Incorporating Sliding Mode Neural Network and Fuzzy Controller for Induction Motor Position Control

Saman Ebrahimi Boukani
Department of Electrical Engineering, Mahabad Branch Islamic Azad University, mahabad, Iran
s.ebrahimi@iau-mahabad.ac.ir
1- Receive Date: 10 September 2022, Revise Date: 6 October 2022, Accept Date:20 November 2022

Abstract*:*

This study presents an incorporating sliding-mode neural-network (SMNN) and fuzzy control system for the position control of an induction motor. In the SMNN control system, a neural network controller is developed to mimic an equivalent control law in the sliding mode control, and a robust controller is designed to curb the system dynamics on the sliding surface for guaranteeing the asymptotic stability property.Moreover, an adaptive bound estimation algorithm is employed to estimate the upper bound of uncertainties. All adaptive learning algorithms in the SMNN control system are derived from the sense of Lyapunov stability analysis, so that system-tracking stability can be guaranteed in the closed-loop system whether the uncertainties occur or not. In spite of these merits, SMNN suffers from chattering problem which can excite unmodeled dynamics and harm the control system. In this paper, to avoid this problem, a combined controller in clued SMNN term and Fuzzy term is proposed. The proposed control scheme possesses three salient merits: (1) it guarantees the stability of the controlled system, (2) no constrained conditions and prior knowledge of the controlled plant is required in the design process, and (3) the chattering is avoided.

Keywords: Sliding-mode control; Neural network; Fuzzy control; Robust control; Bound estimation; Induction motor

1. Introduction

Up to now, indirect field-oriented techniquehas been widely use for the control of induction motor servo drive in high-performance applications [1]. The technique guarantees the decoupling of torque and flux control commands of the induction motor, so makes the induction motor be controlled linearly as a separated excited dc motor. But the decoupled control performance is still influenced by the uncertainties, due to the unpredictable parameter variations, external load disturbances, and unmodeled and nonlinear dynamics. To overcome these drawbacks, optimal control, sliding-mode control, adaptive control and intelligent control are proposed[2-4].

Sliding mode control (SMC) has many good properties, such as strong robustness, disturbance rejection and easy implementation [4]. Sliding mode control is one type of variable-structure control scheme. Normally, two steps, namely the reaching and sliding phases, are necessary in the design of sliding mode controller. Therefore, the sliding mode controller usually consists of an equivalent law and a switching law. The equivalent law is given so that the states can stay on sliding surface. The switching law is used to drive the state trajectory to the sliding manifold. However, usually the switching law is discontinuous part and the frequency of switching in control system is finite high, so undesired chattering exists in control system. Additionally, the sliding control requires the knowledge of mathematical model of the system with bounded uncertainties. Another method, popular in recent years, is based on [5-8].

Neural Networks (NN) have the ability to approximate nonlinear functions. A NN can approximate any smooth function to any desired accuracy, provided that the number of hidden-layer neuron is large enough. In addition, radial Basis Function Neural Network (RBFNN) has an advantage of faster learning ability and less chance of falling into local minimum, in comparison with standard BP neural network. Therefore, RBFNN is quite suitable to design of the equivalent control law.

The motivation of this study is to design an intelligent control scheme for the position control of an induction motor. In the whole design process, no strict constraints and prior knowledge of the controlled plant are required, and the asymptotic stability of the control system can be guaranteed. To accomplish the mentioned motivation, a SMNN control system is developed in this study to control of an IM.

In the past three decades, fuzzy systems have replaced conventional technologies in many applications, especially in control systems. One major feature of fuzzy logic is its ability to express the amount of ambiguity in human thinking. Thus, when the mathematical model of one process does not exist, or exists but with uncertainties, fuzzy logic is an alternative way to deal with the unknown process [9]. But, the huge amounts of fuzzy rules for a high-order system makes the analysis complex. Nowadays, much attention has focused on the combination of fuzzy logic and SMC. The main advantages of the fuzzy control design based on SMC are that the fuzzy rules can be reduced, and the requirement of uncertainty bound can be relaxed. In[10], [11] combined a fuzzy controller with SMC and state feedback control or proportional-integral control to remedy the chattering phenomenon and to achieve zero steady-state error. However, the parameters of membership functions cannot be adjusted to afford optimal control efforts under the occurrence of uncertainties. Ha in [12], [13] adjusted the SMC action during the reaching phase using fuzzy logic for reducing chattering without sacrificing robust performance. Lin *et al.* utilized an adaptive fuzzy SMC system for a permanent magnet synchronous motor drive. However, there still exists some chattering in the control efforts because the sign function is included in the ultimate control law [14]. In this paper, an incorporating SMNN control into fuzzy is proposed to alleviate the chattering phenomena.

Design procedure contains two steps. First, SMNN control design is accomplished and system stability in this case is provided by Lyapunov direct method. When the tracking error would be less than predefined value then a sectorial fuzzy controller (SFC),[15], is responsible for control action. Designing of this kind of fuzzy controller is exactly same as in which has performed in [16].

