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Multi-Step Predictive Control of Permanent Magnet Synchronous Motor Based on Fuzzy PSO Full Parameter Identification

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ABSTRACT: A multi-step deadbeat predictive control method for permanent magnet synchronous motors based on fuzzy adaptive particle swarm optimization (PSO) parameter identification is proposed to address the problem of performance degradation under parameter mismatch conditions. First, this method dynamically adjusts the learning factors of the PSO algorithm through fuzzy control, improving the convergence speed and stability of parameter identification. Secondly, this method can accurately identify key parameters such as stator resistance, inductance, and permanent magnet flux without the need for additional excitation signal injections, effectively solving the problem of the under rank model in traditional identification methods. The experimental results demonstrate that this method significantly improves the dynamic response speed and steady-state control accuracy of the system under parameter mismatch conditions, effectively suppresses speed fluctuations and current surges, improves current ripple characteristics, and provides a high-performance solution for high-precision driving scenarios, such as CNC machine tools.

1. INTRODUCTION

With the transformation and upgrading of high-end manufacturing towards precision and efficiency, computer numerical control (CNC) machine tools, as the core processing equipment, directly determine the quality and performance of workpieces based on machining accuracy. Permanent magnet synchronous motors (PMSMs), which offer outstanding advantages, such as high power density, fast response speed, high control accuracy, and low loss, have become the core driving components of CNC machine tool spindles and feed systems. During CNC machine tool machining, the stability of the spindle speed and smoothness of the feed motion directly affect the dimensional accuracy, surface roughness, and machining efficiency of the workpiece. Therefore, achieving high-precision control of PMSM is the key to improving the machining performance of CNC machine tools. To meet the strict requirements of CNC machine tools for the dynamic response and steady-state accuracy of the drive system, the no-beat multi-step deadbeat predictive control (MDPC) algorithm has been widely studied and applied. This algorithm predicts the multi-step current and speed response in advance, optimizes the calculation of the optimal control quantity, and can effectively improve the dynamic tracking performance and control accuracy of the system. However, the control performance of the no-beat multi-step predictive control algorithm is highly dependent on the accuracy of motor parameters (stator resistance, inductance, permanent magnet flux, etc.) Under actual working conditions, the motor parameters are easily affected by factors such as temperature drift, load fluctuations, and magnetic saturation, leading to parameter mismatch, significantly reducing the control accuracy, causing speed oscillations, and increasing the current ripple. Therefore, achieving accurate and real-time identification of motor parameters is a prerequisite for ensuring the high-performance operation of the no-beat multi-step predictive control algorithm [1–3].

In recent years, many scholars have conducted extensive research on PMSM deadbeat control and parameter identification technology, and have achieved many results. In the research of deadbeat control, Wang et al. proposed a robust deadbeat predictive current control method for PMSMs based on full parameter identification [4]. By introducing a full parameter identification mechanism to compensate for control errors caused by parameter mismatch, the robustness of interior PMSM (IPMSM) drive systems to parameter changes is effectively improved, which is suitable for high-performance industrial drive scenarios. In [5], an enhanced observer based on a prediction error model is designed, which significantly improves the control accuracy and disturbance resistance of the system by real-time estimation and compensation of prediction errors in the deadbeat control system, and solves the problem of cumulative prediction errors in traditional deadbeat control. In [6], a modified deadbeat prediction current control method is proposed, which improves the dynamic response performance of PMSM during transient operation by optimizing the prediction time domain design, shortens the adjustment time of torque and current, and reduces transient oscillations. In [7], a deadbeat predictive current control method based on dynamic weak magnetic control, combined with a torque rise time pre-

