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Improved Model Predictive Current Control for PMSM Motor With Consensus Algorithm

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ABSTRACT

The use of PMSM drives is becoming more prominent in industrial applications due to their benefits of high torque and power density, outstanding efficiency, and excellent reliability. Because of these benefits, various speed control methods for PMSMs have been researched and developed, with each method having its own advantages and limitations. Among these methods, Model predictive control (MPC) is a highly efficient control strategy for permanent magnet synchronous motors (PMSMs) that can manage constrained multi-objective optimization while delivering excellent dynamic performance. However, the accuracy of traditional predictive current control models relies heavily on motor parameters such as inductance and resistance. Additionally, the values of factors in the cost function are often inconsistent, as they are typically determined based on experience. This study introduces a solution to overcome the mentioned drawbacks by integrating MPC with a consensus algorithm and an extended Kalman filter. The consensus algorithm updates the weight values in the cost function for optimal performance, while the extended Kalman filter estimates the motor inductance and resistance, ensuring accurate control for MPC. This improved combined method makes motor speed control more adaptive to changes in resistance and inductance during operation. It ensures a system response with minimal overshoot, reduced steady-state error, and quicker settling time. The simulation results of the scale-down PMSM system are obtained from the Matlab simulation platform.

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1. Introduction

Improving control quality in high-performance motors, especially EV traction motors, is a key research trend. Among AC three-phase motors, PMSMs stand out for efficiency, power sensitivity, and compactness [1], [2]. Common control methods include FOC, DTC, and MPC [3], [4]. FOC and DTC optimize torque per unit current using a PI controller but struggle with PMSM nonlinearity and external loads. DTC's hysteresis-based approach leads to high current fluctuations and switching frequencies. In contrast, MPC offers superior performance and adaptability, making it promising for FOC and DTC..

Model predictive control (MPC) for permanent magnet synchronous motors (PMSMs) is mainly divided into two types such as torque predictive control (MPTC) and current predictive control (MPCC). The finite set model predictive control (FCS-MPC) technique is a widely used method in variable energy applications, the core principle is to utilize system parameters and quality indexes to optimize signal control. The great advances in microprocessor technology have increased the popularity of this MPC method in motor control in particular and systems in general, contributing to improving stability and eliminating the need to use pulse width modulation (PWM) [5].

This paper applies current tracking predictive control (MPCC) for PMSM speed control, but it risks instability at high temperatures due to noise affecting parameters like resistance and inductance. A neural network algorithm [6] can address this but requires a high-performance microprocessor, and controlling both d-axis and q-axis currents complicates optimization. To overcome these issues, a distributed model predictive control (DMPC) with a consensus algorithm [7], [8] is introduced to update

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weights dynamically and optimize each control variable sequentially. An Extended Kalman Filter (EKF) identifies parameters, enhancing stability and adaptability. The paper is organized into five sections.

2. Conventional MPC-based control design and mathematical modeling for PMSM motors

2.1. Mathematical modeling of PMSM

In Model Predictive Control, effective performance hinges on accurate system modeling, making dynamic equations critical [9]. Specifically, the precise mathematical model of a Permanent Magnet Synchronous Motor in the dq-axis reference frame is given as follows [10], [11]:

$$\begin{cases} v_d = Ri_d + L\dfrac{di_d}{dt} - \omega_e L i_q \\ v_q = Ri_q + L\dfrac{di_q}{dt} + \omega_e L i_d + \omega_e \psi_f \end{cases} \tag{1}$$

In these equations, v_d and v_q are dq-axis voltages, while i_d and i_q are dq-axis currents. The term ω_e is the rotor's electrical angular velocity. The parameter ψ_f represents the flux linkage of the permanent magnet, and R is the stator resistance. The d and q-axis inductances are assumed to be equal ($L = L_d = L_q$) [12] .

The dq-axis voltage equation **Error! Reference source not found.** can be rewritten in **Error! Reference source not found.** to simplify computational model development in model predictive control:

$$\begin{cases} \dfrac{di_d}{dt} = \dfrac{v_d}{L} - \dfrac{Ri_d}{L} + \omega_e i_q \\ \dfrac{di_q}{dt} = \dfrac{v_q}{L} - \dfrac{Ri_q}{L} - \omega_e i_d - \dfrac{\omega_e \psi_f}{L} \end{cases} \tag{2}$$

