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Synchronous Reluctance Motor Speed Drive Using Sliding Mode Controller Based on Gaussian Radial Basis Function Neural Network

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Abstract: In this paper, a sliding mode control (SMC) design based on Gaussian radial basis function neural network (GRBFNN) is proposed for the synchronous reluctance motor (SynRM) system robust stabilization and disturbance rejection. This method utilizes Lyapunov function and the steep descent rule to guarantee the convergence of the SynRM drive system asymptotically. Finally, we employ the experiments to validate the proposed method.

Keywords: Sliding Mode Control, Radial Basis Function Neural Network, synchronous reluctance motor, Lyapunov function.

I. INTRODUCTION

In recent decade years, the SynRM [1,2] has been a renewed interesting research subject. The rotor circuit of the SynRM is opened such that the flux linkage of SynRM is directly proportional to the stator currents.

The fast and no error dynamic response is a primary topic in control systems. In real worlds, the real servo systems always include parameter variations and external load disturbances. The sliding mode control [3] has been proven as an effective and robust control technology to overcome the uncertainties in the SynRM [4,5]. The uncertainties, parameter variations and/or external disturbances can be rejected for the sliding mode control when the upper lump uncertainty boundary of the systems is known. In real applications, uncertainty boundaries can easily exceed the assumed magnitude range, under which the sliding mode can not be used. Using high gain control to improve disturbance rejection has been proposed [6]. However, it produces unnecessary deviations from the switching manifold and causes chattering in the control system. Serious chattering can reduce by using the boundary layer which the signum function is replaced by the saturation function. However, it produces the steady state errors. In recent years, some researchers [7,8] proposed the methods to find the uncertainty upper boundaries and reduce the steady state error. Their major concept is to estimate the bounded uncertainties in real-time for the controlled system. Hence, the control signal of the controller is smaller than the conventional sliding mode controller and the chattering phenomenon is also reduced.

In recent years, the neural network of intelligent control has been applied in some motor speed control systems [9,10]. The neural network control does not require mathematical model to approximate nonlinear systems. The radial basis function neural network (RBFNN) theory [11] employs local receptive fields to perform function mapping based on biological receptive fields. The RBFNN is a multilayer perceptron (MLP) feedforward neural network structure. It has been successfully employed in the area of motor control field [12,13]. The RBFNN control1er is an effective method when the systems mathematical model is unknown, or known with uncertainties.

RBFNN [14] is a three-layer feedforward neural network structure. It has the nonlinear transformation of Gaussian basis function in the hidden layer and output layer is the linear combination of hidden layer responses. We proposed the SMC design based on RBFNN concept of SynRM system which the upper lump uncertainty system doesn't know. The SMC is replaced by RBFNN which the sliding surface function S and system control u is the mapping input and output function, respectively. The RBFNN doesn't use the signum function control element. Hence, this system reduces chattering phenomenon and has the response more smooth.

II. MODELING OF THE SYNRM

The d-q equivalent voltage equations of the SynRM with the synchronously rotating rotor reference frame are represented as

$$V_{ds} = R_s i_{ds} + L_{ds}\frac{di_{ds}}{dt} - \omega_r L_{qs} i_{qs} \quad \textbf{(1)}$$

$$V_{qs} = R_s i_{qs} + L_{qs}\frac{di_{qs}}{dt} + \omega_r L_{ds} i_{ds} \quad \textbf{(2)}$$

where the V_{ds} and V_{qs} are direct and quadrature axis terminal voltages, respectively. The i_{ds} and i_{qs} are, respectively, direct axis and quadrature axis terminal currents or the torque producing current. The L_{ds} and L_{qs} are the direct and quadrature axis magnetizing inductances, respectively. The R_s is the stator resistance and ω_r is the speed of the rotor.

The corresponding electromagnetic torque T_e and m otor dynamic equation are given as following

$$T_e = \frac{3}{2}P(L_{ds} - L_{qs})i_{ds}i_{qs} \quad \textbf{(3)}$$

$$T_e - T_L = J\frac{d\omega_r}{dt} + B\omega_r \quad \textbf{(4)}$$

where P , T_L , J and B are the pair of poles, the torque load, the inertia moment of rotor and the viscous friction coefficient, respectively.

