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슬라이딩 모드 관측기를 이용한 유도전동기의 효율 최적화

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Efficiency Optimization with Sliding Mode Observer for Induction Motor

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Abstract - In this paper, search method and sliding mode observer are developed for efficiency optimization of induction motor. The proposed control scheme consists of efficiency controller and adaptive backstepping controller. A search controller for which information of input of fuzzy controller is included in efficiency controller that uses a direct vector controlled induction motor. The search controller is based on the ""Rosenbrock" method and finds the flux level at the minimum input power of induction motor. Once this optimal flux level has been determined, this information is utilized to update the rule base of a fuzzy controller. A sliding mode observer is designed to estimate rotor flux and an adaptive backstepping controller is also used to compensate for mechanical uncertainties in the speed control of induction motor.
Simulation results are presented to validate the proposed controller.

1. INTRODUCTION

Electric machines consume more than 50% of the world electric energy generated. It is a well-known fact that induction motors(IMs) are by far the greatest consumers of electric energy in industrialized countries. Therefore, most of the research effort on efficiency optimization via flux control has been devoted to IMs drives.[1] To improve efficiency in IMs drives is important, mainly, for two reasons: economic saving and reduction of environmental pollution. IMs have a high efficiency at rated speed and torque. However, at light loads, iron losses increase dramatically, reducing considerably the efficiency. To improve the motor efficiency, the flux must be reduced.[2]

This paper presents to minimize electric power losses of induction motor by a proposed efficiency controller and sliding mode observer. The proposed controller has search controller based "Rosenbock" method and fuzzy controller. Search controller determines the optimal flux level that results in the minimum input power of induction motor and this information is utilized to fuzzy controller. The proposed sliding mode flux observer is designed to estimate optimal flux reference.

The adaptive backstepping is one of the most powerful design tool, for uncertain nonlinear systems. As we use adaptive backstepping speed controller, which solves tracking problems of induction motor with uncerta inties.[3]

The proposed controllers guarantee both speed control and efficiency optimization of induction motor. Simulation results are presented to demonstrate the effectiveness of the proposed method.

2. PROBLEM STATEMENT

2.1 INDUCTION MOTOR MODEL

The fifth-order dynamics of induction motor model are described by

$$\begin{aligned}
\frac{d\omega}{dt} &= \mu(\psi_a i_b - \psi_b i_a) - \frac{T_L}{J} - \frac{B}{J}\omega \\
\frac{di_a}{dt} &= \alpha\beta\psi_a + n_p\beta\omega\psi_b - \gamma i_a + \frac{1}{\sigma}u_a \\
\frac{di_b}{dt} &= -n_p\beta\omega\psi_a + \alpha\beta\psi_b - \gamma i_b + \frac{1}{\sigma}u_b \\
\frac{d\psi_a}{dt} &= -\alpha\psi_a - n_p\omega\psi_b + \alpha M i_a \\
\frac{d\psi_b}{dt} &= n_p\omega\psi_a - \alpha\psi_b + \alpha M i_b
\end{aligned} \tag{1}$$

where ω is the rotor speed, ψ_a and ψ_b are the rotor fluxes, i_a and i_b are the stator currents, u_a and u_b are the stator voltages, T_L is load torque, J is the moment of inertia, B is the friction coefficient, R_r and R_s are the rotor and winding resistances, L_r and L_s are the rotor and stator winding inductances, respectively, M is the mutual inductance, $1/\alpha = L_r/R_r$ is the rotor time constant. Let $\mu = n_pM/(JL_r)$, $\sigma = L_s(1 - M^2/(L_sL_r))$, $\beta = M/(\sigma L_r)$, $\gamma = (M^2R_r/\sigma L_r^2) + (R_s/\sigma)$. The state variables i_a, i_b and ω are measurable while state variables ψ_a and ψ_b are not. T_L, J and R_r are uncertain parameters.

