gaussian function is adopted as the membership function. For the jth node

$$\text{net}_j^2 = -\frac{(x_i^2 - m_{ij})^2}{(\sigma_{ij})^2}, \quad y_j^2 = f_j^2(\text{net}_j^2) = \exp(\text{net}_j^2), \quad j = 1, \cdots, n \tag{15}$$

where m_{ij} and σ_{ij} are, respectively, the mean and the standard deviation of the Gaussian function in the jth term of the ith input linguistic variable x_i^2 to the node of layer 2, and n is the total number of the linguistic variables with respect to the input nodes.

Layer 3: rule layer. Each node k in this layer is denoted by $\prod$, which multiplies the input signals and outputs the result of product. For the kth rule node

$$\mathrm{net}_k^3 = \prod_j w_{jk}^3 x_j^3, \quad y_k^3 = f_k^3(\mathrm{net}_k^3) = \mathrm{net}_k^3, \quad k = 1, \cdots, l \tag{16}$$

where x_j^3 represents the jth input to the node of layer 3; w_{jk}^3, which are the weights between the membership layer and the rule layer, are assumed to be unity; $l = (n/i)^i$ is the number of rules with complete rule connection if each input node has the same linguistic variables.

Layer 4: output layer. The single node o in this layer is labeled with $\sum$, which computes the overall output as the summation of all input signals

$$\mathrm{net}_o^4 = \sum_k w_{ko}^4 x_k^4, \quad y_o^4 = f_o^4(\mathrm{net}_o^4) = \mathrm{net}_o^4, \quad o = 1 \tag{17}$$

where the connecting weight w_{ko}^4 is the output action strength of the oth output associated with the kth rule; x_{ko}^4 represents the kth input to the node of layer 4 and $y_1^4 = U_{\mathrm{FNN}}$.

B. On-Line Learning Algorithm

The on-line learning algorithm is a gradient descent search algorithm in the space of network parameters and aims to minimize $S\dot{S}$. Therefore, the $S\dot{S}$ is selected as the error function. Take the first derivative of S and use (5), one can obtain

$$\dot{S} = \dot{\omega}_r - \dot{\hat{\omega}}_r = -\frac{B}{J}\omega_r + \frac{K_t}{J} i_q^* - \frac{T_L}{J} - A_u(\ddot{\theta}_d, E). \tag{18}$$

Substituting (12) into (18) and multiplying both side by S, the following is obtained:

$$S\dot{S} = -\frac{B}{J}\omega_r S + \frac{K_t}{J}(U_{\mathrm{FNN}} + U_S)S - \frac{T_L}{J}S - A_u(\ddot{\theta}_d, E)S. \tag{19}$$

According to the gradient descent method, the weights in the output layer are updated by the following:

$$\begin{aligned}\dot{w}_{ko}^4 &= -\eta \frac{\partial S\dot{S}}{\partial i_q^*}\frac{\partial i_q^*}{\partial w_{ko}^4} = -\eta \frac{\partial S\dot{S}}{\partial U_{\mathrm{FNN}}}\frac{\partial U_{\mathrm{FNN}}}{\partial w_{ko}^4} \\ &= -\eta \left|\frac{K_t}{J}\right| \mathrm{sgn}\left(\frac{K_t}{J}\right) S x_k^4 = -\gamma S x_k^4 \end{aligned} \tag{20}$$

where η is a positive constant, $\gamma = \eta |K_t/J|$ is the learning-rate parameter of the weights and is some positive constant to be determined, $\mathrm{sgn}(\cdot)$ is a sign function, and $\mathrm{sgn}(K_t/J) = 1$. Since the weights in the rule layer are unity, only the approximated error term needs to be calculated and propagated by the following:

$$\delta_k^3 \triangleq -\frac{\partial S\dot{S}}{\partial U_{\mathrm{FNN}}}\frac{\partial U_{\mathrm{FNN}}}{\partial\, \mathrm{net}_o^4}\frac{\partial\, \mathrm{net}_o^4}{\partial y_k^3}\frac{\partial y_k^3}{\partial\, \mathrm{net}_k^3} = -\left|\frac{K_t}{J}\right| S w_{ko}^4 \tag{21}$$

and the nominal values of K_t and J will be used in the above equation. The multiplication is done in the membership layer, and the error term is computed as follows:

$$\begin{aligned}\delta_j^2 &= -\frac{\partial S\dot{S}}{\partial U_{\mathrm{FNN}}}\frac{\partial U_{\mathrm{FNN}}}{\partial\, \mathrm{net}_o^4}\frac{\partial\, \mathrm{net}_o^4}{\partial y_k^3}\frac{\partial y_k^3}{\partial\, \mathrm{net}_k^3}\frac{\partial\, \mathrm{net}_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial\, \mathrm{net}_j^2} \\ &= \sum_k \delta_k^3 y_k^3. \end{aligned} \tag{22}$$

The update laws of m_{ij} and σ_{ij} also can be obtained by the gradient decent search algorithm, i.e.,

$$\dot{m}_{ij} = -\eta_m \frac{\partial S\dot{S}}{\partial m_{ij}} = \eta_m \delta_j^2 \frac{2(x_i^2 - m_{ij})}{(\sigma_{ij})^2} \tag{23}$$

$$\dot{\sigma}_{ij} = -\eta_\sigma \frac{\partial S\dot{S}}{\partial \sigma_{ij}} = \eta_\sigma \delta_j^2 \frac{2(x_i^2 - m_{ij})^2}{(\sigma_{ij})^3} \tag{24}$$

where η_m and η_σ are the learning-rate parameters of the mean and the standard deviation of the Gaussian function. Since the gradient vector is calculated in the direction opposite to the energy flow, the convergence properties of the FNN can depend on the nature convergence characteristics of the gradient search algorithm [9], [10]. On the other hand, the selection for the values of the learning-rate parameters $(\gamma, \eta_m, \eta_\sigma)$ has a significant effect on the network performance. For instance, if the learning-rate parameters are not selected adequately, the resulted U_{FNN} will make the states of the system move toward the direction of divergence. Therefore, the design of a supervisory controller is necessary for the condition of divergence of states to pull the states back to the predetermined bound region and guarantee the stability of the system.

