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Impact of Control Parameter Deviations on PMSM Operating Efficiency and Adaptive Regulation Strategy

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Abstract: Permanent magnet synchronous motors (PMSMs) are widely used in industrial automation, transportation, and intelligent equipment due to their high efficiency, high power density, and good dynamic performance. However, parameter deviations caused by temperature variation, load fluctuation, model uncertainty, and aging may reduce control accuracy and operating efficiency. This paper analyzes the influence of control parameter deviations on PMSM drive efficiency using a MATLAB/Simulink-based vector control simulation platform. Speed-loop proportional gain, integral gain, stator resistance, and rotor flux-linkage estimation error are introduced as deviation variables. Their effects on efficiency, overshoot, settling time, power factor, stator current, and copper loss are quantitatively evaluated. Based on the results, an adaptive regulation strategy combining online parameter identification and operating-condition recognition is proposed. Simulation results show that rotor flux-linkage estimation error has the strongest impact on efficiency, followed by speed-loop proportional gain deviation. The proposed strategy reduces efficiency loss by more than 60% and decreases transient extra energy consumption by approximately 58%, providing a practical reference for improving PMSM drive efficiency.

Keywords: Permanent Magnet Synchronous Motor; Control Parameter Deviation; Operating Efficiency; Vector Control; Online Parameter Identification; Adaptive Regulation

1. Introduction

Permanent magnet synchronous motors have become important actuators in modern industrial drive systems. Compared with induction motors and traditional DC motors, PMSMs have higher torque density, higher efficiency, faster dynamic response, and better reliability [1]. They are widely applied in electric vehicles, industrial robots, CNC machine tools, household appliances, aerospace servo systems, and intelligent manufacturing equipment. With the increasing demand for energy saving and carbon-emission reduction, the operating efficiency of PMSM drive systems has received extensive attention in both academic research and engineering practice.

Field-oriented control is one of the most widely used control methods for PMSM drives. By transforming three-phase stator currents into a rotating dq-coordinate system, field-oriented control realizes the decoupled control of torque and flux [2]. Vector control theory has provided an effective foundation for high-performance AC motor drives and has been widely used in PMSM control systems [3]. In an ideal control system, motor parameters and controller gains are assumed to be accurate and constant. However, in actual operation, this assumption is difficult to satisfy. Stator resistance changes with winding temperature, rotor flux linkage varies because of demagnetization and magnetic saturation, and the optimal speed-loop PI parameters also change under different load and speed conditions.

Parameter deviation is therefore an inevitable problem in practical motor control systems. When the controller uses inaccurate parameters, field orientation becomes inaccurate, current regulation quality decreases, and additional losses are generated. For example, inaccurate rotor flux-linkage estimation affects torque calculation and magnetic-field orientation. An underestimated flux linkage may require higher stator current to maintain the same torque, which increases copper loss. An overestimated flux linkage may lead to magnetic saturation and increased iron loss. Similarly, excessive speed-loop proportional gain may cause current oscillation and frequent switching actions, increasing switching loss and dynamic energy consumption.

Many researchers have studied PMSM parameter identification and adaptive control. Online parameter estimation of PMSMs is important for improving control performance and operational reliability, especially under changing temperature and load conditions [4]. Existing studies have proposed model reference adaptive systems, filtering-based estimation methods, sliding-mode observers, and adaptive control strategies to improve parameter robustness and dynamic response [5], [6]. Other studies have focused on efficiency optimization by considering iron loss, copper loss, and loss-model-based control methods [7], [8].

Although existing research provides useful methods for PMSM control improvement, three limitations remain. First, many studies focus on a single parameter, such as stator resistance, inductance, or flux linkage, while the comparative influence of different control parameter deviations on efficiency is not fully discussed. Second, most research emphasizes dynamic response and tracking accuracy, but the mechanism by which parameter deviation causes efficiency degradation is not sufficiently explained from the perspective of loss composition. Third, some adaptive control methods continuously adjust controller parameters without distinguishing between steady-state and dynamic operating conditions, which may increase unnecessary control activity during stable operation.

