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Parameter Identification of PMSWG Based on ASMDRPSO

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Abstract—Aiming at the problem of poor identification accuracy in traditional particle swarm optimization algorithms, an adaptive search particle swarm optimization algorithm (ASMDRPSO) method for permanent magnet synchronous wind generator (PMSWG) parameter identification is proposed. Firstly, in order to solve the issue of the under-rank equation, a full-rank state equation and fitness function are established. Then, in ASMDRPSO, a dynamic adjustment strategy is adopted in the inertia weight update process to enrich population diversity. In addition, the average best position strategy is designed to avoid getting stuck in a local optimum. Moreover, an adaptive learning radius is supplemented in ASMDRPSO, and the particle search range is enlarged when the ASMDRPSO evolution is stalled. Finally, the simulated and experimental results are presented to verify the stronger optimization ability, stronger robustness, and higher search accuracy of the proposed control strategy than the traditional PSO.

1. INTRODUCTION

PMSWG has the advantages of a simple structure, small moment of inertia, and low power loss [1–4]. In recent years, PMSWG has been applied more and more in the wind power generation industry. With the increasing proportion of wind power capacity in power systems, the stability and reliability of power systems are increasingly influenced by the operating conditions of PMSWG. The parameters of the motor are usually considered constants. The main motor parameters include stator resistance [5], quadrature and direct axis inductance [6], and permanent magnet flux [7]. However, these parameters are subject to change due to factors such as temperature, magnetic saturation, and noise. In order to avoid deviations in the control due to deviations between the actual and set parameters, the relevant motor parameters need to be identified. The control of the PMSWG and the quality of the power fed into the grid is improved by the accurate identification of motor parameters. The identified motor parameters can also be used to determine whether or not the unit is working properly, and the reliability and stability of the PMSWG can be improved. Therefore, it is important to identify the electrical parameters of PMSWG.

In recent years, online parameter identification methods [8–11] have been proposed by scholars. Recursive least square (RLS), extended Kalman filter (EKF), model reference adaptive method (MRAS), genetic algorithm [12], and neural network algorithm [13] are included in the online parameter identification method. In [14], the least square algorithm with a fuzzy forgetting factor is applied to parameter identification. It enables the forgetting factor to be dynamically adjusted, and it can be seen from the identification results that this method is reliable. However, in this method, only the stator resistance is identified. In [15], the EKF method is adopted to identify the two parameters of the motor's inductance and flux linkage. The identification effect is good, but the identification accuracy and speed are affected by the selection of Q and R matrices. In [16], a new MRAS observer is created by combining variable structure control and adaptive control theory. The robustness of the system

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has been improved to a certain extent, but there is still the problem of lack of rank in the system of equations. In [17], a genetic algorithm-based method for parameter identification of Permanent Magnet Synchronous Motor (PMSM) is proposed. The identification effect is good, but the convergence is slow. In [18], a minimum mean square weight convergence neural network algorithm is applied to parameter identification. The identification effect is good, but the identification speed is affected by the selection of the convergence factor.

Due to its straightforward algorithm, particle swarm optimization (PSO) has been frequently employed in the identification of PMSWG parameters. In [19], the results are improved by introducing a time-varying nonlinear decreasing strategy into the updating process of the inertia weight. The inertia weight adaptive updating formula is suggested in [20], but only the stator resistance and load torque are identified, and the error is large. A new approach to motor parameter identification based on particle swarm is developed in [21]. The growth rate operator that reflects the particle state is introduced into the method, and the Improved Comprehensive Learning Particle Swarm Optimizer (ICLPSO) algorithm is formed. It can be seen from the identification results that the algorithm enhances the particle search ability, but it is easy to fall into the local optimal situation.

In order to improve the parameter identification ability of the PSO algorithm for PMSWG, an improved particle swarm optimization (ASMDRPSO) is proposed for PMSWG parameter identification. The contributions of this paper are summed up as follows:

1) The same amount of data is collected in the two cases of d-axis injected negative sequence current and $i_d = 0$ current, and the mathematical model of PMSWG full rank can be obtained.

2) The inertia weight is dynamically changed to enhance population variety and the algorithm's ability to do global searches.

3) In order to avoid being in the local optimum, the average best position method is proposed.

4) The adaptive learning radius is added, the particle search scope expanded, the diversity of the population enhanced, and the search accuracy of the PSO algorithm improved.

5) The maximum number of iterations of the algorithm is related to the running time, and the online identification of parameters is realized. From the simulated and experimental results, it can be concluded that the proposed method has high identification accuracy.

This paper's remaining sections are organized as follows. Section 2 describes the mathematical model of the PMSWG. The principle and function of the suggested method are depicted in Section 3. The principle and design process of parameter identification are presented in Section 4. The pros and cons of the method are examined by simulation and experiments in Section 5, and Section 6 gives the conclusion.

2. MATHEMATICAL MODEL OF PMSWG

In the d-q coordinate system, the PMSWG equation is written as:

$$\begin{cases} u_d = R_s i_d + L_d \dfrac{di_d}{dt} - \omega_e L_q i_q \\ u_q = R_s i_q + L_q \dfrac{di_q}{dt} + \omega_e L_d i_d + \omega_e \psi_f \end{cases} \tag{1}$$

where u_d, u_q are the stator voltages; i_d, i_q are the stator currents; ω_e is the electrical angular velocity; ψ_f is the magnetic chain of permanent magnets; PMSWG inductance $L_d = L_q = L_s$; R_s is the resistance of the stator winding.

