

Article

High Disturbance-Resistant Speed Control for Permanent Magnet Synchronous Motors: A BPNN Self-Tuning Improved Sliding Mode Strategy Without Load Observer

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Abstract

Sliding mode control (SMC) provides robustness and disturbance rejection in permanent magnet synchronous motor (PMSM) control but faces the challenge of speed degradation during sudden load disturbance changes without a load observer. This paper proposes a backpropagation neural network-adjusted improved SMC (BPNN-ISMC). A simplified PMSM model is established by ignoring the disturbance term. An improved arrival law is developed by optimizing the constant-speed approach term of the traditional exponential arrival law and embedding an adaptive term. A BPNN is designed with performance metrics including speed error, its derivative, and maximum error to improve training efficiency. Speed/position estimation combines a sliding mode observer with an extended Kalman filter to suppress jitter. Simulation results demonstrate the significant advantages of the BPNN-ISMC method: in set-point control, overshoot suppression is evident, and the relative error during the stable phase after sudden load disturbance increases is reduced by 93.62% compared to the ISMC method and by 99.80% compared to the SMC method. Compared to the ADRC method, although the steady-state errors are the same, the BPNN-ISMC method exhibits smaller speed fluctuations during sudden changes. In servo control, the root mean square error of speed tracking is reduced by 18.83% compared to the ISMC method, by 89.70% compared to the SMC method, and by 37.14% compared to the ADRC method. This confirms the dynamic performance improvement achieved through adaptive adjustment of neural network parameters.

Keywords: improved SMC; BPNN; load disturbance; PMSM



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1. Introduction

PMSMs possess several advantageous characteristics, including high power density, high power factor, and ease of control, which render them widely applicable in various fields such as industrial automation, new-energy vehicles, and aerospace [1–3]. In industrial applications, automated equipment necessitates motors that can respond rapidly within milliseconds, with precision typically within microseconds. Ensuring high responsiveness and precision in the motor while maintaining high efficiency is of paramount importance, which requires the motor to support low thermal losses and facilitate energy feedback [4]. Currently, the primary requirement for PMSM control systems is efficient control, which guarantees precise speed and torque control capabilities under high-frequency real-time conditions, as well as manageable energy feedback processes. Control demands for PMSMs

are particularly evident in the new-energy vehicle industry. Electric vehicles require motors to provide stable output over extended periods and to respond promptly during operation, thereby ensuring stable and controllable speeds. Energy recovery systems are capable of converting kinetic energy back into electrical energy for storage, and this process also functions as auxiliary braking [5]. Consequently, the high-efficiency four-quadrant operational characteristics of PMSMs can effectively meet the requirements of most motor application scenarios. However, existing PMSM control systems encounter several challenges, such as the controller's sensitivity to variations in motor parameters and its susceptibility to disturbances. When motor parameters fluctuate or disturbances arise, the original controller demonstrates a lack of adaptive capability and resilience against interference [6,7].

Based on the characteristics of the motor, the PMSM is well suited to various control methods, including vector control, direct torque control, and model predictive control. Vector control effectively decouples the phase current into excitation and torque components, enabling the controller to manage these two components independently for precise control [8]. Direct torque control necessitates the monitoring of both torque and magnetic flux magnitudes and implements input phase current control through a magnitude adjustment switching table [9]. Model predictive control requires continuous prediction of the state for the next moment, with the prediction process being ongoing and repetitive [10]. When expanding this method, problems associated with the original model may also arise, such as parameter mismatches, computational burden, and unstable switching frequencies [11]. The response time difference between vector control and direct torque control is minimal; however, vector control's ability to decouple excitation and torque components mitigates mutual interference, resulting in enhanced motor control accuracy. Consequently, in applications that require motor drive, particularly in precision instruments, vector control methods emerge as the preferred choice. While model predictive control accommodates multiple inputs and outputs, takes into account additional constraint conditions, and demonstrates superior control effects, it demands real-time computation of the future state, thereby necessitating support from devices with substantial computing power.

To ensure precision and efficiency in control, vector control methods are commonly employed for motor control. For sensorless control, accurate position estimation is a prerequisite for effective control [12]. Reference [13] suggests utilizing the motor power rating to determine the control gain, thereby simplifying calculations in traditional vector control. Reference [14] introduces a novel vector control method that amalgamates the benefits of simple sine control and field orientation control, incorporating an additional parameter to ascertain the electrical angle between the voltage space vector and the rotor magnetic flux axis, thus reducing computational load and enhancing control efficiency. Reference [15] investigates the Model Reference Adaptive System (MRAS) and the pulsating high-frequency injection method to achieve sensorless vector control across the entire speed range of the motor. Reference [16] presents an innovative sliding mode speed controller based on the improved genetic algorithm (IGA) to further improve the efficacy of sliding mode controllers, leveraging the advantages of genetic algorithms, which enable the sliding mode controller to achieve parameter adaptation. Reference [17] analyzes the reasons behind the suboptimal control performance of a PMSM under PI controller vector control, proposing a combination of the back-stepping method and SMC as a viable solution. It is evident that integrating various control methods can effectively mitigate the deficiencies associated with individual methods; however, this method cannot ascertain the optimal parameters for the controller based on control performance alone.

There are several different control techniques of PMSM speed control, including classical control, modern control, intelligent control, vector control, sensorless control, and

other methods. These different speed control methods can all be controlled by combining modern control methods, such as fuzzy–neural networks, fuzzy–genetic algorithms, and genetic algorithms, which can also provide good control performance [18]. Reference [19] proposes an enhanced control method for adjusting the PID controller parameters with a singleton neuron, which can accelerate the learning speed of the neural algorithm, facilitate online adjustments of the proportional coefficient value, and optimize the control algorithm. Reference [20] employs artificial neural networks (ANNs) to optimize the PID controller parameters, taking into account multiple influencing factors under motor operating conditions as input features for the network, thereby ensuring parameter accuracy. Reference [21] tackles the issue of variations in motor parameters due to temperature, magnetic saturation, and armature reaction by proposing the use of deep neural networks (DNNs) to control the current and speed of PMSM, thereby circumventing the limitations of traditional control methods. Reference [22] develops a speed identification scheme utilizing general regression neural networks (GRNNs) to enhance the control capabilities of the motor state.

The control strategies mentioned above all need to consider the impact of disturbances in their application, but due to the characteristics of different control methods, some methods inherently possess strong disturbance suppression capabilities and do not require the design of additional disturbance observers. For example, traditional PID control typically uses its integral term to effectively reduce errors in most cases. Other control methods lack disturbance suppression capabilities and require the design of additional disturbance observers. For example, in traditional SMC control, output errors are unavoidable when disturbances are present.

In SMC, external disturbances or load changes can be effectively suppressed through various methods. These methods primarily involve improving the design of the sliding mode controller itself or combining it with other control strategies.

1. Robust sliding surface design:

The essence of SMC is designing a sliding surface such that the system state trajectory slides along this surface, thereby achieving system control. In the absence of disturbance observers, robust sliding surface design is critical, primarily involving integral sliding surfaces or higher-order sliding surfaces [23]. Sliding surfaces incorporating integral terms can effectively eliminate steady-state errors. Since integrators have a cumulative effect on persistent disturbances, they can indirectly compensate for the effects of load changes, thereby enhancing the system's disturbance rejection capability [24,25]. Furthermore, due to the cumulative effect of the integral term on continuous interference, the system's ability to resist interference from uncertainties and load changes is enhanced. Reference [26] proposes that the sliding surface of the double integral sliding mode controller (DISMC) uses a double integral of the tracking voltage error term, which effectively eliminates steady-state errors. High-order sliding mode control (HOSMC) can limit the impact of disturbances to the higher-order derivatives of the sliding surface, thereby forcing the system state onto the sliding surface in a shorter time and effectively reducing oscillations, while exhibiting stronger robustness against unmodeled dynamics and external disturbances [27]. Reference [28] proposes a fast high-order terminal sliding mode current controller, which improves the convergence speed of the system under interference, suppresses steady-state chatter, reduces oscillation, and enhances the system's interference resistance robustness by designing the corresponding sliding surface and introducing nonlinear gain.