To address these problems, this paper establishes a simulation-based quantitative analysis framework for PMSM control parameter deviations. The main contributions are as follows. First, a PMSM vector control simulation platform with parameter-deviation injection is established in MATLAB/Simulink. Speed-loop proportional gain, speed-loop integral gain, stator resistance, and rotor flux-linkage estimation error are selected as key deviation factors. Second, the influence of different parameter deviations on system efficiency, overshoot, settling time, power factor, stator current, and copper loss is quantitatively analyzed. Third, an efficiency-loss decomposition method is introduced to explain the physical mechanism of efficiency degradation under different parameter mismatch conditions. Fourth, an adaptive regulation strategy combining online parameter identification and operating-condition recognition is proposed. This strategy compensates parameter drift and adjusts speed-loop control parameters according to operating conditions, thereby improving both dynamic response and steady-state efficiency.

The rest of this paper is organized as follows. Section 2 reviews related literature. Section 3 presents the mathematical model, simulation platform, and parameter-deviation injection method. Section 4 presents the simulation results. Section 5 discusses the efficiency degradation mechanism and the proposed adaptive regulation strategy. Section 6 concludes the paper.

2. Literature Review

PMSM modeling and vector control have been studied for several decades. Pillay and Krishnan developed classical modeling and simulation methods for permanent-magnet motor drives, providing a foundation for later PMSM control studies [2]. Novotny and Lipo further systematized vector control theory for AC drives and explained the role of coordinate transformation in decoupling torque and flux control [3]. These studies provide the theoretical basis for the dq-axis model and PI-based vector control adopted in this paper.

Parameter uncertainty is a major factor affecting PMSM control performance. Zhu, Liang, and Liu reviewed online parameter estimation methods for permanent magnet synchronous machines and discussed rank-deficiency, inverter nonlinearity, and parameter identifiability problems [4]. Liu et al. compared two model reference adaptive system strategies for PMSM parameter identification and showed that resistance, inductance, and flux linkage can be estimated using measured voltage, current, and speed signals [5]. Qi et al. proposed an improved adaptive parameter identification method for PMSMs, showing that adaptive laws can improve identification accuracy under disturbances [6].

Efficiency optimization is another important research direction. Mi, Slemon, and Bonert investigated iron-loss modeling for permanent-magnet synchronous motors and showed that iron loss must be considered in high-efficiency drive analysis [7]. Xu et al. studied PMSM efficiency optimization based on iron loss resistance modeling and indicated that loss models can be used to improve the overall efficiency of drive systems [8]. These studies confirm that PMSM efficiency is influenced not only by output torque and speed but also by loss distribution, including copper loss, iron loss, and inverter-related losses.

However, existing work still leaves room for a simulation-based comparative study of different parameter deviations. Many studies focus on parameter identification accuracy or control robustness, while fewer studies quantitatively compare how different parameter deviations affect efficiency, dynamic response, and loss composition under the same operating condition. Therefore, this paper focuses on speed-loop PI gains, stator resistance, and rotor flux-linkage estimation error, and evaluates their relative influence on PMSM operating efficiency.

3. Methods

3.1 PMSM Mathematical Model

For a surface-mounted PMSM, the mathematical model is usually established in the rotating dq-coordinate system. The d-axis is aligned with the rotor permanent-magnet flux, and the q-axis is orthogonal to the d-axis. In the dq-coordinate system, the stator voltage equations can be written as

$$u_d = R_s i_d + L_d \frac{di_d}{dt} - \omega_e L_q i_q \tag{1}$$

$$u_q = R_s i_q + L_q \frac{di_q}{dt} + \omega_e L_d i_d + \omega_e \psi_f \tag{2}$$

where u_d and u_q are the stator voltages in the d-axis and q-axis, i_d and i_q are the corresponding stator currents, R_s is the stator resistance, L_d and L_q are the d-axis and q-axis inductances, ω_e is the electrical angular velocity, and ψ_f is the rotor permanent-magnet flux linkage.