C. Supervisory Control

The dynamic equation of the PM synchronous servo-motor drive system can be obtained by rewriting (5) as

$$\ddot{\theta}_r = -\frac{B}{J}\dot{\theta}_r + \frac{K_t}{J} i_q^* - \frac{1}{J}T_L = A_P\dot{\theta}_r + B_P i_q^* + C_P T_L \tag{25}$$

where $A_P = -B/J$, $B_P = K_t/J > 0$, and $C_P = -1/J$. Consider the variation of system parameters and external load disturbance, the parameters in (25) are assumed to be bounded, i.e.,

$$\begin{aligned} &|A_P\dot{\theta}_r| \le F^U(\dot{\theta}_r) \\ &|C_P T_L| \le G^U \\ &B_L \le B_P \le B^U \end{aligned}$$

where $F^U(\dot{\theta}_r)$ is a known continuous function; G^U, B_L, and B^U are known constants.

If the parameters of the PM synchronous servo-motor drive system and T_L are well known, the perfect control law can be defined as follows:

$$i_q^* = U^* = \frac{1}{B_P}[-A_P\dot{\theta}_r - C_P T_L + \ddot{\theta}_d + \mathbf{KE}] \tag{26}$$

where $\mathbf{K} = [k_2 \ \ k_1]$. From (12), (25), and (26), an error equation is then obtained as follows:

$$\dot{\mathbf{E}} = \mathbf{\Lambda E} + \mathbf{B_m}[U^* - U_{\mathrm{FNN}} - U_S] \tag{27}$$

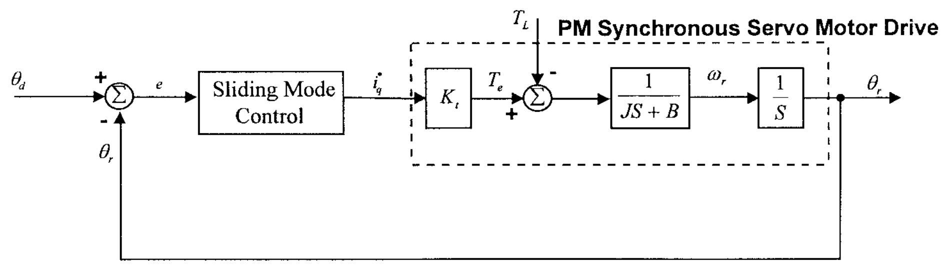


Fig. 4. Block diagram of sliding-mode control system.

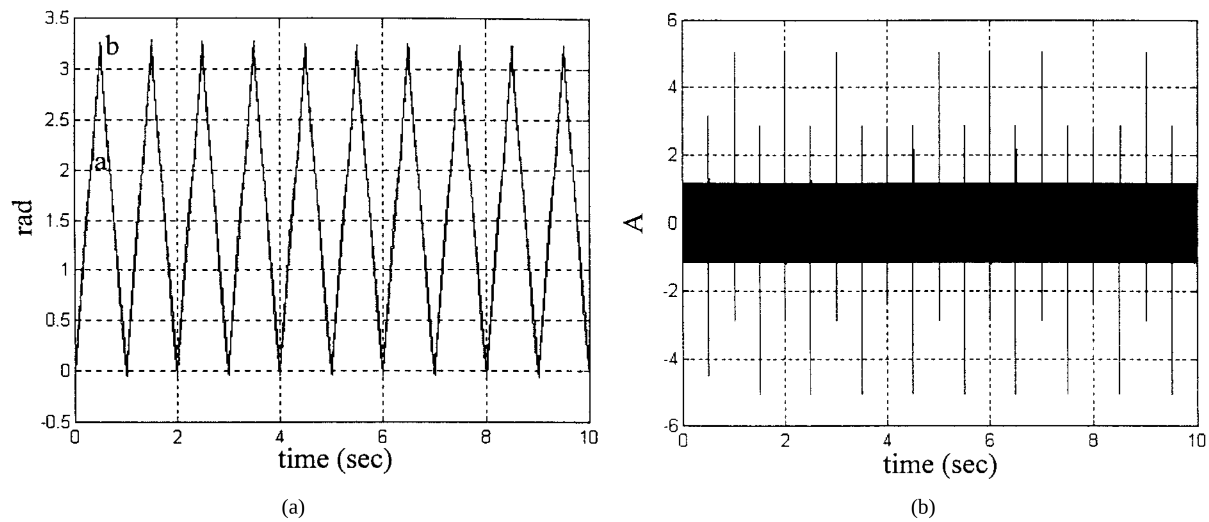


Fig. 5. Simulation results of sliding-mode controller due to periodic triangular reference input at Case 1. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.