2. Improved SMC law:

The SMC law determines how the system approaches and maintains the sliding surface, and its design directly affects the system's disturbance rejection performance. For

example, when using non-singular fast terminal sliding mode control (NFTSMC)/fast terminal sliding mode control (FTSMC), these methods aim to provide finite-time convergence, even ultra-fast convergence, thereby eliminating tracking errors in a shorter time. Due to the fast convergence speed, the system responds very quickly to transient disturbances (such as load shocks), able to quickly pull the speed back to the target value [29]. Reference [30] proposes a sliding surface that can completely eliminate singularities in controller inputs. Its key characteristics include rapid error convergence, high tracking accuracy, and robustness to disturbances. Additionally, incorporating an adaptive law into the SMC law allows the control gain to be dynamically adjusted based on system state or error, thereby addressing unknown disturbances and parameter uncertainties [31]. To improve the speed control performance of PMSM under internal and external disturbances, Reference [32] proposes a new adaptive terminal sliding mode tracking law (ATSMRL) and combines it with continuous fast terminal sliding mode control (CFTSMC). ATSMRL aims to reduce control input effort and dynamically provides advantages such as finite time convergence, high tracking accuracy, and reduced control input jitter. Reference [33] investigates an adaptive sliding mode (ASM) control scheme that constrains the displacement and pitch angle of the suspension system through a predefined performance function (PPF), combined with a highly robust integral terminal SMC method and neural networks to handle unknown terms.

3. Neural network estimation compensation method:

Estimating disturbances using neural networks can also effectively suppress disturbances [34,35]. Integrating neural networks into sliding mode controllers can leverage their powerful nonlinear approximation capabilities to estimate and compensate for unknown disturbances [36,37]. Neural networks learn the patterns of disturbances and generate corresponding compensation signals, thereby indirectly suppressing their effects without explicitly observing the disturbances. Reference [38] proposes a radial basis function neural network adaptive sliding mode controller (RBF-NN ASMC). The controller uses a radial basis function neural network (RBF-NN) control algorithm to compensate for friction disturbance torque in electromechanical actuator systems. By adjusting the neural network weights through an adaptive law, real-time compensation for friction is achieved.

This article presents a control method utilizing BPNN to adjust the parameters of the ISMC, with the objective of effectively mitigating load disturbances, startup overshoot, and startup current within the PMSM control system. Initially, the mathematical model of the PMSM is analyzed, disregarding load disturbances and other interference factors. Subsequently, a sliding mode controller is designed without the inclusion of a load observer, with enhancements to the controller primarily concentrated on the approach law. To tackle the challenge of significant speed reduction and the difficulty in returning to the desired speed during the sudden application of load, modifications and adaptive terms to the control law are proposed. Lastly, a BPNN is employed to adjust the ISMC parameters for optimal system control. The effectiveness of the proposed method is validated through simulation experiments.

2. PMSM Vector Control

Vector control converts the mathematical model of the motor from the natural coordinate system (ABC coordinate system) to the synchronous rotating coordinate system ($d - q$ coordinate system), thereby achieving precise control through decoupling [39].

2.1. PMSM Mathematical Model

This article focuses on the surface-mounted permanent magnet synchronous motor (SPMSM) as the subject of research. The voltage equation of its stator in the $d-q$ coordinate system is presented as follows.

$$\begin{cases} U_d = Ri_d + L_d \frac{di_d}{dt} - P_n \omega_m L_q i_q \\ U_q = Ri_q + L_q \frac{di_q}{dt} + P_n \omega_m L_d i_d + P_n \omega_m \psi_f \end{cases} \quad (1)$$

In the equation, U_d and U_q represent the $d-q$ axis components of the stator voltage; R denotes the stator resistance; i_d and i_q indicate the $d-q$ axis components of the stator current; P_n refers to the number of pole pairs; ω_m signifies the mechanical angular velocity; L_d and L_q are the $d-q$ axis inductance components; and ψ_f represents the magnetic flux of the permanent magnet.

The equation for the electromagnetic torque of the SPMSM is as follows.

$$T_e = \frac{3}{2} P_n i_q (i_d (L_d - L_q) + \psi_f) \quad (2)$$

In the equation, T_e denotes the electromagnetic torque.

The motor output torque T must take into account the load torque T_L (load disturbance) and the damping coefficient B under actual operating conditions.

$$\begin{cases} T = T_e - T_L - B\omega_m \\ T = \frac{d\omega_m}{dt} \end{cases} \quad (3)$$

2.2. Vector Control Principle

The essence of vector control lies in the decomposition of the stator current of a three-phase AC motor into two orthogonal components—the excitation component and the torque component—which correspond to the direct axis current (I_d) and the quadrature axis current (I_q), respectively. The objective is to decouple the dynamic coupling effects inherent in the AC motor, thereby rendering its control characteristics analogous to those of a DC motor. Initially, the three-phase AC current in the ABC coordinate system is transformed into the $\alpha-\beta$ coordinate system utilizing the Clarke transformation method, resulting in two-phase stationary currents. Subsequently, these two-phase stationary currents are converted into the $d-q$ coordinate system through the Park transformation method, where the electrical currents are now represented as I_d and I_q . These two-phase currents directly engage in the control process of the controller, where the speed controller outputs the desired current, and the current controller adjusts based on the current error, thereby generating the necessary voltage. This voltage is then transformed into two-phase stationary voltage using the inverse Park transformation method. In conjunction with Space Vector Pulse Width Modulation (SVPWM), this process produces the inverter control signals. SVPWM generates six fundamental vectors and utilizes the rotation of space vectors to regulate the inverter output of equivalent three-phase electricity.

3. Improved Sliding Mode Controller Design

This paper employs the vector control method with I_d set to 0, disregarding the load torque and motor damping coefficient and relying exclusively on the algorithm to mitigate these two disturbances.

3.1. Sliding Mode Controller

Due to the high symmetry of the d-axis and q-axis magnetic circuits in the SPMSM, it follows that $I_d = I_q$. By combining Equations (1)–(3), we arrive at the following equation.

$$\begin{cases} \dot{i}_q = \frac{1}{L_q}(-Ri_q - P_n\omega_m\psi_f + U_q) \\ \dot{\omega}_m = \frac{3P_n\psi_f}{2J}i_q \end{cases} \quad (4)$$

We then define the state variables of the PMSM system.

$$\begin{cases} e = \omega_{ref} - \omega_m \\ \dot{e} = \dot{\omega}_{ref} - \dot{\omega}_m \end{cases} \quad (5)$$

In the equation, e represents the error between the reference speed ω_{ref} and the actual speed ω_m . It serves as the first state variable, while its derivative constitutes the second state variable.

The surface of the lubricating film can be defined by Equation (5).

$$s = ce + \dot{e} \quad (6)$$

In the equation, c is the sliding mode surface parameter. By substituting into Equation (5) and differentiating the sliding surface, the following expression can be derived.

$$\dot{s} = c\dot{e} - \ddot{e} = c(\dot{\omega}_{ref} - \dot{\omega}_m) + (\ddot{\omega}_{ref} - \ddot{\omega}_m) \quad (7)$$

Substituting Equation (4) into Equation (7) yields the following equation.

$$\dot{s} = c\dot{e} + \ddot{\omega}_{ref} - \frac{3P_n\psi_f}{2J}i_q \quad (8)$$

To ensure that the system reaches the expected value within the specified time and minimizes the impact of load and other disturbances, this paper proposes an improved approach law. This approach law retains the exponential approach term to maintain the controller's linear approach capability. The constant-speed approach term is optimized using a boundary layer saturation function, where ϕ is the boundary layer thickness parameter. When $\phi > s$, it acts as a linear term, causing the system output to approach the target value linearly. Conversely, when $\phi \leq s$, it transforms into a sign term, causing the output to oscillate. The third term is an adaptive term aimed at significantly improving the system's robustness against disturbances caused by load torque.

$$\dot{s} = -\epsilon s - \beta \text{sat}\left(\frac{s}{\phi}\right) + k * \text{sign}(s) \quad (9)$$

In this equation, ϵ represents the coefficient of the exponential approach term, β denotes the coefficient of the constant-speed approach term, $\text{sat}()$ indicates the saturation function, and k refers to the adaptive gain.

$$\begin{cases} \text{sat}\left(\frac{s}{\phi}\right) = \frac{s}{|s| + \phi} \\ k^{(t)} = k^{(t-1)} + \delta |s| T_s \end{cases} \quad (10)$$

In the equation, ϕ denotes the boundary layer thickness; $k^{(t-1)}$ represents the adaptive gain from the previous moment, which is a constant; δ signifies the coefficient of the adaptive term; and T_s refers to the system period. Modifying the boundary layer thickness can alter the range of linear variation in the region where the exponential approaches, effectively

minimizing jitter. Adjusting the coefficient of the adaptive term based on the output from the previous moment allows for the determination of the optimal adaptive gain for the subsequent moment, thereby leading to the derivation of the optimal control law.