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diction algorithm, is proposed to achieve a rapid increase in motor torque and meet the dynamic performance requirements under medium- and high-speed operating conditions. In [8], a robust deadbeat predictive current control (DPCC) and inductance identification method based on an incremental model and current error compensation is proposed. By constructing an incremental deadbeat control model, the sensitivity of the system to parameter changes was reduced, and online identification of inductance parameters was achieved. In [9], an improved deadbeat predictive current control method based on a resistance adaptive position observer is proposed. By adjusting the stator resistance parameters in real-time and compensating for the control deviation caused by resistance drift, the stability of the sensorless deadbeat control system was improved. In [10], an improved deadbeat predictive current control method is proposed, which effectively suppresses the impact of harmonic disturbances on control performance and improves the steady-state accuracy of the system. In [11], a model reference adaptive system combined with parameter identification is proposed to propose an improved deadbeat predictive current control method based on parameter identification. In [12], a two-step mechanical parameter identification method that does not require parameter tuning is proposed. The identification of mechanical parameters is achieved through open-loop speed response and an algebraic estimator, but this method relies on open-loop operating state and is easily limited by model structure. In [13], a parallel cascade parameter identification scheme is proposed, which is based on a parallel cascade extended sliding mode observer and a simplified friction model to achieve collaborative identification of mechanical and electromagnetic parameters. However, this method still requires injecting specific test signals during the self-tuning stage, which interferes with the normal operation of the motor. In [14], an adaptive disturbance estimation and online parameter identification strategy is proposed, which improves the tracking ability of the identification algorithm for time-varying parameters through a fuzzy model. However, this method is not thorough enough in solving the problem of model under-rank under complex working conditions. In [15], a PMSM electric spindle deadbeat control method based on an improved parameter identification algorithm is proposed, attempting to optimize the accuracy of parameter identification, but still not fully solving the problem of under rank in the model recursion process. Overall, most identification methods based on model recursion are limited by the mathematical model structure of the motor, which can easily lead to model under-rank problems, resulting in insufficient parameter identification accuracy and slow convergence speed. To achieve high-precision identification through model recursion, it is often necessary to inject additional excitation signals into the motor winding, which not only interferes with the normal operation of the motor but also leads to a decrease in control performance, making it difficult to adapt to the high-precision and low-disturbance driving requirements of CNC machine tools. Although some scholars have attempted to use intelligent algorithms to optimize the identification process, further research is needed on how to improve identification accuracy and convergence speed without injecting additional signals and solving the problem of model under rank.

In view of the above problems, an MDPC method based on fuzzy particle swarm optimization (FPSO) parameter identification algorithm is proposed to improve the control accuracy and robustness of PMSM for CNC machine tools. This method combines fuzzy control with the particle swarm optimization algorithm to construct an FPSO parameter identifier. By using the adaptive decision-making ability of fuzzy control, the learning factors C_1 and C_2 of the PSO algorithm are adjusted in real time, and the defects of slow convergence speed and ease of falling into local optimum of the traditional PSO algorithm are solved. At the same time, the proposed FPSO identification algorithm does not need to inject any additional excitation signal into the motor and can be used in the normal operation of the motor. The key parameters, such as stator resistance, stator inductance, and permanent magnet flux linkage, are completely identified, which effectively solves the problem of model rank deficiency in the traditional recursive model identification method, and the interference of additional signal injection on the control performance is avoided. The identified accurate parameters are fed back to the deadbeat multi-step predictive controller in real time to optimize the calculation accuracy of the control law and realize the accurate control of motor speed and current under parameter mismatch conditions. Finally, the machining accuracy and stability of CNC machine tools are improved, and a high-performance control scheme is provided for the PMSM drive system of high-end CNC machine tools.

2. MATHEMATICAL MODEL OF PMSM

In the PMSM deadbeat predictive control process, the current equation must be discretized. The current differential equation of the PMSM is as follows:

$$\begin{cases} \frac{\mathrm{d}}{\mathrm{d}t} i_d = \frac{1}{L_s}\left(u_d - R_s i_d + \omega_e L_s i_q\right) \\ \frac{\mathrm{d}}{\mathrm{d}t} i_q = \frac{1}{L_s}\left(u_q - R_s i_q - \omega_e L_s i_d - \omega_e \lambda_f\right) \end{cases} \tag{1}$$

where u_d and u_q are the d-axis and q-axis voltages, respectively; i_d and i_q are the d-axis and q-axis currents, respectively; R_s denotes the stator resistance; L_s represents the stator inductance; ω_e is the electrical angular velocity of the motor; and λ_f stands for the permanent magnet flux linkage.

After discretization, the current equation is:

$$\begin{cases} i_d(k+1) = i_d(k) + \frac{T_s}{L_s}\begin{bmatrix} u_d(k) - R_s i_d(k) + \\ \omega_e(k) L_s i_q(k) \end{bmatrix} \\ i_q(k+1) = i_q(k) + \frac{T_s}{L_s}\begin{bmatrix} u_q(k) - R_s i_q(k) - \\ \omega_e(k)\left(L_s i_d(k) + \lambda_f\right) \end{bmatrix} \end{cases} \tag{2}$$

where T_s is the sampling period.