However, this form is too difficult to control induction motor directly, so we can reinterpret field oriented model by using state feedback transformation as follows

$$\begin{aligned}
\frac{d\omega}{dt} &= \mu\psi_d i_q - \frac{T_L}{J} - \frac{B}{J}\omega \\
\frac{di_q}{dt} &= -\gamma i_q - n_p\beta\omega\psi_d - n_p\omega i_d - \alpha M\frac{i_q i_d}{\psi_d} + \frac{1}{\sigma}u_q \\
\frac{di_d}{dt} &= -\gamma i_d + \alpha\beta\psi_d + n_p\omega i_q + \alpha M\frac{i_q^2}{\psi_d} + \frac{1}{\sigma}u_d \\
\frac{d\psi_d}{dt} &= -\alpha\psi_d + \alpha M i_d \\
\frac{d\rho}{dt} &= n_p\omega + \alpha M\frac{i_q}{\psi_d}
\end{aligned} \tag{2}$$

2.2 ADAPTIVE BACKSTEPPING CONTROLLER

The adaptive backstepping controller is designed for speed control of the induction motor. It provides precisely tracking performance speed reference.

Step1. Speed Control

For speed tracking precisely, we define speed tracking error as

$$e = \omega - \omega_{ref} \tag{3}$$

then the error dynamics equation would be

$$\dot{e}_1 = \dot{\omega} - \dot{\omega}_{ref} = \mu_N \psi_d i_q + F - \dot{\omega}_{ref} \tag{4}$$

We can choose $\alpha_1^* = \mu_N \psi_d i_q$ called "virtual control input".

The following Lyapunov function candidate is chosen

$$V_1 = \frac{1}{2} e_1^2 \tag{5}$$

The time derivatives of (5) can be expressed as

$$\dot{V}_1 = e_1 \dot{e}_1 = (\omega - \omega_{ref})(\alpha_1^* + F - \dot{\omega}_{ref}) \tag{6}$$

For stabilizing, stabilizing function can be chosen as

$$\alpha_1^* = -k_1 e_1 + \dot{\omega}_{ref} - F \tag{7}$$

where k_1 is strictly positive constant. Then it can be called ultimate bounded stable by $\dot{V}_1 = -k_1 e_1^2 \le 0$. However F is uncertainty so stabilizing function is described by using estimation value $\hat{F}$ as follow

$$\alpha_1 = -k_1 e_1 + \dot{\omega}_{ref} - \hat{F} \tag{8}$$

$$\dot{e}_1 = -k_1 e_1 + e_2 + \tilde{F}, \quad \tilde{F} = F - \hat{F} \tag{9}$$

$$\dot{V}_1 = -k_1 e_1^2 + \tilde{F} \tag{10}$$

Step2. Torque Control

For the torque control, we define the error signal e_2 as

$$e_2 = \mu_N \psi_d i_q - \alpha_1 \tag{11}$$

The time derivative of (11) can be expressed as

$$\dot{e}_2 = \mu_N \dot{\psi}_d i_q + \mu_N \psi_d \dot{i}_q - \dot{\alpha}_1 = \phi_1 + k_1 \tilde{F} + \frac{\mu_N \psi_d}{\sigma} u_q \tag{12}$$

where $\phi_1 = k_1(-k_1 e_1 + e_2) - \ddot{\omega}_{ref} + \dot{\hat{F}} - \mu_N n_p \omega \psi_d (\beta \psi_d + i_d)$
$- \mu_N \psi_d i_q (\alpha(\beta M + 1) + \eta)$

Consider the following Lyapunov function candidate

$$V_2 = V_1 + \frac{1}{2} e_2^2 + \frac{1}{2\gamma_4} \tilde{F}^2 \tag{13}$$

By using this function we can find control law and adaptive law.

