Progress In Electromagnetics Research C, Vol. 141, 175-183, 2024
PIER C

(Received 12 January 2024, Accepted 3 February 2024, Scheduled 17 February 2024)

An Adaptive Learning Co-Evolutionary Variational Particle Swarm Optimization Algorithm for Parameter Identification of PMSWG

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ABSTRACT: Targeting the problems of traditional particle swarm algorithm easily falling into local optimum and low recognition accuracy, an adaptive learning co-evolutionary variational particle swarm optimization algorithm (ALCEVPSO) is proposed in this paper to identify the parameters of permanent magnet synchronous wind generator (PMSWG). At first, an adaptive learning strategy is adopted for the inertia weights of the PSO, and the global optimization seeking ability of the PSO is improved. After that, multiple swarm co-evolution strategies are introduced to share the best positions within sub-populations, and by this method, the algorithm's falling into local optimality is avoided. Finally, Cauchy Gaussian mixed variants are introduced, and the population diversity is enriched. The proposed method has the advantages of strong optimization ability and high search accuracy compared with the traditional particle swarm algorithm, which is shown by simulated and experimental results. By this method, the motor parameters of the permanent magnet synchronous motor can be accurately identified.

1. INTRODUCTION

PMSWG has been widely used in various industries due to its simple physical structure and high power factor [1–4]. Ensuring the accuracy of motor parameters is an indispensable prerequisite for achieving high performance control of PMSWG. However, in actual working conditions, the electrical parameters [5–8] of PMSWG are easily affected by magnetic saturation, external temperature, and other factors. In order to realize efficient motor performance, it is increasingly important that motor parameters are accurately recognized.

At present, the commonly recognition methods mainly include: recursive least squares (RLS), genetic algorithm, etc. By introducing a discount factor, a discount least squares method is proposed in [9] to identify the stator resistance and straight and intersecting axis inductances. In this way, the problem of data saturation and noise interference in the traditional RLS algorithm is solved. An extended Kalman filter-based magnetic chain identification scheme for permanent magnet synchronous motors (PMSMs) is proposed in [10], and the identification problems caused by the low-order state equations of PMSM are avoided. The method has a high identification accuracy. A model reference adaptive method (MRAS)-based online parameter identification method in a two-phase stationary coordinate system was used in [11]. In this method, the estimation equations are optimized by using a saturation function in exponential form. By taking this approach, the convergence speed and steady state performance of resistance and inductance discrimination are improved. A novel genetic algorithm is proposed in [12] for simultaneous identification of resistance, dq-axis inductance, and magnetic chain of PMSM, and by this means, the drawbacks of traditional genetic algorithms that require high initial values of the identified parameters are overcome. In [13], an adaptive neural network algorithm is proposed to be used for the parameters of PMSM. In this algorithm, resistance, inductance, and magnetic chain can be identified simultaneously without knowing any parameters of the motor.

Particle Swarm Optimization (PSO) algorithm [14–16] is a new type of intelligent algorithm, which is simple in principle and easy to compute, and is widely used in all kinds of value finding problems. An immune fully learned particle swarm algorithm is proposed in [17]. In this algorithm, the immune mechanism strategy and the fully learned particle swarm algorithm are combined and have a high recognition accuracy. A bimodal adaptive wavelet particle swarm algorithm is proposed in [18]. In this algorithm, the individual polarity values of the particles are used with adaptive wavelet operators. The forward and backward learning abilities of the particles are enhanced, and the convergence speed and search accuracy are improved. An improved PSO is proposed in [19], and in the proposed algorithm, the best position strategy and Cauchy's variation are combined and have a higher accuracy of identification. In [20], the PSO is combined with the average minimum position strategy, which provides more position information to the particles.

To deal with the problem that PSO algorithms are prone to premature maturity, an adaptive learning co-evolutionary particle swarm algorithm is proposed in this paper, and it is applied to PMSWG electrical parameter recognition. The main study of this paper is as follows:

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1) The method of $i_d = -2$ was introduced to solve the problem of under-ranking of permanent magnet synchronous wind turbine, and a full-rank mathematical model is obtained.

