Fuzzy Adaptive Controller Design for IPMSM with System Uncertainties and Disturbances Considering

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Abstract

This paper proposed a T-S fuzzy model based adaptive fuzzy controller for the interior permanent magnet synchronous motors. Firstly, the T-S fuzzy model of the system is built based on the nonlinear dynamic model. Next, the adaptive fuzzy controller is designed to deal with the problems of system uncertainties and external disturbances. This controller includes two phases, one is for system stability and one for compensating the effect of the unknown components. The stability of the system, as well as the convergence of the adaptive law, is mathematically proven through Lyapunov theory. Finally, some simulations are done to verify the effectiveness of the presented scheme. The simulation results show that the proposed algorithm has a good response to the change of reference input, the system parameters variation, and the sudden change of the load torque.

Keywords: adaptive controller, disturbances, fuzzy controller, IPMSM, uncertainties.

1. Introduction*

Permanent magnet synchronous motors (PMSMs) are widely used in the industrial field because of their excellent dynamic characteristics and high performance [1-2]. In the PMSM family, IPMSM is considered in the high-speed range because of its construction. However, the control of the IPMSM is more difficult because of the high nonlinearities. Nowadays, the control design for IPMSM still attracts the attention of many researchers.

Among speed control methods for IPMSM, adaptive control is quite popular because of its flexibility. In [3], an adaptive sliding mode control strategy is used to compensate for the parameter uncertainties for IPMSM. The system has a robust and fast response with the change of the parameters but the algorithm is so complicated. In [4-5], the observer is used to estimate the system uncertainties [4] and disturbance [5] to guarantee that the systems work well in the wide range of speed despite the effect of unknown parameters and disturbances. The adaptive RBF neural network is proposed in [6] for IPMSM using in vehicles without using current sensors. The proposed method yields 99% and 97% tracking accuracy in the presence of parametric uncertainties and friction nonlinearities, respectively. Also considering the current loop, in [7] an adaptive finite-control-set model predictive controller is introduced for current control to deal with the inductance variation. In this scheme, the inductance is identified online by an observer then it is fed to the finite-control-set model predictive controller which needs accurate knowledge of the system parameters. The adaptive algorithms are also used in [8-9] for torque control of IPMSM.

In this paper, an adaptive fuzzy controller is proposed for speed control of the interior permanent magnet synchronous motors. Because of the nonlinearity, the T-S fuzzy model technique is used to linearize the system then the controller scheme is design based on this linear T-S fuzzy model. The proposed controller includes two parts: one is for system stability and the other is for compensating the effect of the unknown components. By this structure, the presented algorithm has ability to cancel the effect of the system uncertainties as well as the external disturbances to the system. The correctness and effectiveness of the proposed algorithm are proven through both mathematic and simulation. The simulation results show that the proposed algorithm has a good response to the change of reference input, the system parameters variation, and the suddenly change of the load torque.

2. Controller design

2.1 Dynamic model of IPMSM

The mathematic model of IPMSM in the *dq* reference frame is given as the follow [10]:

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$$\begin{aligned} \dot{\omega} &= k_1 i_{qs} - k_2\omega - k_3 T_L + k_{11} i_{ds} i_{qs} \\ \dot{i}_{qs} &= -k_4 i_{qs} - k_5\omega + k_6 V_{qs} - k_{10}\omega i_{ds} \\ \dot{i}_{ds} &= -k_7 i_{ds} + k_8 V_{ds} + k_9 \omega i_{qs} \end{aligned} \tag{1}$$

where

$$k_1 = \frac{3}{2}\frac{1}{J}\frac{p^2}{4}\lambda_m,\ k_2 = \frac{B}{J},\ k_3 = \frac{p}{2J},\ k_4 = \frac{R_s}{L_{qs}},$$

$$k_5 = \frac{\lambda_m}{L_{qs}},\ k_6 = \frac{1}{L_{qs}},\ k_7 = \frac{R_s}{L_{ds}},\ k_8 = \frac{1}{L_{ds}},$$

$$k_9 = \frac{L_{qs}}{L_{ds}},\ k_{10} = \frac{L_{ds}}{L_{qs}},\ k_{11} = \frac{3}{2}\frac{1}{J}\frac{p^2}{4}(L_{ds} - L_{qs}).$$

Define

$$\beta = \dot{\omega} = k_1 i_{qs} - k_2\omega - k_3 T_L + k_{11} i_{ds} i_{qs}$$