From equations **Error! Reference source not found.** and **Error! Reference source not found.** where d-q voltage and current are related through resistance and inductance. The MPC algorithm is developed using numerical approximations, discretizing equation **Error! Reference source not found.** ,via the forward Euler method at time steps $(k);(k-1);(k-2)$. The errors of current within the d-q frame are then fully presented as follows:

$$\begin{cases} \bullet \Delta i_d(k) = i_d(k) - i_d(k-1) \\ \qquad = \dfrac{T_s}{L}\left[v_d(k-1) - Ri_d(k-1)\right] + T_s\omega_e(k-1)i_q(k-1) \\ \bullet \Delta i_q(k) = i_q(k) - i_q(k-1) \\ \qquad = \dfrac{T_s}{L}\left[v_q(k-1) - Ri_q(k-1)\right] - \left[T_s\omega_e(k-1)i_d(k-1) + \dfrac{T_s}{L}\psi_m\omega_e(k-1)\right] \end{cases} \tag{3}$$

$$\begin{cases} \bullet \Delta i_d(k-1) = i_d(k-1) - i_d(k-2) \\ \qquad = \dfrac{T_s}{L}v_d(k-2) - \dfrac{T_s R}{L}i_d(k-2) + T_s\omega_e(k-2)i_q(k-2) \\ \bullet \Delta i_q(k-1) = i_q(k-1) - i_q(k-2) \\ \qquad = \dfrac{T_s}{L}v_q(k-2) - \dfrac{T_s R}{L}i_q(k-2) - T_s\omega_e(k-2)i_d(k-2) - \dfrac{T_s\psi_m}{L}\omega_e(k-2) \end{cases} \tag{1}$$

In equations **Error! Reference source not found.** and **Error! Reference source not found.**, $i_d(k)$ and $i_q(k)$ are the d-q axis current components, while $v_q(k)$ and $v_d(k)$ are the corresponding voltage components. R is the stator resistance, L is the stator inductance, T_s is the sampling interval, $\omega_e(k)$ is the angular velocity, and ψ_m is the permanent magnet flux linkage.

Based on equations **Error! Reference source not found.** and **Error! Reference source not found.** , when assuming that the sampling period T_s is extremely short, which causes the motor's electrical speed to satisfy $\omega_e(k-1)\approx\omega_e(k-2)$, the relationship between voltage and current error in dq - axis at the sampling points can be derived as follows, where the resistance and inductance parameters are explicitly separated into a matrix representation [13].

$$\begin{bmatrix} v_d(k-1)-v_d(k-2) \\ v_q(k-1)-v_q(k-2) \end{bmatrix} = \begin{bmatrix} \frac{1}{T_s}\left[\Delta i_d(k)-\Delta i_d(k-1)\right]-\omega_e(k)\Delta i_q(k-1) & \Delta i_d(k-1) \\ \frac{1}{T_s}\left[\Delta i_q(k)-\Delta i_q(k-1)\right]+\omega_e(k)\Delta i_d(k-1) & \Delta i_q(k-1) \end{bmatrix} \begin{bmatrix} L \\ R \end{bmatrix} \quad (5)$$

2.2. Conventional model predictive control for PMSM

In MPC for PMSMs, all switching states of a two-level inverter are replaced to calculate output voltages and estimate corresponding currents. The MPC algorithm minimizes a cost function using predicted currents to find the optimal switching state, which is then applied to the inverter. The implementation steps are as follows :

Firstly, for each of the 8 possible switching states vectors ($U_i=(S_a;S_b;S_c), i=\{0;1;2;...;7\}$) , the corresponding phase voltages ($V_a;V_b;V_c$) are calculated using the following formula:

$$\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} = \frac{V_{dc}}{3}\begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix}\begin{bmatrix} S_a \\ S_b \\ S_c \end{bmatrix}, \quad (6)$$

where $S_a;S_b;S_c$ represent the each phase switching states of the inverter, and V_{dc} represents the input voltage of the two-level inverter. Secondly, the phase voltages are transformed into the d-q reference frame using the following coordinate transformation with electrical rotor angle θ_e :

$$\begin{bmatrix} v_d \\ v_q \end{bmatrix} = \frac{2}{3}\begin{bmatrix} cos(\theta_e) & cos(\theta_e+\frac{4\pi}{3}) & cos(\theta_e+\frac{2\pi}{3}) \\ -sin(\theta_e) & -sin(\theta_e+\frac{4\pi}{3}) & -sin(\theta_e+\frac{2\pi}{3}) \end{bmatrix}\begin{bmatrix} V_a \\ V_b \\ V_c \end{bmatrix} \quad (7)$$