When the motor operates stably, the differential term is approximately considered as 0, $\frac{di_d}{dt} = 0$, $\frac{di_q}{dt} = 0$. Under this condition, Formula (1) can be simplified as:

$$\begin{cases} u_d = R_s i_d + -\omega_e L_q i_q \\ u_q = R_s i_q + \omega_e L_d i_d + \omega_e \psi_f \end{cases} \tag{2}$$

There are four parameters to be identified in Formula (2), but there are only two equations. The equations are rank-deficient equations and have numerous solutions. In conventional vector control, the $i_d = 0$ control strategy is generally used to achieve decoupling of the motor. On this basis, a negative sequence current with $i_d = -2$ is injected into the d-axis to obtain a fourth-order full rank equation system:

$$\begin{cases} u_{d0}(k) = -\omega_{e0}(k) L_q i_{q0}(k) \\ u_{q0}(k) = R_s i_{q0}(k) + \omega_{e0}(k)\psi_f \\ u_{d1}(k) = R_s i_{d1}(k) - \omega_{e1}(k) L_q i_{q1}(k) \\ u_{q1}(k) = R_s i_{q1}(k) + \omega_{e1}(k) L_d i_{d1}(k) + \omega_{e1}(k)\psi_f \end{cases} \tag{3}$$

where variables with subscript "0" are under the control policy of $i_d = 0$, and variables with subscript "1" are under the control policy of $i_d = -2$.

The data collection of the two methods is shown in Figure 1 below. In Formula (3), $\omega_{e0}(k)$, $i_{q0}(k)$, $u_{d0}(k)$, $u_{q0}(k)$ are the k-th sampled data in 0–t_1 time, and $\omega_{e1}(k)$, $u_{d1}(k)$, $u_{q1}(k)$, $i_{d1}(k)$, $i_{q1}(k)$ are the k-th sampled data in t_1–t_2 time.

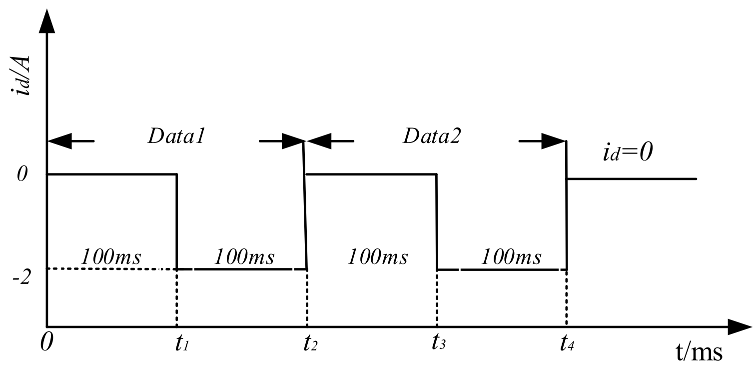

Figure 1. Data sampling diagram.

3. PARTICLE SWARM OPTIMIZATION

PSO is a type of evolutionary calculation technology, submitted by Eberhart and Kennedy in 1995 [22]. The basic idea of the algorithm is to enable the individual optimal value P_{best} and group optimal value G_{best} to be calculated. In the iterative process, the position with the smallest fitness value is continuously approached, and the optimal solution to the problem can be obtained. Compared with other intelligent algorithms, the advantages of simple algorithm, high efficiency, and fast search speed are reflected in the PSO. Therefore, PSO is widely used in the field of PMSWG parameter identification. Its update formula is written as follows:

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(P_{best}^k - x_i^k\right) + c_2 r_2 \left(G_{best}^k - x_i^k\right) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{4}$$

where v_i and x_i are the velocity and position of particle; P_{best} and G_{best} are the best positions for individuals and populations; k is the number of iterations; r_1 and r_2 are random numbers between 0 and 1; c_1 and c_2 are individual and population learning factors; ω is the inertia weight.

The flowchart of particle swarm optimization identification is shown in Figure 2 below.

3.1. Dynamically Regulation Inertia Weight (DRPSO)

PSO performance is affected by inertia weight ω. In this paper, the strategy adopting exponential function is controlled by the weight ω. When the number of generations increases, $e^{-\frac{t}{T_{\max}}}$ is nonlinearly reduced. The betarnd is a random number generated by a beta distribution. In the later iteration period of the algorithm, the global search ability of the algorithm can be increased, and the possibility of the algorithm falling into the local optimum can be reduced. An inertial adjustment factor is added

