

# Fixed-Time Integral Sliding Mode Control Integrating RBF Network and Super-Twisting ESO for SPMSM

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## Research Article

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# Fixed-Time Integral Sliding Mode Control Integrating RBF Network and Super-Twisting ESO for SPMSM

## Abstract

This paper addresses the speed regulation performance degradation in surface-mounted permanent magnet synchronous motor (SPMSM) drive systems caused by model uncertainties, parameter perturbations, and external load disturbances. To enhance both dynamic response and robustness, this paper propose a composite control strategy integrating a radial basis function (RBF) neural network, a fixed-time integral terminal sliding mode controller (FITSMC), and a super-twisting extended state observer (STESO). The FITSMC guarantees fixed-time error convergence with a bounded settling time independent of initial states, while the integral action eliminates steady-state errors. The RBF network online approximates internal parameter variations and unmodeled dynamics, whereas the STESO estimates external load disturbances for feedforward compensation. This coordinated disturbance rejection mechanism reduces the required switching gain, effectively suppressing sliding mode chattering without sacrificing robustness. Rigorous Lyapunov analysis establishes the fixed-time stability of the closed-loop system. Comparative simulations under no-load startup, sudden load change, and full-load operation demonstrate that the proposed RBF-FITSMC-STESO achieves faster convergence, smaller speed drops, and lower steady-state fluctuations than conventional PI control, standard sliding mode control, and FITSMC-STESO without RBF adaptation, confirming its effectiveness for high-performance SPMSM speed regulation.

**Keywords:** Permanent magnet synchronous motor, radial basis function neural network, fixed-time integral terminal sliding mode control, super-twisting extended state Observer, sliding mode chattering.

## 1 Introduction

surface-mounted Permanent magnet synchronous motors (SPMSMs) have become key components in a wide range of industrial and automation applications due to their high power density, high efficiency, and high reliability, demonstrating significant application value in fields such as industrial control, wind power generation systems, and new energy vehicles [1–3]. Currently, vector control is the mainstream approach, encompassing various strategies such as proportional-integral (PI) control

047 and direct torque control [4, 5]. However, conventional linear control techniques, such  
048 as PI controllers, exhibit limitations when facing challenges including system model  
049 uncertainties, external load torque disturbances, and nonlinear characteristics, mak-  
050 ing it difficult to meet the high standards of positioning accuracy and speed regulation  
051 performance required in practical applications [6].

052 Therefore, to enhance the robustness of control systems, researchers have intro-  
053 duced methods such as sliding mode control (SMC) [7, 8] and neural network-based  
054 control [9] as effective solutions to improve control accuracy and stability under uncer-  
055 tain disturbance conditions. Although sliding mode variable structure control possesses  
056 several technical advantages, it suffers from relatively slow response during the initial  
057 startup phase and is accompanied by pronounced chattering, which limits its applica-  
058 bility in high-precision, low-loss scenarios. In [10], a disturbance observer-based sliding  
059 mode control strategy for position tracking of PMSMs is proposed. By employing a  
060 disturbance observer to detect and compensate for external load disturbances and  
061 parameter perturbations in real time, combined with the strong robustness of SMC,  
062 the strategy effectively improves position tracking accuracy and stability, addressing  
063 the problem of performance degradation due to disturbances in conventional SMC.  
064 However, this strategy does not further optimize the response speed or dynamic char-  
065 acteristics during the startup phase. In [11], an intelligent control scheme for PMSMs  
066 integrating SMC with traditional PID control is presented, and a comparative sim-  
067 ulation study of the two control strategies is conducted for an edge-of-things (EoT)  
068 computing scenario. The simulation results verify the application value of SMC in  
069 terms of disturbance rejection and dynamic response compared with PID control in  
070 intelligent PMSM control systems. In [12], a low-speed operation control scheme for  
071 PMSMs based on improved nonsingular fast terminal sliding mode control is pro-  
072 posed. By optimizing the conventional nonsingular fast terminal sliding surface, the  
073 convergence characteristics are enhanced, effectively alleviating the issues of large  
074 speed pulsations and low control accuracy at low speeds while improving stability.  
075 Nevertheless, the robustness and adaptability of this strategy under complex operat-  
076 ing conditions such as heavy loads and multi-condition switching are not considered.  
077 In [13], a sliding mode controller design method incorporating the Harris hawks opti-  
078 mization (HHO) algorithm for PMSM speed regulation systems in electric vehicles  
079 is presented. By leveraging the global optimization capability of the HHO algorithm,  
080 the key parameters of the sliding mode controller are adaptively tuned, effectively  
081 improving speed regulation accuracy and load disturbance rejection capability and  
082 resolving the problems of empirical parameter tuning and suboptimal optimization in  
083 conventional SMC. However, the high computational complexity of the optimization  
084 algorithm requires further validation of its real-time performance in actual electric  
085 vehicle driving scenarios. In [14], a sensorless control method for PMSMs combin-  
086 ing an improved sliding mode observer with a phase-locked loop (PLL) is introduced.  
087 By modifying the reaching law and observation model of the sliding mode observer,  
088 chattering and estimation errors in rotor position observation are reduced. Together  
089 with the phase-tracking characteristics of the PLL, the observation accuracy of the  
090 rotor position and speed under sensorless control is further enhanced, solving the low-  
091 accuracy problem at low speeds. In [15], a multi-objective optimized computational  
092

neural network control strategy is presented. A multi-objective optimization algorithm is used to optimize the weights and thresholds of the neural network, improving its fitting accuracy and control performance. Applied to a non-sinusoidal PMSM drive system, the strategy effectively mitigates torque ripple and speed stability issues, providing a new algorithmic approach for intelligent PMSM control. However, it does not integrate studies on chattering in traditional SMC or achieve complementary advantages between the two strategies. In [16], a hybrid compensation strategy combining parallel adaptive RBF neural network with active disturbance rejection control (ADRC) is designed. Using a parallel structure, the RBF neural network and extended state observer estimate and compensate for disturbances, and the adaptive update law is optimized. When applied to a PMSM control system, the strategy significantly enhances disturbance rejection capability and position tracking accuracy, offering a new solution for high-precision robust control.

Although existing studies have achieved notable progress in improving the steady-state performance of PMSM systems by optimizing sliding surfaces or introducing adaptive mechanisms, most methods struggle to simultaneously achieve comprehensive optimization of system adaptability and chattering suppression [17, 18]. Furthermore, existing observers are mostly limited to estimating a single state variable, making it difficult to provide accurate disturbance estimation and compensation for the system under complex operating conditions [19, 20].

To address these issues, this paper proposes a composite control strategy that integrates a radial basis function (RBF) neural network, fixed-time integral terminal sliding mode control (FITSMC), and a super-twisting extended state observer (STESO), denoted as RBF-FITSMC-STESO. Specifically, FITSMC is introduced into the speed loop to accelerate system convergence. An RBF neural network is employed to adaptively adjust the control gain online, enhancing the system's robustness against parameter perturbations and complex operating environments. Furthermore, an STESO capable of simultaneously estimating the speed and the total disturbance is designed, and the estimated disturbance is feedforward compensated to the FITSMC controller, thereby further accelerating the convergence speed and effectively suppressing sliding mode chattering. Finally, the superiority of the proposed strategy is verified through comparative simulations with five control methods, namely PI, SMC, FITSMC, and FITSMC-STESO.