Thirdly, 7 predicted vectors $U_i=(S_a;S_b;S_c), i=\{0;1;2;...;7\}$ are evaluated to minimize the cost function in equation **Error! Reference source not found.** and achieves the smallest possible absolute difference between the predictive current at (k+1) sampling $i_q(k+1);i_d(k+1)$ and the reference values. Based on equation **Error! Reference source not found.**, the currents at the next step $i_q(k+1);i_d(k+1)$ can be predicted using the forward Euler discretization formula, given as:

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$$\begin{cases} i_d(k+1)=\left(1-\frac{RT_s}{L}\right)i_d(k)+T_s\omega_e i_q(k)+\frac{T_s v_d(k)}{L} \\ i_q(k+1)=\left(1-\frac{RT_s}{L}\right)i_q(k)-T_s\omega_e i_d(k)-\frac{\psi_f\omega_e T_s}{L}+\frac{T_s v_q(k)}{L} \end{cases} \quad (8)$$

Finally, the cost function for each switching state is computed as follows:

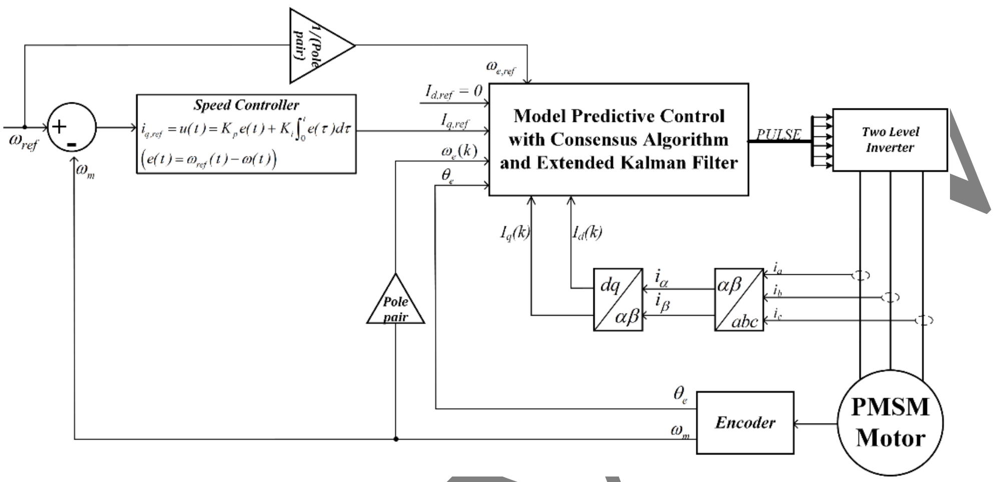

Figure 1. *Overview of PMSM Speed Control System Using MPC and Extended Kalman Filter*

$$Cost(i)=\left|i_{d,ref}-i_{d,p}\right|+\left|i_{q,ref}-i_{q,p}\right| \quad (9)$$

3. Consensus algorithm applications in model predictive control for enhanced PMSM performance

Consensus algorithms are vital in optimization control, ensuring balanced agreement among components [14]. In MPC, the algorithm dynamically updates cost function weights based on parameter changes, converging to an optimal state and improving performance. An Extended Kalman Filter then estimates resistance and inductance, enhancing modeling accuracy and adaptability [13]. Figure 1 illustrates the structure of the PMSM motor speed control system, integrating MPC, a consensus algorithm, and a Kalman filter. A PI controller is employed in the outer loop to determine the reference torque-producing current $i_{q,ref}$. In this cascaded FOC scheme, the inner-loop MPC (augmented by a consensus algorithm and EKF) tracks $i_{q,ref}$ with high bandwidth for torque regulation, while the PI controller chosen for its simplicity and reliability ensures stable speed regulation. The formula of the PI controller is proposed as

$$i_{q,ref}=u(t)=K_p e(t)+K_i\int_0^t e(\tau)d\tau \ \left(e(t)=\omega_{ref}(t)-\omega(t)\right) \quad (10)$$

3.1. Consensus algorithm

The fundamental consensus algorithm, incorporating both continuous time and discrete time integrator agents, is defined as follows [14], [15], [16] :

For continuous time:

$$\dot{w}_i(t)=\sum_{j\in N_i}c_{ij}\cdot(w_j(t)-w_i(t)) \quad (11)$$

For discrete time:

$$w_i(k+1)=w_i(k)+\eta\cdot\sum_{j\in N_i}c_{ij}\cdot(w_j(k)-w_i(k)) \tag{12}$$

where, $i=1,2,...,N$, while N is the total number of agent nodes. The variable w_i represents the state of agent i, while c_{ij} indicates the connection between nodes i and j, ($c_{ij}=0$ if nodes i and j are not linked). The set N_i contains the indices of all agents connected to agent i. The parameter η is the constant edge weight used to adjust the consensus algorithm.