In the above equation, the following assumptions must be added:

1. The stator winding of the motor adopts a symmetrical three-phase structure and ignores the higher-order harmonic components in the current and magnetic flux.

2. Ignore the effects of iron core saturation, eddy currents, and hysteresis losses.

3. The amplitude of the magnetic flux of the rotor permanent magnet remains constant.

4. The control system cycle T_s was set to be much smaller than the mechanical time constant of the motor, ensuring that the electrical angular velocity ω_e could be considered approximately constant within a single control cycle.

3. MDPC ALGORITHM BASED ON FPSO PARAMETER IDENTIFICATION

3.1. Analysis of MDPC Algorithm

During the continuous control process, certain differences exist in the sampling time, calculation period, and pulse width modulation (PWM) update period. The specific process is shown in the following Figure 1.

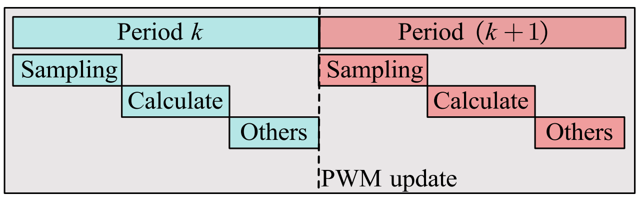

FIGURE 1. Control cycle process diagram.

Owing to the delay of one beat in the controller, when the controller samples at time $t = kT_s$, the PWM obtained by the controller will take effect in the $(k+1)T_s$ carrier cycle. Therefore, the control objective should be the reference value of the current value at time $(k+2)T_s$. Feedback current calculation: The PWM obtained by the controller will take effect during the $(k+1)T_s - (k+2)T_s$ carrier cycle, and the starting point of this PWM action is the current at time $(k+1)T_s$. Therefore, the feedback current should be the current value feedback value at time $(k+1)T_s$.

According to the discretized current equation in Section 2, the voltage equation at time $k+1$ can be expressed as follows:

$$\begin{cases} u_d(k+1) = R_s i_d(k+1) - \omega_e(k+1) L_s i_q(k+1) \\ \qquad + \dfrac{L_s}{T_s}\left[i_d^*(k+2) - i_d(k+1)\right] \\ u_q(k+1) = R_s i_q(k+1) + \omega_e(k+1)(L_s i_d(k+1) + \lambda_f) \\ \qquad + \dfrac{L_s}{T_s}\left[i_q^*(k+2) - i_q(k+1)\right] \end{cases} \tag{3}$$

The current equation can be discretized as follows:

$$\begin{cases} i_d(k+1) = \theta_{d1} i_d(k) + \theta_{d2}\omega_e(k)\, i_q(k) + \theta_{d3} u_d(k) \\ i_q(k+1) = \theta_{q1} i_q(k) + \theta_{q2}\omega_e(k)\, i_d(k) + \theta_{q3} u_q(k) \\ \qquad + \theta_{q4}\omega_e(k) \end{cases} \tag{4}$$

where $\theta_{d1} = (1 - \frac{R}{L_d}T_s)$, $\theta_{d2} = \frac{L_q}{L_d}T_s$, $\theta_{d3} = \frac{T_s}{L_d}$, $\theta_{q1} = \left(1 - \frac{R}{L_q}T_s\right)$, $\theta_{q2} = -T_s\frac{L_d}{L_q}$, $\theta_{q3} = \frac{T_s}{L_q}$, $\theta_{q4} = -\frac{T_s\lambda_f}{L_q}$, $L_d = L_q$.

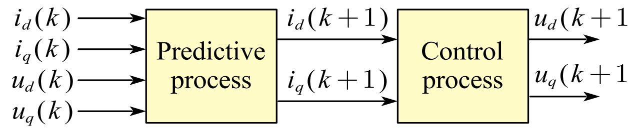

FIGURE 2. Control process diagram.

The structure of the entire control process is shown in Figure 2.

When the parameters are inaccurate, the predicted results are shown in Figure 3, where red represents the predicted current with inaccurate parameters, and blue represents the predicted current with accurate parameters. Calculating the voltage vector based on an inaccurate predicted current will inevitably lead to a decrease or even instability in the control performance. Therefore, it is necessary to improve the robustness of the system parameters and reduce the dependence on the parameters.