where $\mathbf{\Lambda} = \begin{bmatrix} 0 & 1 \\ -k_2 & -k_1 \end{bmatrix}$ is a stable matrix and $\mathbf{B_m} = [0 \;\; B_P]^T$. The Lyapunov function is defined as

$$V_S = \frac{1}{2}\mathbf{E^T P E} \tag{28}$$

where $\mathbf{P}$ is a symmetric positive definite matrix which satisfies the following Lyapunov equation:

$$\mathbf{\Lambda}^T\mathbf{P} + \mathbf{P\Lambda} = -\mathbf{Q} \tag{29}$$

and $\mathbf{Q} > 0$ is selected by the designer. Take the derivative of the Lyapunov function and use (27) and (29), then

$$\begin{aligned}\dot{V}_S &= -\frac{1}{2}\mathbf{E^T Q E} + \mathbf{E^T P B_m}[U^* - U_{\rm FNN} - U_S] \\ &\le -\frac{1}{2}\mathbf{E^T Q E} + |\mathbf{E}^T\mathbf{P B_m}|(|U^*| + |U_{\rm FNN}|) \\ &\quad - \mathbf{E^T P B_m} U_S. \end{aligned} \tag{30}$$

To satisfy $\dot{V}_S \le 0$, the supervisory control U_S is designed as follows [8], [25]:

$$\begin{aligned} U_S = I\,{\rm sgn}(\mathbf{E^T P B_m})\Big[&|U_{\rm FNN}| + \frac{1}{B_L}(F^U(\dot{\theta}_r) + G^U \\ &+ |\ddot{\theta}_d| + |\mathbf{KE}|)\Big] \end{aligned} \tag{31}$$

where

$$I = \begin{cases} I = 1, & \text{if } V_S \ge \bar{V} \\ I = 0, & \text{if } V_S < \bar{V} \end{cases}$$

and $\bar{V}$ is a positive constant. Substitute (26) and (31) into (30) and consider the $I = 1$ case; then

$$\begin{aligned}\dot{V}_S &\le -\frac{1}{2}\mathbf{E^T Q E} + |\mathbf{E^T P B_m}|(|U^*| + |U_{\rm FNN}|) \\ &\quad - \mathbf{E^T P B_m} U_S \\ &= -\frac{1}{2}\mathbf{E^T Q E} + |\mathbf{E^T P B_m}|\Big[\frac{1}{B_P}(|A_P\dot{\theta}_r| + |C_P T_L| \\ &\quad + |\ddot{\theta}_d| + |\mathbf{KE}|) + |U_{\rm FNN}| - |U_{\rm FNN}| \\ &\quad - \frac{1}{B_L}(F^U + G^U + |\ddot{\theta}_d| + |\mathbf{KE}|)\Big] \\ &\le -\frac{1}{2}\mathbf{E^T Q E} \le 0. \end{aligned} \tag{32}$$

Using the designed supervisory control U_S as shown in (31), the inequality $\dot{V}_S < 0$ can be obtained for nonzero value of the tracking error vector $\mathbf{E}$ when $V_S > \bar{V}$.

IV. Simulation

To investigate the effectiveness of the supervisory FNN control system, three simulation cases including large parameter variations and external load disturbance in the shaft are considered here:

$$\text{Case 1: } J = \bar{J}, \quad B = \bar{B}, \quad T_L = 0 \text{ Nm} \tag{33}$$

$$\text{Case 2: } J = 5 \times \bar{J}, \quad B = 5 \times \bar{B}, \quad T_L = 0 \text{ Nm} \tag{34}$$

$$\text{Case 3: } J = \bar{J}, \quad B = \bar{B}, \quad T_L = 5 \text{ Nm occured at 2.4 s.} \tag{35}$$

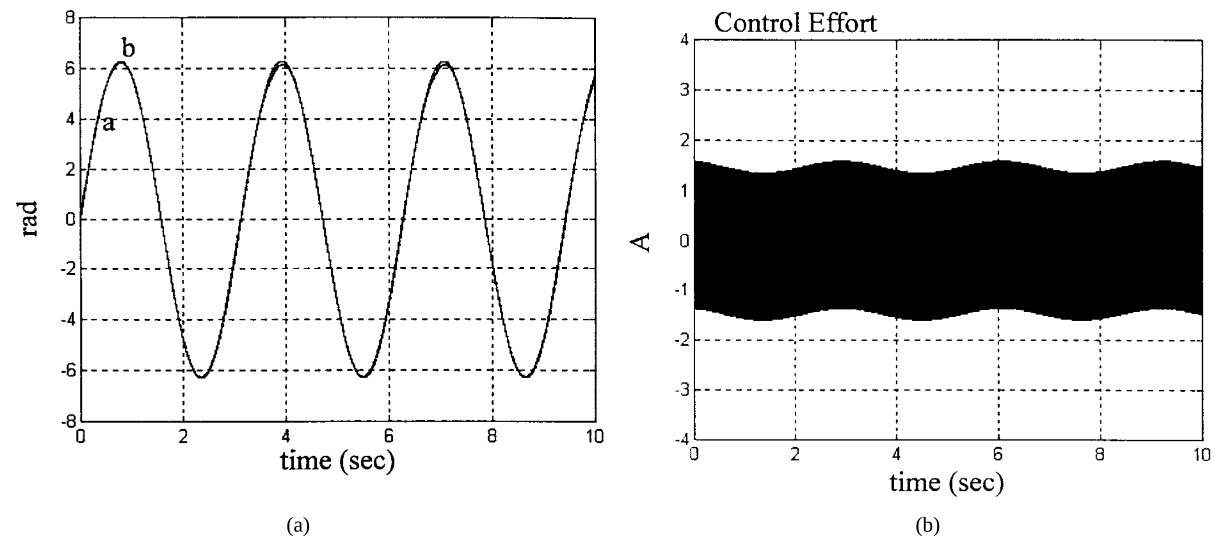


Fig. 6. Simulation results of sliding-mode controller due to periodic sinusoidal reference input at Case 1. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.