Then

$$\begin{aligned} \dot{\omega} &= \beta \\ \dot{\beta} &= k_1 \dot{i}_{qs} - k_2\beta + k_{11}\dot{i}_{ds} i_{qs} + k_{11} i_{ds} \dot{i}_{qs} \\ \dot{i}_{ds} &= -k_7 i_{ds} + k_8 V_{ds} + k_9\omega i_{qs} \end{aligned} \tag{2}$$

After calculating, the model (2) is rewritten as:

$$\begin{aligned} \dot{\omega} &= \beta \\ \dot{\beta} &= -(k_1k_6 + [k_1k_{10} + k_5k_{11}]i_{ds} + k_{10}k_{11}i_{ds}^2 \\ &\quad - k_9k_{11}i_{qs}^2)\omega - k_2\beta - (k_7 + k_4)k_{11}i_{ds}i_{qs} \\ &\quad + (k_1k_6 + k_6k_{11}i_{ds})V_{qs} + k_8k_{11}i_qV_{ds} - k_1k_4i_{qs} \\ \dot{i}_{ds} &= -k_7 i_{ds} + k_8 V_{ds} + k_9\omega i_{qs} \end{aligned} \tag{3}$$

Define

$$\begin{aligned} V_{qd} &= \begin{bmatrix} V_{qs} \\ V_{ds} \end{bmatrix} = M^{-1}(i_{qs}, i_{ds}) \begin{bmatrix} V_{qf} + V_{qbf} \\ V_{df} + V_{dbf} \end{bmatrix} \\ M(i_{qs}, i_{ds}) &= \begin{bmatrix} k_1k_6 + k_6k_{11}i_d & k_8k_{11}i_q \\ 0 & k_8 \end{bmatrix} \end{aligned} \tag{4}$$

$$\begin{aligned} V_{qf} &= k_1k_4i_{qs} + (k_1k_5 + [k_1k_{10} + k_5k_{11}]i_{ds} + k_{10}k_{11}i_{ds}^2 \\ &\quad - k_9k_{11}i_{qs}^2)\omega_d + (k_7 + k_4)k_{11}i_{qs}i_{dsr}, \\ V_{df} &= -k_9\omega_d i_{qs} + k_7 i_{ds} + \dot{i}_{dsr} \\ \omega_e &= \omega - \omega_d, \qquad i_{dse} = i_{ds} - i_{dsr} \end{aligned} \tag{5}$$

With these definitions, the error dynamic model (3) has the following form:

$$\begin{aligned} \dot{\omega}_e &= \beta \\ \dot{\beta} &= -(k_1k_5 + [k_1k_{10} + k_5k_{11}]i_{ds} + k_{10}k_{11}i_{ds}^2 - k_9k_{11}i_{qs}^2)\omega_e \\ &\quad - k_2\beta - (k_7 + k_4)k_{11}i_{qs}i_{dse} + V_{qbf} \\ \dot{i}_{dse} &= k_9 i_{qs}\omega_e + V_{dbf} \end{aligned} \tag{6}$$

In order to deal with the nonlinearities in the model (6), the T-S fuzzy model technique is used in this paper. By using T-S fuzzy model, the local dynamics of each fuzzy rule can be expressed by a linear system model.

Based on the T–S fuzzy approach, the model (6) can be approximated by a third-order r-rule fuzzy model. Thus, the ith rule of the T–S fuzzy model is given as follows:

System rule i: If $(i_{qs}, i_{ds}) = (I_{qi}, I_{di})$ then

$$\begin{aligned} \dot{\omega}_e &= \beta \\ \dot{\beta} &= -(k_1k_5 + [k_1k_{10} + k_5k_{11}]I_{di} + k_{10}k_{11}I_{di}^2 \\ &\quad - k_9k_{11}I_{qi}^2)\omega_e - k_2\beta - (k_7 + k_4)k_{11}I_{qi}i_{dse} + V_{qbf} \\ \dot{i}_{dse} &= k_9 I_{qi}\omega_e + V_{dbf} \end{aligned} \tag{7}$$

The global T–S fuzzy model of the model (7) inferred from (6) is represented as the following:

$$\begin{aligned} \dot{\omega}_e &= \beta \\ \dot{\beta} &= -\sum h_i(k_1k_5 + [k_1k_{10} + k_5k_{11}]I_{di} + k_{10}k_{11}I_{di}^2 \\ &\quad - k_9k_{11}I_{qi}^2)\omega_e - k_2\beta - \sum h_i(k_7 + k_4)k_{11}I_{qi}i_{dse} + V_{qbf} \\ \dot{i}_{dse} &= \sum h_i k_9 I_{qi}\omega_e + V_{dbf} \end{aligned} \tag{8}$$

where $h_i = m_i \Big/ \sum_{j=1}^{r} m_j$, m_i is the membership function of the system respect to ith rule.