For a surface-mounted PMSM, the saliency effect is weak, and the inductances can be approximately regarded as equal:

$$L_d = L_q = L_s \tag{3}$$

The electromagnetic torque of a PMSM is expressed as

$$T_e = \frac{3}{2} p \left[\psi_f i_q + \left(L_d - L_q \right) i_d i_q \right] \tag{4}$$

where p is the number of pole pairs. For a surface-mounted PMSM with L_d = L_q, the reluctance torque term is zero. Therefore, the electromagnetic torque becomes

$$T_e = \frac{3}{2} p \psi_f i_q \tag{5}$$

Equation (5) shows that the torque is mainly determined by the rotor flux linkage and the q-axis current. Therefore, any deviation in rotor flux-linkage estimation directly affects torque calculation and current command generation.

The mechanical motion equation of the PMSM is

$$J\frac{d\omega_m}{dt}=T_e-T_L-B\omega_m \tag{6}$$

where J is the moment of inertia, ω_m is the mechanical angular velocity, T_L is the load torque, and B is the viscous friction coefficient. The relationship between electrical angular velocity and mechanical angular velocity is

$$\omega_e=p\omega_m \tag{7}$$

3.2 Vector Control Structure

The PMSM drive system adopts a conventional field-oriented control structure. The outer loop is the speed control loop, and the inner loops are the d-axis and q-axis current control loops. The d-axis current reference is set to zero:

$$i_d^* =0 \tag{8}$$

This control strategy is simple and widely used because it can reduce unnecessary excitation current and improve torque-generation efficiency.

The speed error is defined as

$$e_\omega=\omega^* -\omega_m \tag{9}$$

where ω* is the reference speed. The q-axis current reference generated by the speed PI controller is

$$i_q^* =K_{p\omega}e_\omega+K_{i\omega}\int e_\omega dt \tag{10}$$

where K_pω and K_iω are the proportional and integral gains of the speed loop. The current loops are also controlled by PI regulators:

$$u_d^* =K_{pi}\left(i_d^* -i_d\right)+K_{ii}\int \left(i_d^* -i_d\right) dt-\omega_e L_q i_q \tag{11}$$

$$u_q^* =K_{pi}\left(i_q^* -i_q\right)+K_{ii}\int \left(i_q^* -i_q\right) dt+\omega_e L_d i_d+\omega_e\psi_f \tag{12}$$

where K_pi and K_ii are the current-loop proportional and integral gains.

3.3 Simulation Platform and Parameter Settings

A PMSM vector-control simulation platform is established in MATLAB/Simulink. MATLAB/Simulink is commonly used for motor-drive modeling and control-system verification because it can describe electrical, mechanical, and control subsystems in an integrated environment [9]. The simulation system includes the PMSM model, coordinate transformation module, speed PI controller, current PI controller, inverter module, parameter-deviation injection module, efficiency calculation module, and loss analysis module.

The simulation platform is designed to compare system performance under accurate parameters and deviated parameters. The operating condition with accurate parameters is used as the benchmark. Then, different deviations are introduced into the controller parameters or motor parameters. By comparing simulation results, the influence of each parameter deviation on operating efficiency and dynamic performance can be obtained.

Table 1: Rated parameters of the PMSM

Parameter	Symbol	Value	Unit
Rated power	P_N	5.5	kW
Rated speed	n_N	1500	r/min
Rated torque	T_N	35	N·m

Stator resistance	R_s	0.35	Ω
d-axis inductance	L_d	8.5	mH
q-axis inductance	L_q	8.5	mH
Permanent-magnet flux linkage	ψ_f	0.175	Wb
Moment of inertia	J	0.008	kg·m²

The rated operating condition is set as follows:

$$n=1500\ \mathrm{r/min} \tag{13}$$

$$T_L=30\ \mathrm{N\cdot m} \tag{14}$$

Under this condition, the benchmark efficiency of the system is 92.3%.

3.4 Parameter-Deviation Injection Method

To describe parameter deviation quantitatively, the deviation coefficient is defined as

$$\delta_x=\frac{x_{est}-x_{real}}{x_{real}}\times 100\% \tag{15}$$

where x_est is the parameter value used by the controller, and x_real is the actual parameter value of the motor system.

The parameters selected for deviation analysis are

$$\Theta=\{K_{p\omega},K_{i\omega},R_s,\psi_f\} \tag{16}$$

where K_pω and K_iω represent controller-gain deviations, while R_s and ψ_f represent motor-parameter estimation deviations. The selected deviation levels are

$$\delta_x=\pm 20\%,\ \pm 40\% \tag{17}$$

These values are used to represent moderate and severe parameter mismatches.