2. Indirect Field-Oriented Induction Motor

Under the assumption of linearity of the magnetic circuit, and neglecting the iron losses in a tree-phase squirrel cage induction motor, the 4th order non-linear model (d-q) frame of the induction motor is

$$\begin{aligned}
\dot{\psi}_{dr} &= \omega_{sl}\psi_{qr} - \frac{R_r}{L_r}\psi_{dr} + L_m\frac{R_r}{L_r}i_{ds} \\
\dot{\psi}_{qr} &= -\omega_{sl}\psi_{dr} - \frac{R_r}{L_r}\psi_{qr} + L_m\frac{R_r}{L_r}i_{qs} \\
\dot{i}_{ds} &= \frac{1}{L_\sigma L_s}u_{ds} - \frac{1}{L_\sigma L_s}(R_s + \frac{R_r L_m^2}{L_r^2})i_{ds} \\
&\quad + \frac{R_r L_m}{L_r^2 L_\sigma L_s}\psi_{dr} + \frac{L_m}{L_r\, L_\sigma L_s}\omega_r\psi_{qr} + \omega_e i_{qs} \\
\dot{i}_{qs} &= \frac{1}{L_\sigma L_s}u_{qs} - \frac{1}{L_\sigma L_s}(R_s + \frac{R_r L_m^2}{L_r^2})i_{qs} \\
&\quad + \frac{R_r L_m}{L_r^2 L_\sigma L_s}\psi_{qr} - \frac{L_m}{L_r\, L_\sigma L_s}\omega_r\psi_{dr} - \omega_e i_{ds}
\end{aligned} \tag{1}$$

Where u_{ds} , u_{qs} are the applied voltages to phases d and q of the stator, respectively; i_{ds} , i_{qs} , are the corresponding stator currents. The rotor flux in the direct axis is given by ψ_{dr} whereas in the quadrature axis it is defined by ψ_{qr} . the rotor speed is given by ω_r and the angular speed of the rotor flux linkage vector by ω_e . R_s , R_r are the stator and rotor resistances; L_s , L_r are the stator and rotor selfinductances; L_m is the stator-rotor mutual inductance. $L_\sigma = 1 - \frac{L_m^2}{L_r\, L_s}$ is the leakage coefficient.

On the assumption that the effects of magnetic saturation, core loss and skin effect are neglected. The electrical model is augmented by the mechanical subsystem given as:

$$\dot{\omega}_r = -\frac{B}{J}\omega_r + \frac{P}{J}(T_e - T_l) \tag{2}$$

$$T_e = \frac{3}{4}P\frac{L_m}{L_r}\left(\psi_{dr}i_{qs} - \psi_{qr}i_{ds}\right) \tag{3}$$

Where J and B denote the motor-load moment of inertia and the viscous friction coefficient; P is the number of pole pairs and T_l is the load torque.

The desired values of rotor flux under the rotor flux linkages oriented in the d-axis are given by:

$$\psi_{dr}^* = L_m i_{ds}^* \tag{4}$$

$$\psi_{qr}^* = 0 \tag{5}$$

Under the complete field-oriented control, the mechanical equation (2) can be equivalently described as [17]:

$$\dot{\omega}_r + a\,\omega_r + f = b\psi_{dr}^* i_{qs}^* \tag{6}$$

Where:

$$a = \frac{B}{J} \quad , \quad b = \frac{3P^2 L_m}{4L_r J} \quad , \quad f = P\frac{T_l}{J} \tag{7}$$

Let $\omega_r = \dot{\theta}_r$, the mechanical equation of IM system can be represented as:

$$\ddot{\theta}_r + a\,\dot{\theta}_r + f = b\psi_{dr}^* i_{qs}^* \tag{8}$$

Furthermore, consider (8) with uncertainties:

$$\begin{aligned}
\ddot{\theta}_r + (\hat{a} + \Delta a)\dot{\theta}_r + (\hat{f} + \Delta f) \\
= (\hat{b} + \Delta b)\psi_{dr}^* i_{qs}^*
\end{aligned} \tag{9}$$

Where the term Δa , Δb and Δf represents the uncertainties of the terms a, b and f respectively $\hat{a}$, $\hat{b}$ and $\hat{f}$ are the nominal values of the terms a, b and f respectively. It shoud be noted that these uncertainties are unknow, and that the precise calculation of its upper bound are, in general, rather difficult to achieve.

Let us define the tracking position error as follows:

$$e = \theta\_r - \theta\_r\hat{}\, * \tag{10}$$

Now the issue of tracking control is to design a control law for i_{qs}^* in such a way that θ_r can track the desired path in the presence of uncertainty and disturbance.

3. Sliding-Mode Control

In order to design a sliding mode controller,two essential steps should be carefully investigated, namely, the selection of sliding mode surface and the design of control law.