Equation (7) is equal to Equation (9), so we have the following equation.

$$c\dot{e} + \ddot{w}_{ref} - \frac{3P_n\psi_f}{2J}i_q = -\epsilon s - \beta \text{sat}\left(\frac{s}{\phi}\right) - k * \text{sign}(s) \quad (11)$$

Assuming that the current response is sufficiently rapid, the following expression is valid.

$$i_q = \frac{2J}{3P_n\psi_f}(c\dot{e} + \ddot{w}_{ref} + \epsilon s + \beta \text{sat}\left(\frac{s}{\phi}\right) + k * \text{sign}(s)) \quad (12)$$

To prove the effectiveness of the designed sliding mode controller, it is necessary to design a Lyapunov function to verify its stability.

$$\begin{cases} v = \frac{1}{2}s^2 + \frac{1}{2\delta}\tilde{k}^2 \\ \dot{\tilde{k}} = k - k^* \end{cases} \quad (13)$$

In the equation, k^* is the minimum gain for suppressing disturbances, and it is a non-negative constant.

By combining Equations (10) and (13), we obtain the following expression.

$$\dot{\tilde{k}} = \delta|s| \quad (14)$$

By substituting Equations (9) and (14) into the derivative of the Lyapunov function, we obtain the following result.

$$\dot{v} = s(-\epsilon s - \beta \text{sat}\left(\frac{s}{\phi}\right) - k * \text{sign}(s)) + \frac{1}{\delta}\tilde{k}\delta|s| \quad (15)$$

The combination of Equation (13) can simplify Equation (15).

$$\dot{v} = -\epsilon s^2 - \beta \text{sat}\left(\frac{s}{\phi}\right)s - k^*|s| \quad (16)$$

In the equation, given that $\epsilon \geq 0$, the first term is non-negative; since $\beta \geq 0$ and $\phi \geq 0$, the second term is also non-negative. Furthermore, $k^* \geq 0$, and thus the third term is non-negative as well. Consequently, all three terms are non-negative, leading us to the following conclusion.

$$\dot{v} \leq 0 \quad (17)$$

In accordance with Lyapunov's stability theorem, we demonstrate that the designed sliding mode controller is effective.

3.2. Current Overshoot Suppression

The overcurrent in the stator may result in motor damage and overspeed, which adversely affects both the motor's lifespan and its control. To mitigate this issue, the current output can be constrained according to the rate of change of current. In contrast to directly limiting the output range, this approach facilitates a more gradual variation in current [40].

The maximum current and the actual current per unit time are illustrated below.

$$\begin{cases} \Delta i_{\max} = i_{\max} T_s \\ \Delta i = i_q^{(t)} - i_q^{(t-1)} \end{cases} \quad (18)$$

In the equation, the $i_{\max}$ represents the maximum rate of change of current.

We then ensure that the current remains within the specified range.

$$\Delta i_q = \begin{cases} \Delta i_{\max} & (\Delta i_q > \Delta i_{\max}) \\ -\Delta i_{\max} & (\Delta i_q < -\Delta i_{\max}) \\ \Delta i_q & (-\Delta i_{\max} < \Delta i_q < \Delta i_{\max}) \end{cases} \quad (19)$$

The current output is as follows.

$$i_q = i_q^{(t-1)} + \Delta i_q \quad (20)$$

3.3. S-Curve Speed Smoothing Method

When employing a sliding mode controller to regulate motor speed, a desire for rapid response and attainment of the desired value often results in considerable control overshoot. This phenomenon not only exerts a substantial impact on the motor but also induces a significant overshoot in the instantaneous phase current, potentially causing irreversible damage to the motor itself.

In order to maintain the control advantages of the sliding mode controller, an S-curve velocity smoothing method is employed. This method facilitates a specified acceleration phase for the motor, during which both the initial speed and acceleration are set to 0. At the conclusion of this phase, the acceleration also reaches 0, allowing for a smooth transition to the desired speed [41,42].

This article employs a quintic polynomial for the purpose of smoothing.

$$\begin{cases} R = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \\ t = \frac{t_r}{t_a} \end{cases} \quad (21)$$

In the equation, R represents the speed reference ratio; t_r denotes the real time; t signifies the normalized time, specifically, $t \in [0,1]$; t_a refers to the set acceleration time; and a_0, a_1, a_2, a_3, a_4 , and a_5 are the polynomial coefficients.

When $t = 0$,

$$\begin{cases} R = a_0 = 0 \\ \dot{R} = a_1 = 0 \\ \ddot{R} = 2a_2 = 0 \end{cases} \quad (22)$$

When $t = 1$,

$$\begin{cases} R = a_0 + a_1 + a_2 + a_3 + a_4 + a_5 = 1 \\ \dot{R} = a_1 + 2a_2 + 3a_3 + 4a_4 + 5a_5 = 0 \\ \ddot{R} = 2a_2 + 6a_3 + 12a_4 + 20a_5 = 0 \end{cases} \quad (23)$$

By combining Equations (22) and (23), we obtain the following.

$$\begin{cases} a_0 = 0 \\ a_1 = 0 \\ a_2 = 0 \\ a_3 = 10 \\ a_4 = -15 \\ a_5 = 6 \end{cases} \quad (24)$$

Thus, the quintic polynomial is expressed as follows.

$$R = 10t^3 - 15t^4 + 6t^5 \quad (25)$$

The desired speed, ω_{ref} , can be achieved through S-curve smoothing by employing a fifth-order polynomial, thereby ensuring a smooth speed, ω_s .

$$\omega_s = \omega_{ref} R \quad (26)$$

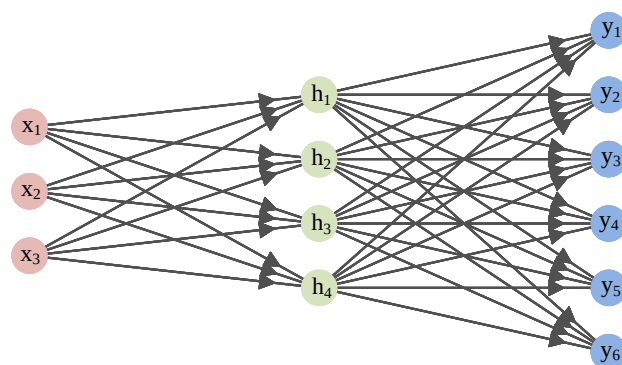
Since the desired input speed is smoothed, it is equivalent to taking the derivative once; thus, the control law is equationed as follows.

$$i_q = \frac{2J}{3P_n\psi_f} (c\dot{e} + \dot{\omega}_s + \epsilon s + \beta \text{sat}(\frac{s}{\phi}) + k * \text{sign}(s)) \quad (27)$$

4. BPNN Design

A BPNN is a form of error-based ANN that continuously adjusts the weights and biases of the network through backpropagation in order to minimize the output error parameters. The network architecture comprises three layers: an input layer, a hidden layer, and an output layer. The input layer is responsible for receiving feature data, the hidden layer conducts nonlinear mapping of the data, and the output layer produces the final results.