The paper is outlined as follows. Section 2 gives the PMSM mathematical model. Section 3 proposes the composite controller with RBF neural network, fixed-time integral sliding mode, and STESO, along with Lyapunov stability analysis. Section 4 presents simulation results and comparisons under various load conditions. Section 5 concludes the paper.

## 2 Mathematical Model of Permanent Magnet Synchronous Motor

Schematic diagram of dq-axis winding structure of surface-mounted permanent magnet synchronous motor (SPMSM) in Figure 1. Without considering hysteresis losses, eddy currents, and core saturation effects of SPMSM, the mathematical model

of the PMSM in the d-q rotating coordinate system corresponding to this figure is given as follows [21].

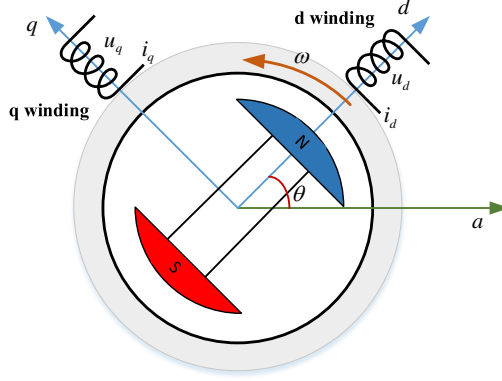


**Fig. 1** Schematic Diagram of dq-axis Winding Structure of PMSM.

Voltage equations:

$$\begin{bmatrix} u_d \\ u_q \end{bmatrix} = \begin{bmatrix} R & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix} + \frac{d}{dt} \begin{bmatrix} \psi_d \\ \psi_q \end{bmatrix} + \omega_e \begin{bmatrix} -\psi_q \\ \psi_d \end{bmatrix} \quad (1)$$

where  $u_d$ ,  $u_q$  and  $i_d$ ,  $i_q$  are the  $d$ - and  $q$ -axis voltages and currents, respectively;  $R$  is the stator resistance;  $\omega_e$  is the electrical angular velocity; and  $\psi_d$ ,  $\psi_q$  are the  $d$ - and  $q$ -axis permanent magnet flux linkages.

Flux linkage equations:

$$\begin{bmatrix} \psi_d \\ \psi_q \end{bmatrix} = \begin{bmatrix} L_d & 0 \\ 0 & L_q \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix} + \begin{bmatrix} \psi_f \\ 0 \end{bmatrix} \quad (2)$$

where  $L_d$  and  $L_q$  are the  $d$ - and  $q$ -axis stator inductances, and  $\psi_f$  is the rotor flux linkage on the  $d$ -axis.

From eqs. (1) and (2), the electromagnetic torque equation of the three-phase permanent magnet synchronous motor can be expressed as:

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

where  $T_e$  is the electromagnetic torque, and  $P_n$  is the number of pole pairs.

Adopting the  $i_d = 0$  vector control strategy, which sets the stator excitation current to zero and satisfies  $L_d = L_q$ , eq. (3) can be simplified as:

$$T_e = \frac{3}{2} P_n \psi_f i_q \quad (4)$$

The electromagnetic torque must satisfy the following motion equation:

$$T_e - T_L = J \frac{d\omega}{dt} + B\omega \quad (5)$$

From eqs. (4) and (5), we obtain:

$$\frac{d\omega}{dt} = \frac{3P_n\psi_f}{2J}i_q - \frac{B\omega}{J} - \frac{T_L}{J} \quad (6)$$

### 3 Design of Sliding Mode Controller and Disturbance Observer

In this section, an RBF-FITSMC-STESO method is designed for the speed loop of the PMSM to enhance speed regulation performance. First, a fixed-time integral terminal sliding mode controller (FITSMC) is developed for the PMSM speed loop, and a radial basis function (RBF) neural network is introduced for feedforward compensation, which improves the convergence speed and robustness of the system. The fixed-time convergence characteristics of the RBF-FITSMC are also analyzed. Then, a super-twisting extended state observer (STESO) is designed as a disturbance observation and compensation unit to estimate and suppress the total disturbance in the PMSM system, thereby further enhancing the robustness of the RBF-FITSMC and effectively suppressing sliding mode chattering. Meanwhile, the stability of the RBF-FITSMC-STESO method is analyzed using the Lyapunov approach [22]. Finally, the implementation flowchart of the proposed method and the control block diagram of the RBF-FITSMC-STESO method applied to the speed loop of the permanent magnet synchronous motor are presented.

#### 3.1 Radial Basis Function Neural Network Algorithm

The RBF neural network is a three-layer feedforward network with a single hidden layer. The hidden layer employs the radial basis Gaussian function as the activation function to achieve a nonlinear mapping from the input space to the hidden-layer space, while the mapping from the hidden layer to the output space is linear [23]. This design significantly accelerates the learning speed and avoids the problem of local minima.

In the structure of the RBF neural network,  $X = [x_1, x_2, \dots, x_n]^T$  is the input vector of the network, and  $n$  denotes the number of nodes in the input layer. Let the radial basis vector of the hidden-layer nodes be  $H = [h_1, h_2, \dots, h_j, \dots, h_m]^T$ , where  $h_j$  is the Gaussian basis function:

$$h_j = \exp\left(-\frac{\|X - C_j\|^2}{2b_j^2}\right), \quad j = 1, 2, \dots, m \quad (7)$$

In this hidden layer, the center vector of the Gaussian basis function for the  $j$ -th node is  $C_j = [c_{j1}, c_{j2}, \dots, c_{ji}, \dots, c_{jm}]^T$ ,  $i = 1, 2, \dots, n$ .  $C_j$  has the same dimension as  $X$  and largely determines the network performance. Let the basis width vector of the hidden-layer nodes be  $B = [b_1, b_2, \dots, b_j, \dots, b_m]^T$ .

Here,  $b_j$  is the radius of the Gaussian basis function for node  $j$ , whose value determines the complexity of the network and can be selected appropriately through experimental and error information.  $\|\cdot\|$  denotes the vector norm, which is typically the Euclidean norm.

The weight vector from the hidden layer to the output layer is  $W = [w_1, w_2, \dots, w_j, \dots, w_m]^T$ . The output function of the network is:

$$\hat{d}_{\text{ref}} = y_m(k) = W^T H(X) = \sum_{j=1}^m w_j h_j(X) = \sum_{j=1}^m w_j \exp\left(-\frac{\|X - C_j\|^2}{2b_j^2}\right) \quad (8)$$

According to the adaptive update rule of the RBF neural network weights, the gradient descent method is employed for derivation. Define the weight error as  $\tilde{W} = W - W^*$ , and take the sliding mode surface  $S$  as the error-driven signal to construct the cost function:

$$E = \frac{1}{2} s^2 \quad (9)$$

Based on the gradient descent principle, the weights are updated along the negative gradient direction of the cost function:

$$\dot{\tilde{W}} = -\rho \frac{\partial E}{\partial W} \quad (10)$$

Taking the derivative of the cost function yields  $\partial E / \partial W = S \cdot \partial S / \partial W = -sH(X)$ . Substituting this into the weight update equation, the adaptive law for the weights is finally derived as:

$$\dot{\tilde{W}} = \rho s H(X) \quad (11)$$

where  $\rho > 0$  is the adaptive gain, and  $s$  is the sliding mode surface defined in the following subsection.