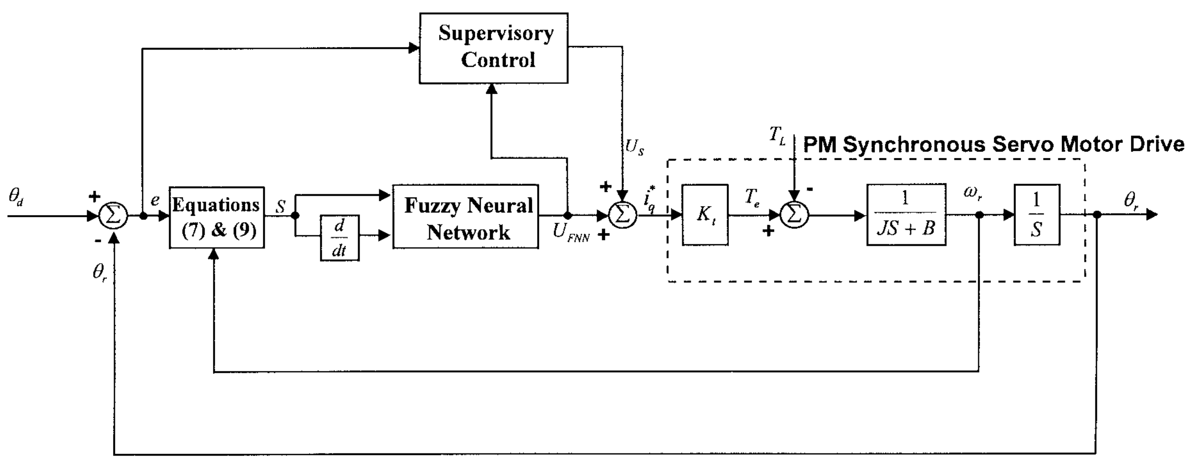


Fig. 7. Block diagram of supervisory FNN control system.

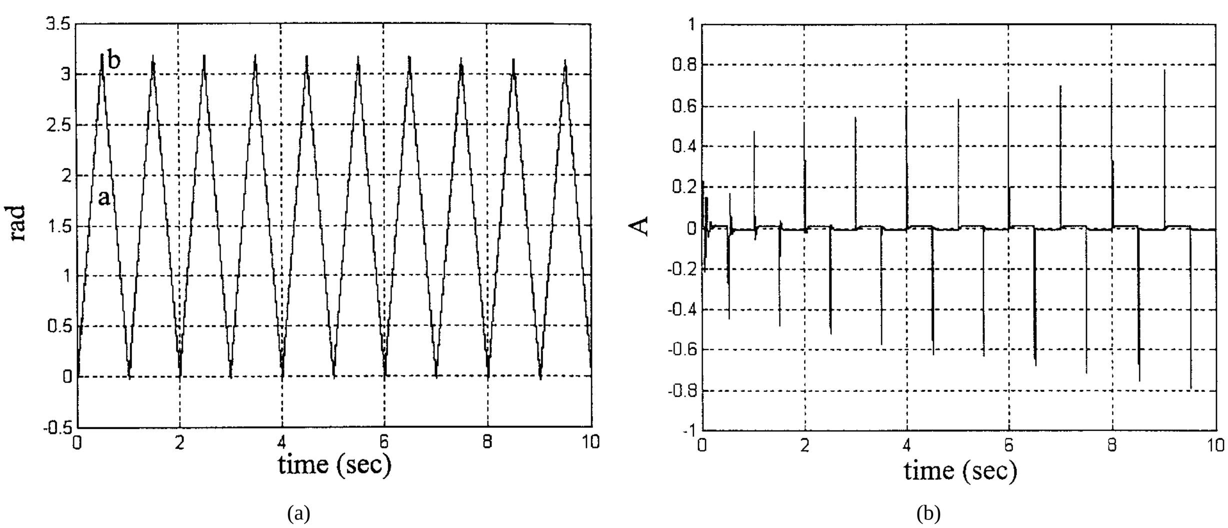


Fig. 8. Simulation results of supervisory FNN controller due to periodic triangular reference input at Case 1. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.

A. The Sliding-Mode Control

To compare the control performance of the supervisory FNN controller with the sliding-mode controller, the sliding-mode control law designed by Slotine and Li [4] as follows:

$$i_q^* = \hat{B}_P^{-1}[\hat{U} - Z\,\mathrm{sgn}(S')] \tag{36}$$

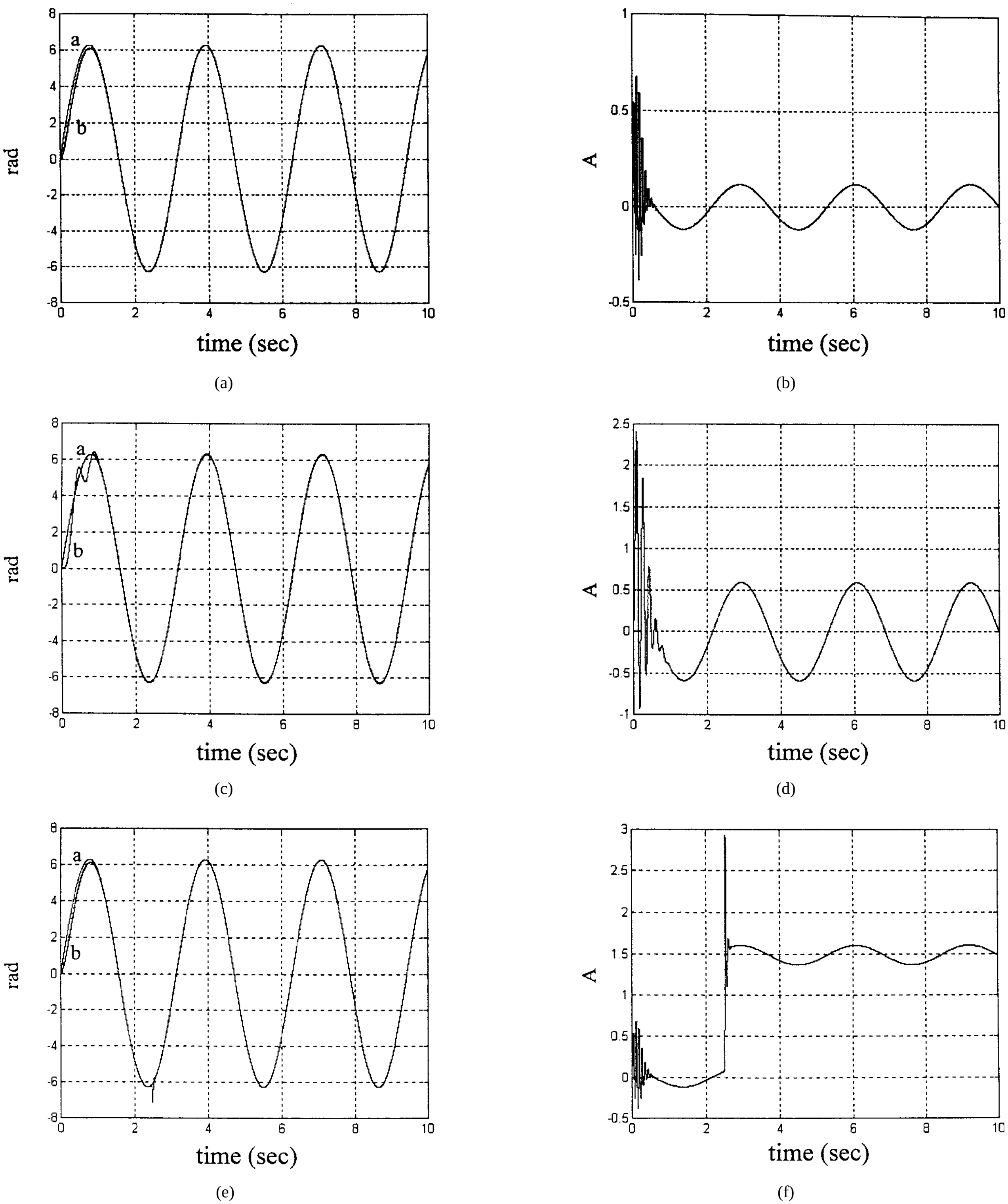


Fig. 9. Simulation results of supervisory FNN controller due to periodic sinusoidal reference input. (a) Tracking response at Case 1. Desired position: a; rotor position: b. (b) Control effort at Case 1. (c) Tracking response at Case 2. Desired position: a; rotor position: b. (d) Control effort at Case 2. (e) Tracking response at Case 3. Desired position: a; rotor position: b. (f) Control effort at Case 3.

is adopted in this study, where $\hat{B}_P$ is the geometric mean of the B_P bounded by (B_L, B^U); $S' = \dot{e} + \lambda e$ in which λ is a positive constant; $\tilde{U}$ is the equivalent control; Z is the selected gain to satisfy the sliding condition. The block diagram of the sliding-mode control system is shown in Fig. 4. The simulation is carried out using "Matlab" package. The simulation results of the sliding-mode control system due to periodic triangular and sinusoidal reference inputs at Case 1 are shown in Figs. 5(a) and 6(a), and the associated control effort are shown in Figs. 5(b) and 6(b). Though favorable tracking responses

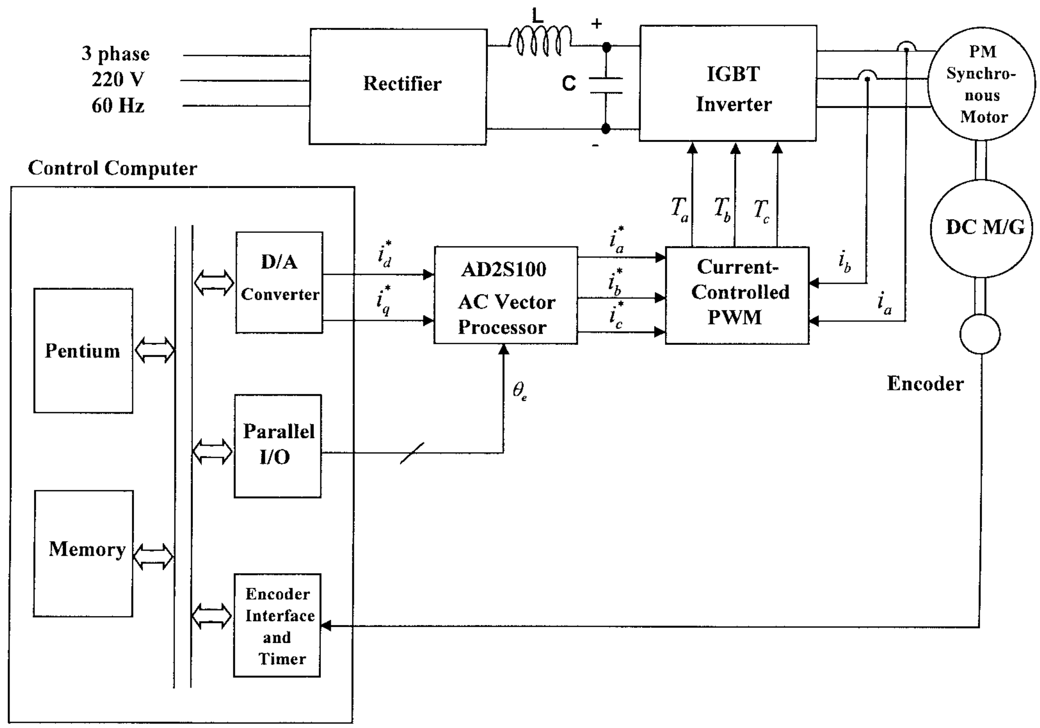
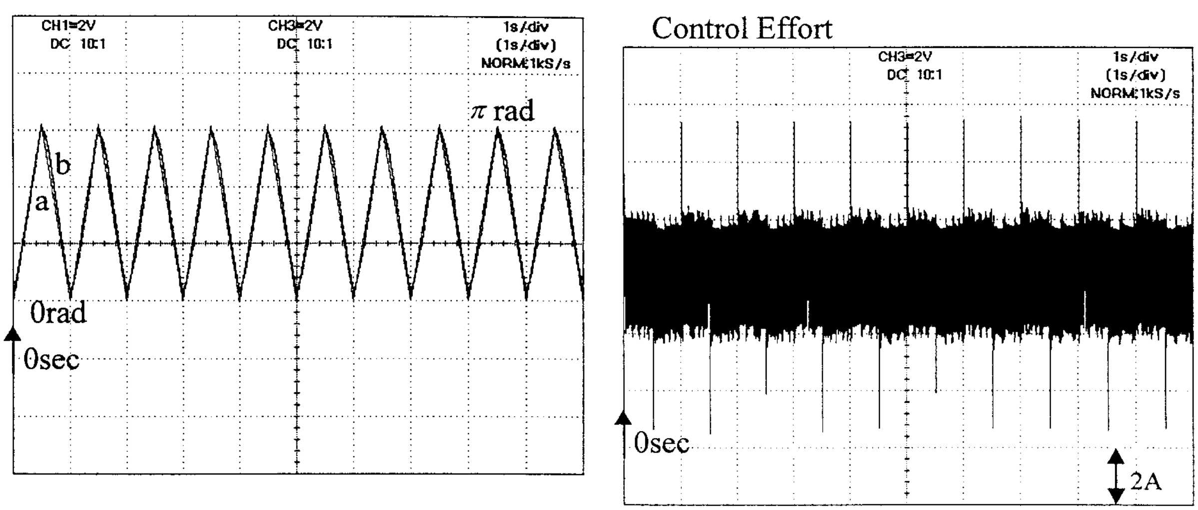