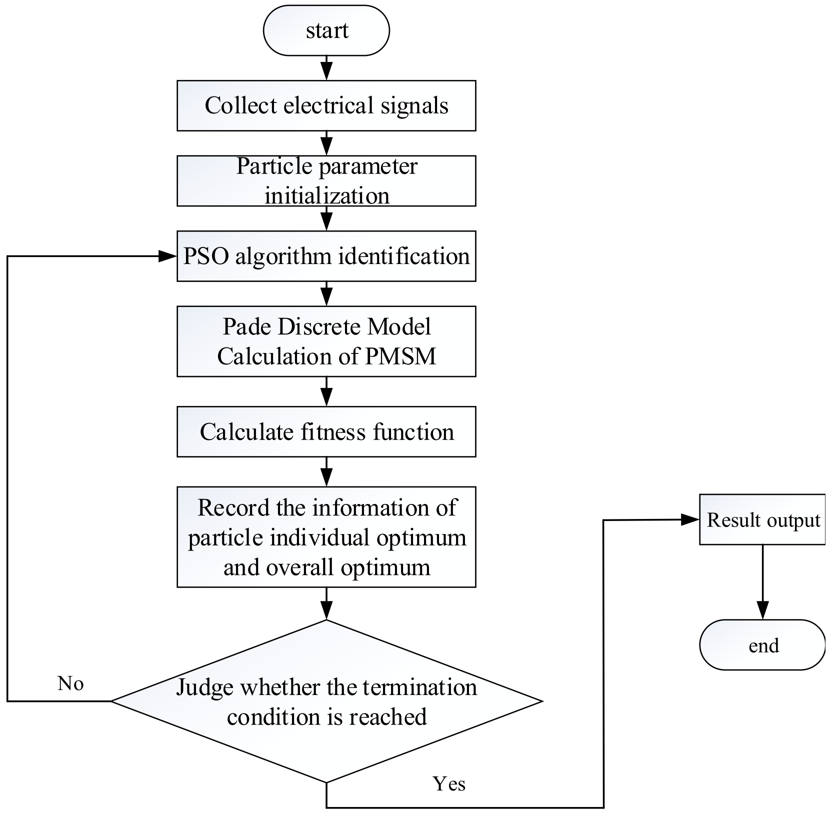

Figure 2. PSO parameter identification flow chart.

to control the deviation degree of the inertial weight, making the adjustment of ω more reasonable. The inertial weight expression is expressed as:

$$\omega = \omega_{\min} + (\omega_{\max} - \omega_{\min}) * e^{-\frac{t}{T_{\max}}} + \delta * betarnd(p, q) \tag{5}$$

where $\omega_{\max}$ is the initial inertia weight, taken as 0.9; $\omega_{\min}$ is the final inertia weight, taken as 0.4; t is the current number of iterations; $T_{\max}$ is the maximum number of iterations; δ is the inertial adjustment factor, taken as 0.1; $p = 1$, $q = 3$.

It can be seen from Formula (5) that in the identification process, the inertia weight ω is decreased nonlinearly. Meanwhile, the random adjustment strategy of beta distribution is introduced to generate a random quantity to adjust ω. Through this method, the search ability in the early stage of PSO is enhanced, and the search accuracy in the later stage of PSO is improved.

3.2. PSO Algorithm of Average Best Position (MDRPSO)

On the basis that the inertia weight is dynamically adjusted, the average best position algorithm is introduced. In this algorithm, the experience of other particles in flight should be learned by the current particle. Mathematically, the strategy is defined as the average of the best positions of all particles. The formula is expressed as:

$$P_{md} = \frac{1}{m} \sum\nolimits_{i=1}^{m} P_{id} = \frac{1}{m} (P_1 + P_2 + P_3 + \ldots + P_m) \tag{6}$$

Update Equation (4) to

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(P_{md}^k - x_i^k\right) + c_2 r_2 \left(G_{best}^k - x_i^k\right) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{7}$$

After the particle velocity update formula is updated from Formula (2) to Formula (5), the amount of information obtained by the particles increases. When the self-optimal position information P_i is referenced, in the average optimal position strategy, the empirical information of other particles is also referenced. When this strategy is introduced, the ability of particle swarms to work together is improved, and the ability of the algorithm to search globally is also enhanced. As a result, the behavior of particles can be better determined. An improved algorithm can increase its potential to be optimized, and the probability of the algorithm falling into a local optimum is reduced.

3.3. Adaptive Search PSO Algorithm (ASMDRPSO)

On the basis that the average best position strategy is introduced, in order to avoid the occurrence of PSO falling into a local optimum, in this paper, an adaptive learning radius is added to the update formula. By this way, the particle search range is expanded, the diversity of the population enhanced, and the search accuracy of the PSO algorithm improved. The adaptive search radius H^k is expressed as:

$$H^k = \frac{P_{best} + G_{best}}{2} + \frac{P_{best} - G_{best}}{2} * \frac{1}{k+1} * \sin(2\pi r) \tag{8}$$

where r is a random number between 0 and 1.

After adding the adaptive search radius, Formula (7) is rewritten as:

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(P_{md}^k - x_i^k\right) + c_2 r_2 \left(G_{best}^k - x_i^k\right) + c_3 r_3 \left(H^k - x_i^k\right) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{9}$$

where c_3 is a non-negative constant, and r_3 is a random number between 0 and 1.

In the PSO algorithm where the adaptive search radius is added, the learning vector is added to the velocity equation, then, the particle velocity update formula is updated from Formula (7) to Formula (9). In this way, the particle search radius is increased; the local optima can be avoided; better locations can be found; and particles can be made to depart the existing zone. It can be concluded that the diversity of the population is enhanced, and the convergence accuracy is improved.

4. PRINCIPLE OF PARAMETER IDENTIFICATION

For a system in which the model is known but the parameters are unknown, the parameter identification problem can be used as an optimization problem. The idea of PMSWG parameter identification is that the difference between the output of the reference model and the adjustable model is calculated, and the parameters of the adjustable model are continuously modified by the fitness function. In order to minimize the difference between the reference model and adjustable model, the optimal solution to the output of the algorithm is the identified motor parameters. The motor dynamic model can be expressed as:

$$\begin{cases} \dot{x} = f(\rho, x, u) \\ \dot{y} = g(\rho, x) \end{cases} \tag{10}$$

where x is the state variable, ρ the actual parameter, u the system input, and y the system output.

For parameters of the motor to be identified, an adjustable model with the same structure is designed.

$$\begin{cases} \dot{\hat{x}} = f(\hat{\rho}, x, u) \\ \dot{\hat{y}} = g(\hat{\rho}, x) \end{cases} \tag{11}$$

where $\hat{x}$ is the state variable of the adjustable model, $\hat{\rho}$ the actual adjustable parameter, and $\hat{y}$ the adjustable model output.