### 3.2 Fixed-Time Integral Terminal Sliding Mode Controller

Fixed-time integral terminal sliding mode control (FITSMC) is a sliding mode control strategy that balances fast convergence and steady-state accuracy. By designing a sliding mode surface that includes an integral term and a terminal power term, the system states converge to the equilibrium point within a fixed time, and the upper bound of the convergence time is independent of the initial conditions. The adopted fixed-time reaching law further accelerates the system's approach to the sliding mode surface while effectively suppressing the chattering phenomenon inherent in conventional sliding mode control [24, 25].

The fixed-time integral terminal sliding mode surface can be designed as:

$$s = e + k_1 \int_0^t \varphi_1(e) d\tau \quad (12)$$

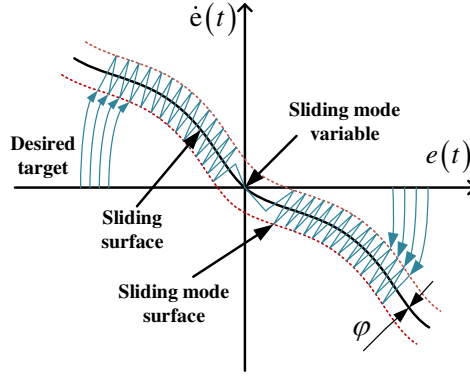


**Fig. 2** Schematic diagram of the FITSMC sliding mode surface.

$$\varphi_1(e) = \begin{cases} \text{sgn}^{\alpha_1}(e), & |e| \leq 1 \\ \text{sgn}^{\beta_1}(e), & |e| > 1 \end{cases} \quad (13)$$

where  $k_1 > 0$  is the integral gain, and  $0 < \alpha_1 < 1$  and  $\beta_1 > 1$  are the power exponents, satisfying  $\text{sgn}^\gamma(e) = |e|^\gamma \text{sgn}(e)$ . The schematic diagram of the fixed-time integral terminal sliding mode surface is shown in Figure 2.

Meanwhile, the fixed-time convergence reaching law is given as:

$$\dot{s} = -k_2\varphi_2(s) - \eta \text{sgn}(s) \quad (14)$$

$$\varphi_2(s) = \begin{cases} \text{sgn}^{\alpha_2}(s), & |s| \leq 1 \\ \text{sgn}^{\beta_2}(s), & |s| > 1 \end{cases} \quad (15)$$

where  $k_2 > 0$  is the reaching law gain,  $0 < \alpha_2 < 1$  and  $\beta_2 > 1$  are the power exponents, and  $\eta > D$  is the switching gain.

By differentiating both sides of the sliding mode surface eq. (10), we obtain:

$$\dot{s} = \dot{e} + k_1\varphi_1(e) = \dot{\omega}_m^{\text{ref}} - \frac{K_{t0}}{J_0}i_q + \frac{B_0}{J_0}\omega_m + d + k_1\varphi_1(e) \quad (16)$$

Substituting the reaching law eq. (14) into eq. (16), the control law can be constructed as:

$$i_q^{\text{ref}} = \frac{J_0}{K_{t0}} \left[ \dot{\omega}_m^{\text{ref}} + \frac{B_0}{J_0}\omega_m + k_1\varphi_1(e) + k_2\varphi_2(s) + \eta \text{sgn}(s) \right] \quad (17)$$

Considering the dynamic equation of the PMSM speed loop in (6). Under the action of the control law (17), if the total system disturbance is neglected (i.e.,  $d(t) = 0$ ), then the speed tracking error will converge to zero within a fixed time, and the upper bound of the convergence time is completely determined by the controller parameters, independent of the initial system states.

To prove the fixed-time stability of the closed-loop system, the convergence characteristic of the sliding mode surface  $s$  is first analyzed. The following positive definite Lyapunov function is selected:

$$V = \frac{1}{2}s^2 \quad (18)$$

Differentiating both sides of eq. (18) with respect to time and substituting the sliding mode surface dynamics  $\dot{s}$  yields:

$$\dot{V} = s(-\eta_1|s|^{\alpha_2} \text{sgn}(s) - \eta_2|s|^{\beta_2} \text{sgn}(s)) = -\eta_1|s|^{\alpha_2+1} - \eta_2|s|^{\beta_2+1} \quad (19)$$

Eq. (19) utilizes the property  $s \cdot \text{sgn}(s) = |s|$ . Since  $\eta_1, \eta_2 > 0$ , we have  $\dot{V} \leq 0$ , and the system is Lyapunov stable.

To express  $\dot{V}$  as a function of  $V$ , substituting  $|s| = \sqrt{2V}$  into eq. (19) yields:

$$\dot{V} = -\eta_1(2V)^{\frac{\alpha_2+1}{2}} - \eta_2(2V)^{\frac{\beta_2+1}{2}} \quad (20)$$

The exponents in eq. (20) satisfy  $0 < \frac{\alpha_2+1}{2} < 1$  (since  $0 < \alpha_2 < 1$ ) and  $\frac{\beta_2+1}{2} > 1$  (since  $\beta_2 > 1$ ). Therefore, eq. (20) exhibits the typical form of fixed-time convergence, ensuring that the convergence time is bounded and independent of the initial conditions.

According to the fixed-time stability theory (Polyakov, 2011) [26], for a system described by  $\dot{V} = -aV^{\gamma_1} - bV^{\gamma_2}$  with  $a, b > 0$ ,  $0 < \gamma_1 < 1$ , and  $\gamma_2 > 1$ , the upper bound of the convergence time is given by  $T \leq \frac{1}{a(1-\gamma_1)} + \frac{1}{b(\gamma_2-1)}$ . Consequently, the time  $T_s$  for the sliding mode surface  $s$  to converge to zero from any initial state satisfies:

$$T_s \leq \frac{1}{\eta_1(1-\alpha_2)} + \frac{1}{\eta_2(\beta_2-1)} \quad (21)$$

This upper bound is independent of the initial value  $V(0)$ , thereby proving the fixed-time convergence of the sliding mode surface.

After the sliding mode surface reaches  $s = 0$ , the system enters the sliding mode. At this stage, the differential equation of the tracking error can be obtained from the sliding mode surface equation. Differentiating both sides of the equation and setting  $s = 0$  yields:

$$\dot{e} = -k_1|e|^{\alpha_1} \text{sgn}(e) - k_2|e|^{\beta_1} \text{sgn}(e) \quad (22)$$

To analyze the convergence rate of the error  $e$ , a second Lyapunov function  $W = \frac{1}{2}e^2$  is introduced. Differentiating it and substituting into eq. (22) gives:

$$\dot{W} = e(-k_1|e|^{\alpha_1} \text{sgn}(e) - k_2|e|^{\beta_1} \text{sgn}(e)) = -k_1|e|^{\alpha_1+1} - k_2|e|^{\beta_1+1} \quad (23)$$

Substituting  $|e| = \sqrt{2W}$  into eq. (23) yields:

$$\dot{W} = -k_1(2W)^{\frac{\alpha_1+1}{2}} - k_2(2W)^{\frac{\beta_1+1}{2}} \quad (24)$$

The exponents in eq. (24) satisfy  $\frac{1}{2} < \frac{\alpha_1+1}{2} < 1$  (since  $0 < \alpha_1 < 1$ ) and  $\frac{\beta_1+1}{2} > 1$  (since  $\beta_1 > 1$ ). Therefore, eq. (24) also exhibits the typical form of fixed-time convergence.