Fig. 10. Computer control PM synchronous servo-motor drive system.



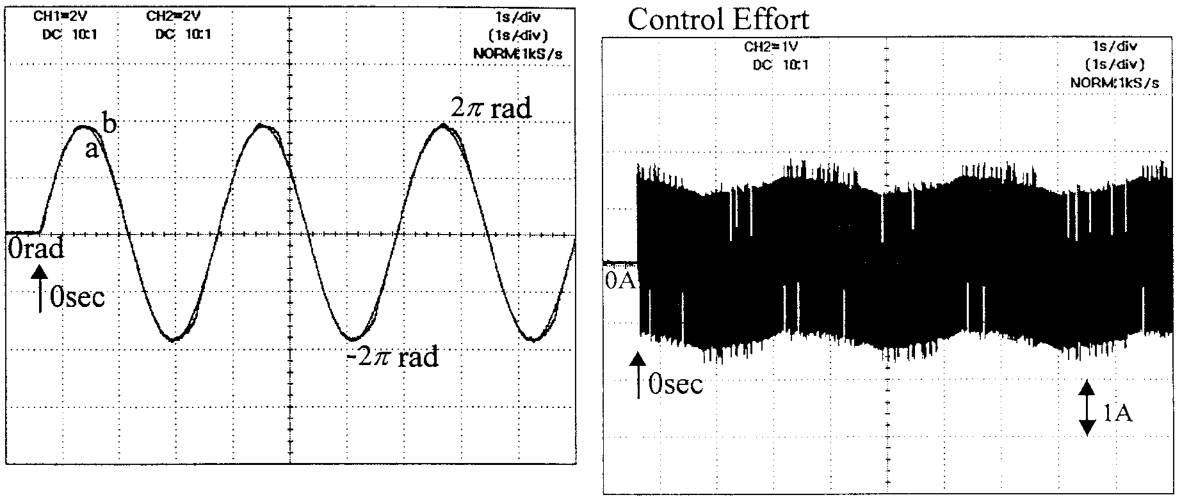
(a) (b)

Fig. 11. Experimental results of sliding-mode controller due to periodic triangular reference input at nominal condition. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.

can be obtained by the sliding-mode controller, the chattering control efforts caused by the switching operation result in degenerate tracking accuracy.

