Study on control of switched reluctance motor based on self-adaptive DRNN neural network

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Abstract. In view of the nonlinear characteristics of the switched reluctance motor, a feedforward feedback control method based on Diagonal Recurrent Neural Networks (DRNN) adaptive neural network is proposed. The controller consists of a PI feedback controller and a self-adaptive DRNN feed-forward controller. The PI feedback controller takes the error of the target speed and the actual speed as the input to improve the stability of the control system. The DRNN neural network is adopted for the feed-forward controller, and the feed-forward controller uses the output of the feedback controller as performance error to improve the transient response of the control system. The simulation results illustrate that the control system can track the target speed, reduce the system overshoot and improve the static and dynamic performance of the control system, and not sensitive to motor parameters, which has strong robustness.

1. Introduction

Switched reluctance motors (SRM) have the advantages of simple structure, low manufacturing cost, wide speed governing range, and high reliability and efficiency. It has certain application prospects in new energy electric vehicles, wind power generation, mining machinery, oilfield pumping units and other fields\cite{1~3}. However, the double salient pole structure of the stator and rotor and the switch power supply cause the drive system of SRM to become a system with high torque ripple and highly coupled multivariable. In addition, SRM has the characteristics of large variation of model parameters and unknown external load disturbance, which makes it difficult for classical PID controller to achieve high speed governing accuracy and performance.

With the development of advanced control theory, modern control theory and intelligent control theory have been widely applied in SRM control. Reference \cite{4,5} designed the adaptive TSK fuzzy model and adaptive fuzzy cerebellar model joint speed controller, and the network weight adaptive law was adopted by the Lyapunov stability principle. They also introduced the sign function to realize the compensate control of the regulating error, and got a good effect for the speed regulation. But the introduction of the sign function will cause chattering of control variable. In \cite{6}, the author applies RBF neural network and BP neural network respectively to SRM model identification and speed regulation, and a neural network PID control strategy was proposed with adjustable parameters. In \cite{7}, the author proposed a compound control strategy combining integral sliding mode control and neural network compensation. It used BP neural network compensation control to reduce the dithering of sliding surface, which had better adaptability and robustness for parameter change and external load disturbance. In \cite{8}, the author designed a speed controller based on a direct adaptive RBF neural network with minimal learning parameters, which effectively inhibited the influence of parameter...
perturbation and load disturbance on the speed. A new Maximum Power Point Tracking controller was designed to Photovoltaic system supplied SRM based on PI controller. The developed PI controller was used to reach MPPT by monitoring the voltage and current of the PV array and adjusting the duty cycle of the DC/DC converter [9]. In [10], a novel method for speed control of SRM (8/6 poles) was proposed via Ant Colony Optimization (ACO). The design problem of the proposed controller was formulated as an optimization problem and ACO was employed to search for optimal parameters of PI controller.

In this paper, a feed-forward and feedback control method based on Diagonal Recurrent Neural Network (DRNN) is proposed to solve the problem of strong coupling and highly nonlinear. The feedback control adopts the traditional PI control. The feed-forward control adopts the DRNN neural network control. The hidden layer of the DRNN neural network has feedback dynamic network, so it can reflect the dynamic characteristics of the system directly. It has a high transient response ability and can overcome the shortcomings of the traditional PI controller in anti-interference, and improves the robustness of the control system.

2. Mathematical model of SRM
SRM uses a double salient pole structure. The stator pole has winding while the rotor pole has no winding. It follows that the magnetic flux always closes along the path with the least reluctance to generate the electromagnetic torque and drags the rotor to rotate. Ignoring the influence of winding inductance, the electromagnetic torque of SRM can be expressed as follows:

\[ T_e = \sum_{j=1}^{m} \frac{1}{2} \frac{dL(\theta, i)}{d\theta} \]

where \( \theta \) is the angle of the motor, \( L(\theta, i) \) is winding inductance, \( m \) is the number of motor phases, and \( i \) is winding current.

The motion equation of SRM is expressed as follows:

\[ T_e = T_L + F\omega + J \frac{d\omega}{dt} \]

where \( T_L \) is the load torque of the motor, \( F \) is viscous friction coefficient, and \( J \) is moment of inertia.