In order for the parameter ρ to be identified, the outputs of the reference model and adjustable model need to be compared. The schematic diagram of parameter identification is shown in Figure 3. u_d, u_q, i_d, i_q are the voltages and currents on d-axis and q-axis; R_s is the stator resistance; L_d, L_q are the stator inductances of the d-axis and q-axis; ω_e is the electrical angular velocity; ψ_f is the permanent

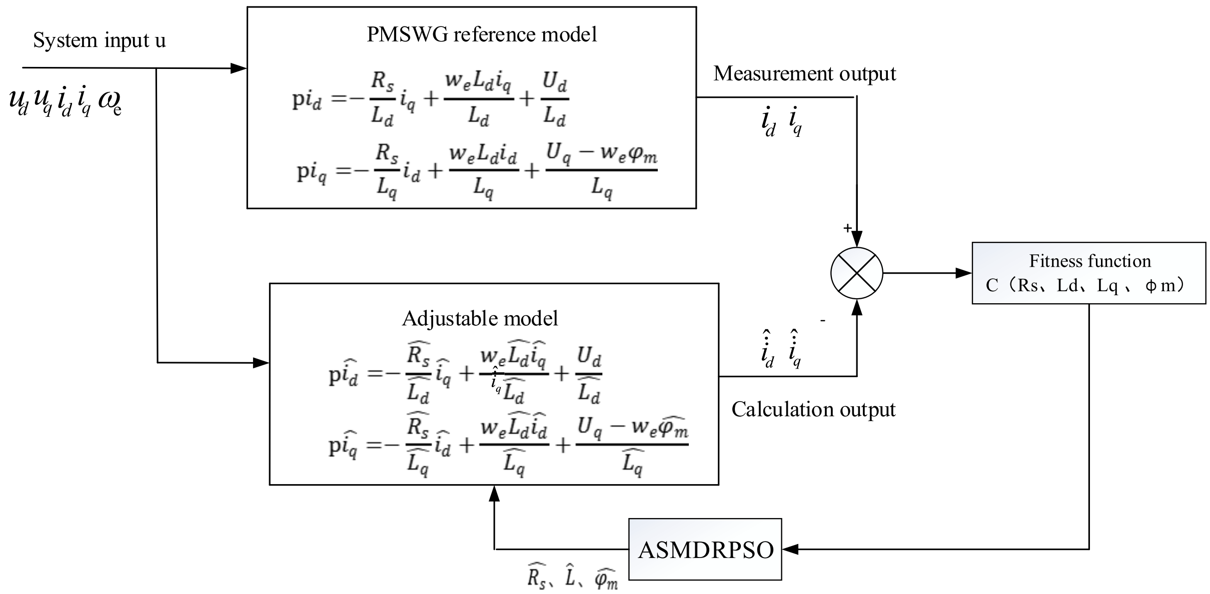

Figure 3. Schematic diagram of PMSWG parameter identification.

magnet flux linkage. The outputs $\hat{\dot{i}}_d$ and $\hat{\dot{i}}_q$ of the adjustable model are calculated by Equation (1). By calculating the fitness function, the corresponding fitness values of stator resistance R_s, quadrature and direct axis inductance L_d and L_q, and permanent magnet flux ψ_f particles are obtained. After comparison, the particle with the best position is selected to participate in the next operation iteration. This loops until the value of the fitness function approaches zero, or the maximum number of iterations is reached, when the loop is stopped. The values of the output resistance, inductance, and flux linkage can be considered as the real values of the system. For the PMSWG vector control system, the fitness function is defined as:

$$C(R_s, L_d, L_q, \psi_f) = \left(i_d - \hat{\dot{i}}_d\right)^2 + \left(i_q - \hat{\dot{i}}_q\right)^2 \tag{12}$$

The identification steps of ASMDRPSO algorithm are as follows:

Step 1: Collect electrical signals, including current and voltage in the quadrature axis and direct axis and rotational speed.

Step 2: Set relevant initial parameters, such as population size, inertia weight, individual and group learning factors.

Step 3: Update the speed and position of each particle, and calculate the fitness function value of each particle.

Step 4: Compare the fitness value of each particle with the best location pbest in the history of the individual, and the memory retains the least fitness solution to update the pbest.

Step 5: Compare the fitness value of each particle with the best location gbest in the population history, and the memory retains the solution with the lowest fitness to update the gbest.

Step 6: Judge whether the termination condition is reached. If the maximum number of iterations is reached, the memory outputs the pbest, and the algorithm operation ends. Otherwise, return to step 3 to continue the next cycle.

5. SIMULATION AND EXPERIMENTAL ANALYSIS

5.1. Simulation Analysis

In order to confirm the algorithm's effectiveness, the parameter identification model is established in Matlab/Simulink. The schematic diagram is shown in Figure 4.

Motor rated parameters are shown in Table 1.