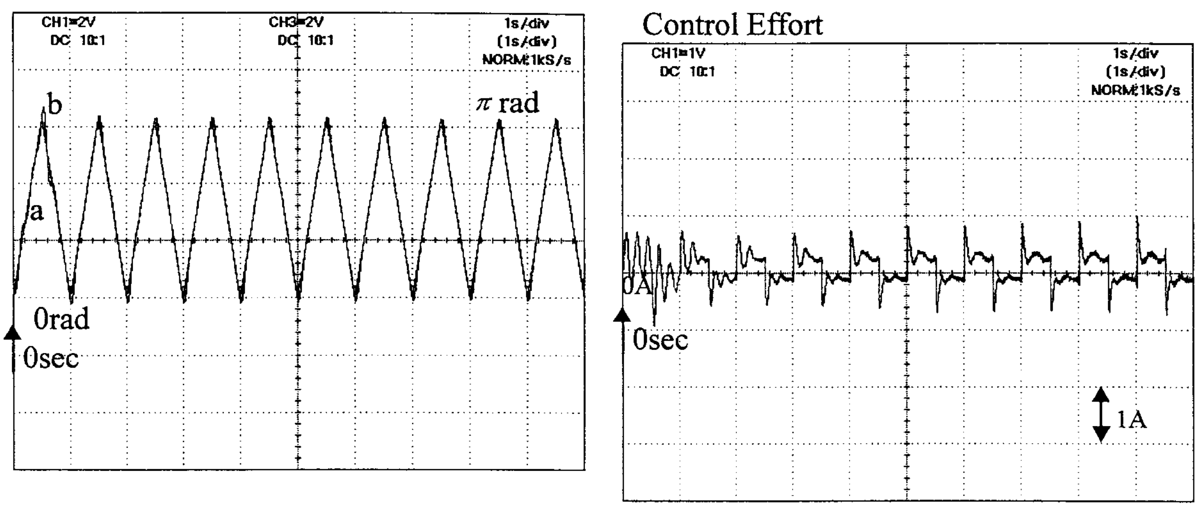
B. The Supervisory FNN Control

The block diagram of the supervisory FNN control system is shown in Fig. 7 where the inputs of the FNN are $S(t)$ and its derivative; the output of the FNN is $U_{\rm FNN}$; the output of the supervisory control is U_S. The FNN architecture shown in Fig. 3 is a general form of network, which is fully connected between two layers. Usually, some heuristics can be used in initializing the number of rules for practical applications. The FNN architecture in [19] is adopted in this study for both the simulation and experimentation. The connecting weights between the output and rule layers of the FNN are initialized with random number $[0, 1]$ and the parameters of Gaussian functions are initialized with random number $[-3, 3]$. The FNN has two, six, nine, and one neuron(s) at the input, membership, rule, and output layers, respectively. The training of the FNN is carried out every 2 ms. The simulation results of the supervisory FNN control system due to a periodic triangular reference input at Case 1 and a periodic sinusoidal reference input at Case 1, 2, and 3 with the associated control efforts are shown in Figs. 8 and 9, respectively. Since the



(a) (b)

Fig. 12. Experimental results of sliding-mode controller due to periodic sinusoidal reference input at nominal condition. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.



(a) (b)

Fig. 13. Experimental results of supervisory FNN controller due to periodic triangular reference input at nominal condition. (a) Tracking response. Desired position: a; rotor position: b. (b) Control effort.

weights of the FNN are randomly initialized, accurate tracking performance for the sinusoidal reference input is obtained after 400 times of on-line training of the FNN. However, the chattering phenomenon does not exist in the control efforts of the supervisory FNN controller as shown in Figs. 8(b), 9(b), 9(d), and 9(f). Moreover, the robust control performance of the supervisory FNN controller, both in the conditions of parameter variations and external load disturbance, are obvious as shown in Figs. 9(c) and (e).

The control performance of the supervisory FNN controller can be improved especially in the first cycle of periodic command tracking if the initial formation procedure [26] is implemented instead of the random initialization. The initial formation procedure, which is aimed at extracting the connective weights and membership functions from the process of the iterative learning, is used to initial the parameters of the FNN to speed up the convergence process. However, the extracted parameters including the connective weights and membership functions are effective only under the same operating conditions, e.g., the same reference input. In other words, the initial formation procedure is a off-line training process. In this study, to show the on-line learning capability of the FNN for different periodic reference inputs, random initialization is adopted to initial the parameters of the FNN.

V. EXPERIMENTATION

A block diagram of the computer control system for the field-oriented PM synchronous servo-motor drive is shown in Fig. 10 [24]. The proposed control system is implemented using a Pentium computer. The current-controlled voltage-source inverter (VSI) is implemented by insulated-gate bipolar