According to formula (1) and (2), there is a restrictive relation between motor phase current, angular velocity and load torque. In the actual control system, these quantities are time-varying, so the control system is often disturbed. The traditional PID controller is difficult to get satisfactory effect. The neural network has good nonlinear approximation ability and PID has the advantages of simple control structure and quick adjustment. Therefore, in this paper, we propose a SRM compound control strategy of feed-forward and feedback based on DRNN adaptive neural network.

3. Control system design
3.1. Adaptive neural network control system
The diagram of SRM feed-forward and feedback adaptive neural network control structure is shown in figure 1. The control system includes feed-forward DRNN neural network control and feedback PI control. The PI controller uses the error of the actual angular velocity (\( \omega_a \)) and the target angular velocity (\( \omega_d \)) to achieve small systematic error to improve the stability of the system. DRNN neural network control realizes feed-forward control and improves the transient response ability of control system. It includes two layers of structure DRN_N and DRN_C. The two layers can adaptive learn based on performance errors \( u_0 \), and the purpose of learning is to make \( u_0 \) zero. The first layer uses the angular velocity and load torque as input, and outputs the pulse width control signal (\( g^* \)) of PWM pulse width modulator, so as to speeds up the response capability of the system. The second layer takes the angular acceleration and the load torque change rate as input, and outputs the pulse width control signal (\( g^{**} \)) of the PWM pulse width modulator to enhance the transient response capability of
the control system. The feed-forward DRNN neural network can learn to feedback the output of PI controller and decides the total output of the control system. It has strong adaptive learning ability.

The input and output controlled by DRN_N and DRN_C, as well as the total output of feed-forward and feedback adaptive neural network control system, are as follows:

\[
\begin{align*}
    x &= \begin{bmatrix} \dot{\omega} \\ T_L \end{bmatrix}, \\
    y &= g' \\
    x' &= \begin{bmatrix} \dot{\omega} \\ T_L \end{bmatrix}, \\
    y' &= g'' \\
    g &= g_1 + u_o = g' + g'' + u_o
\end{align*}
\]  

\[(3)\]

![Figure 1. Structure diagram of SRM control system.](image)

3.2. DRNN network algorithm

DRNN network is a dynamic network with feedback. It uses the associated layer to store the internal state to make it have the function of mapping dynamic characteristics, so that the system has the ability to adapt to the time-varying characteristics. It greatly improves the transient response ability and enhances the robustness of the control system. The DRNN network structure is shown in figure 2.

![Figure 2. Structure diagram of DRNN network.](image)

The DRNN network is a three-layer forward network. In this network structure, set \( I = [I_1, I_2, \ldots, I_n] \) as the input vector, \( I_i(k) \) as the neuron input of input layer, \( w_{ij} \) as the weight vector of input layer; set \( X_j(k) \) as the output of \( j \) neuron of the association layer, \( S_j(k) \) as the input
sum of the associated neurons, \( f(\cdot) \) as the S function, \( w^O_j \) as the weight vector of correlation layer; set \( w^I_j \) as the weight vector of the output layer, and \( y(k) \) as the output of the DRNN network.

The output of DRNN network’s output layer is:
\[
y(k) = \sum_j w^O_j X_j(k)
\]
(5)

The output of DRNN network’s association layer is:
\[
X_j(k) = f(S_j(k))
\]
(6)

The input of DRNN network’s association layer is:
\[
S_j(k) = w^D_j X_j(k-1) + \sum_i (w^I_{ij} I_i(k))
\]
(7)

Performance index function \( E(k) = \frac{1}{2} u_0(k)^2 \)

According to the gradient descent algorithm, the weight learning algorithm of each layer is as follows:

\[
\Delta w^O_j(k) = -\frac{\partial E(k)}{\partial w^O_j} = u_0(k) \frac{\partial y(k)}{\partial w^O_j} = u_0(k)X_j(k)
\]
(8)

\[
w^O_j(k) = w^O_j(k-1) + \eta_O \Delta w^O_j(k) + \alpha (w^O_j(k-1) - w^O_j(k-2))
\]
(9)

\[
\Delta w^I_{ij}(k) = -\frac{\partial E(k)}{\partial w^I_{ij}} = u_0(k) \frac{\partial y(k)}{\partial w^I_{ij}} = u_0(k) \frac{\partial X_j(k)}{\partial w^I_{ij}} = u_0(k)w^O_{ij} Q_{ij}(k)
\]
(10)

\[
w^I_{ij}(k) = w^I_{ij}(k-1) + \eta_I \Delta w^I_{ij}(k) + \alpha (w^I_{ij}(k-1) - w^I_{ij}(k-2))
\]
(11)

\[
\Delta w^D_j(k) = -\frac{\partial E(k)}{\partial w^D_j} = u_0(k) \frac{\partial y(k)}{\partial w^D_j} = u_0(k) \frac{\partial X_j(k)}{\partial w^D_j} = u_0(k)w^I_{ij} P_{ij}(k)
\]
(12)

\[
w^D_j(k) = w^D_j(k-1) + \eta_D \Delta w^D_j(k) + \alpha (w^D_j(k-1) - w^D_j(k-2))
\]
(13)