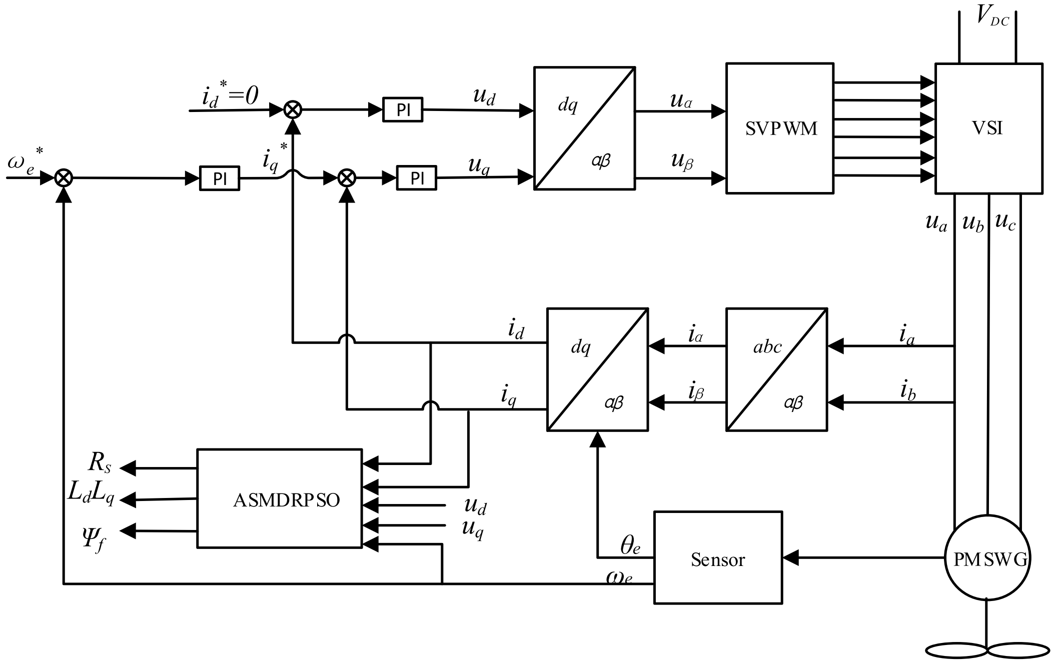

Figure 4. Structure block diagram of vector control.

Table 1. Main parameters of the motor.

Parameter	numerical value
polar logarithm	4
Stator resistance/Ω	0.958
Stator d-axis inductance/mH	0.0012
Stator q-axis inductance/mH	0.0012
Permanent magnet flux linkage/Wb	0.1827
Rated speed/(r/min)	1000
Rated Power (kW)	1.0
Rated voltage/V	380

In the simulation, the motor parameters are set to: in closed-loop speed control, the given speed is 1000 r/min, and the population size is set to 30. The number of iterations is taken as the ratio of running time to sampling time. The learning factor $C1 = C2 = 1.6$, and the running time of the simulation system is taken as 0.4 s and the sampling time taken as $1e-6$ s. ASMDRPSO, MDRPSO, DRPSO and PSO were run 5 times at a torque of 10 N·m and a speed of 1000 r/min, and the average value was taken as the final output value.

The identification results and errors are shown in Table 2.

It can be seen from Table 2 that in the PSO algorithm, it is easy to be trapped in local optimization, and the shortcomings of large precision errors are enlarged. The maximum recognition error is calculated to be 8.53%, and the convergence rate is slow in the later stage. The accuracy of PSO is surpassed by the improved DRPSO, MDRPSO, ASMDRPSO algorithms, and the error accuracy of ASMDRPSO is controlled within 2.3%. The advantages of good robustness, high recognition accuracy and fast convergence speed are reflected in ASMDRPSO.

Table 2. Average results of motor parameter identification under selected working conditions.

Parameter	PSO	DRPSO	MDRPSO	ASMDRPSO
Stator resistance/Ω	1.023	0.9987	0.9892	0.9873
Error/%	6.78%	4.25%	3.26%	2.11%
Stator d-axis and q-axis inductance/mH	0.001282	0.001253	0.001239	0.001225
Error/%	6.83%	4.42%	3.25%	2.08%
Permanent magnet flux linkage/Wb	0.18426	0.18376	0.18346	0.18311
Error/%	8.53%	5.80%	4.16%	2.24%

5.2. Experimental Verification

In this paper, the RT-LAB experimental platform is used to realize the hardware-in-the-loop simulation (HILS) of the PMSWG drive system. The RT-LAB experimental platform is shown in Figure 5, and the hardware-in-the-loop simulation configuration diagram of the PMSWG control system RT-LAB is shown in Figure 6. The platform contains a TMS320F2812 DSP controller, an RT-LAB (OP5600) simulator, a motor drive model built in RT-LAB, and a host computer. The DSP controller with running algorithm is TMS320F2812, and RT-LAB plays inverter and PMSM. The sampling frequency of the experimental system is 10 kHz.

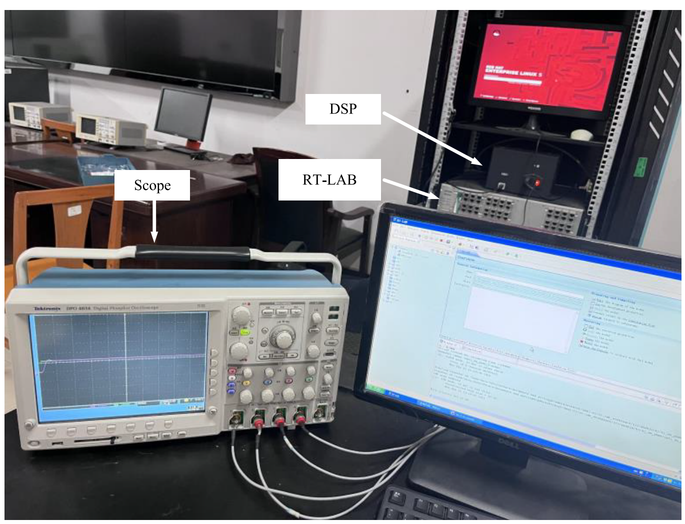

Figure 5. RT-LAB experimental platform.