2) Adaptive learning strategy is adopted for the inertia weights. The exploration ability of the algorithm is further enhanced, and the population becomes more diverse.

3) Multiple population co-evolution strategies are invoked, and the best position of the population is shared. With the improved algorithm, the optimization ability is improved, and the particle search range is expanded.

4) The Cauchy Gaussian mixed mutation operation is introduced. The particles can explore more unknown fields, and more excellent values can be obtained.

The structure of this document is as follows: The PMSWG equations and under-rank problem solution are covered in Section 2. The ALCEVPSO algorithm's principle and significance are covered in Section 3. The PMSWG-based parameter identification principle and flow are covered in Section 4. The algorithm's viability is confirmed through emulation and experiments in Section 5, and Section 6 concludes the paper.

2. PMSWG EQUATION AND UNDER-RANK PROBLEM SOLVING

Assuming that PMSWG magnetic saturation, structural asymmetry, iron loss, and magnet eddy current loss are neglected, the equation of the ideal PMSWG in the dq-axis is given by the following equation:

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

where physical quantities u_d, u_q are the voltages along the d-q axis; physical quantities i_d, i_q are the currents along the d-q axis; ω_e is the electrical angular speed; ψ_f is the rotor magnetic linkage; L_d and L_q are the inductance of PMSWG; R_s is the resistance of PMSWG.

When the motor is operated in a long-term steady state, the influence of the differential term is weak. Under this condition, Eq. (1) can be simplified as: Under the control strategy with $i_d = 0$, (2) can be simplified as

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

Equation (2) has four parameters to be determined, but the number of equations is two. The equations are under-rank equations and have no unique solution. To achieve simplification and coupling lifting of the motor, $i_d = 0$ is usually used. Under the control strategy with $i_d = 0$, (2) can be simplified as:

$$\begin{cases} u_d = -L_q \omega_e i_q \\ u_q = \psi_f \omega_e + R_s i_q \end{cases} \tag{3}$$

On the basis of this strategy being employed, a negative sequence current of $i_d = -2$ is injected into the d-axis, and a fourth order full rank system of equations is obtained. After this fourth-order equation is discretized, it is expressed as Equation (4):

$$\begin{cases} u_{d1}(k) = -L_q \omega_{e1}(k) i_{q1}(k) \\ u_{q1}(k) = R_s i_{q1}(k) + \psi_f \omega_{e1}(k) \\ u_{d2}(k) = R_s i_{d2}(k) - L_q \omega_{e2}(k) i_{q2}(k) \\ u_{q2}(k) = R_s i_{q2}(k) + L_d \omega_{e2}(k) i_{d2}(k) + \psi_f \omega_{e2}(k) \end{cases} \tag{4}$$

where the subscripts "1" and "2" indicate under the control strategies of $i_d = 0$ and $i_d = -2$, respectively.

The data sampling for the two control methods at $i_d = 0$ and $i_d = -2$ is shown in Fig. 1.

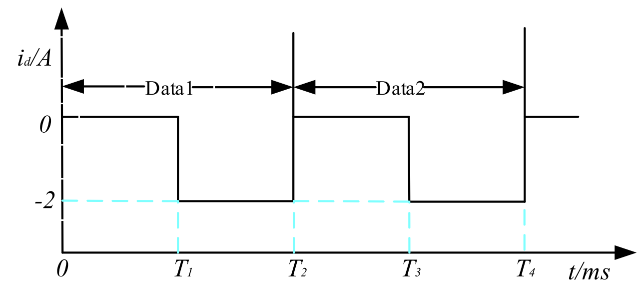

FIGURE 1. Current sampling plots at $i_d = 0$ and $i_d = -2$.