3.2. Kalmal Filter algorithm

To estimate the two parameters, the stator circuit resistance and the inductance of the stator winding, of the motor, we rewrite equation **Error! Reference source not found.** as, while the voltages v_d, v_q are taken from the optimal switching vector combination selected by the MPC controller:

$$Y(k)=A(k)*X(k) \tag{13}$$

$$\begin{cases} Y(k)=\left[v_d(k-1)-v_d(k-2) \quad v_q(k-1)-v_q(k-2)\right] \\ A(k)=\begin{bmatrix} \dfrac{1}{T_s}\left[\Delta i_d(k)-\Delta i_d(k-1)\right]-\omega_e(k)\Delta i_q(k-1) & \Delta i_d(k-1) \\ \dfrac{1}{T_s}\left[\Delta i_q(k)-\Delta i_q(k-1)\right]+\omega_e(k)\Delta i_d(k-1) & \Delta i_q(k-1) \end{bmatrix} \\ X(k)=\left[L(k) \quad R(k)\right]^T \end{cases} \tag{2}$$

Matrix multiplication is typically used to find $X(k)$. However, since the matrix $A(k)$ is time-varying, there may be moments when it becomes non-invertible. Therefore, we apply the Kalman algorithm to address this issue. First, we rewrite Equation (12) in the form of a discrete state-space equation as follows:

$$\begin{aligned} X(k+1)&=X(k)+v_k \\ Y(k)&=A(k)*X(k)+w_k \end{aligned} \tag{15}$$

where v_k is system noise and w_k is measurement noise.

As stated in [17], the implementation process of the Kalman Filter algorithm involves the following steps. First, the Kalman gain is computed using the formula below:

$$K(k)=P(k)A(k)^T\left[A(k)P(k)A(k)^T+v_k\right]^{-1} \tag{16}$$

With the initialization condition $P(k)$ being positive definite and $v_k=0.01*I_2$, this ensures that equation (15) is always invertible. Next, the estimated state is calculated using:

$$\hat{X}(k+1)=\hat{X}(k)+K(k)\left[Y(k)-A(k)\hat{X}(k)\right] \tag{17}$$

Finally, the covariance matrix is updated as follows:

$$P(k+1)=\left[I-K(k)A(k)\right]P(k) \tag{18}$$

3.3. Consensus algorithm applications with Kalmal Filter in model predictive control

From equation **Error! Reference source not found.**, the estimated matrix value $\hat{X} = \left[\hat{L}; \hat{R} \right]^T$ will be updated in equation **Error! Reference source not found.** regarding the calculation of dq-axis currents at the next time step:

$$\begin{cases} i_{d,p} = i_d(k+1) = \left(1 - \dfrac{\hat{R}T_s}{\hat{L}}\right) i_d(k) + T_s \omega_e i_q(k) + \dfrac{T_s v_d(k)}{\hat{L}} \\ i_{q,p} = i_q(k+1) = \left(1 - \dfrac{\hat{R}T_s}{\hat{L}}\right) i_q(k) - T_s \omega_e i_d(k) - \dfrac{\psi_f \omega_e T_s}{\hat{L}} + \dfrac{T_s v_q(k)}{\hat{L}} \end{cases} \tag{19}$$