The selection of sliding mode surface is based on desired motion of the system. considering the simplicity of design, we define a sliding surface as:

$$s = \dot{e} + \lambda e \qquad (11)$$

In general, there are several forms of the sliding mode control law. One type of control law consists of an equivalent control law u_{eq} and a switch control law u_{dis}. The control law can be described as $u = u_{eq} + u_{dis}$. The equivalent control law represents the linear part of the control force, which is usually derived from sliding mode surface and the differential of sliding mode surface. So, it highly depends on the parameters of the control model. The switch control law is a discontinuous control law which enforces the system states towards the sliding mode surface. A possible choice of the switching law is $u_{dis} = K.sign(s)$, where K is a constant, which is used to represent the maximum of switching control law. And function $sign(s)$ is defined as:

$$sign(s) = \begin{cases} -1 & s < 0 \\ 1 & s > 0 \end{cases} \qquad (12)$$

In this study, to define the equivalent control law, we assume that the sliding mode surface is constant, i.e.,

$$s = \dot{s} = \ddot{e} + \lambda\dot{e} = 0 \qquad (13)$$

Substituting Eq.(8) and (10) into Eq.(13) then

$$\dot{s} = -a\,\dot{\theta}_r - f + b\psi^*_{dr} i^*_{qs} - \ddot{\theta}^*_r + \lambda\dot{e} = 0 \qquad (14)$$

By solvingEq.(14) we can define the equivalent control law as follows:

$$i^*_{qseq} = -\left(\hat{b}\psi^*_{dr}\right)^{-1}\left[-\hat{a}\dot{\theta}_r - \ddot{\theta}^*_r + \lambda\dot{e} + \hat{f}\right] \qquad (15)$$

Therefore, control law can be described as follow:

$$i^*_{qs} = i^*_{qseq} + i^*_{qsdis} \qquad (16)$$

Remark: The decoupling control method with compensation is to choose inverter output voltages such that:

$$u_{qs} = \left(K_{pq} + \frac{K_{iq}}{s}\right)\left(i^*_{qs} - i_{qs}\right) \qquad (17)$$

$$u_{ds} = \left(K_{pd} + \frac{K_{id}}{s}\right)\left(i^*_{ds} - i_{ds}\right) \qquad (18)$$

4. sliding-Mode Neural-Network Control System

In order to control position of an induction motor, a SMNN control system is proposed in this section. A general function of a three-layer NN can be represented in the following form [18]:

$$y = U_{NN}(e, V, W, m, p) \equiv WQ(Ve) \qquad (19)$$

where the tracking error$e$is the input state of the NN; $V \in R^{k\times 1}$ is the input-to-hidden layer interconnection weight vector, in which $k$is the hidden layernodes;$W \in R^{1\times k}$ is the hidden-to-output layer interconnection weight vector; the activefunction usedin the NN is chosen as $Q(Ve) = exp[-(Ve - m)^2/p^2] \in R^{k\times 1}$, in which$m \in R^{k\times 1}$and $p \in R^{k\times 1}$ are the adjustable parameter vectors of the radial basis functions(RBF); y is the output of NN. Thus, an optimal NN controller U^*_{NN}will be designedto mimic the equivalent control law shown in Eq. (6) such that

$$i^*_{qseq} = U^*_{NN}(e, V^*, W^*, m^*, p^*) \equiv W^*Q^*(V^*e) + \varepsilon \qquad (20)$$

Where ε is a minimum reconstructederror vector; V^* , W^* , m^* and p^* are optimalparameter vectors of V, W, m and p in the NN. The control law for the SMNNcontrol system is assumedto take the following form:

$$i_{qs}^* = \widehat{U}_{NN}\left(e, \widehat{V}, \widehat{W}, \widehat{m}, \hat{p}\right) + i_{qsdis}^* \equiv \widehat{W}\widehat{Q}\left(\widehat{V}e\right) + i_{qsdis}^* \quad (21)$$

Where $\widehat{U}_{NN}$ is a NN controller; i_{qsdis}^* is a robust controller; $\widehat{V}$, $\widehat{W}$, $\widehat{m}$ and $\hat{p}$ are someestimates of the optimal parameter vectors, as provided by tuning algorithms to beintroduced. The NN control $\widehat{U}_{NN}$is usedto mimic the equivalent control law dueto the uncertain system dynamics, and the robust control i_{qsdis}^* is designed to keep thecontrolled system dynamics on the sliding surface, that is, curb the system dynamicsonto $S(t) = 0$ for all times. After some straightforwardmanipulation, the error equationgoverning the closed-loop system can be obtained through Eqs. (14) and (15) as

$$i_{qseq}^* - i_{qs}^* = \dot{s}(t) \quad (22$$

Moreover, $\tilde{i}_{qs}$ is defined as

$$\tilde{i}_{qs} = i_{qseq}^* - i_{qs}^* = W^*Q^* + \varepsilon - \widehat{W}\widehat{Q} - i_{qsdis}^* = \widetilde{W}Q^* + \varepsilon + \widehat{W}\widetilde{Q} - i_{qsdis}^* \quad (23)$$