3. PARTICLE SWARM OPTIMIZATION

The basic principle of particle swarm algorithm is that the optimal solution of a complex problem is obtained by collaborating among the particles. In particle swarm algorithm, each particle is randomly ordered, and each particle is a solution to the problem. During the iteration process, the individual optimal solution and population optimal solution are tracked through the fitness function. Individual and group position information is shared among the particles, and the merit of the current position is evaluated through the fitness function. The ideal solution to the algorithmic problem is eventually found when the particles progressively get closer to the point where the adaption value is minimized. The velocity and displacement update formulae for the particle swarm algorithm are as follows:

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 (P_{best}^k - x_i^k) + c_2 r_2 (G_{best}^k - x_i^k) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{5}$$

where the physical quantity v_i is the current velocity of the particle; the physical quantity x_i is the current displacement of the particle; P_{best} is the optimal value of the individual; G_{best} is the optimal value in the population; k is the current number of iterations; r_1 and r_2 are random numbers belonging to the interval [0, 1]; c_1 and c_2 are the acceleration factors; and ω is the inertia weight.

The flowchart of particle swarm algorithm applied to parameter identification is shown in Fig. 2.

3.1. Adaptive Learning Inertia Weighting Algorithm

In the particle swarm search process, inertia weight is an important parameter that affects the performance of PSO, and the

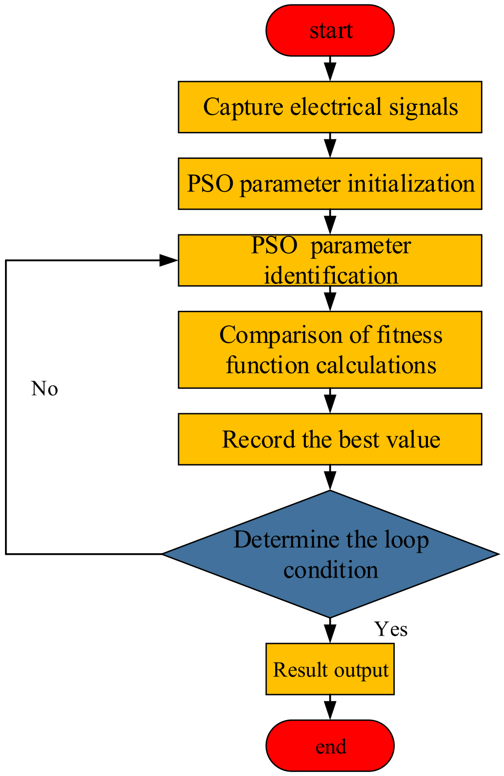

FIGURE 2. PSO parameter identification flow chart.

detection and exploitation ability of the algorithm is controlled by the inertia weights ω. When the inertia weights are large, the particle swarm global search ability is strong, and the local search ability is weak. However, the opposite is true when the weight inertia is small. If the inertia weights are constant, the real-time optimization search ability is weak. For the particles of the same population, we hope that the global and local searching ability of the particles is dynamically adjusted in different periods, so the adaptive learning inertia weight expression is introduced within the population, and the expression is:

$$\omega = (\omega_1 - \omega_2) * \tan\left(0.875\left(1 - \left(\frac{t}{T_{\max}}\right)^k\right)\right) + \omega_2 \quad (6)$$

where physical quantity ω_1 represents the most initial inertia weight; physical quantity ω_2 represents the most final inertia weight; t is the current number of iterations of the loop; $T_{\max}$ is the given maximum number of iterations; and k is the control factor.

From Equation (6), it can be seen that in the process of particle optimization, ω are always in nonlinear change, and are constantly updated by self-learning. The inertia weights are nonlinearly decreasing in the whole search process. With the control factor introduced, the nonlinear nature of the algorithm is increased, and the global search ability of the algorithm in the early stage and the local optimization ability in the late stage are guaranteed. In addition, the problem of falling into local optimization in the search process is solved, and particles falling into local optimality are avoided, which can find a better position faster, and the convergence speed is accelerated.

3.2. Multiple Swarm Co-Evolutionary Approach

In the general case, the global searching ability and local searching ability of particles are contradictory, and the detection ability and exploitation ability of particles are also contradictory. If a certain region can be finely searched by a particle, it is difficult to jump out from this region to another region for a large-scale search. This will lead to the particles easily fall into the local optimal state in the optimization process, so in order to coordinate the detection ability and exploitation ability of the particle swarm algorithm, multiple swarms co-evolutionary approach is introduced on the basis of adopting adaptive learning inertia weights.