$$u_q = -\frac{\sigma}{\mu_N \psi_d}(e_1 + k_2 e_2 + \phi_1) \tag{14}$$

$$\dot{\hat{F}} = \gamma_4 (e_1 + k_1 e_2)$$

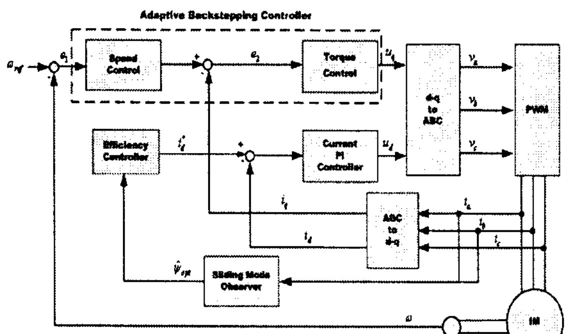

Fig. 1. Proposed Control System

2.3 EFFICIENCY CONTROLLER

2.3.1 Search Method

Search control(SC) is utilized with measured input power of induction motor for efficiency optimization. For a given load torque and speed, at steady state, t-he flux is iteratively adjusted (normally reduced) until the point of minimum input power is reached. The p-roposed search algorithm is based on "Rosenbrock" method[2], because it is a very simple method and is guaranteed to converge.

The stator current i_{ds}^* is changed gradually in one di-rection while we are approaching ($\Delta P(n) < 0$) to the optimum flux. When the algorithm detects we are m-oving away ($\Delta P(n) > 0$), the flux is changed in the other direction, until the required accuracy is achieved.

$$i_{ds}^*(n+1) = i_{ds}^*(n) + k \Delta i_{ds}^*(n), \quad \begin{cases} k = 1, & \text{if } \Delta P(n) < 0 \\ k = -\frac{1}{2}, & \text{if } \Delta P(n) > 0 \end{cases} \tag{15}$$

where $\Delta P(n) = P(n) - P(n-1)$ and $\Delta i_{ds}^*(n) = i_{ds}^*(n) - i_{ds}^*(n-1)$, for $n > 1$, whereas $\Delta i_{ds}^*(1) < 0$.[1]

2.3.2 Efficiency Controller

The Efficiency controller is formed by the combined SC and fuzzy controller as shown Fig. 2.

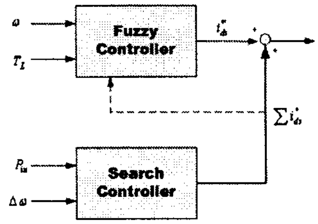

Fig. 2. Efficiency Controller

$$i_{ds}^*(k) = i_{ds}^{*'}(k) + \Sigma i_{ds}^* \tag{16}$$

where $i_{ds}^{*'}$ is obtained from a fuzzy controller, Σi_{ds}^* is output of the SC.

2.3.3 Fuzzy Controller

The SC identifies an optimum flux level, the rule base must be updated by this process. First, identify the fuzzy set and rule base for input variables T_L, ω. Next compute degree of the membership function and calculate the proportionality factor as followed

$$T_L \text{ and } \omega : \mu_{Ri} = \min(\mu_{T_L}, \mu_\omega) \tag{17}$$

$$K = \frac{\sum_{i=A}^{D} \mu_{Ri} \times \sum \Delta i_{ds}(p.u.)}{\sum_{i=A}^{D} \mu_{Ri}^2} \tag{18}$$

The correction term is

$$\Delta I_i(n) = K \times \mu_{Ri} \tag{19}$$

and then get the new value for the each rule by

$$I_i(n+1) = I_i(n) + \Delta I_i(n), \quad (i = A, B, C, D) \tag{20}$$

The primary flux reference current $i_{ds}^{'*}$ is obtained by fuzzy sup-min inference and the defuzzification as

$$i_{ds}^{'*} = \frac{\sum_{i=A}^{D} (I_i \times \mu_{Ri})}{\sum_{i=A}^{D} \mu_{Ri}} \tag{21}$$

2.4 SLIDING MODE OBSERVER

The sliding mode observer is designed to estimate rotor flux reference. We assume that only speed and stator currents are available for measurements, rotor fluxes ψ_a and ψ_b are not.