As illustrated in Figure 1, the input layer comprises three neurons that represent three features reflecting motor speed information, specifically the desired speed, speed error, and the derivative of speed error. To enhance computational efficiency, the hidden layer is composed of four neurons. The output layer consists of six neurons, each corresponding to one of the six controller parameters that require adjustment.



Input Layer $\in \mathbb{R}^3$ Hidden Layer $\in \mathbb{R}^4$ Output Layer $\in \mathbb{R}^6$

Figure 1. BPNN structure diagram.

Hidden layer computation:

$$h_j = \tanh\left(\sum_{i=1}^3 w_{ij}x_i + b_j\right) \quad (28)$$

In the equation, h_j represents the output of the hidden layer; w_{ij} denotes the weight of the hidden layer; x_i signifies the input feature; b_j corresponds to the bias of the hidden layer; i indicates the index of the input layer neuron; j represents the index of the hidden layer neuron; and $\tanh()$ is the hyperbolic tangent activation function, which enhances gradient flow and is particularly well suited for controlling systems with bounded outputs.

Output layer computation:

$$y_k = \sigma\left(\sum_j^4 w_{jk}h_j + b_k\right) \quad (29)$$

In the equation, y_k denotes the result of the output layer calculation; w_{jk} represents the weights of the output layer; b_k signifies the bias associated with the output layer; k indicates the index of the neuron in the output layer; and σ refers to the Sigmoid function, which effectively regulates the parameters within a reasonable range.

Considering the control requirements, the designed motor control system is anticipated to exhibit a minimal average speed error, a low fluctuation frequency, and a limited maximum error. Consequently, the performance indicators established encompass error terms, error derivative terms, and maximum error terms.

$$L = |e| + 0.5|\dot{e}| + 0.3 \max(|e|) \quad (30)$$

In the equation, e denotes the speed error, with the error term carrying the highest weight, followed by the error derivative and the maximum error.

The learning rate has a direct impact on the performance of BPNN. A larger learning rate results in faster training speeds; however, it may lead to oscillations and the potential to overlook the optimal solution. Conversely, a smaller learning rate slows down the training process and increases the likelihood of encountering local optima. To mitigate this issue, this paper proposes an adaptive learning rate that adjusts according to the changes in performance metrics. Specifically, as the error term increases, the learning rate decreases, thereby reducing the risk of significant oscillations in the system.

$$\eta = \frac{\eta_b}{1 + 2\delta_p} \quad (31)$$

In the equation, η_b represents the base learning rate.

We then design gradient error signals and compute the error terms for each layer.

$$\begin{cases} \delta_p = 0.01\text{sign}(e) + 0.005\text{sign}(\dot{e}) \\ \delta_2 = \delta_p \sigma'(y) \\ \delta_1 = w_2^T \delta_2 \odot \tanh'(h) \end{cases} \quad (32)$$

In the equation, δ_p represents the gradient error signal; δ_2 denotes the error term for the output layer; δ_1 refers to the error term for the hidden layer; w_2 signifies the weight of the output layer; y indicates the output value of the output layer; and h represents the output value of the hidden layer.

Based on the aforementioned equation, one can calculate both the gradient of the weights and the gradient of the bias.

$$\begin{cases} \Delta w_2 = -\eta(\delta_2 y^T) \\ \Delta b_2 = -\eta \delta_2 \\ \Delta w_1 = -\eta(\delta_2 x^T) \\ \Delta b_1 = -\eta \delta_1 \end{cases} \quad (33)$$

In this equation, x represents the network input; Δw_2 denotes the gradient of the output layer weight; Δb_2 signifies the gradient of the output layer bias; Δw_1 indicates the gradient of the hidden layer weight; and Δb_1 refers to the gradient of the hidden layer bias.

The essence of backpropagation in a BPNN lies in updating the weights to progressively minimize the output error. To enhance the adjustment speed and effectiveness, a momentum term is incorporated.

$$\begin{cases} v_{w2}^{(t)} = \mu v_{w2}^{(t-1)} + \Delta w_2 \\ v_{b2}^{(t)} = \mu v_{b2}^{(t-1)} + \Delta b_2 \\ v_{w1}^{(t)} = \mu v_{w1}^{(t-1)} + \Delta w_1 \\ v_{b1}^{(t)} = \mu v_{b1}^{(t-1)} + \Delta b_1 \end{cases} \quad (34)$$

In the equation, μ represents the momentum coefficient; v_{w2} denotes the momentum of the output layer weights; v_{b2} signifies the momentum of the output layer biases; v_{w1} indicates the momentum of the hidden layer weights; and v_{b1} refers to the momentum of the hidden layer biases.

The momentum term allows for the updating of weights and biases.

$$\begin{cases} w_2^{(t)} = w_2^{(t-1)} + v_{w2}^{(t)} \\ b_2^{(t)} = b_2^{(t-1)} + v_{b2}^{(t)} \\ w_1^{(t)} = w_1^{(t-1)} + v_{w1}^{(t)} \\ b_1^{(t)} = b_1^{(t-1)} + v_{b1}^{(t)} \end{cases} \quad (35)$$

In the equation, b_2 represents the bias of the output layer; w_1 denotes the weight of the hidden layer; and b_1 signifies the bias of the hidden layer.

By using the BPNN structure designed above, quick adjustment of six parameters of the improved sliding mode controller for PMSM can be achieved.

5. Sliding Mode Observer

5.1. Back EMF Estimation

Given that this paper employs a surface-mounted PMSM, the voltage equation in the $\alpha - \beta$ coordinate system can be articulated as follows.

$$\begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} = \begin{bmatrix} R + pL & 0 \\ 0 & R + pL \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \begin{bmatrix} E_\alpha \\ E_\beta \end{bmatrix} \quad (36)$$

In the equation, R represents the stator resistance; L denotes the stator inductance; $\begin{bmatrix} u_\alpha & u_\beta \end{bmatrix}^T$ signifies the stator voltage; $\begin{bmatrix} i_\alpha & i_\beta \end{bmatrix}^T$ indicates the stator current; and $\begin{bmatrix} E_\alpha & E_\beta \end{bmatrix}^T$ refers to the back electromotive force, which is expressed by the following equation.

$$\begin{bmatrix} E_\alpha \\ E_\beta \end{bmatrix} = P_n \omega_m \psi_f \begin{bmatrix} -\sin \theta_e \\ \cos \theta_e \end{bmatrix} \quad (37)$$

Based on Equation (36), the following current equation can be derived.

$$\frac{d}{dt} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \frac{1}{L} \begin{bmatrix} -R & 0 \\ 0 & -R \end{bmatrix} \begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} + \frac{1}{L} \begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} - \frac{1}{L} \begin{bmatrix} E_\alpha \\ E_\beta \end{bmatrix} \quad (38)$$

To obtain an estimate of the back electromotive force, the following equation is utilized.

$$\frac{d}{dt} \begin{bmatrix} \hat{i}_\alpha \\ \hat{i}_\beta \end{bmatrix} = \frac{1}{L} \begin{bmatrix} -R & 0 \\ 0 & -R \end{bmatrix} \begin{bmatrix} \hat{i}_\alpha \\ \hat{i}_\beta \end{bmatrix} + \frac{1}{L} \begin{bmatrix} u_\alpha \\ u_\beta \end{bmatrix} - \frac{1}{L} \begin{bmatrix} \hat{E}_\alpha \\ \hat{E}_\beta \end{bmatrix} \quad (39)$$

In the equation, $[\hat{i}_\alpha \ \hat{i}_\beta]^T$ represents the estimated stator current, while $[\hat{E}_\alpha \ \hat{E}_\beta]^T$ denotes the estimated back electromotive force, as expressed in the following manner.

$$\begin{bmatrix} \hat{E}_\alpha \\ \hat{E}_\beta \end{bmatrix} = \begin{bmatrix} k_{slide} \text{sign}(\hat{i}_\alpha - i_\alpha) \\ k_{slide} \text{sign}(\hat{i}_\beta - i_\beta) \end{bmatrix} \quad (40)$$

In this equation, k_{slide} represents the magnification factor. By adjusting this factor, it is possible to align the estimated stator current with the actual stator current. When the difference between Equations (38) and (39) is zero, the estimated back electromotive force corresponds to the actual value.