The thinking of the algorithm is that the whole population is divided into multiple subpopulations, and for particles of different populations, the information is communicated by the subpopulations. Co-evolution is accomplished by sharing the information of the G_{best} in the current subpopulation. In this paper, particles are divided into three subpopulations with the same particle population, making the following definitions: S1 (base population), S2 (base population), S3 (integrated population). The particles in the sub-clusters are guaranteed to fly in the same search space, and the three sub-clusters continuously exchange information during the search process to improve the co-evolution capability. The information exchange and evolution pattern among the subclusters are shown in Fig. 3.

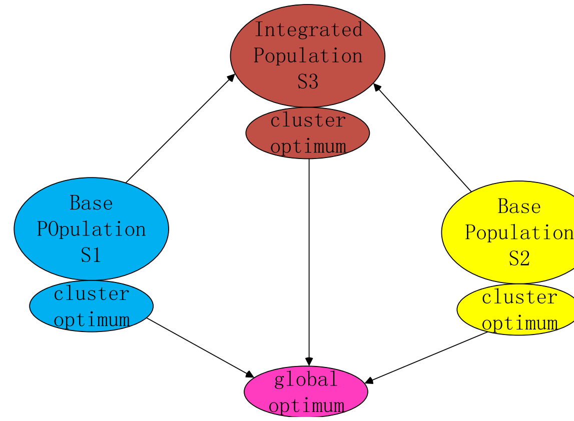

FIGURE 3. Chart of patterns of information exchange and cooperation among clusters.

After the co-evolution strategy is introduced, the degree of interconnection between particles is deepened. Furthermore, the optimal position information is shared; the experience information of other particles is borrowed; and the collaborative working ability of the particle swarm is improved. The information of all sub-clusters is utilized by the integrated cluster S3, where no cluster exists in isolation, and they are interconnected. By this method, more information can be utilized by the particles to decide their behavior. Therefore, in the improved algorithm, the search performance in the neighborhood of the already searched global optimum is enhanced. At the same time, as the information of the optimal position is shared, the probability of the particle near the optimal position is increased, which accelerates the speed of the particle searching

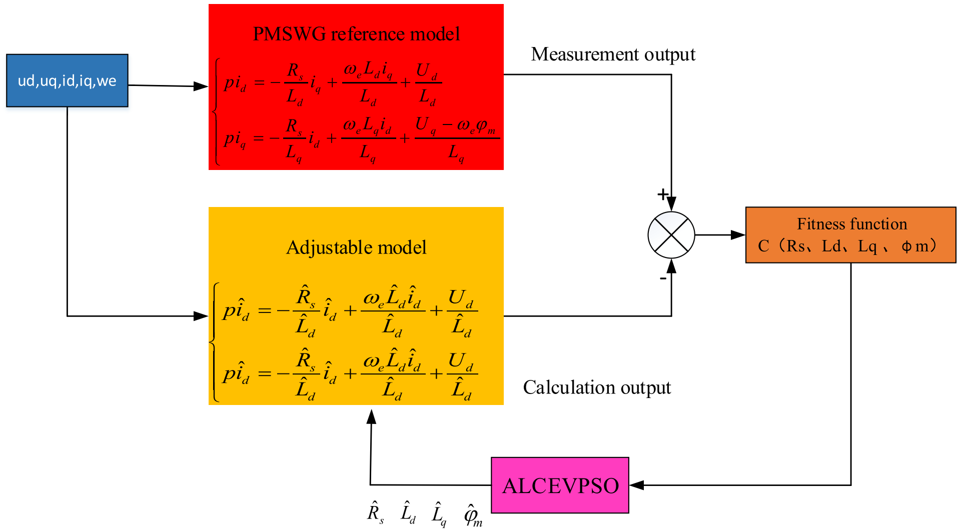

FIGURE 4. PMSWG parameter recognition schematic.

for the optimal position, thus shortening the convergence time, and the optimal value can be reached more quickly.