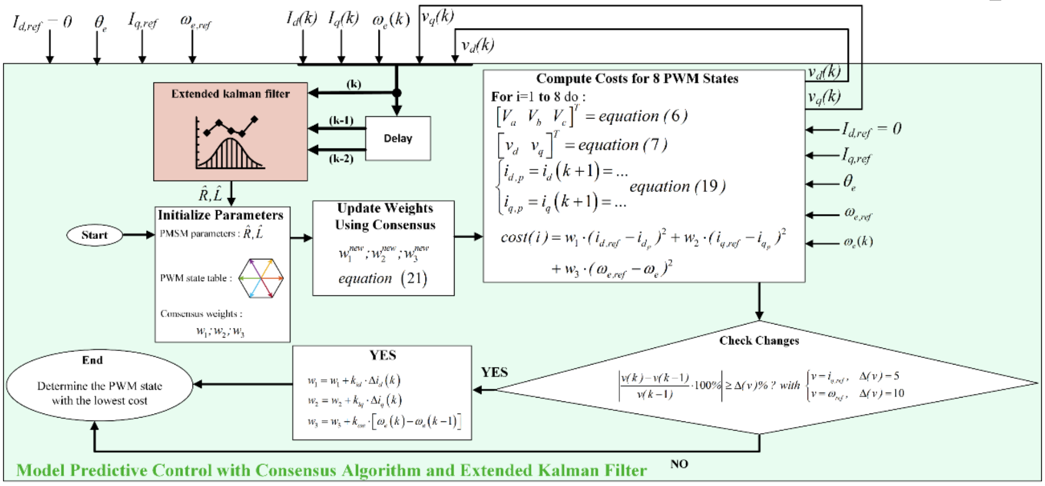

Figure 2. *Diagram of MPC with Consensus Algorithm and Extended Kalman Filter*

For each possible predicted switching state vector, the cost function is refined from equation (6) and integrated with a consensus algorithm to update the weights. The improved cost function is expressed as follows:

$$cost(i) = w_1 \cdot (i_{d,ref} - i_{d_p})^2 + w_2 \cdot (i_{q,ref} - i_{q_p})^2 + w_3 \cdot (\omega_{e,ref} - \omega_e)^2 \tag{20}$$

Each element in the total equation represents an error component multiplied by a corresponding weight. However, the weights $w_1; w_2; w_3$ are often tuned based on experience, so it is necessary to use a consensus algorithm to balance the error components flexibly to help respond to each control condition more adaptively.

The process of updating each weight to generate the new values w_1^{new}, w_2^{new} and w_3^{new} using the consensus algorithm from the equation **Error! Reference source not found.** is outlined below:

$$w_i^{new} = w_i + \sum_{j \neq i} k_i \cdot (-w_i + w_j);\ i = 1,2,3 \tag{21}$$

If there are no changes in the reference values of current and speed, the weights w_1, w_2, w_3 will gradually converge to a common value through the equation **Error! Reference source not found.** [18], [19]. Conversely, if the reference values $i_{q,ref}$ or $\omega_{e,ref}$ experience a variation exceeding 5% for $i_{q,ref}$ and 10% for $\omega_{e,ref}$, the weights w_1, w_2, w_3 will immediately take on new values as shown in the equation **Error! Reference source not found.**, and the consensus algorithm will resume in the following iteration.

$$\begin{cases} w_1 = w_1 + k_{id} \cdot \Delta i_d(k) \\ w_2 = w_2 + k_{iq} \cdot \Delta i_q(k) \\ w_3 = w_3 + k_{\omega e} \cdot \left[\omega_e(k) - \omega_e(k-1) \right] \end{cases} \tag{22}$$

In equation **Error! Reference source not found.**, the gain factors k_{id}, k_{iq} and $k_{\omega e}$ must be carefully adjusted according to real operating conditions. Depending on the fine-tuned gain values, the weights $w_1; w_2; w_3$ can be updated significantly or minimally. Therefore, a basic condition is introduced in the equation **Error! Reference source not found.** to ensure the weights are always maintained within the range of min_weight and max_weight. If a weight becomes smaller than min_weight it will be set to min_weight. Similarly, if it exceeds max_weight, it will be limited to max_weight.

$$min\_weight \le w_1, w_2, w_3 \le max\_weight \tag{23}$$

All details of the model predictive control combined with the consensus algorithm and the extended Kalman filter are illustrated in a diagram in Figure 2**.**

4. Simulation result

To assess the stability of the proposed method in comparison to the conventional MPC method and the proposed MPC method under conditions of parameter mismatch, simulations were conducted using MATLAB/Simulink. The motor parameters used in the simulations are listed in Table 1, and the system's sampling time is set to 20 µs. This sampling time can be completely achieved when using the hardware of Texas Instrument TMS320F28379D microprocessor.

Table 1. *PMSM Parameters*

Parameter	Description	Value
λ_f	Nominal flux linkage	0.175 (Wb)
R_s	Nominal stator resistance	2.875 (Ω)
L_s	Nominal stator inductance	$1.53(mH)$
p	Number of pole pair	4
V_{dc}	DC Voltage Source	$30V$
T_L	Torque Load	$0.5Nm$