We define the observer sliding surface in the following manner.

$$\begin{cases} s_\alpha = \hat{i}_\alpha - i_\alpha \\ s_\beta = \hat{i}_\beta - i_\beta \end{cases} \quad (41)$$

Design a Lyapunov function to verify stability.

$$V = \frac{1}{2}s^2 \quad (42)$$

Taking the sliding surface s_α as an example, combined with Equations (40) and (41), the derivative of the Lyapunov function has the following expression.

$$\dot{V} = \begin{cases} \frac{1}{L}(\bar{i})(E_\alpha - k_{slide}) - \frac{R}{L}(\bar{i})^2 & (\hat{i}_\alpha > i_\alpha) \\ \frac{1}{L}(\bar{i})(E_\alpha + k_{slide}) - \frac{R}{L}(\bar{i})^2 & (\hat{i}_\alpha < i_\alpha) \\ \bar{i} = \hat{i}_\alpha - i_\alpha \end{cases} \quad (43)$$

To ensure that the derivative of the Lyapunov function is less than or equal to zero, the following expression must be satisfied.

$$k_{slide} > |E_\alpha| \quad (44)$$

Similarly, the sliding mode surface s_β should satisfy the following.

$$k_{slide} > |E_\beta| \quad (45)$$

Therefore, to ensure effective observation, k_{slide} must satisfy the following criteria.

$$k_{slide} > \max\{|E_\alpha|, |E_\beta|\} \quad (46)$$

5.2. Rotor Position Estimation

The estimated back electromotive force represents a high-frequency switching signal, which is rendered continuous through the application of low-pass filtering.

$$\begin{bmatrix} E_\alpha^* \\ E_\beta^* \end{bmatrix} = \begin{bmatrix} \frac{\omega_c}{s_L + \omega_c} k_{slide} \text{sign}(\hat{i}_\alpha - i_\alpha) \\ \frac{\omega_c}{s_L + \omega_c} k_{slide} \text{sign}(\hat{i}_\beta - i_\beta) \end{bmatrix} \quad (47)$$

In the equation, s_L is the Laplace operator, $[E_\alpha^* \ E_\beta^*]^T$ represents the filtered stator voltage, and ω_c denotes the cutoff frequency of the low-pass filter.

We then utilize the arctangent function to estimate the position of the rotor:

$$\theta_{eq} = -\arctan\left(\frac{E_\alpha^*}{E_\beta^*}\right) \quad (48)$$

Owing to the phase delay induced by the low-pass filter, which impacts the estimation of the rotor position, error compensation is necessary.

$$\theta_e = \theta_{eq} + \arctan\left(\frac{\omega_e}{\omega_c}\right) \quad (49)$$

In the equation, ω_e is the electrical angular velocity.

The differentiation of Equation (49) results in the estimated rotor speed.

$$\omega_e = \frac{\sqrt{(E_\alpha^*)^2 + (E_\beta^*)^2}}{\psi_f} \quad (50)$$

Therefore, the mechanical angular velocity can be obtained.

$$\omega_m = \frac{\omega_e}{P_n} \quad (51)$$

The estimated rotor position and speed are influenced by chattering resulting from the switched characteristics of sliding mode observation; therefore, this paper employs the EKF to refine the estimated output.

6. Simulation Experiments and Analysis

To evaluate the effectiveness of the proposed method, this paper employs Matlab/Simulink simulation software (version R2025a) for analysis. The motor parameters utilized for verification are presented in Table 1.

Table 1. Parameters of PMSM.

Parameter Type	Value
Rated Voltage	300 V _{dc}
Rated Torque	8 N · m
Rated Speed	2000 rpm
Operating Frequency	100 Hz
Number of Phases	3
Pole Pairs	4
Stator Resistance	0.9585 Ω
Stator Inductance	0.00525 H
Permanent Magnet Flux Linkage	0.1827 Wb
Moment of Inertia	0.0006329 kg · m ²

As illustrated in Figure 2, the control system primarily comprises four components: feedback, control, coordinate transformation, and drive. Firstly, a sliding mode observer is employed to monitor the motor's position and speed, which, after filtering, serves as the input for the controller. Secondly, the BPNN utilizes the relevant speed information as feature input to learn and adjust the parameters of the improved sliding mode controller in real time. Finally, the improved sliding mode controller generates the desired current q , while the current loop's PI controller produces the d-axis and q-axis voltages. Following coordinate transformation to the $\alpha - \beta$ coordinate system, these voltages are integrated with SVPWM to yield the inverter control signal, resulting in the three-phase current output of the PMSM.

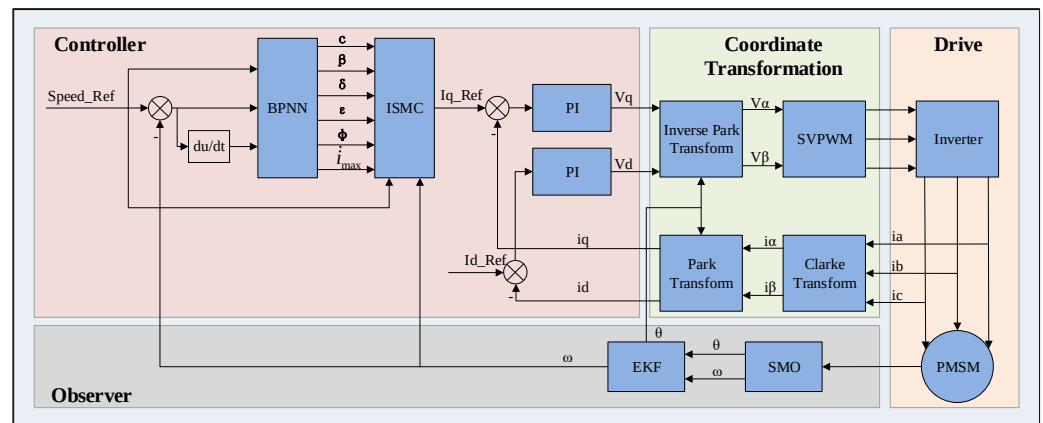


Figure 2. Structure diagram of PMSM vector control system under BPNN-ISM.

With the exception of the parameters adjusted by BPNN, all other relevant parameters are set to fixed values, as illustrated in Table 2. The following control parameters are empirical values determined through experimental optimization. For example, the base learning rate η_b should balance learning speed and oscillation risk while ensuring convergence stability. The number of hidden layer neurons in the BPNN is a compromise between network complexity and computational efficiency, and its nonlinear fitting capability has been verified through grid search to be sufficient to meet control requirements. BPNN weights are initialized using small random numbers combined with non-zero biases, which avoids gradient vanishing while breaking symmetry.

Table 2. Parameters of the PMSM vector control system.

Parameter Type	Value
S-curve Velocity Smoothing Time t_a	0.01 s
d-Axis Proportional Coefficient	5
d-Axis Integral Coefficient	3
q-Axis Proportional Coefficient	5
q-Axis Integral Coefficient	30
ISMIC Initial Parameters c	110
ISMIC Initial Parameters β	27
ISMIC Initial Parameters δ	0.116
ISMIC Initial Parameters ϵ	190
ISMIC Initial Parameters ϕ	0.35
Maximum Rate of Change of Current $i_{\max}$	1300
Base Learning Rate η_b	0.0005
Momentum Coefficient μ	0.95
Amplification Factor k_{slide}	300
Cutoff Frequency of Low-Pass Filter ω_e	1000
Load Torque	10 N · m

6.1. Rotor Position Observation

Effective control capability is predicated on precise feedback parameters. In the realm of motor control, the primary methods for acquiring feedback parameters consist of sensor detection and sensorless observation. These two approaches exhibit fundamental distinctions, the former is contingent upon the accuracy of the sensing element to guarantee the reliability of the parameters, whereas the latter relies on the observation algorithm. This paper employs a sliding mode observer to estimate the rotor position and speed of the PMSM.