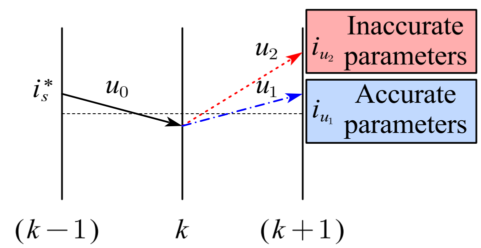

FIGURE 3. Predicted results chart.

3.2. Parameter Identification Algorithm Based on FPSO

In the actual control of the above assumptions, the deviation between the predicted and actual currents is widened owing to the neglect of parameter drift and external disturbances. To suppress this adverse effect, real-time estimation of PMSM parameters is required. PMSM parameter estimation can be mainly divided into signal injection method and intelligent algorithm based full parameter identification. The signal injection method identifies motor parameters by actively injecting voltage/current excitation signals of specific frequencies into the control system and observing the system response. This inevitably results in output disturbances and torque ripple, limited bandwidth and dynamic performance, and sensitivity to non-ideal factors, which are not conducive to high-precision control. Therefore, an FPSO-based PMSM parameter identification algorithm was introduced. This algorithm can iterate the corresponding parameters in real time based on signals such as the current and voltage of the motor. The main structure of the PSO parameter identification algorithm is shown in Figure 4.

PSO is an intelligent algorithm that uses particle swarm optimization to search for the optimal solution. In motor parameter identification, each particle represents a set of motor parameters to identify. The position of the particle is the parameter value, and the speed is the direction and step size of parameter iteration adjustment. The update of the two is the core execution logic of the PSO algorithm. We considered the parameters of the motor, such as resistance, inductance, and magnetic flux, as particles and iteratively updated them according to the pro-

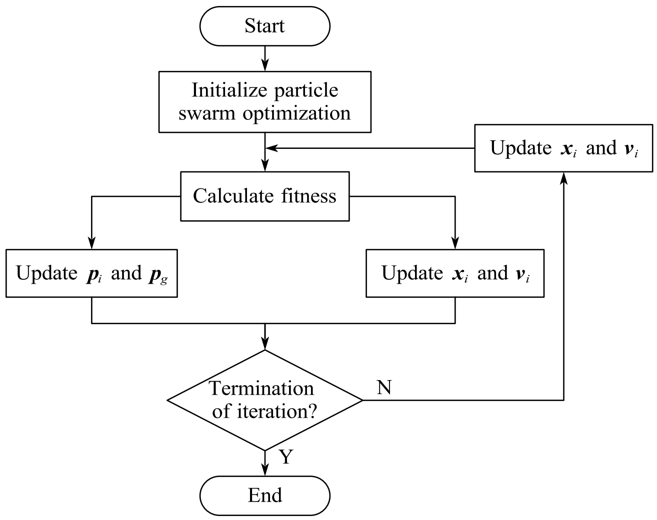

FIGURE 4. The PSO parameter identification algorithm.

cess shown in Figure 1. The iterative formula for the particles is as follows:

$$\mathbf{x}_i^{k+1} = \mathbf{x}_i^k + \mathbf{v}_i^{k+1} \tag{5}$$

where particle **x** represents the parameters R, L_s, λ_f, etc.

After the particle position update is completed, it is necessary to allow the particles to adaptively adjust their movement direction and step size in the parameter search space by combining their own historical best experience, the global best experience of the group, and inertia preservation to avoid a blind search. Based on the speed update results, the actual position of particles in the parameter search space is updated; a parameter iteration optimization is completed; and the optimal parameter solution is gradually approached. The particle velocity is expressed as follows:

$$\mathbf{v}_i^{k+1} = \boldsymbol{\omega}\mathbf{v}_i^k + \mathbf{c}_1\mathbf{r}_1\left(\mathbf{p}_i^k - \mathbf{x}_i^k\right) + \mathbf{c}_2\mathbf{r}_2\left(\mathbf{p}_g^k - \mathbf{x}_i^k\right) \tag{6}$$

In (6), the coefficient $\boldsymbol{\omega}$ is the inertia weight, which is adjusted to control the degree to which the particles inherit the previous iteration speed. Its essence is to balance the global and local search capabilities of the PSO. In addition, to address the complex and variable working conditions of motor parameter identification, exponential weight reduction is adopted to further improve the accuracy of the local search in the later stage. The expression is:

$$\boldsymbol{\omega}(k) = \boldsymbol{\omega}_{\min} + (\boldsymbol{\omega}_{\max} - \boldsymbol{\omega}_{\min}) \cdot e^{-\alpha \cdot \frac{k}{k_{\max}}} \tag{7}$$

where α is the attenuation coefficient used to control the attenuation rate.