The global T-S fuzzy model (8) can be rewritten in the form of state space model as the following:

$$\dot{x} = \sum_{i=1}^{r} h_i(A_i x + Bu) \tag{9}$$

where

$$A_i = \begin{bmatrix} 0 & 1 & 0 \\ (k_1k_5 + [k_1k_{10} + k_5k_{11}]I_{di} + k_{10}k_{11}I_{di}^2 - k_9k_{11}I_{qi}^2 & -k_2 & -(k_7 + k_4)k_{11}I_{qi} \\ k_9 I_{qi} & 0 & 0 \end{bmatrix} \tag{10}$$

$$B_i = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix};$$

In considering the system uncertainties and input disturbances, the model (9) becomes:

$$\dot{x} = \sum_{i=1}^{r} h_i[(A_i + \Delta A_i)x + B(u + d)] \tag{11}$$

where

$$\Delta A_i = \begin{bmatrix} 0 & 1 & 0 \\ -\xi_{1i} & -\xi_2 & -\xi_{3i} \\ \xi_{4i} & 0 & 0 \end{bmatrix} \quad (12)$$

$$\begin{aligned} \xi_{1i} &= (\Delta k_1 \Delta k_5 + [\Delta k_1 \Delta k_{10} + \Delta k_5 \Delta k_{11}] I_{di} \\ &\quad + \Delta k_{10} \Delta k_{11} I_{di}^2 - \Delta k_9 \Delta k_{11} I_{qi}^2 \\ \xi_2 &= \Delta k_2 \\ \xi_{3i} &= (\Delta k_7 + \Delta k_4) \Delta k_{11} I_{qi} \\ \xi_{4i} &= \Delta k_9 I_{qi} \end{aligned} \quad (13)$$

and d is the input disturbances which satisfies bounded condition $\|d\| \le D$ (D is a positive scalar).

2.2 Adaptive controller design

The purpose of this section is to build an adaptive controller which can deal with system uncertainties and input disturbances for the system (11). This controller is determined by the following theorem.

Theorem: Consider the uncertain system (11), if there exists a positive scalar D so that $D \ge \|d\|$ and a positive symmetric P that satisfies the following condition

$$PA_i + A_i^T P - PBR^{-1}B^T P < -Q \quad (14)$$

where Q and R are positive symmetric matric with feasible size then the controller

$$\begin{aligned} u &= \sum_{i=1}^{r} h_i [-K_i x + \frac{1}{2} B^T (x^T P)^T - D\,\mathrm{sgn}(B^T Px) - \mu\hat{\gamma}] \\ &= \sum_{i=1}^{r} h_i [-Kx + u_s - \mu\hat{\gamma}] \end{aligned} \quad (15)$$

will keep the state of uncertain system (11) converge to zero.

In (15), γ is determined by the adaptive law:

$$\dot{\hat{\gamma}}^T = \mu x^T PB \quad (16)$$

in which $K = R^{-1}B^T P$, μ is positive scalar.

Proof

Substituting (15) and (16) into (11) to get the following result:

$$\begin{aligned} \dot{x} &= \sum_{i=1}^{r} h_i [(A_i - BK_i)x + Bu_s - B\mu\hat{\gamma} + Bd + f(x)] \\ &= \sum_{i=1}^{r} h_i (A_i - BK_i)x + Bu_s + Bd + (f(x) - \mu B\gamma^*) \\ &\quad + (\mu B\gamma^* - B\mu\hat{\gamma}) \\ &= \sum_{i=1}^{r} h_i (A_i - BK_i)x + Bu_s + Bd - w^* + (\mu B\gamma^* - B\mu\hat{\gamma}) \end{aligned} \quad (17)$$

where γ^* is the ideal approximation parameters, w^* is minimum approximation, and

$$f(x) = \sum_{i=1}^{r} h_i \Delta A_i x \quad (18)$$

Choose the Lyapunove function

$$V = x^T Px + (\hat{\gamma} - \gamma^*)^T (\hat{\gamma} - \gamma^*) \quad (19)$$