As illustrated in Figure 3, this paper employs two types of input signals—set-point and time-varying—which effectively demonstrate the proposed control algorithm's efficacy

in both set-point control systems and servo control systems. To accurately depict the relationship between the actual rotor position and the observed position, the position curve is wrapped, resulting in a sawtooth waveform. By selecting any time interval from 0.16 to 0.17 s, it can be observed that the rotor's observed position curves for both control systems closely align with the actual position curves, exhibiting minimal observation error, thereby validating the accuracy of the sliding mode observer.

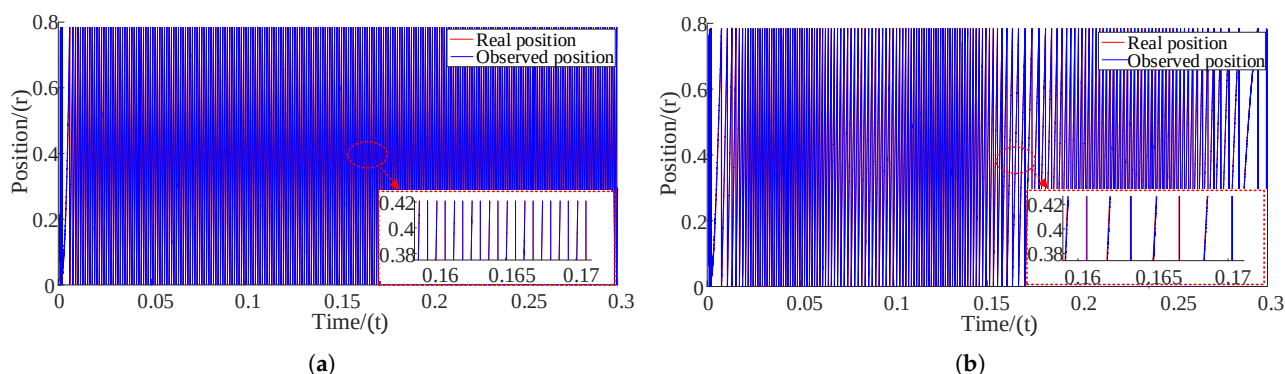


Figure 3. Observational results of PMSM rotor position. (a) Position observation curve (set-point). (b) Position observation curve (servo).

The rotational speed, as another crucial feedback parameter, has a direct impact on the control effectiveness. As illustrated in Figure 4, during set-point control, the output of the observer typically aligns with the actual output throughout the motor startup phase, steady phase, and load phase. However, it is notable that the observed value lags slightly behind the actual value by approximately 0.0005 s, a characteristic lag that arises following parameter filtering. From the steady phase onward, it is evident that the use of a sliding mode observer results in high-frequency jitter in the output parameters due to the switching capability of the sign function. While the filter can effectively mitigate this issue, the observed value continues to exhibit a degree of jitter. In the case of servo control, the observed value is noticeably closer to the desired value, with smaller fluctuations compared to the actual value; nonetheless, it still experiences the same lag and jitter as seen in set-point control.

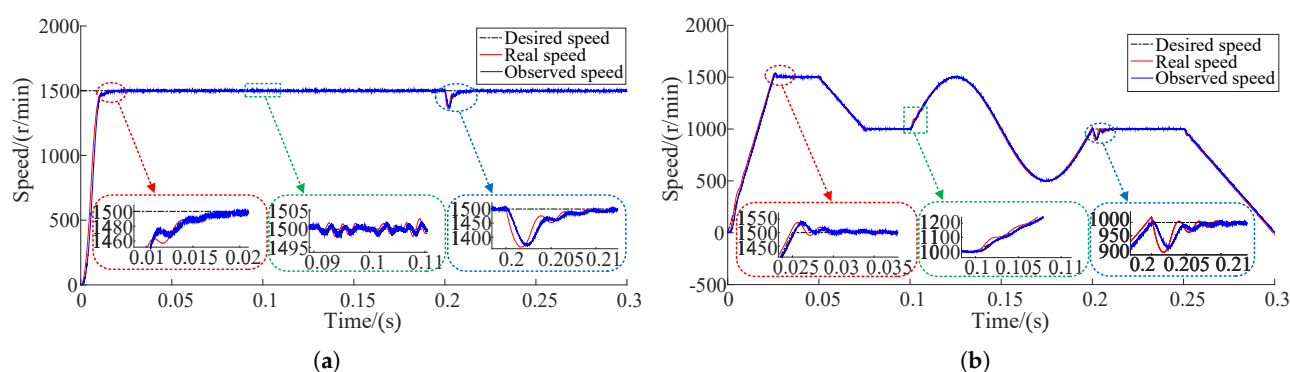


Figure 4. Observational results of PMSM rotor speed. (a) Speed observation curve (set-point). (b) Speed observation curve (servo).

Overall, the sliding mode observer has good observation capabilities and can quickly estimate the rotor position and speed.

6.2. Controller Parameter Adjustment.

Upon verifying the observation effects of the observer, we enhance the control capability of the controller based on the analysis conducted by the observer. As previously mentioned, the control component can be categorized into two modules: BPNN and ISMC.

Based on the system simulation time and the designated operating cycle of the neural network, the number of speed value updates can be determined. In this study, the operating cycle of the BPNN is established at 1 microsecond, resulting in a total of 300,000 updates. As illustrated in Figure 5, the training performance of the BPNN is depicted by the linear relationship between the desired value of servo control and the output value. It is evident that the fitted curve closely aligns with the desired curve, and the linear correlation coefficient R (Pearson correlation coefficient) approaches 1, indicating a robust linear positive correlation between the desired value and the system output value, signifying that the output value can effectively track the input signal.

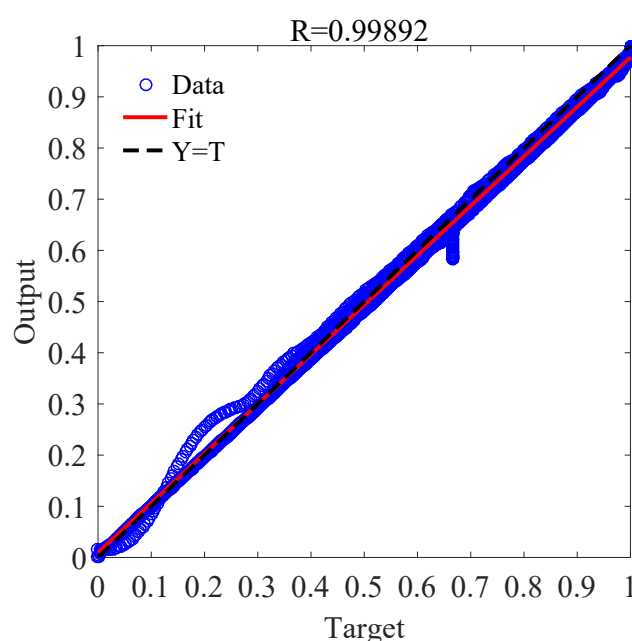


Figure 5. Training results of the BPNN based on servo control.

As illustrated in Figure 6, the output of the BPNN consists of six parameters for the controller, namely c , ϵ , β , ϕ , δ , and $i_{\max}$. The first five parameters pertain to the control law, while the sixth parameter serves as the current adjustment parameter. It is evident that when the PMSM control system initiates operation, the BPNN supplies an initial set of values to the controller. As the operational time progresses, the BPNN promptly adjusts the parameters to align with the current operating state, encompassing both the motor starting phase and the steady-state phase of set-point control. Depending on the smoothing time t_a established in the S-shaped speed smoothing curve, the motor starting phase is completed within 0 to t_a s. Upon the completion of the starting phase, the motor transitions into the steady operating phase, prompting corresponding changes in the six parameters. At 0.2 s, a sudden load disturbance is introduced, yet no significant fluctuations in the control parameters are observed, indicating that the controller exhibits strong robustness under parameter control during the steady operating phase. In the context of servo control, given that the expectation is a continuously varying time-dependent signal, the BPNN is capable of adjusting the controller parameters more rapidly during the starting phase.