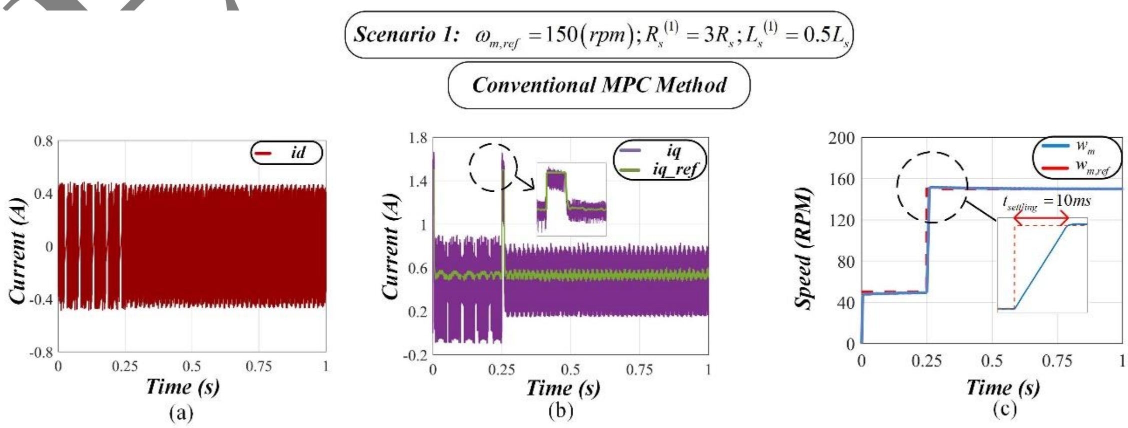

Figure 3. *Steady-state response of Conventional MPC. (a) and (b): Current responses; (c): Speed response*

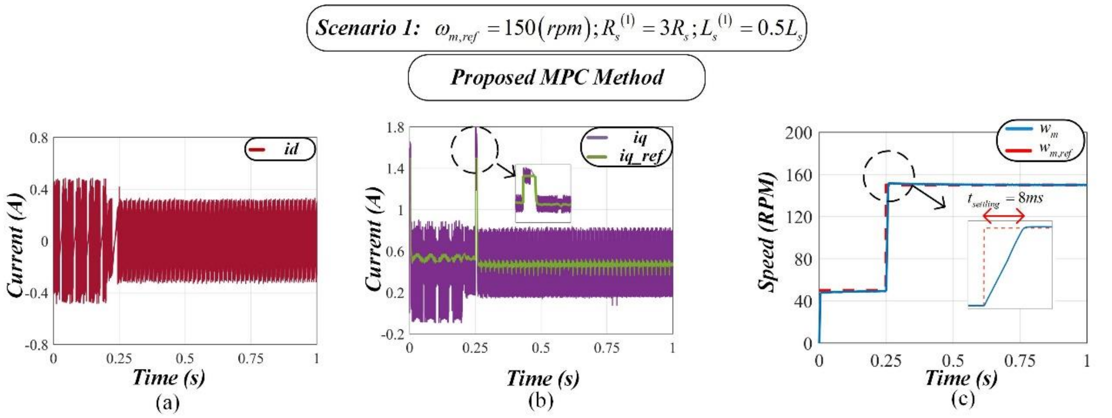

Figure 4. *Steady-state response of Proposed MPC. (a) and (b): Current responses; (c): Speed response*

To examine the impact of motor parameter mismatch, this paper conducts two scenarios. The first scenario is a steady-state response investigation, the scenario is analyzed by setting a fixed reference speed of 150 rpm, and the motor parameters are adjusted to values other than the nominal value, specifically $R_s^{(1)} = 3R_s, L_s^{(1)} = 0.5L_s$. The second scenario is dynamic response investigation, the system is assessed under varying reference motor speeds. Also, the motor parameters are modified to $R_s^{(2)} = 0.5R_s, L_s^{(2)} = 5L_s$. In both two scenarios, the proposed MPC method begins by initializing the motor with the nominal values of stator resistance, inductance and flux linkage in Table 1. At $t = 0.2s$, the EKF estimator updates the estimated values of $\hat{R}_s$ and $\hat{L}_s$ for the controller.

The d-axis current responses of the conventional MPC method are shown in Figure 3(a). The d-axis steady-state current exhibits fluctuations around reference values $\left(i_{d,ref} = 0\right)$, accompanied by a steady-state error $\Delta i_d = \left|i_{d.\max} - i_{d,ref}\right| \approx 0.4(A)$. In contrast, the steady-state error of the d-axis current using proposed MPC method is $\Delta i_d = \left|i_{d,\max} - i_{d,ref}\right| \approx 0.3(A)$, which is smaller than that of the conventional one, as shown in Figure 4(a).