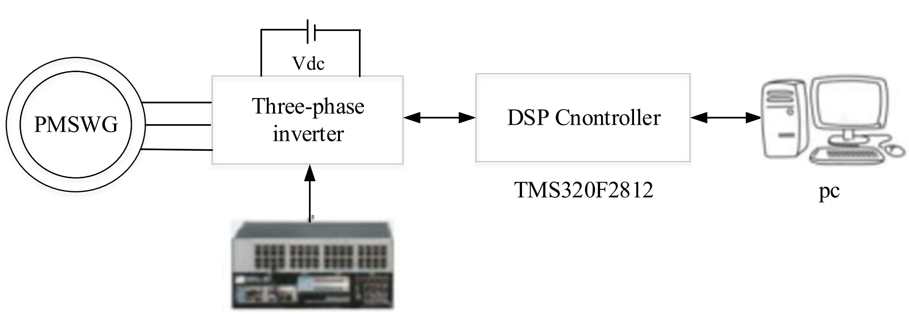

Figure 6. RT-LAB hardware in the loop system configuration.

The experiment is conducted under conditions similar to those in the simulation, and their identification curves are presented in Figures 7–9. The experimental results for all methods under general situation are shown in Table 3.

The stator resistance identification curve under the selected working condition is shown in Figure 7.

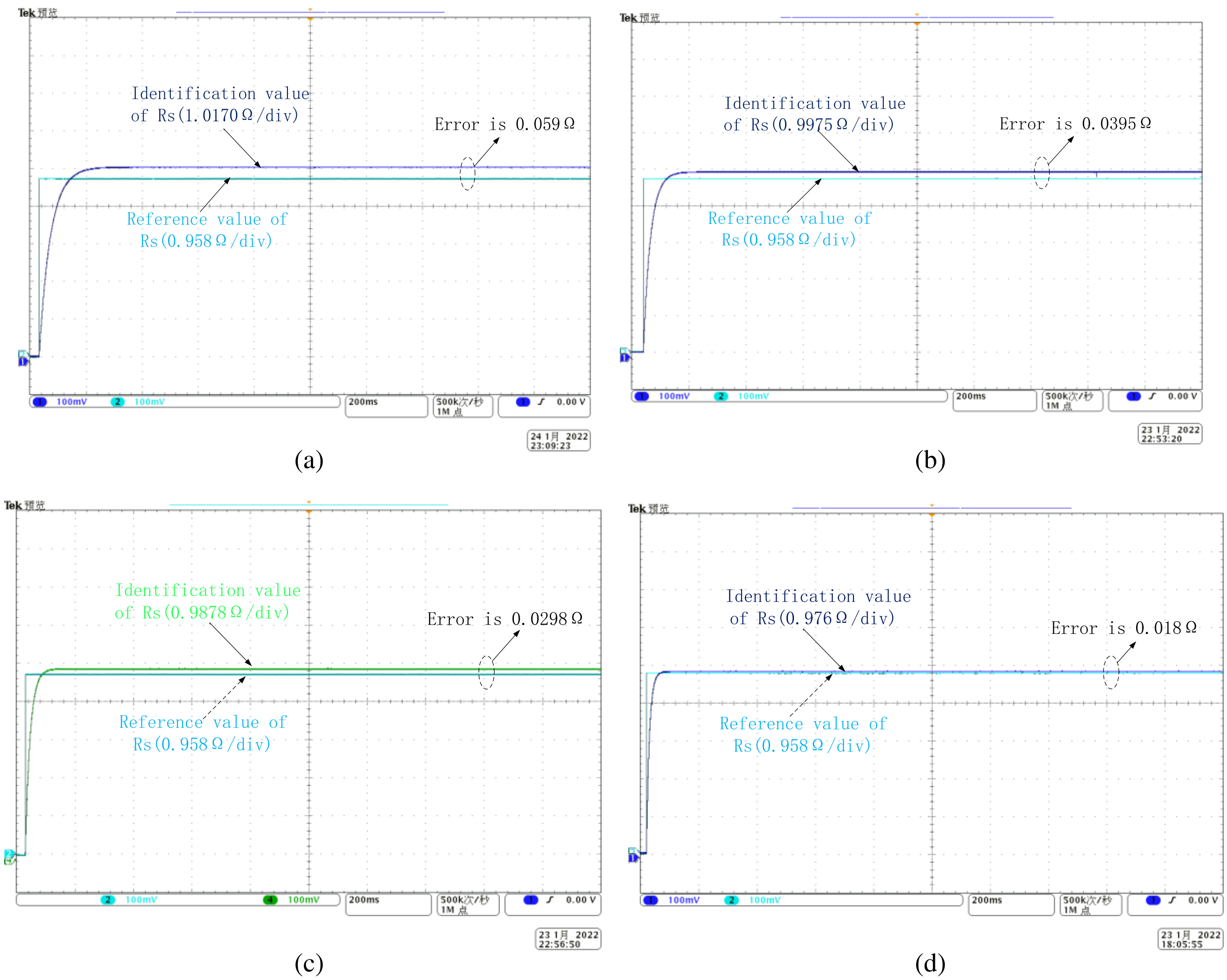

Figure 7. Identification curve of stator resistance under specified working conditions. (a) PSO. (b) DRPSO. (c) MDRPSO. (d) ASMDRPSO.

Table 3. Experiment results of motor parameter identification under selected operating conditions.

Parameter	PSO	DRPSO	MDRPSO	ASMDRPSO
Stator resistance/Ω	1.0170	0.9975	0.9878	0.9760
Error/%	6.78%	4.25%	3.26%	2.11%
Stator d-axis and q-axis inductance/mH	1.2790	1.2480	1.2365	1.2185
Error/%	6.83%	4.42%	3.25%	2.08%
Permanent magnet flux linkage/Wb	0.1843	0.1837	0.1833	0.1830
Error/%	8.53%	5.80%	4.16%	2.24%

The identification curve can be analyzed from the figure in two ways: stabilization time and error. In the PSO, the identified resistance value differed from the reference value by nearly 6.16%. The recognition error rate of DRPSO is calculated as 4.12%, MDRPSO is calculated as 3.11%, and ASMDRPSO is calculated as 1.87%. The PSO convergence time is 0.34 s, the DRPSO is shortened by 0.08 s, the MDRPSO is shortened by 0.17 s, and the ASMDRPSO is shortened by 0.24 s.