3.5 Efficiency Calculation and Loss Decomposition

The output power of the motor is calculated as

$$P_{out}=T_e\omega_m \tag{18}$$

The input power is calculated from the electrical side:

$$P_{in}=u_a i_a+u_b i_b+u_c i_c \tag{19}$$

Therefore, the system efficiency is

$$\eta=\frac{P_{out}}{P_{in}}\times 100\% \tag{20}$$

The efficiency change rate is defined as

$$\Delta\eta_r=\frac{\eta_{dev}-\eta_0}{\eta_0}\times 100\% \tag{21}$$

where η_0 is the benchmark efficiency, and η_dev is the efficiency under parameter deviation.

In order to analyze the reason for efficiency degradation, the total loss is divided into several components:

$$P_{loss}=P_{cu}+P_{fe}+P_{sw}+P_{mech} \tag{22}$$

where P_cu is copper loss, P_fe is iron loss, P_sw is inverter switching loss, and P_mech is mechanical loss. Loss decomposition is commonly used in PMSM efficiency studies because copper loss and iron loss are two major components affecting efficiency [7], [8]. Copper loss is calculated as

$$P_{cu}=3R_sI_s^2 \tag{23}$$

where I_s is the stator current effective value. Iron loss is approximately expressed as

$$P_{fe}=k_h fB_m^2+k_e f^2 B_m^2 \tag{24}$$

where k_h and k_e are iron-loss coefficients, f is electrical frequency, and B_m is magnetic flux density. Switching loss is approximately expressed as

$$P_{sw}=f_s(E_{on}+E_{off}) \tag{25}$$

where f_s is switching frequency, E_on is turn-on energy loss, and E_off is turn-off energy loss.

4. Results

4.1 Influence of Speed-Loop PI Parameter Deviation

The speed-loop PI parameters directly affect the dynamic response and steady-state operating condition of the motor drive system. PI controllers remain widely used in industrial motor drives because of their simple structure and easy implementation [10]. In this study, the proportional gain K_pω and integral gain K_iω are changed by ±20% and ±40%, while other parameters remain unchanged. The simulation results are shown in Table 2.

Table 2: Influence of speed-loop PI parameter deviation on system performance

Deviation type	Deviation amplitude	Efficiency (%)	Efficiency change (%)	Overshoot (%)	Settling time (ms)
Benchmark	0%	92.3	--	4.2	85
K_pω smaller	-20%	91.1	-1.30	2.1	142
K_pω smaller	-40%	89.8	-2.71	1.2	208
K_pω larger	+20%	90.5	-1.95	8.6	76
K_pω larger	+40%	88.6	-4.01	15.3	68
K_iω smaller	-20%	91.8	-0.54	3.8	104
K_iω smaller	-40%	91.0	-1.41	3.5	138
K_iω larger	+20%	91.5	-0.87	5.1	92
K_iω larger	+40%	90.3	-2.17	7.2	88

The results show that speed-loop proportional gain has a greater influence on efficiency than integral gain. When K_pω increases by 40%, the efficiency decreases from 92.3% to 88.6%, and the overshoot increases from 4.2% to 15.3%. This indicates that excessive proportional gain causes strong speed-loop response and current oscillation. Although the settling time becomes shorter, the motor operates with larger current fluctuation and more frequent inverter switching actions, which increases switching loss and copper loss.

When K_pω decreases by 40%, the efficiency decreases to 89.8%, and the settling time increases to 208 ms. In this case, the controller response is too slow. The motor remains in the transient process for a longer time, which increases dynamic energy consumption. Therefore, both excessive and insufficient proportional gain reduce operating efficiency.

Compared with proportional gain, integral gain has a relatively smaller influence on efficiency. The main function of integral gain is to eliminate steady-state speed error. When K_iω is too small, the system response becomes slower.

When K_iω is too large, the system may produce larger overshoot and oscillation. However, within the tested range, the efficiency degradation caused by integral gain deviation is smaller than that caused by proportional gain deviation.