The double S function of the neurons in the correlation layer is:
\[
f(x) = \frac{1 - e^{-x}}{1 + e^{-x}}
\]
(14)

\[
P_{ij}(k) = \frac{\partial X_j(k)}{\partial w^D_{ij}} = f'(S_j) X_j(k-1)
\]
(15)

\[
Q_{ij}(k) = \frac{\partial X_j(k)}{\partial w^I_{ij}} = f'(S_j) I_i(k)
\]
(16)

Where \( \eta_I, \eta_D, \eta_O \) is the learning rate of input layer, correlation layer and output layer respectively, and \( \alpha \) is inertia coefficient.

4. Simulation results

To verify the effectiveness of the control strategy above, propose the SRM motor model and the feedforward and feedbackadaptive neural network control system based on the DRNN network on the Matlab /Simulink. The simulation study of the SRM control system shown in figure1.

The rated voltage and rated speed of the motor are \( U_N = 48V \) and \( \omega_N = 150\text{rad/s} \), respectively. The phase resistance of stator is \( R = 0.005\Omega \). The moment of inertia is \( J = 0.005\text{kg} \cdot \text{m}^2 \). The viscous friction coefficient is \( F = 0.002\text{N} \cdot \text{m} \cdot \text{s} \). The proportional coefficient of PI control is \( k_p = 5 \), and the integral coefficient is \( k_i = 2 \). The structure of DRNN network adopts 3-7-1 layer. The learning rate of
input layer, correlation layer and output layer $\eta_I, \eta_D, \eta_O$ as well as the inertia coefficient $\alpha$ are 0.35, 0.35, 0.35, 1.

In order to test the anti load interference performance of the system, the initial target speed and initial load of the system are $100\, \text{rad/s}$ and $3\, \text{N} \cdot \text{m}$, respectively, and the target speed is set to $150\, \text{rad/s}$ at the time of $t = 0.1\, \text{s}$. The comparison between PI and the control method designed in this paper is carried out. The simulation results are shown in figure 3 and figure 4.

![Motor simulation waveform with traditional PI control method](image1)

**Figure 3.** Motor simulation waveform with traditional PI control method.

![Motor simulation waveform with traditional PI control method](image2)

**Figure 4.** Motor simulation waveform with traditional PI control method.

In figure 3 (a), when the speed of the target is abrupt, it can be seen that quite smooth response with no or less ripples. On the contrary, in figure 4 (a), the speed curve is oscillatory. The PI controller has poor anti-interference ability compared with the control system designed in this paper. In addition, it can be found that under the control of the traditional PI controller, the pulsation of phase current is large and the torque ripple is obvious. Under the control strategy introduced in this paper, the phase current pulsation is small, the torque is stable, and it shows good dynamic performance.

### 5. Conclusions

Because of the high nonlinear characteristics of SRM, in order to obtain high speed regulation precision and control performance, this paper designs a feed-forward and feedback SRM control system based on DRNN adaptive neural network. The control system designed in this paper is compared with the traditional PI control system. The following conclusions can be concluded:

1. Under the control method introduced in this paper, the angular velocity of the target can be traced well, the steady state error and the torque ripple are small, and the control system has better dynamic response ability.

2. Under the control method introduced in this paper, when the motor speed suddenly changed, the oscillation of angular velocity is small and the control system has good steady state performance. The control system is insensitive to the change of the object parameters and has better robustness.

3. Through simulation experiments, it is verified that the proposed controller based on DRNN is not obvious for motor load disturbance, and has better adaptive control ability. In the future work, the proposed controller will be applied to practical applications based on rapid prototyping technology.
Acknowledgements
This work was supported by the National Natural Science Foundation of China (51475091), the Natural Science Foundation of Zhejiang Province, China (LY17E050004) and the Science-Technology Foundation of Taizhou, Zhejiang Province, China (162gy50).

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