Where $\widetilde{W} = W^* - \widehat{W}$ and $\widetilde{Q} = Q^* - \widehat{Q}$. The linearization technique is employedtotransform the nonlinear active functions into partially linear form so that the expansionof $\widetilde{Q}$ in a Taylor series to obtain [18]

$$\widetilde{Q} = Q_V\widetilde{V}e + Q_m\widetilde{m} + Q_p\tilde{p} + Q_n \quad (24)$$

Where

$$Q_V = \left[\frac{\partial Q_1}{\partial(Ve)} \quad \frac{\partial Q_2}{\partial(Ve)} \quad \cdots \quad \frac{\partial Q_k}{\partial(Ve)}\right]_{Ve=\widehat{V}e} \epsilon R^{k\times k},$$

$$Q_m = \left[\frac{\partial Q_1}{\partial m} \quad \frac{\partial Q_2}{\partial m} \quad \cdots \quad \frac{\partial Q_k}{\partial m}\right]_{m=\widehat{m}} \epsilon R^{k\times k},$$

$$Q_p = \left[\frac{\partial Q_1}{\partial p} \quad \frac{\partial Q_2}{\partial p} \quad \cdots \quad \frac{\partial Q_k}{\partial p}\right]_{p=\hat{p}} \epsilon R^{k\times k},$$

$$\widetilde{V} = V^* - \widehat{V} \;, \widetilde{m} = m^* - \widehat{m} \;, \tilde{p} = p^* - \hat{p}$$

$Q_n \epsilon R^{k\times 1}$ is a vector of higher-order terms. Rewriting Eq.(24), one can obtain:

$$Q^* = \widehat{Q} + Q_V\widetilde{V}e + Q_m\widetilde{m} + Q_p\tilde{p} + Q_n \quad (25)$$

Substituting Eq.(25) into Eq.(23), it is revealed that

$$\begin{aligned}\tilde{i}_{qs} &= W^*Q^* + \varepsilon - \widehat{W}\widehat{Q} - i_{qsdis}^* \\ &= W^*[\widehat{Q} + Q_V\widetilde{V}e + Q_m\widetilde{m} + Q_p\tilde{p} + Q_n] + \varepsilon - \widehat{W}\widehat{Q} - i_{qsdis}^* \\ &= (W^* - \widehat{W})\widehat{Q} + (\widehat{W} + \widetilde{W})Q_V\widetilde{V}e + (\widehat{W} + \widetilde{W})Q_m\widetilde{m} + (\widehat{W} + \widetilde{W})Q_p\tilde{p} + W^*Q_n + \varepsilon - i_{qsdis}^* \\ &= \widetilde{W}\widehat{Q} + \widehat{W}Q_V\widetilde{V}e + \widehat{W}Q_m\widetilde{m} + \widehat{W}Q_p\tilde{p} + E - i_{qsdis}^*\end{aligned} \quad (26)$$

Where the uncertain term $E = \widetilde{W}Q_V\widetilde{V}e + \widetilde{W}Q_m\widetilde{m} + \widetilde{W}Q_p\tilde{p} + W^*Q_n + \varepsilon$ is assumed to be bounded by $\|E\| < \psi$.

Theorem 1. Consider the motor dynamic represented by Eq.(1), if the SMNN control law is designed as Eq.(21), in which the adaptation laws of the NN controller are designed as Eq.(27) and the robust controller is designed as Eq.(28) , then the system dynamic can be always kept on the sliding surface such that asymptotical stability can be guaranteed.

$$\dot{\widehat{W}} = \eta_1\left(\widehat{Q}s^T\right)^T, \dot{\widehat{V}} = \eta_2\left(es^T\widehat{W}Q_V\right)^T, \dot{\widehat{m}} = \eta_3(s^T\widehat{W}Q_m)^T, \dot{\hat{p}} = \eta_4(s^T\widehat{W}Q_p)^T \quad (27)$$

$$i_{qsdis}^* = \hat{\psi}(t).sign(s)\;, \dot{\hat{\psi}}(t) = \eta_5 s^T.sign(s) \quad (28)$$

Where η_1 , η_2 , η_3 , η_4 and η_5 are positive constant; $\hat{\psi}$ is the estimated value of the uncertain term bound ψ .