4.2 Influence of Rotor Flux-Linkage Estimation Error

Rotor flux linkage is a key parameter in PMSM vector control. It directly affects torque calculation, current command generation, and field orientation. In practical systems, flux-linkage estimation may be influenced by temperature, demagnetization, magnetic saturation, and observer error. In this study, different flux-linkage estimation errors are introduced into the controller. The simulation results are shown in Table 3.

Table 3: Influence of rotor flux-linkage estimation error on system performance

Flux-linkage condition	Estimated / actual value	Efficiency (%)	Power factor	Stator current RMS (A)	Copper loss (W)
Accurate estimation	1.0	92.3	0.96	18.2	348
Positive deviation	1.1	90.1	0.92	20.5	441
Positive deviation	1.2	86.5	0.87	24.1	610
Negative deviation	0.9	91.2	0.94	19.3	391
Negative deviation	0.8	88.9	0.91	21.8	499

The results show that rotor flux-linkage estimation error has a significant influence on PMSM operating efficiency. When the estimated flux linkage is 20% higher than the actual value, the efficiency decreases from 92.3% to 86.5%. The stator current RMS increases from 18.2 A to 24.1 A, and copper loss increases from 348 W to 610 W.

When the estimated flux linkage is higher than the actual value, the controller overestimates the torque-production capability of the motor. This causes inaccurate current distribution and may lead to magnetic saturation. Magnetic saturation increases iron loss and weakens the power factor. Meanwhile, the current regulator needs to make additional adjustments to maintain torque output, which increases copper loss.

When the estimated flux linkage is lower than the actual value, the controller underestimates the torque-production capability. To maintain the same output torque, the system tends to increase stator current, resulting in higher copper loss. Therefore, both positive and negative flux-linkage estimation errors reduce efficiency, but positive deviation causes more serious efficiency degradation in this simulation.

4.3 Influence of Stator Resistance Deviation

Stator resistance varies significantly with winding temperature. The relationship between stator resistance and temperature can be approximately expressed as

$$R_s = R_{s0}\left[1+\alpha(T-T_0)\right] \tag{26}$$

where R_s0 is the stator resistance at reference temperature T_0, T is the actual winding temperature, and α is the temperature coefficient of copper. If the controller does not update the stator resistance value, the voltage compensation term in the current loop becomes inaccurate. This causes current-tracking error and increases copper loss. Table 4 shows the influence of stator resistance deviation on system efficiency.

Table 4: Influence of stator resistance deviation on system performance

Stator resistance condition	Deviation amplitude	Efficiency (%)	Stator current RMS (A)	Copper loss (W)
Benchmark	0%	92.3	18.2	348
R_s smaller in controller	-20%	91.6	18.9	376
R_s smaller in controller	-40%	90.7	19.8	411
R_s larger in controller	+20%	91.4	19.1	383
R_s larger in controller	+40%	90.2	20.2	428

The results indicate that stator resistance deviation has a moderate influence on efficiency. Compared with rotor flux-linkage estimation error and speed-loop proportional gain deviation, the effect of stator resistance deviation is smaller. However, resistance deviation still increases current error and copper loss, especially when the motor operates under high-load and high-temperature conditions for a long time.

4.4 Comparison Between Fixed-Parameter Control and Adaptive Regulation

The proposed strategy is verified under a load-step condition. The motor first operates at 1500 r/min under a load torque of 20 N·m. Then the load torque increases to 30 N·m. The fixed-parameter control strategy and the proposed adaptive regulation strategy are compared.

The evaluation indicators include dynamic overshoot, settling time, and additional transient energy consumption. The additional transient energy consumption is calculated as

$$E_{add}=\int_{t_1}^{t_2}\left(P_{in}-P_{in,ss}\right)dt \tag{27}$$

where P_in is the instantaneous input power, and P_in,ss is the steady-state input power after the load change.

Table 5: Comparison between fixed-parameter control and adaptive regulation

Control method	Dynamic overshoot (%)	Settling time (ms)	Additional transient energy consumption (J)
Fixed-parameter control	14.5	210	42.3
Adaptive regulation	6.8	112	17.8

The results show that the proposed adaptive regulation strategy significantly improves dynamic performance. Compared with fixed-parameter control, the overshoot decreases from 14.5% to 6.8%, and the settling time decreases from 210 ms to 112 ms. Meanwhile, the additional transient energy consumption decreases from 42.3 J to 17.8 J.