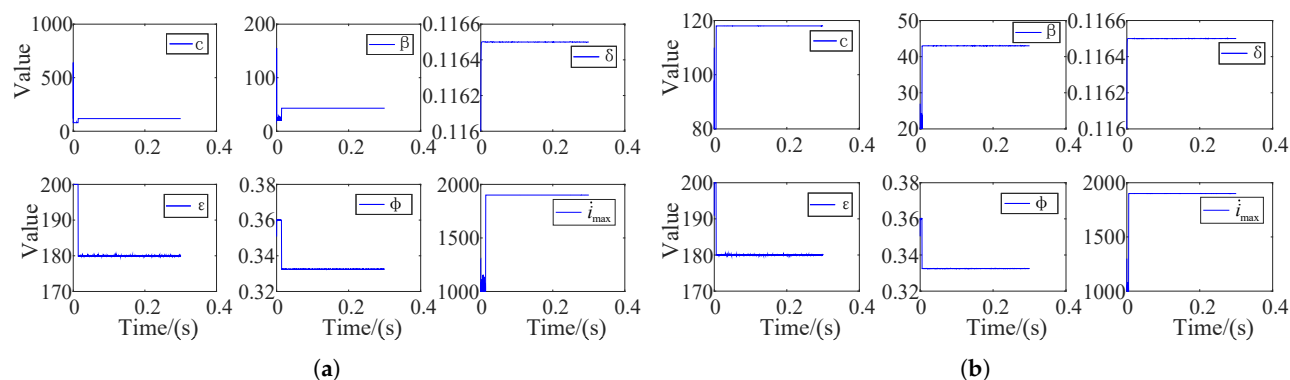


Figure 6. Variation curve of the BPNN output control parameters. (a) Variation curve of control parameters (set-point). (b) Variation curve of control parameters (servo).

6.3. Motor Output Analysis

Reasonable parameters enable the controller to generate optimal control signals, which prompt the motor to respond accordingly. The current, as a physical quantity regulated by the inner loop controller, responds first. As illustrated in Figure 7, during the set-point control, the three-phase stator current of the motor exhibits three distinct states, corresponding to the starting stage, steady stage, and load stage. In the starting stage, the stator current reaches a peak of approximately 17 A, subsequently decreasing around 0.01 s as it transitions into the steady stage. At 0.2 s, a sudden load disturbance is introduced, resulting in an increase in the three-phase stator current, which manifests a symmetric sine wave pattern, with a maximum amplitude of about 14.8 A. In servo control, at the moment of a sudden change in motor speed, the stator current experiences an overshoot, while in other stages, it aligns with the changes in the input signal. When tracking a ramp signal, the maximum value of the current stabilizes and varies based on the slope. When following a set-point signal, the current approaches 0 A. In the case of a sine signal, the magnitude of the current is dictated by the slope at the corresponding time points of the sine wave, demonstrating a pattern of initially decreasing and then increasing. At 0.2 s, when a sudden load disturbance is applied, the variation in current is influenced by both the magnitude of the load and the slope of the signal.

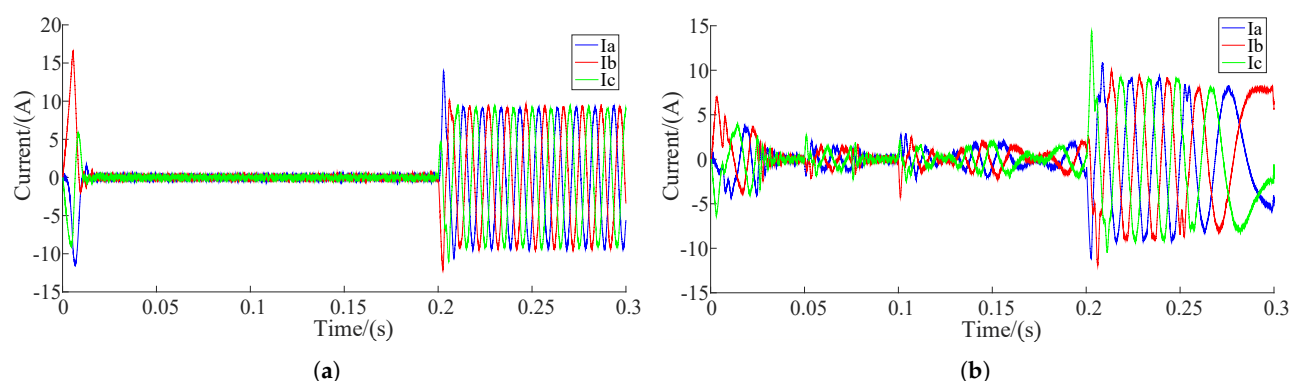


Figure 7. Three-phase stator current of PMSM under BPNN-ISM control. (a) Current variation (set-point). (b) Current variation (servo).

As shown in Figure 8, to highlight the advantages of BPNN-ISM, the three-phase stator currents in the ABC coordinate system are converted to the $d-q$ coordinate system for comparative analysis of ISMC, SMC, and ADRC. During the set-point control process in the startup phase, all four control methods exhibit current overshoot. Without restricting the current output range, the maximum startup current for SMC is approximately 49 A,

for ISMC approximately 22 A, for ADRC approximately 46 A, and for BPNN-ISMC, the current equals the maximum stator current, approximately 17 A. After the startup phase, the current approaches 0 A. At 0.2 s, a sudden load disturbance is applied, causing the current of BPNN-ISMC, ISMC, and ADRC to increase sharply and stabilize after 0.01 s, while the SMC current does not exhibit overshoot during this period. Since the load is the same, the steady-state values of the three methods remain consistent, at approximately 9.5 A. Generally, the direct starting current of a motor is 4 to 7 times the rated current. In this paper, a motor with a rated current of approximately 6 A is used, indicating that under BPNN-ISMC control, the starting current is maintained within three times the rated current, thereby achieving soft starting of the PMSM. In terms of servo control, the maximum starting current of BPNN-ISMC and ADRC is slightly lower than that of ISMC and SMC. In other stages, SMC exhibits the smallest current fluctuations. Considering the expected input, when the system transitions to low speed (approximately 0.29 s), SMC encounters difficulties in maintaining torque output to counteract the load torque.

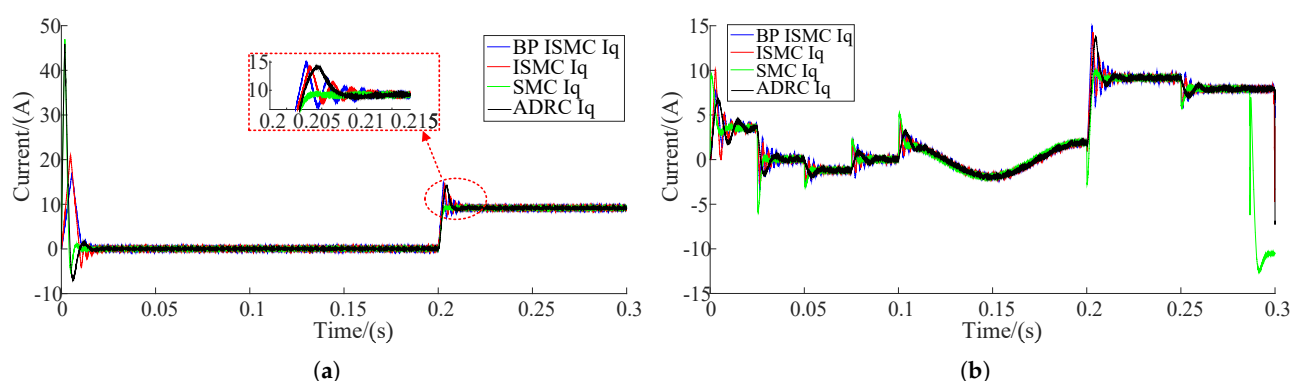


Figure 8. Current variation in d - q coordinate system under different control methods. (a) d - q axis current (set-point). (b) d - q axis current (servo).