Similarly, the time  $T_e$  for the error  $e$  to converge to zero satisfies:

$$T_e \leq \frac{1}{k_1(1-\alpha_1)} + \frac{1}{k_2(\beta_1-1)} \quad (25)$$

Summing the convergence time of the sliding mode surface and the convergence time of the error yields the total convergence time of the system from any initial state to steady state:

$$T_{\text{total}} = T_s + T_e \leq \frac{1}{\eta_1(1-\alpha_2)} + \frac{1}{\eta_2(\beta_2-1)} + \frac{1}{k_1(1-\alpha_1)} + \frac{1}{k_2(\beta_1-1)} \quad (26)$$

Since all terms are determined solely by the controller parameters  $\eta_1, \eta_2, \alpha_2, \beta_2, k_1, k_2, \alpha_1, \beta_1$  and are independent of the initial system states, the closed-loop system satisfies fixed-time stability.

### 3.3 Super-Twisting Extended State Observer

The super-twisting extended state observer (STESO) is a disturbance observation and compensation unit based on the super-twisting algorithm. By treating the total system disturbance as an extended state variable, an extended state equation is constructed that simultaneously observes both the speed and the disturbance, enabling synchronous and accurate estimation of the motor speed and unknown disturbances [27].

The speed loop dynamic equation from eq. (6) is given as:

$$J\dot{\omega} = \frac{3}{2}p\psi_f i_q - T_L - B\omega + d(t) \quad (27)$$

where  $d(t)$  is the total system disturbance. The total disturbance is treated as an extended state variable. The system states are defined as:

$$x_1 = \omega, \quad x_2 = d(t) \quad (28)$$

The extended state equation is given as:

$$\begin{cases} \dot{x}_1 = \frac{K_{t0}}{J_0} i_q - \frac{B_0}{J_0} \omega_m - x_2 \\ \dot{x}_2 = \dot{d}(t) \end{cases} \quad (29)$$

where  $h(t) = \dot{d}(t)$  is the unknown but bounded derivative of the disturbance, satisfying the boundedness condition  $|h(t)| \leq H$ , with  $H > 0$  being a positive constant.

$$\begin{cases} \dot{\hat{x}}_1 = \frac{K_{t0}}{J_0} i_q - \frac{B_0}{J_0} \omega_m - \hat{x}_2 + \lambda_1 |e|^{1/2} \text{sgn}(e) \\ \dot{\hat{x}}_2 = \lambda_2 \text{sgn}(e) \end{cases} \quad (30)$$

where  $\hat{e} = \hat{x}_1 - x_1$ ,  $\hat{x}_1$  is the estimated value of the speed  $\omega$ , and  $\hat{x}_2$  is the estimated value of the total disturbance  $d(t)$ . Here,  $\lambda_1$  and  $\lambda_2$  are the observer gains, satisfying

$$\lambda_1 > 2\sqrt{H} \text{ and } \lambda_2 > \frac{\lambda_1^2 H}{\lambda_1^2 - 4H} \quad [28].$$

The observer outputs the estimated disturbance:

$$\hat{d}_{\text{eso}} = \hat{x}_2 \quad (31)$$

Feedforward compensating  $\hat{d}_{\text{eso}}$  to the fixed-time integral terminal sliding mode speed controller can quickly counteract the influence of disturbances, thereby enhancing system robustness.

### 3.4 Stability Analysis

The stability of the RBF-FITSMC-STESO control strategy is rigorously proved using Lyapunov theory. A composite Lyapunov function incorporating the weight error of the RBF neural network and the sliding mode surface variable is constructed. By combining the approximation capability of the RBF neural network, the fixed-time convergence characteristic of FITSMC, and the finite-time observation characteristic of STESO, the derivative of the Lyapunov function is shown to be always less than or equal to zero after differentiation [29].

Introducing the reaching law of FITSMC from eq. (15) into the RBF disturbance estimation from eq. (8) and the STESO disturbance estimation from eq. (30) for composite compensation, the overall control law is designed with the overall reaching law constructed as:

$$i_q^{\text{ref}} = \frac{J_0}{K_t} \left[ \dot{\omega}_m^* + \frac{B_0}{J_0} \omega_m + k_1 \phi_1(e) + k_2 \phi_2(s) + \eta \text{sgn}(s) - \hat{d}_{\text{ref}} - \hat{d}_{\text{eso}} \right] \quad (32)$$

By setting  $d_{\text{total}} = d_{\text{rbf}} + d_{\text{eso}}$  from equation (30), we obtain:

$$i_q^{\text{ref}} = \frac{J_0}{K_{t0}} \left[ \dot{\omega}_m^* + \frac{B_0}{J_0} \omega_m + k_1 \varphi_1(e) + k_2 \varphi_2(s) + \eta \text{sgn}(s) - \hat{d}_{\text{total}} \right] \quad (33)$$

The sliding mode surface  $s$  will converge to zero within a fixed time, and consequently the system tracking error  $e$  will also converge to zero within a fixed time, with the upper bound of the convergence time being independent of the initial system states.

A Lyapunov function candidate is constructed as:

$$V = \frac{1}{2} s^2 + \frac{1}{2\rho} \tilde{W}^T \tilde{W} + \frac{1}{2} \tilde{x}_1^2 + \frac{1}{2} \tilde{x}_2^2 \quad (34)$$

where  $\tilde{W} = W^* - W$  is the RBF weight error ( $W^*$  denotes the ideal weight).

Combining eqs. (14) and (32) yields:

$$\dot{s} = -k_2 \varphi_2(s) - \eta \text{sgn}(s) + \left( d - \hat{d}_{\text{rbf}} - \hat{d}_{\text{eso}} \right) \quad (35)$$

According to the RBF approximation theory, we have:

$$d = W^{*T} \mathbf{H}(X) + \varepsilon, \quad |\varepsilon| \leq \varepsilon^* \quad (36)$$

where  $\varepsilon$  is the approximation error, and  $\varepsilon^* > 0$  is the upper bound of  $\varepsilon$ .