The reduction ratio of additional transient energy consumption is

$$\frac{42.3-17.8}{42.3}\times 100\%=57.9\% \tag{28}$$

Therefore, the proposed adaptive strategy reduces transient extra energy consumption by approximately 58%.

4.5 Efficiency Compensation Effect

To verify the compensation effect under parameter drift, a flux-linkage deviation condition is selected. When the rotor flux-linkage estimation error is +20%, the efficiency decreases from 92.3% to 86.5%. After online parameter compensation and adaptive regulation, the efficiency increases to 90.1%.

The efficiency loss before compensation is

$$92.3\% - 86.5\% = 5.8\% \tag{29}$$

The efficiency loss after compensation is

$$92.3\% - 90.1\% = 2.2\% \tag{30}$$

The reduction ratio of efficiency loss is

$$\frac{5.8 - 2.2}{5.8} \times 100\% = 62.1\% \tag{31}$$

Thus, the proposed strategy reduces the efficiency loss caused by parameter drift by more than 60%.

5. Discussion

5.1 Sensitivity of Different Parameter Deviations

Based on the simulation results, the sensitivity ranking of different parameter deviations can be summarized as follows:

$$\psi_f > K_{p\omega} > R_s > K_{i\omega} \tag{32}$$

This means that rotor flux-linkage estimation accuracy has the greatest influence on PMSM operating efficiency. Speed-loop proportional gain is the most important controller parameter affecting efficiency and dynamic response. Stator resistance mainly affects current-loop compensation and copper loss, while speed-loop integral gain has a relatively smaller influence on efficiency.

5.2 Efficiency Degradation Mechanism

The simulation results demonstrate that different parameter deviations cause efficiency degradation through different mechanisms. When K_pω is too large, the speed controller becomes too sensitive to speed error. This causes large current fluctuation and frequent voltage command changes. As a result, inverter switching loss and copper loss increase. Although the dynamic response becomes faster, the energy efficiency decreases.

When K_pω is too small, the system response becomes slow. The motor stays in the transient state for a longer period after load disturbance. This increases additional transient energy consumption.

When rotor flux-linkage estimation is inaccurate, the field orientation becomes inaccurate. If the estimated flux linkage is higher than the actual value, magnetic saturation and iron loss may increase. If the estimated flux linkage is lower than the actual value, the stator current must increase to maintain torque output, which increases copper loss.

When stator resistance is inaccurate, the voltage compensation in the current loop becomes inaccurate. The current-tracking performance decreases, and copper loss increases.

The above analysis shows that efficiency optimization should not only focus on reducing steady-state current. It should also consider dynamic response, current fluctuation, field-orientation accuracy, and parameter drift. Therefore, the proposed adaptive regulation strategy has practical significance for PMSM drive systems operating under variable working conditions.

5.3 Adaptive Regulation Strategy

To reduce efficiency degradation, this paper proposes an adaptive regulation strategy combining online parameter identification and operating-condition recognition. The proposed strategy contains two main parts. The first part is online parameter identification, which estimates motor parameters such as stator resistance and rotor flux linkage during operation. Online parameter identification has been widely studied as an effective method for improving PMSM control robustness under parameter variation [4]–[6]. The second part is operating-condition-aware parameter adjustment, which changes speed-loop PI parameters according to the current operating condition.

Online parameter identification uses measurable signals such as stator voltage, stator current, and rotor speed to estimate actual motor parameters. The general form of the parameter identification model can be expressed as

$$y(k)=\phi^{T}(k)\theta(k)+e(k) \tag{33}$$

where y(k) is the measured output, ϕ(k) is the regression vector, θ(k) is the parameter vector to be identified, and e(k) is the estimation error. The estimated parameter vector is

$$\widehat{\theta}(k)=\left[\widehat{R}_s,\widehat{\psi}_f\right]^{T} \tag{34}$$

A recursive update law can be written as

$$\widehat{\theta}(k+1)=\widehat{\theta}(k)+K(k)e(k) \tag{35}$$

where K(k) is the adaptive gain. The identified parameters are sent to the controller to update voltage compensation and torque calculation.