The permanent magnet flux linkage identification curve under the selected working condition is shown in Figure 8. It can be seen from Figure 8 that ASMDRPSO has the fastest response speed. The shorter the time to reach the stable value, the smaller the overshoot fluctuation, followed by MDRPSO and DRPSO, and the worst PSO effect. The identification errors of PSO, DRPSO, MDRPDSO and ASMDRPSO are calculated to be 8.76%, 5.47%, 3.28%, and 1.64%, respectively. It can be seen that ASMDRPSO has the best control effect.

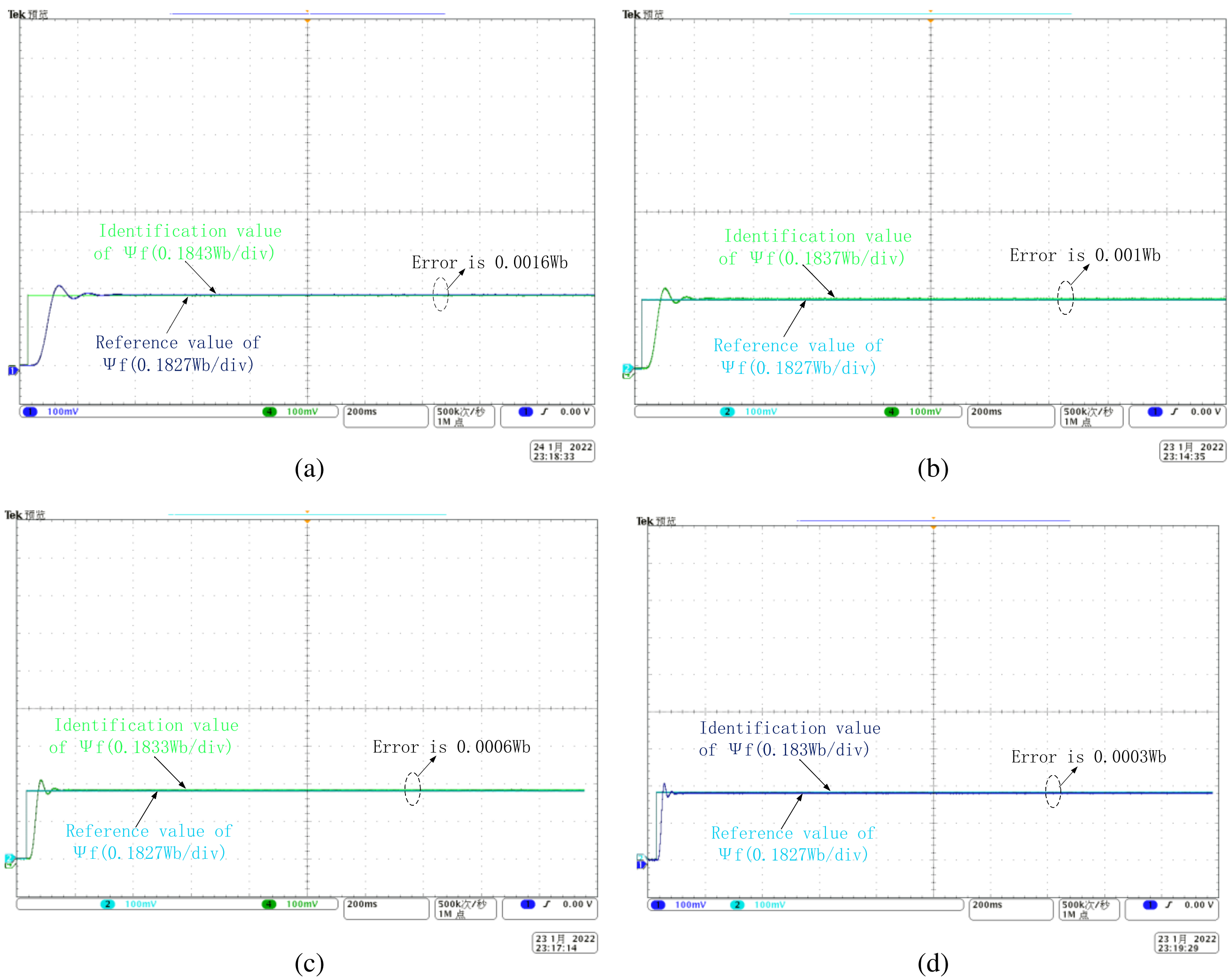

Figure 8. Identification curve of permanent magnet flux linkage under specified working conditions. (a) PSO. (b) DRPSO. (c) MDRPSO. (d) ASMDRPSO.

The inductance identification curves are shown in Figures 9(a)–(d). It can be seen from Figure 9 that ASMDRPSO is closest to the actual curve, and the advantage of the smallest overshoot is reflected. The shortest equilibration time and strongest robustness are reflected in ASMDRPSO. The recognition time of PSO is 0.34 s, and the recognition error is calculated to be 6.58%. The recognition time of DRPSO is 0.26 s, and the recognition error is calculated as 4%. The recognition time of MDRPSO is