By combining eqs. (34) and (35) into eq. (33), we obtain:

$$\dot{V} = s \left[ -k_2 \varphi_2(s) - \eta \operatorname{sgn}(s) + \tilde{W}^T \mathbf{H}(X) + \varepsilon - \tilde{x}_2 \right] - \frac{1}{\rho} \tilde{W}^T \dot{W} + \tilde{x}_1 \dot{\tilde{x}}_1 + \tilde{x}_2 \dot{\tilde{x}}_2 \quad (37)$$

Combining eqs. (9), (27), and (28) yields:

$$\begin{cases} \dot{\tilde{x}}_1 = -\lambda_1 |\tilde{x}_1|^{1/2} \operatorname{sgn}(\tilde{x}_1) - \tilde{x}_2 \\ \dot{\tilde{x}}_2 = -\lambda_2 \operatorname{sgn}(\tilde{x}_1) + \dot{d}(t) \end{cases} \quad (38)$$

From eq. (35), we obtain:

$$\dot{V} = -k_2 s \varphi_2(s) - \eta |s| + \varepsilon s - s \tilde{x}_2 + \tilde{x}_1 \left( -\lambda_1 |\tilde{x}_1|^{1/2} \operatorname{sgn}(\tilde{x}_1) - \tilde{x}_2 \right) + \tilde{x}_2 \left( -\lambda_2 \operatorname{sgn}(\tilde{x}_1) + \dot{d}(t) \right) \quad (39)$$

Due to the finite-time convergence property of the observer, when  $t > T_0$ , we have  $\tilde{x}_1 = \tilde{x}_2 = 0$ . Consequently, eq. (39) reduces to:

$$\dot{V} = -k_2 s \varphi_2(s) - \eta |s| + \varepsilon s \quad (40)$$

According to the fixed-time stability theory (Polyakov, 2011) [29], the sliding mode surface  $s$  will converge to zero within a fixed time  $T_s$ :

$$T_s \leq \frac{1}{k_2} \left( \frac{1}{1 - \alpha_2} + \frac{1}{\beta_2 - 1} \right) \quad (41)$$

Similarly, the tracking error  $e$  will converge to zero within a fixed time  $T_e$ :

$$T_e \leq \frac{1}{k_1} \left( \frac{1}{1 - \alpha_1} + \frac{1}{\beta_1 - 1} \right) \quad (42)$$

Based on the above analysis, after the sliding mode surface converges to  $s = 0$ , the system error  $e$  will converge to zero within a fixed time. Therefore, the total convergence time of the system error  $e$  can be expressed as:

$$T_{\text{total}} = T_s + T_e \leq \frac{1}{k_2} \left( \frac{1}{1 - \alpha_2} + \frac{1}{\beta_2 - 1} \right) + \frac{1}{k_1} \left( \frac{1}{1 - \alpha_1} + \frac{1}{\beta_1 - 1} \right) \quad (43)$$

This upper bound depends only on the controller parameters and is independent of the initial system states, thereby guaranteeing fixed-time convergence of the system under arbitrary initial conditions.

## 4 Simulation and Experimental Results

To enhance the control accuracy and disturbance rejection capability of the permanent magnet synchronous motor (PMSM) speed regulation system, a composite control strategy integrating a radial basis function (RBF) neural network, fixed-time integral terminal sliding mode control (FITSMC), and a super-twisting extended state observer (STESO) is proposed. In this strategy, STESO is first employed to observe and compensate the total system disturbance in real time, effectively mitigating the



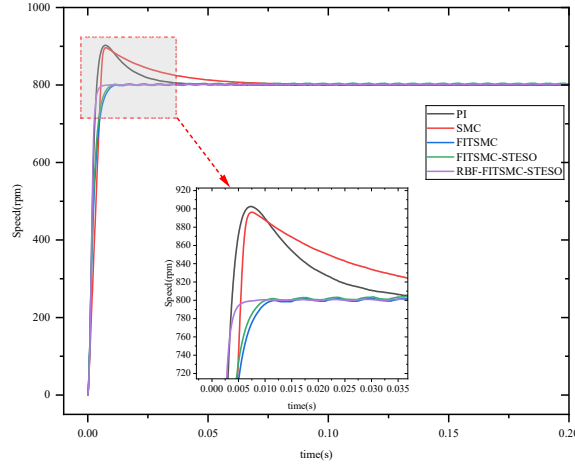


**Fig. 4** Speed response waveform of the PMSM under no-load conditions.

#### 4.1 Comparative Analysis of No-Load Startup Performance

Under no-load startup conditions, the reference speed is set to 800 r/min, and the simulation duration is 0.2 s. The performance comparison of the five control methods is shown in Figure 4. The RBF-FITSMC-STESO control method exhibits superior dynamic performance compared to PI, conventional SMC, FITSMC, and FITSMC-STESO: its speed rising edge is the steepest, allowing it to approach the reference speed in the shortest time with minimal overshoot—almost no noticeable overshoot—and the steady-state convergence process is smooth without oscillation. In contrast, PI control exhibits the largest overshoot and the slowest response speed. Conventional SMC also shows significant overshoot and oscillation. Although FITSMC and FITSMC-STESO achieve improved performance, they still fall short of RBF-FITSMC-STESO. This demonstrates that after introducing the improved RBF neural network with dual adaptive switching gains, the dynamic response and steady-state accuracy of the control method are significantly enhanced, effectively achieving the optimization objectives of fast response, low overshoot, and high stability under no-load startup conditions, thereby verifying the superiority of the proposed RBF-FITSMC-STESO control method.

As shown in Table 2, PI control exhibits the largest speed overshoot of 102.59 rpm, with a settling time of 0.0625 s. Conventional SMC control achieves an overshoot of 96.34 rpm but suffers from a prolonged settling time of 0.1065 s, indicating poor dynamic response performance. Both FITSMC and FITSMC-STESO achieve zero overshoot (0.00 rpm), with settling times significantly reduced to 0.0114 s and 0.0101 s, respectively, representing a substantial improvement over PI and SMC. The proposed RBF-FITSMC-STESO control also achieves zero overshoot (0.00 rpm) and attains

the fastest settling time among all control methods, requiring only 0.0084 s to reach steady state.

**Table 2** Performance comparison of the five control methods under no-load startup.

| Control Method   | Speed Overshoot (rpm) | Settling Time (s) |
|------------------|-----------------------|-------------------|
| PI               | 102.59                | 0.0625            |
| SMC              | 96.34                 | 0.0660            |
| FITSMC           | 0.00                  | 0.0114            |
| FITSMC-STESO     | 0.00                  | 0.0101            |
| RBF-FITSMC-STESO | 0.00                  | 0.0084            |

As shown in Figure 5, the probability density distribution curves of the steady-state speed of the PMSM under three control strategies are presented, with a target speed of 800 rpm. Significant differences in speed distribution characteristics are observed among the different control algorithms. The mean steady-state speeds of FITSMC, FITSMC-STESO, and RBF-FITSMC-STESO are 800.34 rpm, 800.29 rpm, and 800.02 rpm, respectively. Among these, the mean value of RBF-FITSMC-STESO is the closest to the target speed, demonstrating the highest control accuracy. In terms of speed fluctuation characteristics, the standard deviations of speed for the three methods are 0.80901 rpm, 0.90921 rpm, and 0.38878 rpm, respectively. The widths of the corresponding probability density curves intuitively reflect the level of chattering. The curve of FITSMC-STESO exhibits the widest distribution, indicating larger speed fluctuations and poor chattering suppression. Conventional FITSMC ranks second in this regard. In contrast, the curve of RBF-FITSMC-STESO is the narrowest with the highest peak, indicating that the speed is concentrated around the target value and that chattering is significantly suppressed. The comparative results demonstrate that optimizing FITSMC-STESO with the RBF neural network not only effectively improves speed control accuracy but also greatly reduces steady-state chattering, thereby verifying the superiority of the proposed method in PMSM speed control.