The FPSO algorithm is used to identify the parameters of the deadbeat current prediction model of a permanent magnet synchronous motor, and the fitness function is defined as:

$$fitness = \sum_{k=1}^{n} \left\{ [i_d(k) - i_d^*(k)]^2 + \left[i_q(k) - i_q^*(k)\right]^2 \right\} \tag{8}$$

To improve the convergence speed of the coefficient adjustment in the parameter identification process of PSO, fuzzy control was used to dynamically adjust the main parameters c_1, c_2 of PSO. The theoretical basis for its adjustment is as follows: global exploration stage: large c_1 + small $c_2 \rightarrow$ quickly traversing the input parameter space to avoid missing the optimal solution. Local refinement stage: small c_1 + large $c_2 \rightarrow$ fine adjustment of input parameter values to improve identification accuracy. According to this process, the input parameter for fuzzy control were determined as the number of PSO iterations, and the output parameters were c_1 and c_2. The main implementation process of fuzzy control is divided into

1. Determine the input and output variables. The input variable was the number of PSO iterations, and the output variables were c_1 and c_2.

2. Fuzzification, which uses several symbolic labels to describe fuzzy sets of one input and two outputs, that is, zero (Z), positive small (PS), median (PM), and positive large (PB). In this study, the fuzzy domain of the number of iterations was set to [0, 3], and the fuzzy subset was set to Z, PS, PM, and PB. The actual domain and quantization factor of the number of iterations were determined according to the error parameter. The output variables of the fuzzy controller were c_1 and c_2; the fuzzy domain was set to [0.1, 1]; and the fuzzy subset was set to PS, PM, PB. According to the actual control effect, the actual values of c_1 and c_2 can be quantified. To simplify the calculation, the input and output variables were subjected to a triangular membership function distribution curve, as shown in Figure 5.

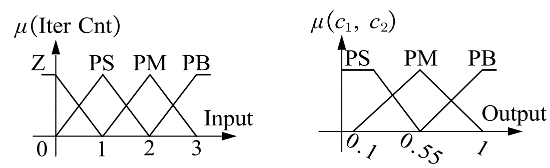

FIGURE 5. Membership function of input and output.

3. Establish fuzzy rules and fuzzy reasoning, and the fuzzy rule library consists of multiple IF-THEN rules. In actual code, an array is used to store the corresponding fuzzy rules, and the corresponding output values are calculated through the written membership function. The form of the rules in this design is shown in Table 1.

TABLE 1. The form of the rules.

	Iter Cnt k			
	Z	PS	PM	PB
c_1, c_2 $k < 50\%$	PB/PS	PB/PS	PM/PM	PS/PB
c_1, c_2 $k > 50\%$	-	PS/PB	PM/PM	PB/PS

4. Defuzzification, in order to smooth the output, using the center of gravity method for defuzzification operation. The specific expressions are as follows:

$$u = \frac{\sum_{i=1}^{4} \sum_{j=1}^{4} \omega_{i,j} u_{i,j}}{\sum_{i=1}^{4} \sum_{j=1}^{4} \omega_{i,j}} \tag{9}$$

3.3. The Structure of the Proposed Algorithm

A block diagram of the MDPC based on FPSO parameter identification is shown in Figure 6. According to Section 2.1, the MDPC can effectively achieve high-performance motor drive control by replacing the current loop in the field-oriented control (FOC). However, the operating conditions of the motor are complex, and the parameters are variable. Moreover, the MDPC relies on the accuracy of the motor parameters. To improve the performance of motor control, the PSO parameter identification algorithm is introduced into the MDPC control to achieve accurate parameter identification and effectively enhance the control performance. In this algorithm, the input parameters of the FPSO were the sampled current, voltage, speed, angle, and other parameters of the motor. After multiple iterations, the corresponding motor parameter identification results were output. The identified motor parameters are mainly used for MDPC control. According to the MDPC control model shown in (3), the parameter identification results were applied to the control process to achieve high-performance control. After the MDPC calculation and coordinate transformation, the voltage in the stationary coordinate system is generated as the input part of the space vector pulse width modulation (SVPWM). Finally, after the SVPWM calculation, six driving signals were obtained.