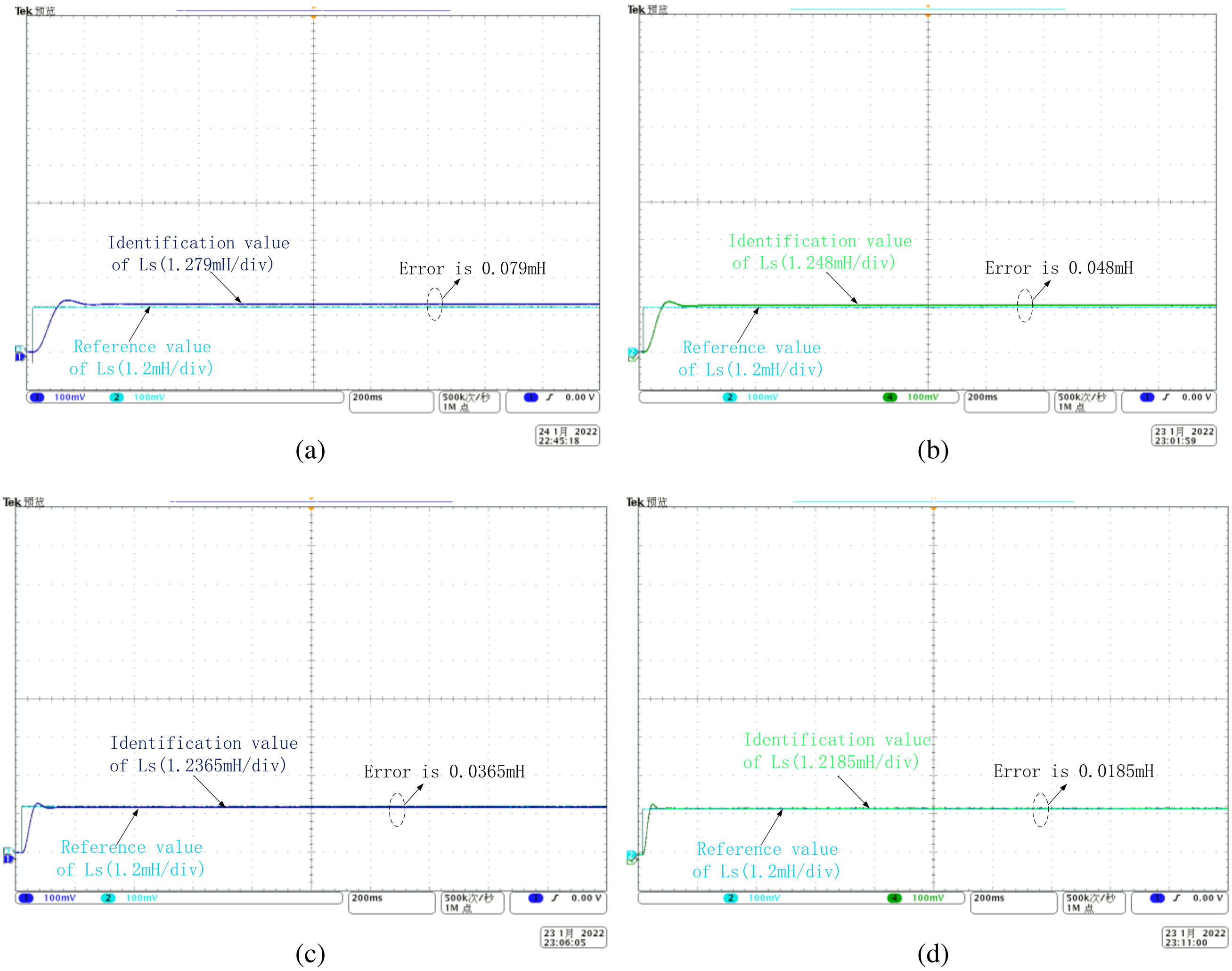

Figure 9. Identification curve of stator d-axis and q-axis inductance under specified working conditions. (a) PSO. (b) DRPSO. (c) MDRPSO. (d) ASMDRPSO.

0.18 s, and the recognition error is calculated as 3.04%. The recognition time of ASMDRPSO is 0.09 s, and the recognition error is calculated as 1.54%.

The experimental results of the four identification methods are shown in Table 3.

In summary, the problems of long recognition times and large recognition errors are reflected in the traditional PSO. The recognition accuracy and speed of the improved ASMDRPSO, DRPSO, and MDRPSO have been improved. Among them, ASMDRPSO has the best recognition effect, with a calculated recognition error of less than 1.9% and a recognition time of less than 0.1 s. MDRPSO is close to ASMDRPSO in accuracy, but the advantages of faster convergence and smaller errors are reflected in ASMDRPSO. From the experimental results, it can be concluded that ASMDRPSO outperforms the other three methods in terms of parameter recognition and has high recognition accuracy.

6. CONCLUSION

In this research, a novel ASMDRPSO parameter identification technique is suggested, and the full-rank identification equation is established. The problem of poor accuracy of traditional particle swarm optimization can be improved by this method, which can also be better applied to the parameter identification of PMSWG. According to the simulation and experimental results under the selected working conditions, the following conclusions are drawn:

1) The maximum iteration number of the algorithm is related to the running time. The online identification of PMSWG stator resistance, quadrature and direct axis inductance, and permanent magnet flux linkage are realized.

2) In this paper, dynamic adjustment of inertia weight, introduction of average optimal position, and increase of adaptive learning radius are adopted in parameter identification. It is realized that the optimization ability of the algorithm is maximized, the diversity of the population enhanced, and the scope of exploration expanded.

3) The advantages of high recognition accuracy, small error rate, and fast convergence speed are shown in ASMDRPSO. Compared with PSO, DRPSO, and MDRPSO, the recognition accuracy is improved, the robustness enhanced, and the convergence time shortened.

4) Under the specified working conditions, the strong parameter tracking ability of ASMDRPSO is reflected, and the identification error is controlled within 1.9%. In comparison with PSO, the recognition error is reduced by 4%, and the time to reach equilibrium is shortened by 0.2 s.

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