$$\frac{d\hat{\psi}_a}{dt} = -\alpha \hat{\psi}_a - n_p \omega \hat{\psi}_b + \alpha M \hat{i}_a - \frac{\omega_{aeq}}{\beta} - \frac{k_0}{\beta} sat(\tilde{i}_a / \Phi)$$

$$\frac{d\hat{\psi}_b}{dt}=n_p\omega\hat{\psi}_a-\alpha\hat{\psi}_b+\alpha M\hat{i}_a-\frac{\omega_{beq}}{\beta}-\frac{k_0}{\beta}sat(\tilde{i}_b/\Phi)$$

$$\frac{d\hat{i}_a}{dt}=\alpha\beta\hat{\psi}_a+n_p\beta\omega\hat{\psi}_b-(\alpha\beta M+\eta)i_a+\frac{1}{\sigma}u_a+v_{aeq}+k_0sat(\tilde{i}_a/\Phi) \quad (22)$$

$$\frac{d\hat{i}_b}{dt}=-n_p\beta\omega\hat{\psi}_a+\alpha\beta\hat{\psi}_b-(\alpha\beta M+\eta)i_b+\frac{1}{\sigma}u_b+v_{beq}+k_0sat(\tilde{i}_b/\Phi)$$

where $\hat{\psi}_a$, $\hat{\psi}_b$, $\hat{i}_a$, $\hat{i}_b$ are the estimation of ψ_a, ψ_b, i_a, i_b and v_{aeq}, v_{beq}, ω_{aeq}, ω_{beq} are will be designed, k_0 d-etermining speed of reaching to sliding surface is stri-ctly positive constant.

Denoting the estimation errors as follows

$$\tilde{i}_a=i_a-\hat{i}_a,\ \tilde{i}_b=i_b-\hat{i}_b,\ \tilde{\psi}_a=\psi_a-\hat{\psi}_a,\ \tilde{\psi}_b=\psi_b-\hat{\psi}_b \quad (23)$$

We introduce new unknown error variables as

$$z_a=\tilde{i}_a+\beta\tilde{\psi}_a\ ,\ z_b=\tilde{i}_b+\beta\tilde{\psi}_b \quad (24)$$

Combining (22) and (23), observer error dynamics is

$$\frac{d\tilde{\psi}_a}{dt}=-\alpha\tilde{\psi}_a-n_p\omega\tilde{\psi}_b+\frac{\omega_{aeq}}{\beta}+\frac{k_0}{\beta}sat(\tilde{i}_a/\Phi)$$

$$\frac{d\tilde{\psi}_b}{dt}=n_p\omega\tilde{\psi}_a-\alpha\tilde{\psi}_b+\frac{\omega_{beq}}{\beta}+\frac{k_0}{\beta}sat(\tilde{i}_b/\Phi) \quad (25)$$

$$\frac{d\tilde{i}_a}{dt}=\alpha\beta\tilde{\psi}_a+n_p\beta\omega\tilde{\psi}_b-\gamma i_a(1-L_s)-v_{aeq}-k_0sat(\tilde{i}_a/\Phi)$$

$$\frac{d\tilde{i}_b}{dt}=-n_p\beta\omega\tilde{\psi}_a+\alpha\beta\tilde{\psi}_b-\gamma i_b(1-L_s)-v_{beq}-k_0sat(\tilde{i}_b/\Phi)$$

We can rewrite error dynamics using (z_a, z_b),

$$\frac{dz_a}{dt}=-\gamma i_a(1-L_s)-v_{aeq}+\omega_{aeq}$$

$$\frac{dz_b}{dt}=-\gamma i_b(1-L_s)-v_{beq}+\omega_{beq}$$

$$\frac{d\tilde{i}_a}{dt}=-\alpha\tilde{i}_a-n_p\omega\tilde{i}_b+\alpha z_a+n_p\omega z_b-\gamma i_a(1-L_s)-v_{aeq}-k_0sat(\tilde{i}_a/\Phi) \quad (26)$$

$$\frac{d\tilde{i}_b}{dt}=n_p\omega\tilde{i}_a-\alpha\tilde{i}_b-n_p\omega z_a+\alpha z_b-\gamma i_b(1-L_s)-v_{beq}-k_0sat(\tilde{i}_b/\Phi)$$