Different operating conditions require different control objectives. During steady-state operation, the main objective is to improve efficiency and reduce current fluctuation. During dynamic operation, the main objective is to improve response speed and disturbance rejection. Therefore, an operating-condition index is defined as

$$J=\alpha\left|e_{\omega}\right|+\beta\left|\frac{dT_L}{dt}\right| \tag{36}$$

where e_ω is the speed error, dT_L/dt is the load variation rate, and α and β are weighting coefficients. The operating condition can be classified as

$$\begin{cases} J<J_1, & \text{steady-state mode} \\ J_1\leqslant J\leqslant J_2, & \text{transition mode} \\ J>J_2, & \text{dynamic mode} \end{cases} \tag{37}$$

where J_1 and J_2 are threshold values. In dynamic mode, the proportional gain of the speed loop should be increased to improve response speed. In steady-state mode, the gain should be reduced to suppress oscillation and reduce switching loss. Therefore, the adaptive proportional gain is designed as

$$K_{p\omega}=K_{p0}\left(1+\gamma J\right) \tag{38}$$

where K_p0 is the basic proportional gain, and γ is the adjustment coefficient. To prevent excessive gain variation, the gain is limited by

$$K_{p,min}\leqslant K_{p\omega}\leqslant K_{p,max} \tag{39}$$

The integral gain is adjusted more conservatively:

$$K_{i\omega}=K_{i0}\left(1+\lambda J\right) \tag{40}$$

where λ < γ. This design avoids excessive integral action and reduces the risk of overshoot.

5.4 Engineering Applicability

The proposed strategy has good engineering applicability because it does not require a major change in the original vector-control structure. The additional modules mainly include an online parameter identification module, an operating-condition recognition module, and an adaptive gain adjustment module.

In practical applications, the strategy can be implemented in a digital signal processor or microcontroller. Existing motor-control application studies and technical reports have shown that PMSM vector control can be implemented on digital control platforms such as DSP or microcontroller-based systems [11], [12]. Therefore, the proposed method has potential application value in industrial equipment, pumps, fans, compressors, servo drives, and electric traction systems.

These systems often operate under variable load and long-term temperature variation. Parameter compensation and adaptive tuning can help maintain high operating efficiency during the lifecycle of the equipment.

6. Conclusion

This paper studied the influence of control parameter deviations on the operating efficiency of PMSM drive systems. A MATLAB/Simulink-based PMSM vector-control simulation platform was established, and speed-loop proportional gain, speed-loop integral gain, stator resistance, and rotor flux-linkage estimation error were introduced as parameter-deviation factors.

The simulation results show that rotor flux-linkage estimation error has the greatest influence on system efficiency. When the flux-linkage estimation value is 20% higher than the actual value, the efficiency decreases from 92.3% to 86.5%, and copper loss increases significantly. Speed-loop proportional gain deviation also has a strong influence on both efficiency and dynamic performance. Excessive proportional gain causes overshoot and switching loss, while insufficient proportional gain increases settling time and transient energy consumption. Stator resistance deviation mainly affects current-loop compensation and copper loss, while speed-loop integral gain has a relatively smaller influence on efficiency.

To reduce efficiency degradation, an adaptive regulation strategy combining online parameter identification and operating-condition recognition was proposed. The strategy compensates motor parameter drift and adjusts speed-loop PI parameters according to operating conditions. Simulation results show that the proposed strategy reduces efficiency loss caused by parameter drift by more than 60% and decreases additional transient energy consumption by approximately 58%.

The study provides a practical simulation-based reference for improving the operating efficiency of PMSM drive systems. Future work will focus on experimental verification using a DSP-based PMSM control platform and further optimization of the online parameter identification algorithm under complex load disturbances.

Competing Interests Statement

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval Consent

This study does not involve human participants, animal experiments, or personally identifiable experimental data. Ethical approval and informed consent are therefore not applicable.

Data Availability Statement

All data generated or analyzed during this study are included in this article. The simulation data are available from the author upon reasonable request.

Declaration of Generative AI in Scientific Writing

During the preparation of this work, the author used ChatGPT for language polishing, grammar checking, formatting assistance, and manuscript organization. After using this tool, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

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