3.3. Cauchy-Gaussian Mixed Variant

In order to make PSO jump out of the local optimum, on the basis of the population co-evolution strategy was introduced. A hybrid mutation strategy of Cauchy mutation and Gaussian mutation is introduced in the algorithm. The Cauchy variation is introduced; the diversity of the population is expanded; and global aggregation is raised. The introduction of Gaussian variation can make the algorithm's local search ability enhanced and the convergence speed improved. Therefore, in this paper, the optimal value is taken as Cauchy Gaussian mixed mutation operation, and the Gaussian mutation formula is as follows:

$$P_{best} = P_{best} * (1 + 1 * randn) \tag{7}$$

The Cauchy variation formula is shown in the following equation:

$$\begin{cases} Cauchy = \tan\left(\pi * \left(rand - \frac{1}{2}\right)\right) \\ G_{best} = G_{best}(1 + 1 * Cauchy) \end{cases} \tag{8}$$

where *Cauchy* is a Cauchy-distributed random number, *randn* a Gaussian-distributed random number, and *rand* a random number between 0 and 1.

After the Cauchy Gaussian mixed-variant operation is introduced, in the pre-algorithmic stage, the particle search range is extended, and more unknown regions can be explored. At the same time, the state of particles falling into the local optimum is avoided, so that it is easy to jump out of the current local optimal solution, and the diversity of the population is enriched. In the late stage of the algorithm, the particles are constantly close to the optimal position, which helps to improve the convergence speed of the algorithm, so that the particles get the optimal solution faster and shorten the convergence time.

4. PRINCIPLE OF PARAMETER IDENTIFICATION

The principle of parameter identification using the adaptive learning co-evolutionary variational particle swarm algorithm (ALCEVPSO) algorithm is as follows: Set up a reference model and an adjustable model. With the ALCEVPSO algorithm, the electrical parameters in the adjustable model are constantly updated. When the outputs of the two models satisfy the minimum values, the outputs are taken as the actual motor parameters. The schematic diagram of PMSWG parameter identification based on ALCEVPSO is shown in Fig. 4. The fitting function is defined as:

$$Q(L_d, \psi_f, R_s, L_q) = \left(i_d - \hat{\dot{i}}_d\right)^2 + \left(i_q - \hat{\dot{i}}_q\right)^2 \tag{9}$$

5. SIMULATION AND EXPERIMENTAL ANALYSIS

5.1. Simulation Analysis

In order to verify the discriminative performance merits of the ALCEVPSO algorithm, a vector control system simulation model in a d-q coordinate system is built in Matlab/Simulink environment, and the schematic diagram is shown in Fig. 5.

The PMSWG parameters are presented in Table 1.

TABLE 1. PMSWG parameters table.

Parameter	Numerical value
Number of pole pairs of the motor	4
resistance/Ω	0.958
Stator d-axis inductance/mH	1.2
Stator q-axis inductance/mH	1.2
magnet flux linkage/Wb	0.1827
Given speed/(r/min)	1000
Given Power (kW)	1.0
Given voltage/V	380