Proof. Define the following Lyapunov function candidate:

$$L_a\left(s(t), \tilde{\psi}(t), \widetilde{W}, \widetilde{V}, \widetilde{m}, \tilde{p}\right) = \frac{1}{2}s^Ts + \frac{1}{2\eta_1}tr\left(\widetilde{W}\widetilde{W}^T\right) + \frac{1}{2\eta_2}tr\left(\widetilde{V}^T\widetilde{V}\right) + \frac{1}{2\eta_3}\widetilde{m}^T\widetilde{m} + \frac{1}{2\eta_4}\tilde{p}^T\tilde{p} + \frac{1}{2\eta_5}\tilde{\psi}^2(t) \quad (29)$$

Where tr(.) is the trace operator, and the estimation error is defined as $\tilde{\psi}(t) = \psi - \hat{\psi}(t)$. Differentiating Eq.(29), one can obtain that

$$\dot{L}_a = s^T\dot{s} + \frac{1}{\eta_1}tr\left(\widetilde{W}\dot{\widetilde{W}}^T\right) + \frac{1}{\eta_2}tr\left(\dot{\widetilde{V}}^T\widetilde{V}\right) + \frac{1}{\eta_3}\dot{\widetilde{m}}^T\widetilde{m} + \frac{1}{\eta_4}\dot{\tilde{p}}^T\tilde{p} + \frac{1}{\eta_5}\tilde{\psi}\dot{\tilde{\psi}} \quad (30)$$

Substituting Eqs .(22) and (26) into Eq. (30), one can obtain:

$$\dot{L}_a = s^T[\widehat{W}\hat{Q} + \widehat{W}Q_V\tilde{V}e + \widehat{W}Q_m\tilde{m} + \widehat{W}Q_p\tilde{p} + E - i^*_{qsdis}] - \frac{1}{\eta_1}tr\left(\widetilde{W}\dot{\widehat{W}}^T\right) - \frac{1}{\eta_2}tr\left(\dot{\hat{V}}^T\tilde{V}\right) - \frac{1}{\eta_3}\dot{\hat{m}}^T\tilde{m} - \frac{1}{\eta_4}\dot{\hat{p}}^T\tilde{p} - \frac{1}{\eta_5}\tilde{\psi}\dot{\hat{\psi}}$$
$$= tr\left\{\widetilde{W}\left[\hat{Q}s^T - \frac{1}{\eta_1}\dot{\widehat{W}}^T\right]\right\} + tr\left\{\left[es^T\widehat{W}Q_V - \frac{1}{\eta_2}\dot{\hat{V}}^T\right]\tilde{V}\right\} + \left[s^T\widehat{W}Q_m - \frac{1}{\eta_3}\dot{\hat{m}}^T\right]\tilde{m} + \left[s^T\widehat{W}Q_p - \frac{1}{\eta_4}\dot{\hat{p}}^T\right]\tilde{p} + s^T\left(E - i^*_{qsdis}\right) - \frac{1}{\eta_5}\tilde{\psi}\dot{\hat{\psi}} \quad (31)$$

If the adaptation laws of the NN controller are chosen as Eq. (27) and the robust controller is designed as Eq. (28), Eq. (31) can be rewritten as

$$\dot{L}_a = s^TE - \hat{\psi}(t)s^T.sign(s) - \frac{1}{\eta_5}\tilde{\psi}\dot{\hat{\psi}}$$
$$= s^TE - \hat{\psi}(t)s^T.sign(s) - \frac{1}{\eta_5}\psi\,\dot{\hat{\psi}} + \frac{1}{\eta_5}\hat{\psi}\dot{\hat{\psi}}$$
$$= s^TE - \psi s^T.sign(s) \le \|s^T\|(\|E\| - \psi) \equiv -\propto\|s^T\| \le 0 \quad (32)$$

Since $\dot{L}_a \le 0$, $\dot{L}_a\left(s(t),\tilde{\psi}(t),\widetilde{W},\tilde{V},\tilde{m},\tilde{p}\right)$ is a negative semi-definite function, that is, $L_a\left(s(t),\tilde{\psi}(t),\widetilde{W},\tilde{V},\tilde{m},\tilde{p}\right) \le L_a\left(s(0),\tilde{\psi}(0),\widetilde{W},\tilde{V},\tilde{m},\tilde{p}\right)$, which implies $s(t),\widetilde{W},\tilde{V},\tilde{m}$ and $\tilde{p}$ are bounded. Let function $(t) \equiv\propto \|s^T\| \le -\dot{L}_a$, and integrate function $F(t)$ with respect to time

$$\int_0^t F(\tau)d\tau \le L_a\left(S(0),\bar{\psi}(0),\widetilde{W},\check{V},\tilde{m},\tilde{p}\right) - L_a\left(S(t),\bar{\psi}(t),\widetilde{W},\check{V},\tilde{m},\tilde{p}\right) \quad (33)$$

Because $L_a\left(S(0),\bar{\psi}(0),\widetilde{W},\check{V},\tilde{m},\tilde{p}\right)$ is bounded, and $L_a\left(S(t),\bar{\psi}(t),\widetilde{W},\check{V},\tilde{m},\tilde{p}\right)$ is nonincreasing and bounded, the following result is obtained:.