The current angle for the maximum power factor control (MPFC) strategy is $\phi = \pm\tan^{-1}(\sqrt{L_{ds}/L_{qs}})$ [2]. Therefore by electromagnetic torque (3), we can find the torque current command as following

$$I_s = \sqrt{i_{ds}^2 + i_{qs}^2} \quad \textbf{(5)}$$

$$i_{ds}^* = \sqrt{\frac{|T_e^*|}{\frac{3}{4}P(L_{ds} - L_{qs})}}\cos(\tan^{-1}(\sqrt{L_{ds}/L_{qs}})) \quad \textbf{(6)}$$

$$i_{qs}^* = sign(T_e^*)\sqrt{\frac{|T_e^*|}{\frac{3}{4}P(L_{ds} - L_{qs})}}\sin(\tan^{-1}(\sqrt{L_{ds}/L_{qs}})) \quad \textbf{(7)}$$

III. SLIDING MODE CONTROL (SMC)

We can rewrite the motor dynamic equation of (4) as follows:

$$\begin{aligned}\dot{\omega}_r &= (-\frac{B_m}{J_m})\omega_r + (\frac{1}{J_m})(T_e - T_L) \\ &= a\omega_r + b(T_e - T_L) \\ &= a_o\omega_r + b_o(u(t) + f)\end{aligned} \quad \textbf{(8)}$$

where

$$a \equiv -\frac{B_m}{J_m} = a_o + \Delta a$$

$$b \equiv \frac{1}{J_m} = b_o + \Delta b$$

$$u \equiv T_e$$

$$f \equiv \frac{1}{b_o}(\Delta a\omega_r + \Delta bu(t) - bT_L)$$

$$J_m \equiv J_{mo} + \Delta J_m$$

$$B_m \equiv B_{mo} + \Delta B_m$$

The subscript index "o" indicates nominal system value; "Δ" symbol expresses uncertainty, and f is the lump uncertainty. Defining the velocity error $e(t) = \omega_{ref} - \omega_r$, ω_{ref} is the velocity command.

The sliding function is defined as

$$S = e(t) + c\int_{-\infty}^{t} e(\tau)d\tau,\ c > 0 \quad \textbf{(9)}$$

The input control $u(t)$ (the electromagnetic torque T_e) can be defined

$$u(t) = u_{eq}(t) + u_n(t) \quad \textbf{(10)}$$

To satisfy equivalent control concept $\dot{S}(e) = 0$, we get

$$\dot{S} = (\dot{\omega}_{ref} - a_o\omega_r - b_o u_{eq} + ce) - b_o(u_n + f) \quad \textbf{(11)}$$

Let $|f| \le K$, we set

$$u_{eq} = \frac{1}{b_o}(\dot{\omega}_{ref} - a_o\omega_r + ce) \quad \textbf{(12)}$$

$$u_n = Ksign(S) \quad \text{or} \quad u_n = Ksat(S) \quad \textbf{(13)}$$

Hence, the sliding condition $S(e)\dot{S}(e) < 0$ can be guaranteed. The chattering phenomenon exists in the $sign(\cdot)$ function and steady state error exists in $sat(\cdot)$ function

IV. SLIDING MODE CONTROLLER BASED ON RBFNN

In real world, most of the physical systems have certain nonlinear and various uncertainties. However, specific and reliable system uncertainty boundaries are difficult obtained for practical applications. Therefore, a model-free neural network (NN) control [15] was employed for controlling dynamic absorbers without knowing the systems model. The error back propagation NN has the disadvantages of slower learning speed and local minimal convergence. Hence, we use the RBFNN to solve these problems and develop a model-free controller structure based on RBFNN. The structure of the SMC based on RBFNN model is shown in Fig. 1. The RBFNN model has j receptive field units. We select the Gaussian function $\varphi_j(S) = \exp\left(-\left(S - c_j\right)^2/(2b_j^2)\right)$ as the receptive field units, where S is the sliding surface function and c_j, b_j are the spread factor and central position of the Gaussian function, respectively. j is the number of hidden layer neurons. The output u of the RBFNN is the sum of weights which the output can be described as