## 4.2 Comparative Analysis of Performance Under Load Conditions

To verify the disturbance rejection capability of the proposed control method under actual operating conditions, a step load torque is applied to evaluate its anti-disturbance performance. The performance comparison is shown in Figure 6, and the specific parameter values are listed in Table 3. The reference speed is set to 800 rpm, and a load torque of 12 N·m is applied at  $t = 0.1$  s.

From the speed response curves shown in Figure 6, it can be observed that under the operating condition with a reference speed of 800 rpm, when the system experiences both load increase and load decrease disturbances, the RBF-FITSMC-STESO control strategy exhibits the best dynamic performance and disturbance rejection capability. At the instant of disturbance application, it achieves the smallest speed fluctuation and recovers to the reference speed with the fastest convergence rate, while

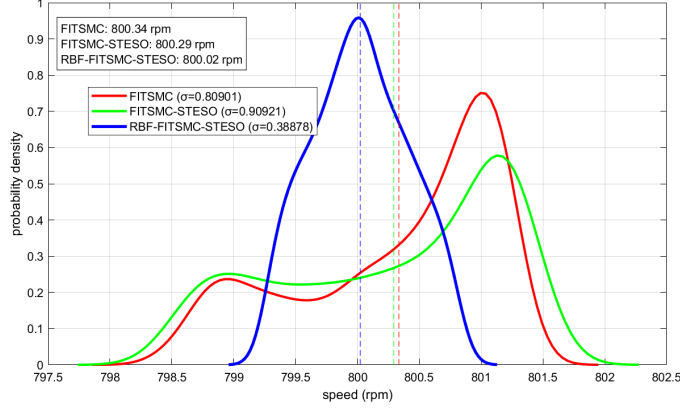


**Fig. 5** Probability density distribution of the steady-state speed of the PMSM.

effectively suppressing speed oscillations. In contrast, PI control and conventional SMC control exhibit significant speed drops and overshoots under disturbances, with slower recovery to steady state and more severe oscillations. Although FITSMC and FITSMC-STESO achieve some improvements over PI and SMC, they still fall short of RBF-FITSMC-STESO in terms of anti-disturbance speed and chattering suppression. This demonstrates that the proposed RBF-FITSMC-STESO control strategy possesses both fast dynamic response and excellent disturbance rejection capability, enabling rapid recovery to the reference speed under load disturbance conditions, significantly improving the dynamic stability and robustness of the system, thereby verifying the superiority of the proposed method in disturbance rejection scenarios.

As shown in Table 3, PI control exhibits the largest speed drop under load disturbance, reaching 148.96 rpm, and has the longest recovery time of 0.0735 s. Conventional SMC control achieves a speed drop of 72.51 rpm with a recovery time of 0.0646 s, indicating that its disturbance rejection performance needs improvement. FITSMC and FITSMC-STESO reduce the speed drop to 63.51 rpm and 51.57 rpm, respectively, and shorten the recovery time to 0.0095 s and 0.0073 s, respectively, representing a significant enhancement in disturbance rejection capability over PI and SMC. The proposed RBF-FITSMC-STESO control achieves the smallest speed drop of only 39.87 rpm, with a drop settling time of just 0.0007 s and a recovery time of only 0.0033 s, demonstrating the fastest anti-disturbance response and the smallest speed fluctuation among all control methods.

**Table 3** Performance comparison of five control methods under load startup.

| Control Method   | Speed Drop (rpm) | Drop Settling Time (s) | Recovery Time (s) |
|------------------|------------------|------------------------|-------------------|
| PI               | 148.96           | 0.0038                 | 0.0735            |
| SMC              | 72.51            | 0.0035                 | 0.0646            |
| FITSMC           | 63.51            | 0.0009                 | 0.0095            |
| FITSMC-STESO     | 51.57            | 0.0008                 | 0.0073            |
| RBF-FITSMC-STESO | 39.87            | 0.0007                 | 0.0033            |

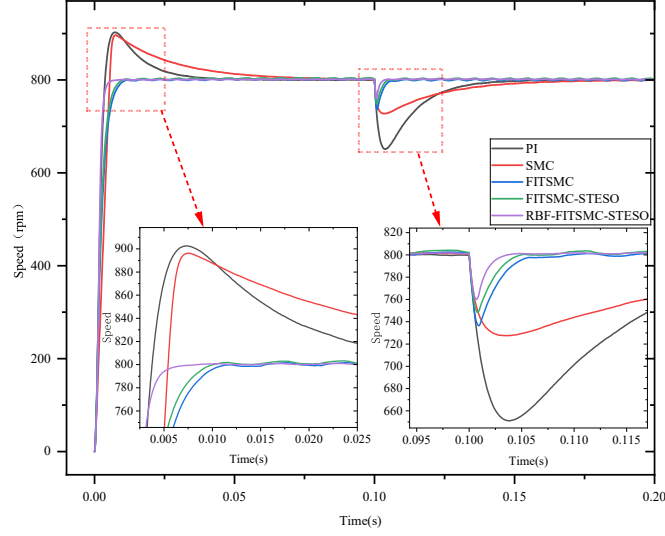


**Fig. 6** Speed response waveform of the PMSM under load conditions.

As shown in Figure 7, a normalized radar chart compares the performance of five control strategies—PI, SMC, FITSMC, FITSMC-STESO, and RBF-FITSMC-STESO—under sudden torque application conditions. The chart evaluates five key performance metrics: speed drop, drop settling time, recovery time, steady-state fluctuation, and maximum deviation. The outer circle represents the baseline value of 1 for PI control, and smaller metric values (closer to the center) indicate better performance. Conventional PI control exhibits the worst performance, with all metrics at the outermost circle. SMC control achieves some improvement over PI but still lags far behind advanced sliding mode-based control strategies across all metrics. FITSMC control, leveraging the fast convergence characteristic of terminal sliding mode, significantly reduces dynamic response time and suppresses steady-state fluctuations. Building upon this, FITSMC-STESO control, which incorporates an extended state observer, further enhances disturbance estimation and compensation capabilities, achieving comprehensive optimization of all performance metrics. The proposed RBF-FITSMC-STESO control, by virtue of the online adaptive compensation capability of the radial basis function neural network, effectively attenuates the inherent chattering of sliding mode control. It achieves optimal performance in key metrics including speed drop, recovery time, steady-state fluctuation, and maximum deviation. Overall, its performance is significantly superior to the other control algorithms, demonstrating excellent dynamic response and disturbance rejection capability under sudden load torque conditions.