Consider the following Lyapunov function candidate

$$V_o=\frac{1}{2}\left[\tilde{i}_a^2+\tilde{i}_b^2+z_a^2+z_b^2+\frac{1}{\gamma_o}\left(\tilde{z}_a^2+\tilde{z}_b^2\right)\right] \quad (27)$$

We can describe the adaptive law by using the time derivative of (27) as follow

$$\dot{\hat{z}}_a=\dot{z}_a-\dot{\tilde{z}}_a=\gamma_3\tilde{i}_a+n_p\omega\tilde{i}_b$$

$$\dot{\hat{z}}_b=\dot{z}_b-\dot{\tilde{z}}_b=\gamma_3\tilde{i}_b-n_p\omega\tilde{i}_a \quad (28)$$

$$\dot{\hat{\theta}}=\gamma_2\{[\hat{z}_a+\beta(\hat{\psi}_a-M\hat{i}_a)]\tilde{i}_a+[\hat{z}_b+\beta(\hat{\psi}_b-M\hat{i}_b)]\tilde{i}_b\}$$

2.5 SIMULATION

The proposed control algorithm has been simulated for 2.2KW induction motor. At t=2s, a 7Nm load torq-ue which is unknown to the controller is applied. And the load torque is reduced to 4Nm at t=4s. Initial val-ues of rotor fluxes were assumed to be $\psi_a(0)=\psi_b(0)=0.001$ while the initial conditions of the flux estimates were $\hat{\psi}_a(0)=\hat{\psi}_b(0)=0.001$. All other initial conditions were assumed to be zero. The speed reference start to change to 1200rpm at 0.4s and to 1800rpm at 3s.

The speed tracking performance is shown in Fig. 3, the flux amplitude tracking performance is shown in Fig. 4. The d-q axis currents are shown in Fig. 5.

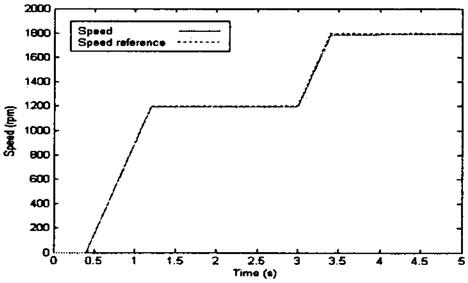

Fig. 3. Speed Tracking Performance

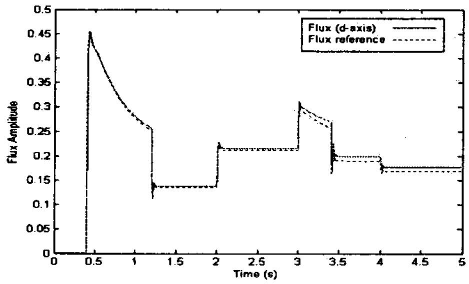

Fig. 4. Optimal Flux Tracking Performance

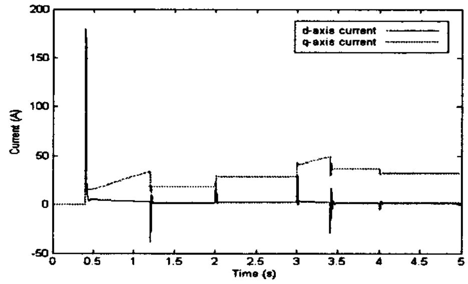

Fig. 5. d-q Axis Currents

3. CONCLUSION

The proposed control scheme that uses a direct vector controlled can achieve both efficiency optimization and speed tracking of induction motor with uncertainties. The proposed efficiency controller based search control and sliding mode observer which find optimal flux reference can minimize energy loss of induction motor.

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