$$u = \sum_{j=1}^{5} w_j\varphi_j(S) \quad \textbf{(14)}$$

$$\varphi_j(S) = \exp\left(-\frac{\left(S - c_j\right)^2}{2b_j^2}\right), \quad j = 1, \cdots, 5 \quad \textbf{(15)}$$

where

$$\theta = \left[\varphi_1(S), \varphi_2(S), \cdots, \varphi_5(S)\right]^T, \quad W = [w_1, w_2, \cdots, w_5]^T$$

$$c_1 = \frac{2000\pi}{6}, c_2 = \frac{2000\pi}{12}, c_3 = 0, c_4 = -\frac{2000\pi}{12}, c_5 = -\frac{2000\pi}{6}$$

$$b_1 = b_2 = b_3 = b_4 = b_5 = 500\pi$$

According the SMC reaching condition $S\dot{S} < 0$, the adaptive rules of this structure derive from the steep descent method to minimize the value of the performance index $S\dot{S}$ with the weight w_j as follows:

$$\dot{w}_j = -\eta \frac{\partial S\dot{S}}{\partial w_j} = -\eta \frac{\partial S\dot{S}}{\partial u}\frac{\partial u}{\partial w_j} = \eta \cdot S \cdot b_o \cdot \varphi_j(S) \quad \textbf{(16)}$$

where η is the learning rate.

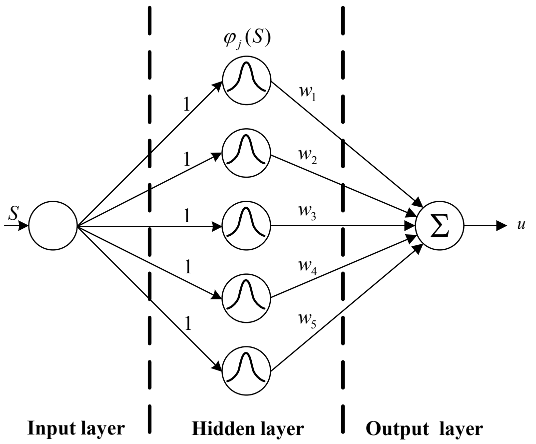


Fig. 1. The structure of the RBFNN model

V. EXPERIMENTAL RESULTS

The block diagram of the experimental SynRM system is shown in Fig. 2. The controller is adopted by a dSPACE DS1104 control board. The nominal parameters of 0.37 KW three-phase SynRM are shown in Table 1. The sampling period of control rules is set as 0.3 $m$sec. The reference model transfer function of Fig. 2 is set as $\frac{\omega_{ref}(s)}{\omega_r^*(s)} = \frac{81}{s^2 + 18s + 81}$, where s is the Laplace operator. Fig. 3 shows the response for the reference command of is $\omega_r^* = 500$ rev/min under a 0.3 Nt-m machine load at the beginning. In Fig. 4, the reference command is $\omega_r^* = 500$ rev/min under a 0.3 Nt-m machine load at the beginning and a 1.0Nt-m load disturbance is added at t=5 sec. From Fig. 3 and 4, the proposed controller has good velocity performance.

Table 1. The parameters of SynRM (0.37KW)

$R_s = 4.2\Omega$	$P = 1$
$L_{ds} = 0.328\,H\ (f = 60Hz)$	$L_{qs} = 0.181$ H (f = 60Hz)
$J_{mo} = 0.00076\ kg\text{-}m^2$	$B_{mo} = 0.00012\ Nt\text{-}m/rad/sec$
$c = 6$	$\eta = 0.0086$