In the context of motor inner ring control, the error of the physical quantity of current should approach zero throughout the control process. As shown in Figure 9, the current error exhibits different behaviors under the four control methods. It is worth noting that the errors of BPNN-ISMC, ISMC, and ADRC are generally smaller than those of SMC, especially during the start-up phase and in response to sudden changes in speed, where SMC exhibits significant error peaks.

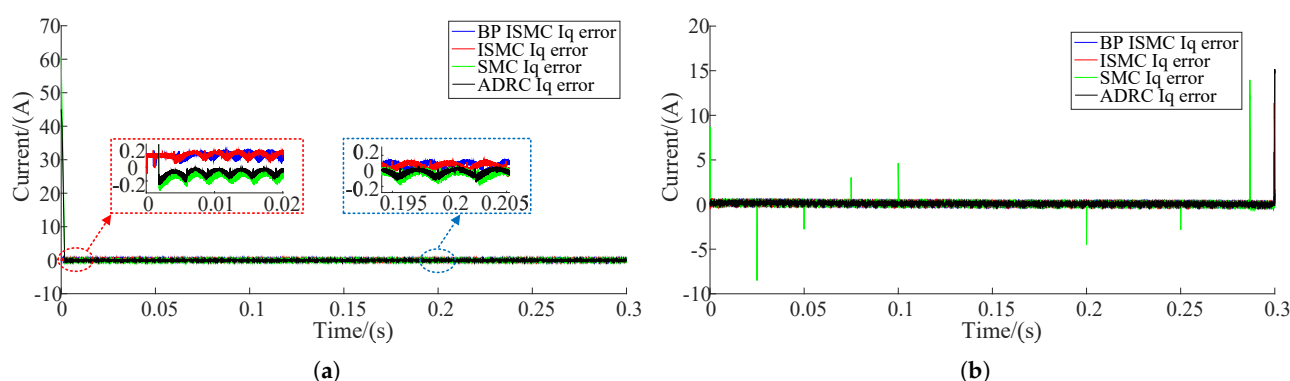


Figure 9. Current error dynamics in the d - q frame under different control strategies. (a) d - q axis current error (set-point). (b) d - q axis current error (servo).

As shown in Figure 10, there are significant differences in the speed control performance of the four methods. In the set-point control scenario, SMC and ADRC exhibit the fastest response speed during the motor startup phase, with peak values reaching

$$\begin{cases} \Delta E_1 = \frac{E_{ISM C} - E_{BPNN-ISM C}}{E_{ISM C}} \\ \Delta E_2 = \frac{E_{SM C} - E_{BPNN-ISM C}}{E_{SM C}} \\ \Delta E_3 = \frac{E_{ADRC} - E_{BPNN-ISM C}}{E_{ADRC}} \end{cases} \quad (52)$$

In the equation, ΔE_1 , ΔE_2 , and ΔE_3 represent the relative error improvement percentages of the BPNN-ISM C control method compared to the ISM C, SMC, and ADRC control methods, respectively; $E_{BPNN-ISM C}$, $E_{ISM C}$, $E_{SM C}$, and E_{ADRC} represent the relative errors of the four control methods, respectively.

In servo control, SMC-related errors are the most significant, with values fluctuating with changes in speed and load. In contrast, the errors of BPNN-ISM C, ISM C, and ADRC remain small, exhibiting sudden changes only when speed and load vary and quickly returning to 0 r/min after the change. Compared to ISM C and ADRC, BPNN-ISM C exhibits smaller amplitude changes during speed transitions, resulting in a more stable value closer to 0 r/min. Considering the characteristics of the input signal in servo control, the performance of the four methods is evaluated using the root mean square error. Using Equation (53), the root mean square errors for BPNN-ISM C, ISM C, SMC, and ADRC are calculated to be 18.16 r/min, 23.60 r/min, 176.17 r/min, and 28.89 r/min, respectively. Therefore, the RMS error of BPNN-ISM C is 18.83%, 89.70%, and 37.14% smaller than that of ISM C, SMC, and ADRC, respectively. This further demonstrates that ISM C and BPNN-ISM C possess enhanced interference resistance and tracking capabilities, with BPNN-ISM C exhibiting superior performance.

$$\begin{cases} \Delta R_1 = \frac{R_{ISM C} - R_{BPNN-ISM C}}{R_{ISM C}} \\ \Delta R_2 = \frac{R_{SM C} - R_{BPNN-ISM C}}{R_{SM C}} \\ \Delta R_3 = \frac{R_{ADRC} - R_{BPNN-ISM C}}{R_{ADRC}} \end{cases} \quad (53)$$

In the equation, ΔR_1 , ΔR_2 , and ΔR_3 represent the root mean square error improvement percentages of the BPNN-ISM C control method compared to the ISM C, SMC, and ADRC control methods, respectively; $R_{BPNN-ISM C}$, $R_{ISM C}$, $R_{SM C}$, and R_{ADRC} represent the relative errors of the four control methods, respectively.

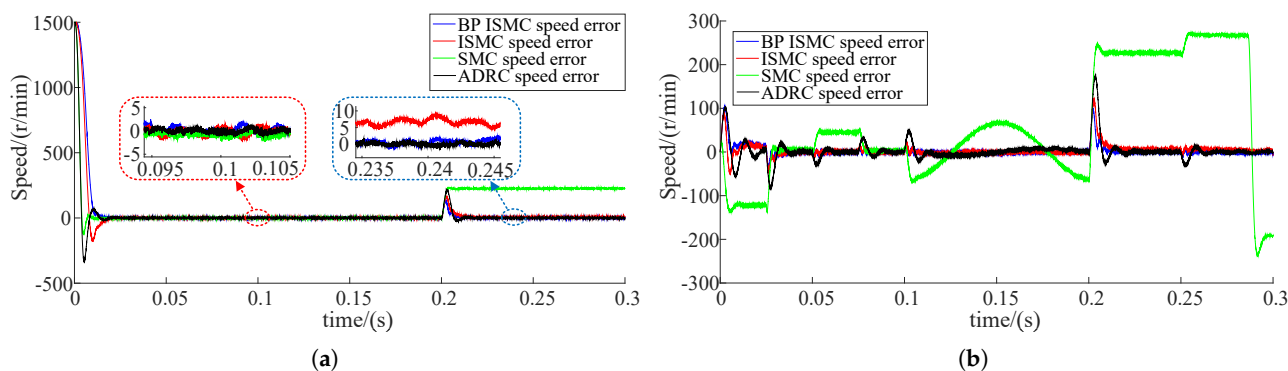


Figure 11. Comparative speed tracking error analysis under different control strategies. (a) Speed tracking error (set-point). (b) Speed tracking error (servo).

7. Conclusions

This article discusses the necessity of a load observer in SMC for effectively mitigating load disturbances. By enhancing the approaching rate of the sliding mode controller and integrating it with a BPNN, a control method that utilizes BPNN to adjust the improved sliding mode controller is developed. The validity and advantages of the proposed method

are demonstrated through comparisons with the vector control method, utilizing $I_d = 0$, and the sensorless sliding mode observation technique.

The SMC method proposed in this paper, based on BPNN adaptive tuning, demonstrates excellent dynamic performance and robustness in the field of motor control. With a calculation cycle of microseconds, the system can efficiently suppress most operational disturbances as long as the disturbance frequency does not exceed the BPNN bandwidth. Although in ultra-high-frequency interference scenarios, due to the sampling frequency limitations of neural networks and controllers, the system performance lags behind traditional load observers, in typical application scenarios, this method can fully replace traditional observer schemes. It ensures control accuracy and dynamic response while significantly simplifying system hardware design complexity, demonstrating excellent engineering application value.

In the future, this method can be further optimized to improve control performance, such as by enhancing the adaptability of the controller and expanding the linear range of the SMC law, thereby significantly suppressing oscillation phenomena. Additionally, the proposed method is implemented through optimized network structure and efficient matrix operations, achieving microsecond-level computation cycles on mainstream embedded controllers such as the STM32. The simple BPNN network structure has minimal forward propagation and parameter update times, consuming only a small amount of CPU resources, fully meeting real-time control requirements. This lightweight design retains the adaptive advantages of neural networks while overcoming the computational bottlenecks of traditional deep networks on embedded platforms.

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