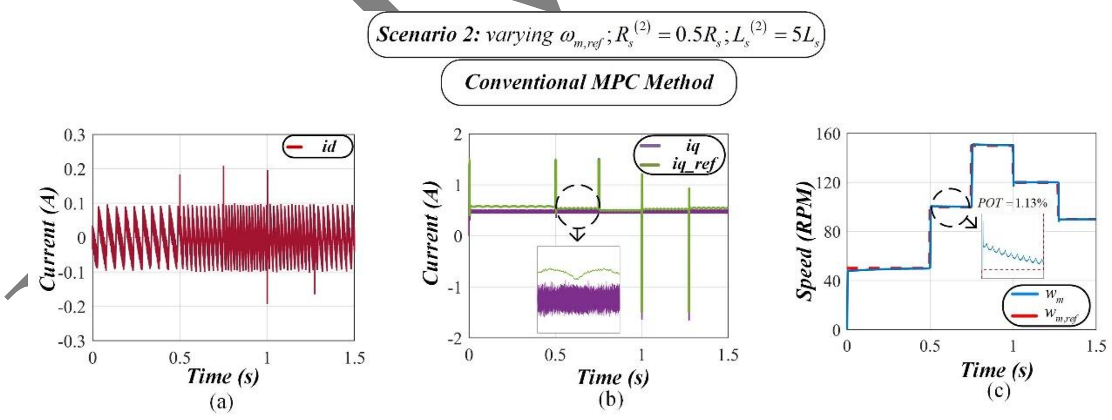

Figure 5. *Dynamic response of Conventional MPC. (a) id current response; (b): iq current response; (c): Speed response*

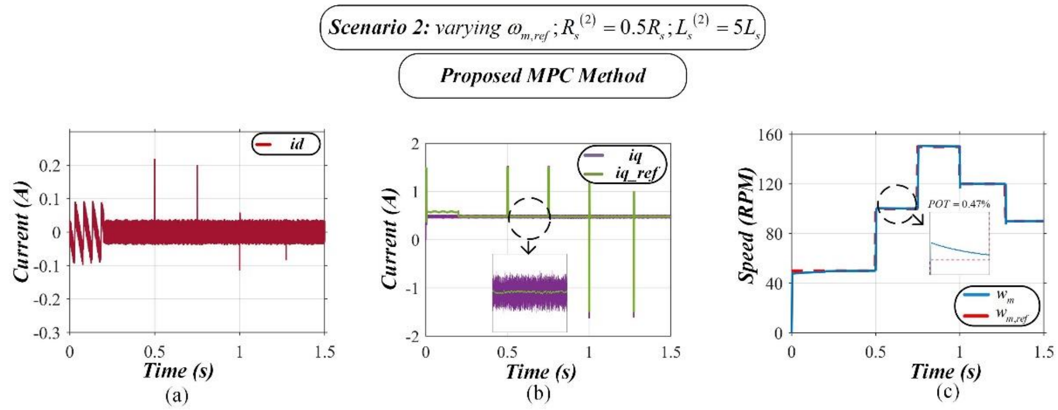

Figure 6. *Dynamic response of Proposed MPC. (a) id current response; (b): iq current response; (c): Speed response*

During motor acceleration, when the reference current is set to 1.5 A from 0.25s to 0.26 s , the q-axis feedback current of the conventional MPC method in Figure 3(b) shows a slight offset $\Delta i_q = \left| i_{q,avr} - i_{q,ref} \right| \approx 0.28(A)$ due to deviations in the model parameters. However, the offset in the q-axis current in Figure 4(b) is notably improved to $\Delta i_q = \left| i_{q,avr} - i_{q,ref} \right| \approx 0.03(A)$. The motor's speed responses are illustrated in Figures 3(c) and 4(c). The settling time for the conventional MPC method is 10 ms, whereas the proposed MPC method achieves steady-state in just 8 ms, thanks to enhanced d-axis and q-axis current settling performance, as evaluated using the 5% standard.

In Scenario 2, the conventional MPC method's d-axis current fluctuates around the reference by $0.1(A)$(Figure 5a) . The proposed MPC method (Figure 6a) significantly improves this response. Updating estimated parameters $\hat{R}_s$ and $\hat{L}_s$ reduces steady-state error, enhancing FOC efficiency.

The q-current response of the conventional MPC method, illustrated in Figure 5(b), reveals a consistent deviation of the feedback q-axis current from the reference current at different motor speeds. For instance, when the motor speed is set to 100 rpm, the average deviation between the feedback current $\left(i_{q,avg}\right)$ and the reference current is $69.5(mA)$. However, with the proposed MPC method, as shown in Figure 6(b), this deviation is minimized to just $3(mA)$ after correcting the motor parameters. Figures 5(c) and 6(c) compare motor speed responses. The conventional MPC method exhibits an overshoot of 1.13%, whereas the proposed method reduces the overshoot to 0.47%.