$$\lim_{t\to\infty}\int_0^t F(\tau)d\tau < \infty \quad (34)$$

Also, $\dot{F}(t)$ is bounded, so by Barbalat's Lemma [19,20], it can be shown that $\lim_{t\to\infty} F(t) = 0$. That is, $s(t) \to 0$ as $t \to \infty$. As a result, the SMNN control system is asymptotically stable. Moreover, the tracking error vector of the control system, $e(t)$,will converge to zero according to $s(t) \to 0$

5. Fuzzy Controller Design

In this section, the SFC class of fuzzy controller studied in [9] is considered which has two-input one-output rules used in the formulation of the knowledge base. These IF-THEN rules have following form

$$If\ x_1\ is\ A_1^{l_1}\ and\ x_2\ is\ A_2^{l_2}\ then\ y\ is\ B^{l_1l_2} \quad (35)$$

Where $x = [x_1x_2]^T = [e\ \dot{e}]^T\epsilon U = U_1 \times U_2$ and $y = i^*_{qs}\epsilon V \subset R$. For each input fuzzy set $A_j^{l_j}$ in $x_j \subset U_j$ and output fuzzy set $B^{l_1l_2}$ in $y\epsilon V$ exist an input membership function $\mu_{A_j^{l_j}}(x_j)$ and output membership function $\mu_{B^{l_1l_2}}(x_j)$ shown in Fig. 1 and Fig. 2, respectively.

The fuzzy system considered here has following specifications: Singleton fuzzifier, triangular membership functions for each inputs, singleton membership functions for the output, rule base defined by (35), (see Table. 1), product inference and center average defuzzifier.

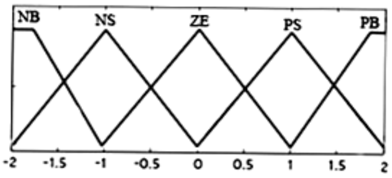


Fig. 1. input membership function

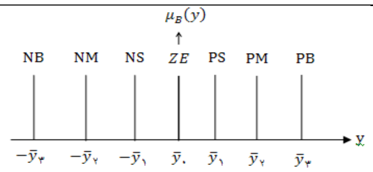


Fig. 2. Output membership functions

Table1. The fuzzy rule base for obtaining output y

x_2	x_1				
	NB	NS	ZE	PS	PB
NB	NB	NM	NM	PS	ZE
NS	NM	NM	NS	PS	PS
ZE	NM	NS	ZE	PS	PM
PS	NS	PS	PS	PM	PM
PB	ZE	PS	PM	PM	PB

6. Incorporating smnn and sfc

In this paper, for obtaining advantages of both sliding mode and sectorial fuzzy controllers and also minimizing the drawbacks of the both of them, the following control law is proposed:

$$i_{qs}^{*} = \begin{cases} \hat{W}\hat{Q}(\hat{V}e) + i_{qsdis}^{*} & when\ |e| \geq \alpha \\ y & when\ |e| < \alpha \end{cases} \quad (36)$$

Whereα is strictly positive small parameter which can be determined adaptively or set to a constant value. So, while the magnitude of error is greater than or equal toα , SMNN drives the system states, errors in our case, toward sliding surface and as soon as the magnitude of error becomes less thanα , then the SFC which is designed independent of initial conditions, controls the system. Since the SMNN has faster transient response, the response of the system controlled by (36) is faster than the case of SFC. Additionally, in spite of the torque boundedness, since the SFC controls the system in the steady state, the proposed controller (36) has less set-point tracking error. Also, since near the sliding surface the proposed controller switch from SMNN to SFC, therefore the chattering is avoided here.

7. Simulation Results

The induction motor used in this case study is a 1.5 KW, 220 V, two pole, 6.31 A, 50 HZ motor having the following parameters: $R_r = 3.805 \pm 50\Omega\%$, $R_s = 4.85 \pm 50\Omega\%$, $L_r = 0.274 \pm 50\%$ H , $L_m = 0.258 \pm 50\%$ H , $L_s = 0.274 \pm 50\%$ H , $J_n = 0.031 \pm 50\%$, $B_n = 0.008$, $\omega_n = 1428$. In addition, the overall structure of incorporating SMNN and fuzzy control technique in the induction motor can be shown in Figs. 3 and 4. In this simulation, the parameters of PI controllers are initially tuned by the Ziegler-Nichols method, then they are tuned through simulation to get satisfactory response. The parameters of RBF neural network and SFC in the proposed control scheme are as follows:

$-\bar{y}_3 = -10 , -\bar{y}_2 = -8 , -\bar{y}_1 = -6 , \bar{y}_0 = 0 , \bar{y}_1 = 6$

$\bar{y}_2 = 8 , \bar{y}_3 = 10 \quad \eta_1 = 10 , \eta_2 = 10 , \eta_3 = 20 , \eta_4 = 20 , \eta_5 = 20$

Theψ_{dr}^{*} is set to1Wb and ψ_{qr}^{*} is set to 0Wb.