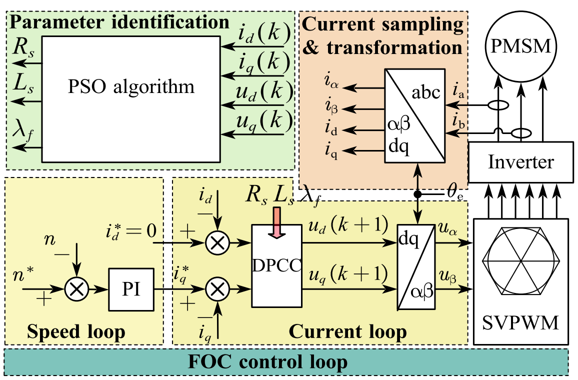

FIGURE 6. The block diagram of the proposed algorithm.

4. EXPERIMENTAL VERIFICATION

To verify the effectiveness of the proposed algorithm, experiments were conducted on the platform shown in Figure 7.

In this experimental platform, the main control unit was the TMS320F28379D dual-core and dual coprocessor chip of the TI company. In the control process, the speed loop calculation, coordinate transformation calculation, and SVPWM algorithm calculation were completed in CPU1, and the current loop MDPC calculation and current sampling are completed in CLA1. The FPSO was completed in CPU2. The main parameters of the prototype used in the experimental platform are listed in Table 2.

The resistance parameters were measured using a multimeter, and the inductance parameters were measured by a digital bridge at the frequency of 1 kHz. The flux parameters were the nominal values provided by the motor manufacturer. Based on the above conditions, the following experiments were performed.

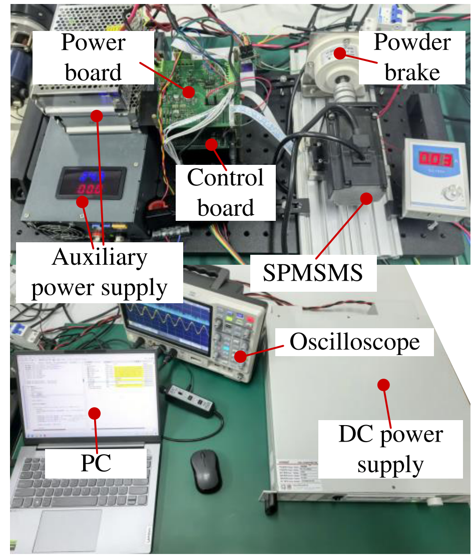

FIGURE 7. Schematic diagram of the experimental platform.

TABLE 2. Parameters of the prototype.

Parameters	Value
Stator resistance R_s (Ω)	1.6
Inductance L_s (H)	0.005075
Pole Pairs	4
Permanent magnet flux λ_f (Wb)	0.0825
Rated speed n_N (r/min)	3000
Rated power P(kW)	0.2
Rated voltage U (V)	220
Rated current I (A)	2.1
Rated torque T_e (N·m)	0.64

First, an experiment was conducted on single-step predictive control without beat, in which there was no parameter identification, and the parameter settings were in a state of mismatch. The waveform diagram of the speed and current in this scenario is shown in Figure 8. From the figure, it can be seen that the system exhibits a significant loss of control. In the initial stage of start-up, there was a severe fluctuation of up to 5200 r/min in the speed, and at the same time, there was a significant oscillation in the dq axis current. The peak value of the d-axis current was approximately 13 A, and the q-axis current showed a significantly negative shift. The essence of this phenomenon is the serious mismatch between the nominal parameters and the actual motor parameters, resulting in significant deviations in the calculation of the deadbeat control law. The misjudgment of control variables causes system instability, resulting in a complete loss of control during the start-up phase and the inability to meet the basic requirements of CNC machine tools for drive system stability.