The time derivative of (19) along with (11) is given by:

$$\begin{aligned} \dot{V} &= 2x^T P\dot{x} - 2\dot{\hat{\gamma}}^T (\gamma^* - \hat{\gamma}) \\ &= 2x^T P[\sum_{i=1}^{r} h_i (A_i - BK_i)x + Bu_s + Bd - w^* \\ &\quad + (\mu B\gamma^* - B\mu\hat{\gamma})] - 2x^T \mu PB(\gamma^* - \hat{\gamma}) \\ &= 2x^T P\sum_{i=1}^{r} h_i (A_i - BK_i)x + 2x^T PBu_s \\ &\quad + 2x^T PBd - 2x^T Pw^* \\ &< -2x^T Pw^* + 2x^T PBu_s + 2x^T PBd \\ &< -(x^T P)(x^T P)^T - w^{*T} w^* + x^T PBB^T (x^T P)^T \\ &\quad - 2x^T PBD\,\mathrm{sgn}(B^T Px) + 2x^T PBd \\ &< -(x^T P)(x^T P)^T - w^{*T} w^* \\ &\quad - 2x^T PBD\,\mathrm{sgn}(B^T Px) + 2x^T PBd \\ &< \dot{V} < -(x^T P)(x^T P)^T - w^{*T} w^* \\ &\quad - 2\|x^T PB\| D + 2\|x^T PB\| \|d\| < 0 \end{aligned} \quad (20)$$

The (20) is negative then the system (11) is exponentially stability or the state of uncertain system (11) converge to zero as $t \to \infty$.

3. Illustrative example

In this section a prototype IPMSM is used to verify the effectiveness of the proposed controller. The nominal parameters of the IPMSM are given: rated power P_{rated} = 390 W; rated torque T_{rated} = 1.5 $N \cdot m$; p = 4; R_s = 2.48 Ω; L_{qs} = 113.91 mH; L_{ds} = 74.98 mH; λ_m = 0.193 $V \cdot sec/rad$; J = 0.00042 $kg \cdot m^2$; B = 0.0001 $N \cdot m \cdot sec/rad$.

From the above parameters, all coefficients of model (1) are as follow:

$$k_1 = 2757.1,\ k_2 = 0.2,\ k_3 = 4761.9,$$

$$k_4 = 21.8,\ k_5 = 1.7,\ k_6 = 8.8,\ k_7 = 33.1$$

$$k_8 = 13.3,\ k_9 = 1.5,\ k_{10} = 0.7,\ k_{11} = -556.1$$

As mention in Section 2, the system model is approximated by T-S fuzzy technique. In this paper, for the purpose of simplicity, two rules are used.

Solving (12) by using LMI tool of Matlab/Simulink with Q = 0.02eye(3), R = 15eye(2), the controller gain is given by

$$K_1 = \begin{bmatrix} 0 & 158.7 & -4000 \\ 0 & 4000 & -170.1 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} -0.011 & 158.7 & 0 \\ 0 & 0 & -170.1 \end{bmatrix}$$

The controller (13) is rewritten as

$$\begin{aligned} u &= \sum_{i=1}^{2} h_i[-K_i x + \frac{1}{2}B^T(x^T P)^T - D\,\mathrm{sgn}(B^T P x) - \mu\hat{\gamma}] \\ &= \sum_{i=1}^{2} h_i[-K_i x + u_s - \mu\hat{\gamma}] \end{aligned} \quad (21)$$

where $D = 0.3,\ \mu = 25$.

The block diagram of the overall system is shown in Fig.1.

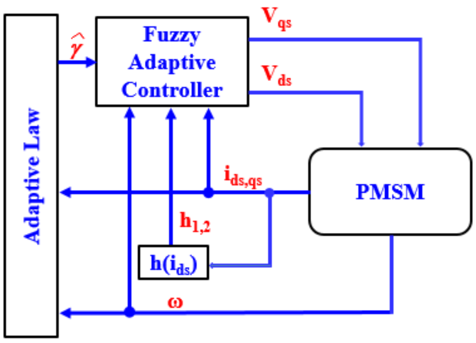

Fig. 1. Block diagram of the closed-loop system.