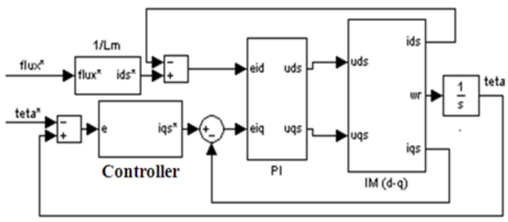


Fig. 3. Overall induction motor control scheme

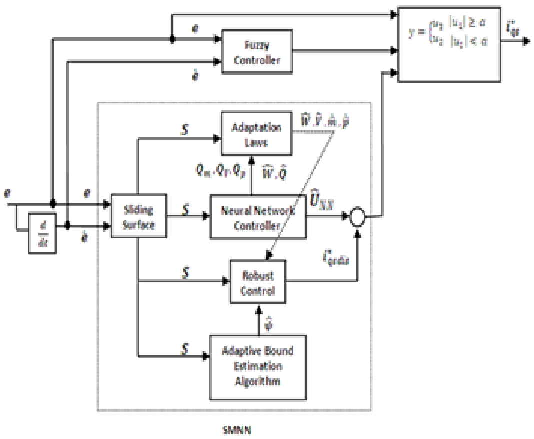
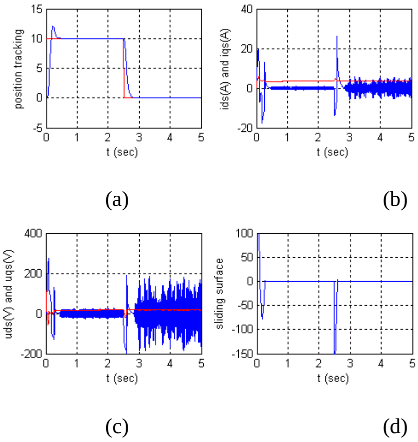


Fig. 4. Incorporating SMNN and fuzzy control

For our proposed controller (36), the constant $\alpha = 0.5$ is supposed. Additionally, to show the improvement achieved from applying the proposed method of this paper (incorporating SMNN and SFC), the simulation results of applying this method are compared with the related results of the SMNN case. The tracking response and control effort in the case of SMNN have been shown in Fig. 5. Figures show serious chattering obviously exists in SMNN controller and

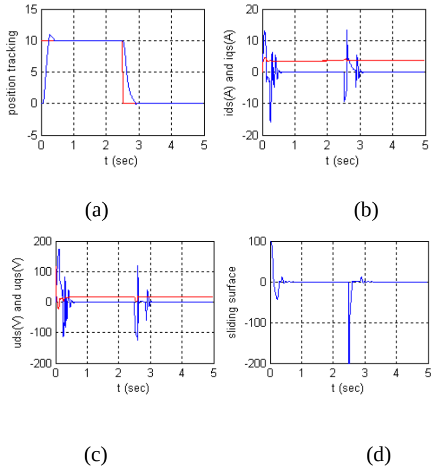
In the case of control law proposed in the present paper, The tracking response is depicted and the associated control effort are depicted in Fig. 6. From the simulated results, there are no chattering phenomena in the control effort.

In order to show the robustness of the proposed method, we supposed $R = 1.5\hat{R}$, $L = 1.5\hat{L}, J = 1.5\hat{J}$, $T_l = 4\,sin(3t)$, other conditions are the same as above. In this case the tracking error and control effort are shown in Fig. 7. The result shows that the proposed scheme is robust to resistance, inductance and moment of inertia uncertainty and time-varying external load disturbance.



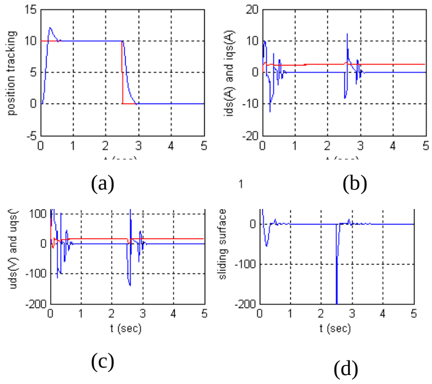
(a) (b) (c) (d)

Fig. 5. Simulated response to a pulse change using SMNN controller.(a) Tracking response. (b) d and q-axis current response. (c) d and q-axis voltage response.(d) sliding mode surface



(a) (b) (c) (d)

Fig. 6. Simulated response to a pulse change using incorporating SMNN and SFCcontroller. (a) Tracking response. (b) d and q-axis current response. (c) d and q-axis voltage response.(d) sliding mode surface



(a) (b) (c) (d)

Fig. 7. Simulated response to a pulse change using incorporating SMNN and SFCcontroller. (a) Tracking response. (b) d and q-axis current response. (c) d and q-axis voltage response.(d)

Conclusions

Since the dynamic characteristics of an induction motor are highly nonlinear and the complete dynamic model is difficult to obtain precisely,a SMNN control system has been successfully designed in this study to control the system. Inthe SMNN control system, all the system dynamics can be unknown and no strict constraints were required in the design process. But simulation results shown that the problem of this controller is chattering phenomenon.In this note, a new combination of sliding mode neural network control and fuzzy control is proposed which is called incorporating SMNN and Fuzzy controller. The simulation result have validated the satisfactory performance of the proposed method, such as perfect decoupling, strong robustness and reduced chattering, in comparison with SMNN.