Figure 9 shows the waveform diagrams of the speed and current under multi-step predictive control with no beat. Under parameter mismatch conditions, although the performance of non-

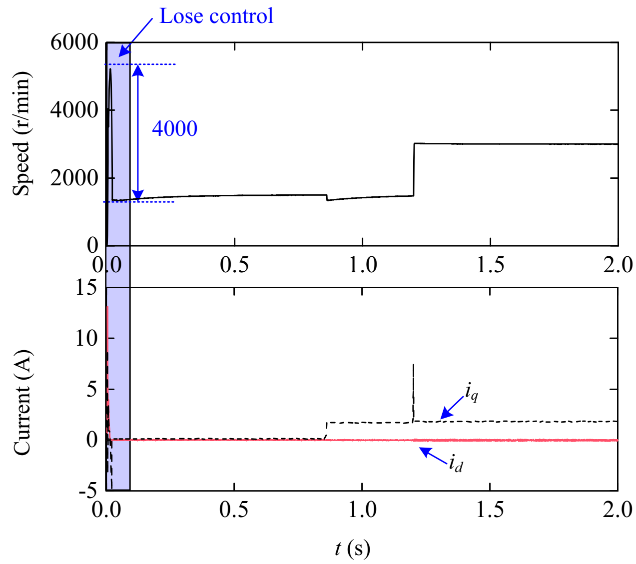

FIGURE 8. Waveform diagram of DPCC with inaccurate parameters.

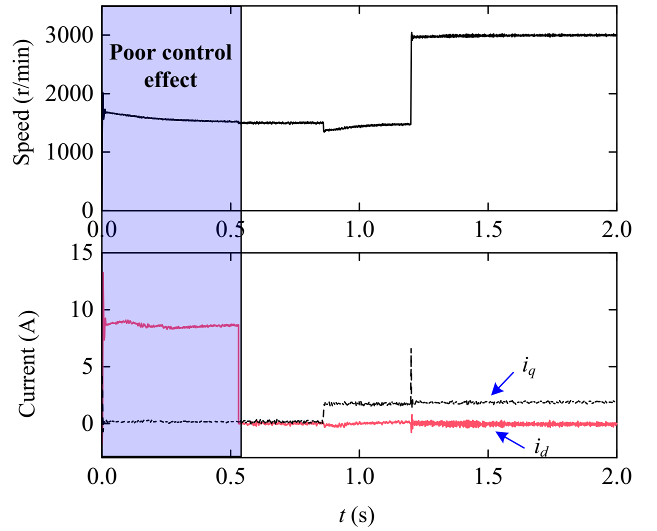

FIGURE 9. Waveform diagram of MDPC with inaccurate parameters.

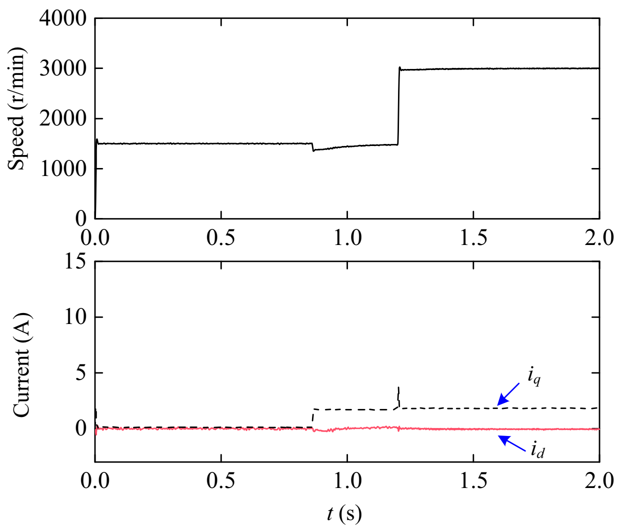

FIGURE 10. Waveform diagram of MDPC with accurate parameters.