In the torque response comparison of the PMSM under load conditions, the RBF-FITSMC-STESO control algorithm demonstrates significant comprehensive superiority. As shown in Figure 8, during the startup phase, the algorithm exhibits no obvious

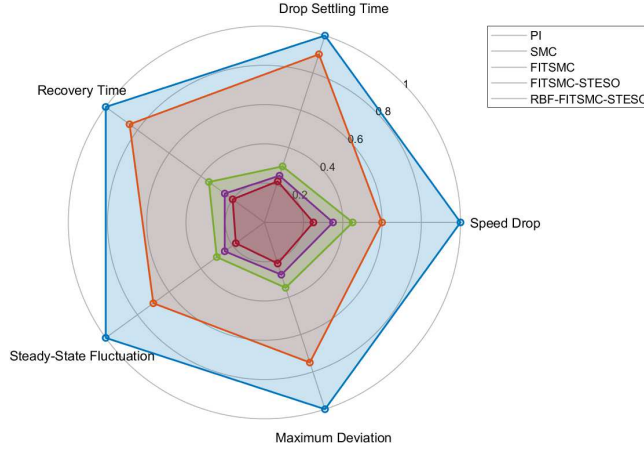


**Fig. 7** Performance comparison chart of the PMSM under sudden torque application.

overshoot and no severe oscillation, and it quickly tracks the reference torque in the shortest time. Its dynamic response smoothness and rapidity are superior to those of PI, SMC, FITSMC, and FITSMC-STESO. Under steady-state conditions, its torque ripple amplitude is much lower than that of the compared algorithms, with the torque curve exhibiting almost no fluctuation, significantly improving steady-state control accuracy. When subjected to a step load disturbance at 0.10 s, the algorithm achieves the smallest torque drop and recovers to the reference torque within a very short time without oscillation, demonstrating strong disturbance rejection robustness. These advantages are attributed to the synergistic effects of the adaptive compensation of the RBF neural network, the finite-time convergence characteristic of fixed-time terminal sliding mode control, and the disturbance estimation and compensation of STESO, effectively addressing the issues of large overshoot, high torque ripple, and weak disturbance rejection capability inherent in conventional algorithms, thereby providing excellent control performance for high-precision PMSM drive systems.

### 4.3 Comparative Analysis of Control Performance Under Full-Load Operating Conditions

To comprehensively evaluate the control performance of each control strategy under different load conditions, the reference speed is set to 800 r/min, and step load torques of 6 N·m (light load), 12 N·m (rated load), and 24 N·m (overload) are applied at  $t = 0.1$  s. This section analyzes the results from two dimensions: horizontal comparison (different control methods under the same load) and self comparison (the same control method under different loads) [30].

As shown in Figure 9, the RBF-FITSMC-STESO algorithm demonstrates significant performance advantages over the four comparison methods—PI, SMC, FITSMC, and FITSMC-STESO—across the full load range. From a horizontal comparison perspective, the proposed algorithm achieves the lowest speed drop and the shortest recovery time under all operating conditions. Notably, under a 24 N·m overload, it achieves speed drop reductions of 44%, 36%, 31%, and 17% compared to PI, SMC,

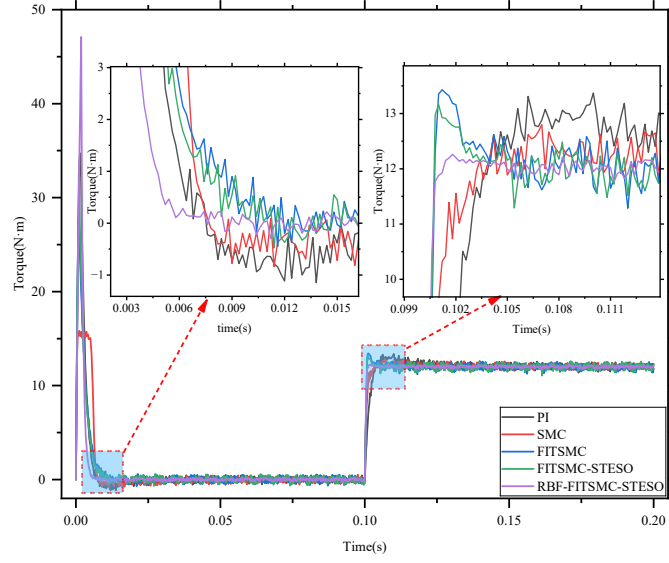


**Fig. 8** Torque response comparison of the PMSM under load conditions.

FITSMC, and FITSMC-STESO, respectively, along with recovery time reductions of 92%, 92%, 42%, and 32%, respectively. From a vertical (self-comparison) perspective, the performance degradation of the proposed algorithm from light load to overload is much smaller than that of the other four methods, with both the speed drop increase and the recovery time increase being the lowest. These results indicate that, leveraging the synergistic effects of neural network online compensation and the disturbance observer, RBF-FITSMC-STESO achieves excellent steady-state performance and dynamic robustness across the full load range.

As shown in Figure 10, in the horizontal comparison under the same load torque condition, the proposed RBF-FITSMC-STESO algorithm demonstrates significant performance advantages. Under a light load of 6 N·m, its maximum speed drop is only 11.0 rpm, and its recovery time is as low as 0.0022 s, far superior to PI control (74.2 rpm, 0.0590 s), as well as superior to SMC (28.8 rpm, 0.0531 s), FITSMC (14.8 rpm, 0.0044 s), and FITSMC-STESO (12.4 rpm, 0.0024 s). Under a rated load of 12 N·m, its speed drop is only 39.9 rpm, and its recovery time is only 0.0033 s, significantly outperforming PI control (149.0 rpm, 0.0735 s), as well as SMC (72.5 rpm, 0.0646 s), FITSMC (63.5 rpm, 0.0095 s), and FITSMC-STESO (51.6 rpm, 0.0073 s). Under the most severe overload condition of 24 N·m, its advantages are further highlighted, achieving a maximum speed drop of only 166.7 rpm and a recovery time of only 0.0064 s, compared to PI control (297.3 rpm, 0.0809 s), SMC (262.3 rpm, 0.0784 s), FITSMC (241.2 rpm, 0.0111 s), and FITSMC-STESO (200.2 rpm, 0.0094 s). These results fully

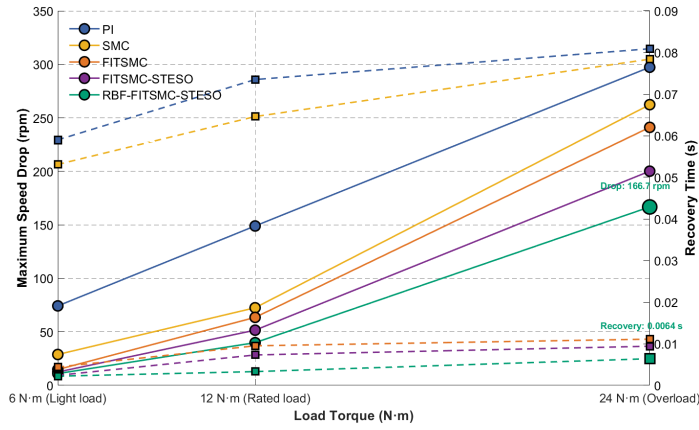


**Fig. 9** Performance comparison of PMSM control algorithms under load disturbance rejection.

verify the proposed algorithm's fast disturbance suppression capability and excellent dynamic disturbance rejection performance under full load conditions.