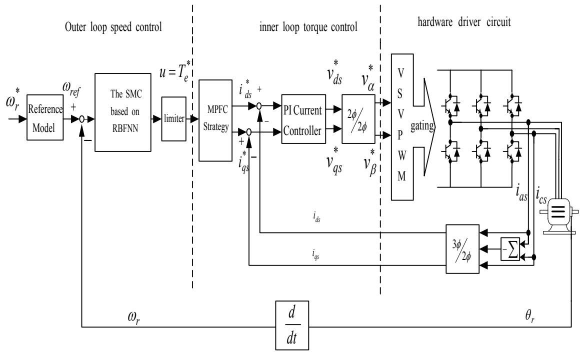
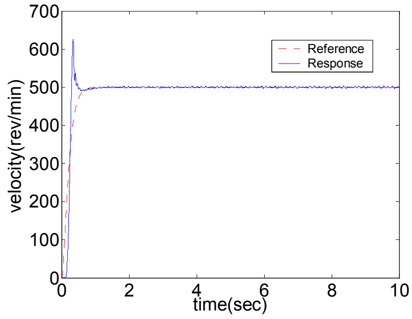
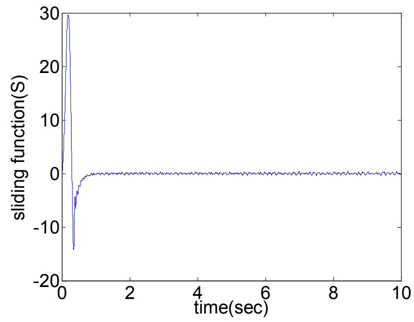


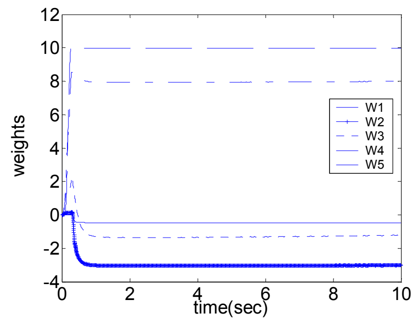
Fig. 2. The block diagram of the experimental SynRM drive system



(a)

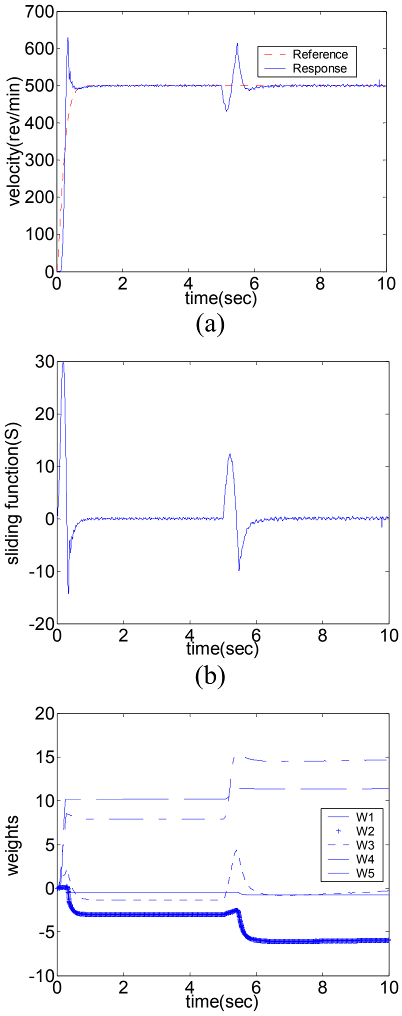


(b)



(c)

Fig. 3. Experimental results of the SMC based on RBFNN due to $\omega_r^* = 500$ rev/min under a 0.3 Nt-m machine load at the beginning (a) rotor velocity (b) sliding function (c) weights



(a) (b) (c)

Fig. 4. Experimental results of the SMC based on RBFNN due to $\omega_r^* = 500$ rev/min under 0.3Nt-m to 1.0Nt-m load torque step disturbance. (a) rotor velocity (b) sliding function (c) weights

VI. CONCLUSION

In this paper, a complete model analysis for the sliding mode controller based on radial basis function neural network of SynRM speed drive is presented. The proposed RBFNN is employed to model the relationship between the sliding function and the systems control law in real-time which has the adaptive rules. It derives from the steep descent method to minimize the value of the performance index $S\dot{S}$. Hence, the chattering problem can be minimized with the proposed control. Finally, we employ the experimental results to validate the proposed method.

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