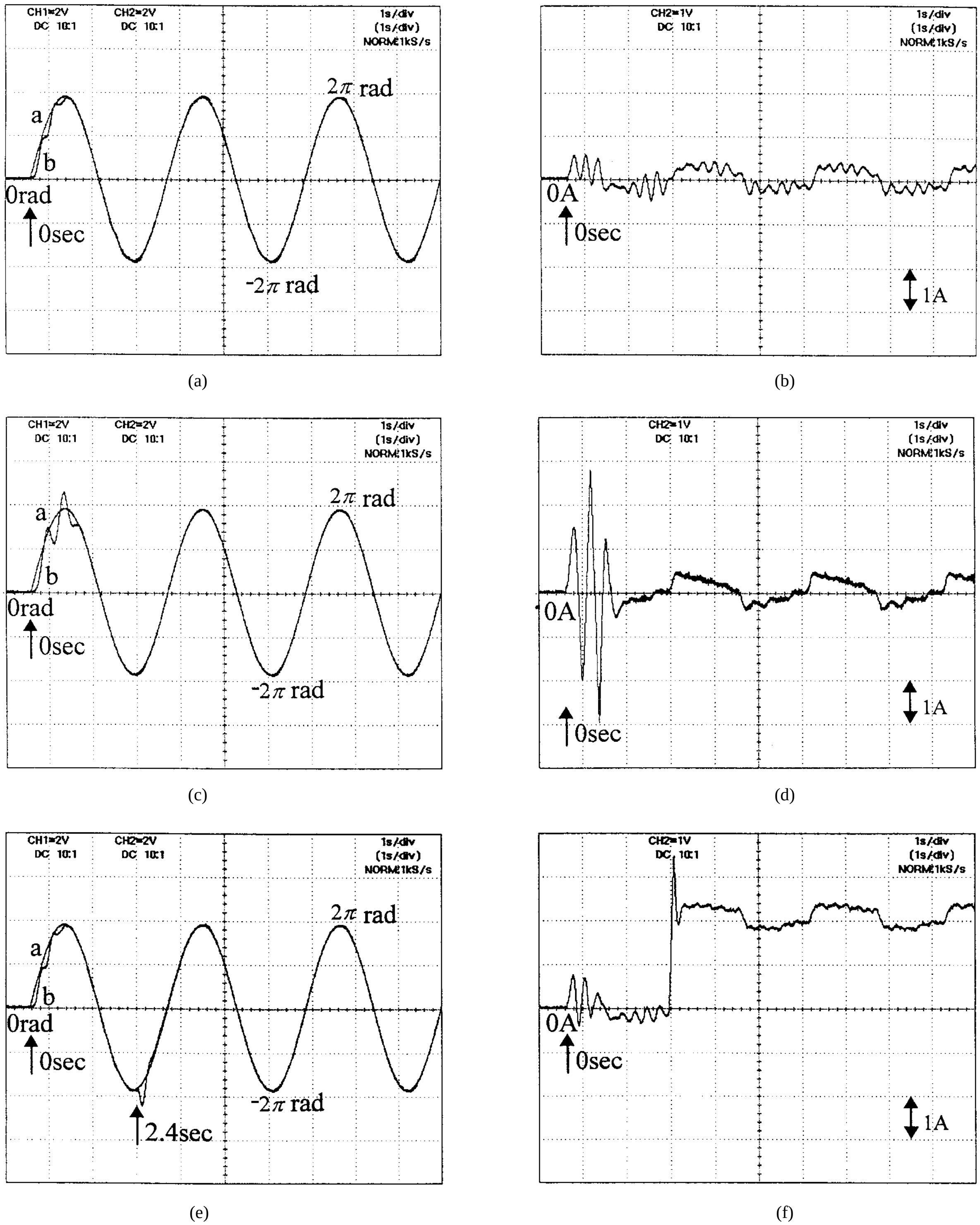


Fig. 14. Experimental results of supervisory FNN controller due to periodic sinusoidal reference input. (a) Tracking response at nominal condition. Desired position: a; rotor position: b. (b) Control effort at nominal condition. (c) Tracking response at inertia variation. Desired position: a; rotor position: b. (d) Control effort at inertia variation. (e) Tracking response at nominal inertia with disturbance. Desired position: a; rotor position: b. (f) Control effort at nominal inertia with disturbance.

transistor (IGBT) switching components with a switching frequency of 15 kHz. To reduce the calculation burden of the central processing unit (CPU) and to increase the accuracy of the three-phase command currents, the coordinate transformation in the field-oriented mechanism is implemented by an AD2S100 ac vector processor [24]. The experimentation is carried out using *Turbo C* package and the sampling rates of the sliding-mode controller and the supervisory FNN controller including the on-line training algorithm are both 2 ms.

A. The Sliding-Mode Control

The experimental results of the sliding-mode controller due to periodic triangular and sinusoidal reference inputs at the nominal condition are shown in Figs. 11(a) and 12(a), where the 0 s indicates the beginning of tracking control and the associated control efforts are shown in Figs. 11(b) and 12(b). Though favorable tracking responses can be obtained by the sliding-mode controller as in the simulation, the chattering phenomena existed in the control efforts result inaccurate tracking responses. Moreover, the chattering control efforts will wear the bearing mechanism and might excite unstable system dynamics.

B. The Supervisory FNN Control

Some experimental results are provided here to demonstrate the effectiveness of the supervisory FNN controller. Two conditions of rotor inertia are tested here; one is the nominal inertia, and the other is the increasing of the rotor inertia to approximate three times the nominal value. The connecting weights between the output and rule layers and the Gaussian functions of the FNN are initialized with random numbers as in the simulation. First, the experimental results due to a periodic triangular reference input at the nominal condition are shown in Fig. 13(a) and (b); accurate tracking response is obtained after approximate 500 times of on-line training. Next, the experimental results due to a periodic sinusoidal reference input at the nominal condition are shown in Fig. 14(a) and (b), and the experimental results at the inertia variation condition are shown in Fig. 14(c) and (d). Accurate tracking responses are obtained after approximate 500 times of on-line training for the above two test conditions. Moreover, the experimental results due to a periodic sinusoidal reference input at the condition of nominal inertia with 1.6 Nm step-load disturbance occurred at 2.4 s are shown in Fig. 14(e) and (f). After the occurrence of the step-load disturbance, only 200 times of on-line training are needed to resume accurate tracking response. Moreover, large control efforts of the supervisory FNN controller are needed due to parameter variations and external load disturbance as shown in Fig. 14(d) and (f).

Compared with the FNN control strategy proposed in [19], the stability of the supervisory FNN control system can be guaranteed. Moreover, the integral-proportional (IP) controller implemented in [19] is only designed to track step command. Therefore, the FNN control system proposed in [19] cannot have smooth and accurate command tracking responses for periodic triangular and sinusoidal reference inputs. On the other hand, due to the powerful on-line learning capability of the FNN, the proposed supervisory FNN controller can track both the periodic triangular and sinusoidal reference inputs precisely.

VI. Conclusion

A supervisory FNN position controller have been successfully developed in this study for the tracking of periodic reference inputs. Since the PM synchronous motors are adopted in many tracking control applications, the proposed controller is implemented using a PM synchronous servo-motor drive. Though favorable tracking responses can be obtained by the sliding-mode controller, the chattering phenomena will result in inaccurate tracking responses and wear the bearing mechanism; moreover, it might excite unstable system dynamics. On the other hand, the proposed supervisory FNN controller combines the advantages of the sliding-mode control with robust characteristics and the FNN with on-line learning ability; furthermore, the system states have been proved to be stabilized around a predetermined bound region. The merits of the supervisory FNN position controller have been demonstrated by tracking periodic triangular and sinusoidal reference inputs in both the simulation and experimentation.

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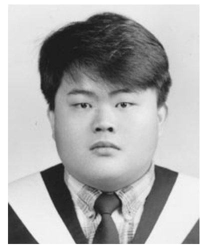

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