In order to verify the robustness of the proposed, the simulation is done under some conditions: nominal system parameters; variation of load torque and some system parameters (R_s, L_{qs}, L_{ds}); existing output disturbances. In each case, the response of the proposed scheme is compared with the fuzzy controller

$$u_f = -\sum_{i=1}^{2} h_i K_i x \quad (22)$$

The simulation results are illustrated in Figs.2-4.

Fig.2 is the speed response of the proposed scheme and the fuzzy controller under condition that the system parameters are nominal and no change of load torque. It can be seen that for both cases the tracking errors are almost zero but the proposed controller has a faster response.

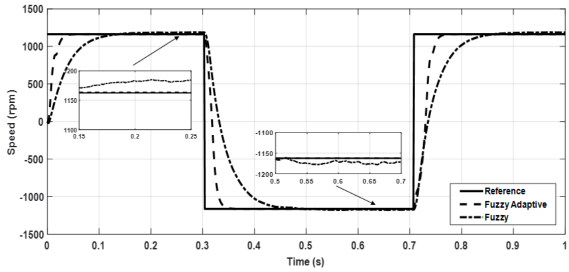

Fig. 2. Speed responses with the nominal system parameters.

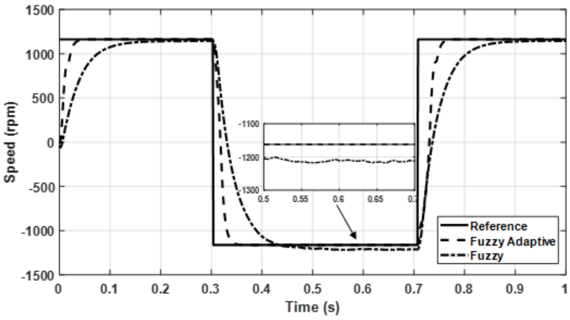

Fig. 3. Speed responses with the 50% change of system parameters.

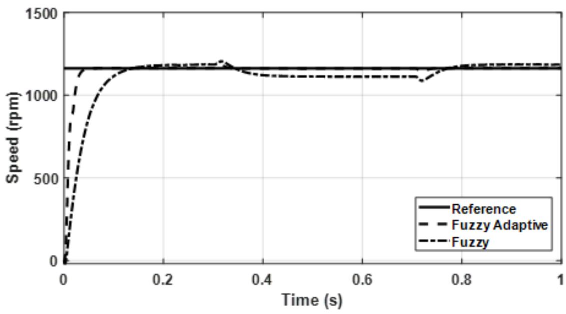

Fig. 4. Speed responses with the nominal system parameters and suddenly change of load torque.

In Fig.3, with a 50% change of the system parameters, the speed error of the adaptive fuzzy controller is still about zero. Meanwhile, in the case of the fuzzy controller, this error is considerable (about 40 rpm). Also, the presented algorithm has the smaller settling time.

In Fig.4, the reference speed is constant, but the load torque changes from 0.5Nm to 1Nm at 0.3s then back to 0.5Nm at 0.7s. In this scenario, the proposed controller is still robust under the effect of the load torque. With the fuzzy controller, as the torque increases from 0.5Nm to 1Nm, the motor speed decreases about 60rpm then backs to the previous speed when the torque reduces to 0.5Nm. This means that the fuzzy controller system is sensitive to the change of the load torque.

4 Conclusions

An adaptive fuzzy logic controller based on T-S fuzzy model is proposed in this paper. The controller has two parts: the state feedback part is designed based on LMI technique to keep the stability of the system; and the adaptive part is used to compensate for system uncertainties and external disturbances. The stability of the system and the convergence of the adaptive law are guaranteed by mathematical proof. Finally, the comparison of the adaptive fuzzy controller and the fuzzy scheme are executed to verify the effectiveness of the proposed structure. The simulation results show that the proposed algorithm has the good response to the change of reference input, the system parameters variation, and the suddenly change of the load torque.

In comparison with [11], the proposed model has the following advantages:

- [11] is used for PMSM, our controller is designed for IPMSM which is more nonlinear than PMSM.

- [11] can solve the matched disturbances only (see equation (14) in the [11]), our model can solve both matched disturbances and system parameter uncertainties (see equation (11) in our paper).

- [11] used the sliding mode technique to cancel the effect of the matched disturbances, our controller used adaptive law to adapt to the change of the system parameters.

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