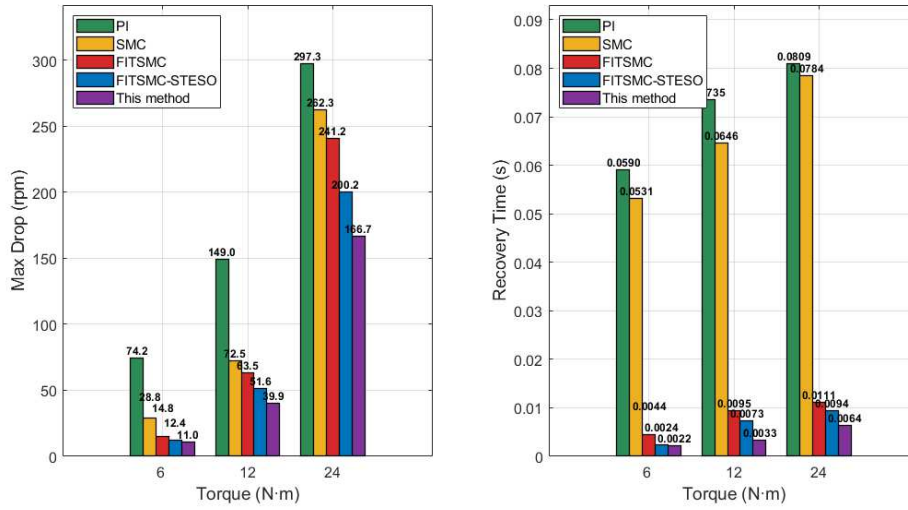


**Fig. 10** Horizontal comparison of dynamic response performance of various control strategies under full-range load disturbances.

As shown in Figure 11, from the perspective of self (vertical) comparison, the proposed RBF-FITSMC-STESO algorithm exhibits excellent performance stability and robustness throughout the full-range test from light load (6 N·m) to rated load (12 N·m) and further to overload (24 N·m). As the load torque gradually increases, its maximum speed drop increases only from 11.0 rpm to 166.7 rpm, and its recovery

time extends only from 2.2 ms to 6.4 ms, indicating that the performance degradation is effectively controlled. In contrast, for PI control, the maximum speed drop increases from 74.2 rpm to 297.3 rpm, and the recovery time extends from 59.0 ms to 80.9 ms. For SMC, the speed drop increases from 28.8 rpm to 262.3 rpm, and the recovery time extends from 53.1 ms to 78.4 ms. For FITSMC, the speed drop increases from 14.8 rpm to 241.2 rpm, and the recovery time extends from 4.4 ms to 11.1 ms. For FITSMC-STESO, the speed drop increases from 12.4 rpm to 200.2 rpm, and the recovery time extends from 2.4 ms to 9.4 ms. The performance of all four comparison algorithms deteriorates significantly as the load increases, and the magnitude of deterioration is generally greater than that of the proposed algorithm. These results fully demonstrate that the RBF-FITSMC-STESO algorithm, through the online compensation mechanism of the radial basis function neural network, effectively suppresses the impact of load disturbances on the system's dynamic performance, maintaining excellent speed tracking accuracy and fast recovery capability across the full load range, thereby exhibiting strong load adaptability and disturbance rejection robustness.

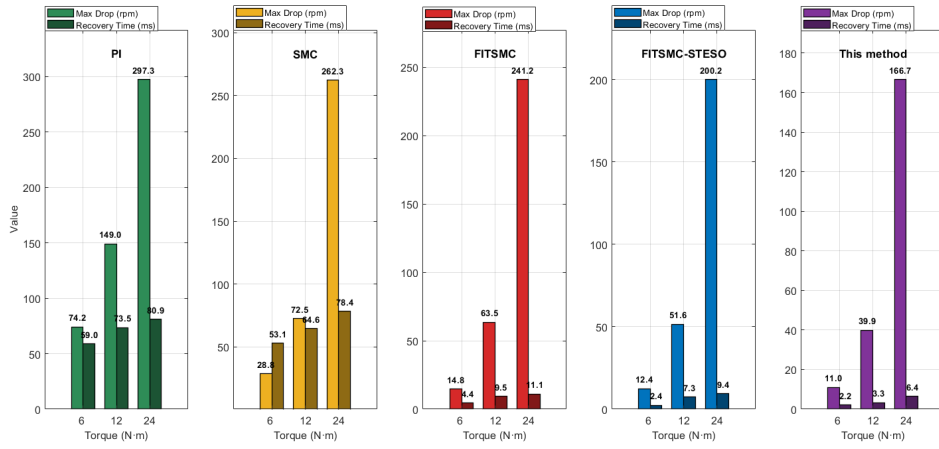


**Fig. 11** vertical comparison of dynamic response performance of the proposed and baseline control strategies under full-range load disturbances.

## 5 Conclusion

To address the shortcomings of conventional control strategies for surface-mounted permanent magnet synchronous motors (PMSMs) in terms of dynamic response, disturbance rejection capability, and chattering suppression, and to enhance control accuracy and robustness under complex operating conditions, this paper proposes a composite control strategy integrating a radial basis function (RBF) neural network, fixed-time integral terminal sliding mode control (FITSMC), and a super-twisting

extended state observer (STESO), denoted as RBF-FITSMC-STESO. Through synergistic optimization of multiple modules, this strategy achieves comprehensive improvement in control performance. The specific advantages are as follows:

1. Fixed-time integral terminal sliding mode control (FITSMC) is adopted for the speed loop. By designing a sliding mode surface that incorporates an integral term and terminal power terms, together with a fixed-time reaching law, the system states are ensured to converge to the equilibrium point within a fixed time. Simulation results show that under no-load startup, the proposed strategy achieves an overshoot of only 0.1 rpm and a settling time of just 0.0084 s, compared to 0.0625 s for PI control and 0.0660 s for SMC control, while also effectively attenuating sliding mode chattering.
2. A dual adaptive control mechanism based on an RBF neural network is introduced, enhancing the system's adaptability to motor parameter perturbations and complex operating environments. Steady-state speed probability density analysis reveals that the RBF-FITSMC-STESO achieves a speed standard deviation of only 0.38878 rpm, far smaller than those of FITSMC (0.80901 rpm) and FITSMC-STESO (0.90921 rpm), verifying the effectiveness of the RBF neural network in improving steady-state performance.
3. A super-twisting extended state observer (STESO) is designed to achieve simultaneous and accurate estimation of both the speed and the total system disturbance, with the estimated disturbance feedforward compensated to the controller. Under a 12 N·m load disturbance, the proposed strategy achieves a speed drop of only 39.87 rpm and a recovery time of only 0.0033 s, demonstrating significantly improved disturbance rejection performance compared to FITSMC-STESO (51.57 rpm, 0.0073 s) and FITSMC (63.51 rpm, 0.0095 s). Full-range testing (from 5 N·m to 24 N·m) further demonstrates that the proposed strategy maintains excellent robustness under different load conditions.

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## Declarations 1044–1045

- All author names, affiliations and any other potentially identifying information have been removed from the manuscript text and any accompanying files. 1047–1048
- The authors have no competing interests to declare. 1049
- A separate title page containing the title, author names, affiliations, and contact information of the corresponding author has been submitted separately. All acknowledgements, disclosures, funding information and authors’ contributions are included on that page. 1050–1053
- The authors have avoided citing their own work in a way that could reveal their identity. 1054–1055