References

[1] Guo, Z., J. Zhang, Z. Sun, and C. Zheng. "Indirect Field Oriented Control of Three-Phase Induction Motor Based on Current-Source Inverter." *Journal of Procedia Engineering* 174: 588–594.2017.

[2] Hussien, M.G. A new robust sensorless vector-control strategy for wound-rotor induction motors."Aust. J. Electr. Electron. Eng.17, 132–137.2020.

[3] Sabha Raj Arya and Mahesh Pudari"Sensorless Adaptive control of VSI-Fed Induction Motor Drive with Optimized MLP-Neural Network," Aust. J. Electr. Electron. Eng., 2023.

[4] V. I. Utkin, "Sliding Mode Control Design Principles and Applications to Electric Drives", *IEEE Trans. Ind. Electron*, 1993, 40, (3), pp. 23-36.

[5] Koshkouei, A. J. and Zinober, A. S. I., sliding mode controller-observer design for SISO linear systems. Int. J. systems Science, 29, 1363-1373,1998.

[6] Drakunov, S. V. and Utkin, V. I., Sliding mode control in dynamicsystems. Int. J. Control, 55, 1029-1037, 1992.

[7] Gu, X.; Xu, W.; Zhang, M.; Zhang, W.; Wang, Y.; Chen, T. "Adaptive Controller Design for Overhead Cranes With Moving Sliding Surface." In Proceedings of the 2019 Chinese Control Conference (CCC), Guangzhou, China, 27–30 July 2019.

[8] Mohammed Golam Sarwer, Md. Abdur Rafiq and B.C. Ghosh,"Sliding Mode Speed Controller of a D.C Motor Drive", Journal ofElectrical Engineering, The Institution of Engineers, Bangladesh ,Vol.EE 31, No. I & II, December 2004

[9] L. X. Wang, A Course in Fuzzy Systems and Control. EnglewoodCliffs, NJ: Prentice-Hall, 1997.

[10] Chin CS, Lin WP. Robust genetic algorithm and fuzzy inference mechanism embedded in a sliding-mode controller for an uncertain underwater robot. *IEEE/ASME Trans Mechatron* 2018; 23(2): 655–665.

[11] Fei, J.; Chen, Y.; Liu, L.; Fang, Y. "Fuzzy multiple hidden layer recurrent neural control of nonlinear system using terminal sliding-mode controller." IEEE Trans. Cybern.2022, 52, 9519–9534.

[12] Q. P. Ha, "Robust sliding mode controller with fuzzy tuning," *Electron. Lett.*, vol. 32, no. 17, pp. 1626–1628, Aug. 1996.

[13] Q. P. Ha, "Sliding performance enhancement with fuzzy tuning," *Electron. Lett.*, vol. 33, no. 16, pp. 1421–1423, Jul. 1997.

[14] F. J. Lin and S. L. Chiu, "Adaptive fuzzy sliding-mode control for PM synchronous servo motor drives," Proc. Inst. Elect. Eng. Contr. Theory *Appl.*, vol. 145, no. 1, pp. 63–72, 1998.

[15] Pablo J. P;Luis T. A;Selene L. Cardenas-M;Jorge A. Lopez-R;Nohe R. C-C." Stability Analysis for Mamdani-Type Integral Fuzzy-Based Sliding-Mode Control of Systems Under Persistent Disturbances" IEEE Transactions on Fuzzy Systems,2022. Vol. 30.

[16] Santibanez V., Kelly R., Liama L. A."A Novel Global Asymptotic Stable Set–Point Fuzzy Controller with Bounded Torques for Robot Manipulators " IEEE Transactions on Fuzzy Systems, 2005. – Vol. 13. – No. 3. – P. 362–372.

[17] B. K. Bose, "Power Electronics and AC Drives", Book. Prentic Hall. Englewood Cliffs, New Jersey. 1980

[18] F.L. Lewis, A. Yesildirek, K. Liu, Multilayer neural-net robot controller with guaranteed tracking performance, IEEE Trans. Neural Networks 7 (1996) 388.

[19] K.J. Astrom, B. Wittenmark, Adaptive Control, Addison-Wesley, New York, 1995.

[20] J.J.E. Slotine, W. Li, AppliedNonlinear Control, Prentice-Hall, EnglewoodCli4s, NJ, 1991.