The estimated resistance and inductance responses, shown in Figures 7 and 8, demonstrate the effectiveness of the EKF algorithm in accurately identifying motor parameters. The error in Figures 7 and 8 are calculated below:

$$error = \frac{estimated_{value} - real_{value}}{real_{value}} * 100\% \tag{24}$$

5. Conclusion

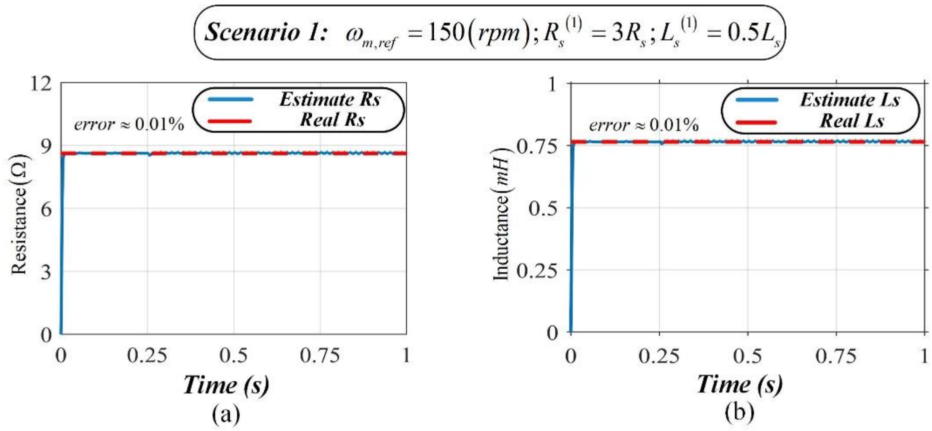

Figure 7. *Estimated responses of EKF Method in Scenario 1.*
(a) Estimated Resistance response; (b) Estimated Inductance response.

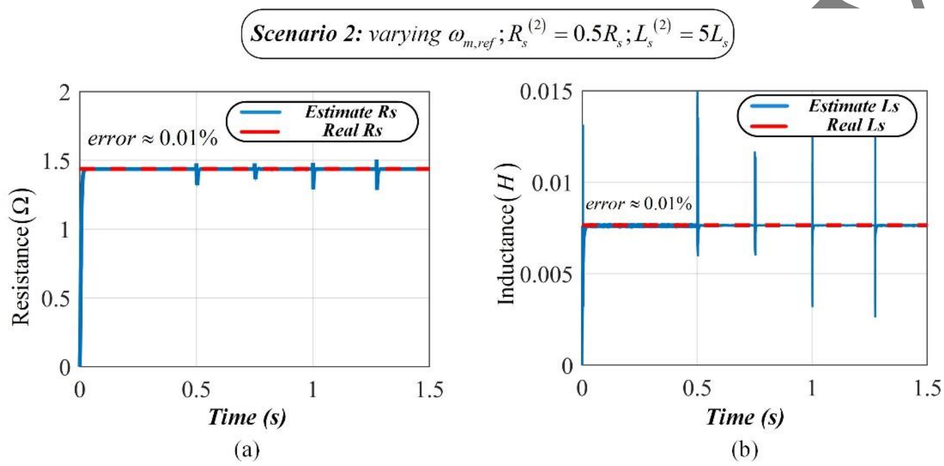

Figure 8. *Estimated responses of EKF Method in Scenario 2.*
(a) Estimated Resistance response; (b) Estimated Inductance response.

The MPCC method in this paper combines a consensus algorithm and an extended parameter identifier EKF. Thus, the control system improves the ability to control the motor speed under parametric disturbances, such as variations in stator resistance and inductance. Simulations comparing this method with the conventional MPC show significant improvements: the steady-state current ripple for i_d reduces from $0.4A$ to $0.3A$, dynamic ripple decreases from $0.1A$ to $0.05A$, and i_q dynamic offset drops from $69.5mA$ to $3mA$. These improvements result in a reduced overshoot, faster steady-state time, and a marked improvement in the overall response of the motor speed control. Therefore, the method's effectiveness in the problem of PMSM motor speed control under the condition of circuit parameter uncertainty is demonstrated.

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Conflict of Interest

The authors declare no conflict of interest.

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