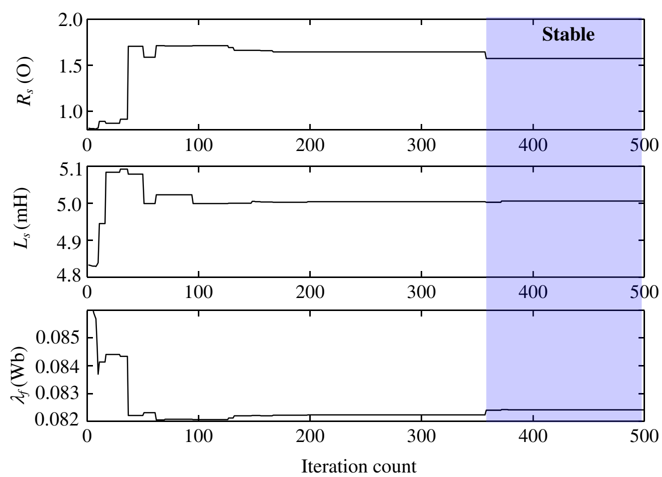

FIGURE 11. Parameter identification result chart under fixed coefficient.

differential multi-step control improves compared with non-identification scenarios, there are still significant shortcomings. At the beginning of the start-up, the speed convergence process lasted for more than 0.5 s and was accompanied by continuous oscillation. The q-axis current remained at a relatively high level of approximately 8 A, and the steady-state ripple was also quite noticeable. This is because, although the no-beat multi-step control introduces a multi-step prediction mechanism, it still relies on accurate motor parameter models. Parameter mismatch leads to cumulative prediction errors, resulting in a slow dynamic response and insufficient steady-state accuracy of the system, which cannot meet the requirements of CNC machine tools for fast response and high-precision control.

Figure 10 shows the speed and current waveforms of the proposed algorithm. The control strategy proposed in this study has been fundamentally improved. The speed can quickly converge to the target value during the start-up phase without significant overshoot or oscillation. The amplitude of the q-axis current surge is significantly reduced; the steady-state ripple is controlled within ± 0.2 A; and the d-axis current remained 0.

In terms of parameter identification performance, the PSO parameter identification results with fixed coefficients are shown in Figure 11. From the figure, it can be seen that the parameters only enter a stable convergence state after approximately 350 iterations, and the convergence process of stator resistance R_s, inductance L_s, and permanent magnet flux λ_f is relatively long. The FPSO parameter identification shown in Figure 12 only requires approximately 120 iterations to enter a stable convergence state, and the convergence speed of each parameter is approximately twice that of the fixed coefficient PSO, with no significant fluctuations after convergence. This indicates that the dynamic adjustment of learning factors in PSO by fuzzy control effectively solves the shortcomings of slow convergence speed and susceptibility to local optima in traditional PSO, significantly improving identification efficiency and stability.

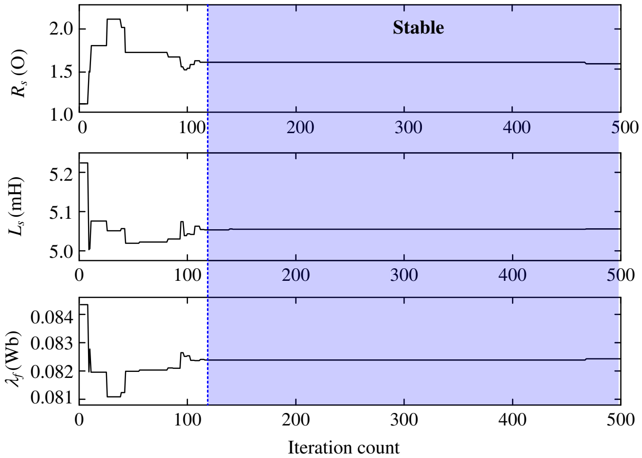

FIGURE 12. Parameter identification results under fuzzy PSO.

5. CONCLUSION

This study proposes an MDPC based on FPSO algorithm parameter identification to solve the problem of poor control performance of deadbeat control when parameter errors are large. The proposed FPSO algorithm can fully identify key parameters such as stator resistance, inductance, and permanent magnet flux of the motor without the need for additional excitation signal injection, effectively solving the problem of model under rank in traditional identification methods. Compared with fixe dcoefficient PSO, the parameter convergence speed of this algorithm is improved by approximately two times. The experimental results show that this method significantly improves the dynamic response speed and steady-state control accuracy of a deadbeat control system. In parameter identification scenarios, the system experiences a severe loss of control, and the performance improvement of the MDPC is limited under parameter mismatches. After parameter identification, the PMSM control performance was significantly improved. The proposed method provides an effective solution for the high-performance control of permanent magnet synchronous motors under parameter mismatch conditions and is particularly suitable for scenarios such as CNC machine tools that require strict driving accuracy and stability, and has good engineering application prospects.

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