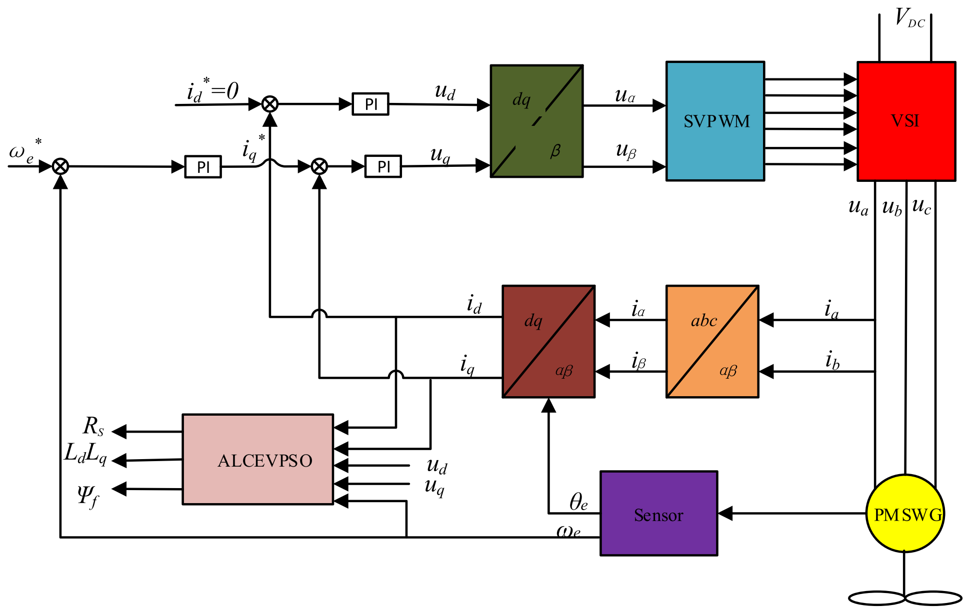

FIGURE 5. Block diagram of vector control structure based on ALCEVPSO parameter identification.

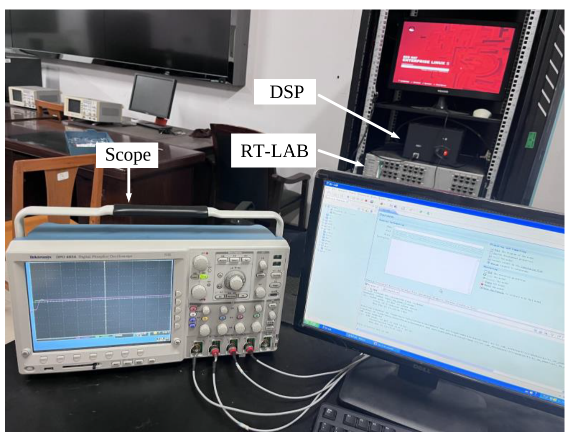

FIGURE 6. Experimental physics platform.

TABLE 2. Simulation results of motor parameter identification.

Parameter	PSO	ALPSO	ALCEPSO	ALCEVPSO
Stator resistance/Ω	1.0191	0.9976	0.9812	0.9699
Error/%	6.38%	4.13%	2.42%	1.24%
Stator d-axis and q-axis inductance/mH	1.2672	1.2412	1.2223	1.2131
Error/%	5.60%	3.43%	1.86%	1.09%
Permanent magnet flux linkage/Wb	0.1951	0.1902	0.1874	0.1848
Error/%	6.79%	4.11%	2.57%	1.15%

In the simulation, the parameters of the motor are set as follows: rated speed 1000 r/min and population size of 20. Collect sampling data for $i_d = 0$ and $i_d = -2$ in the same situation, and the acceleration factor $C_1 = C_2 = 1.5$. The sampling time is taken as 5e–5s.

Table 2 displays the identification findings for the simulation example.

5.2. Experimental Verification

The Simulink simulation model is imported into RT-Lab, and the semi-physical simulation experiment of the PMSWG drive system is achieved, in order to confirm the viability of PMSWG parameter identification ALCEVPSO. Fig. 6 depicts the experimental physics platform, and Fig. 7 shows the RT-LAB configuration.

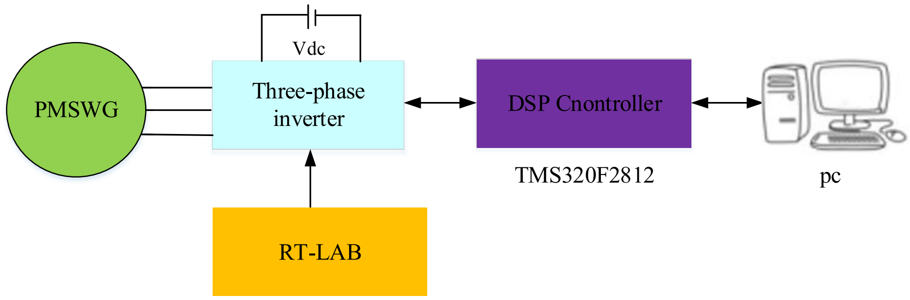

FIGURE 7. RT-LAB configuration diagram.

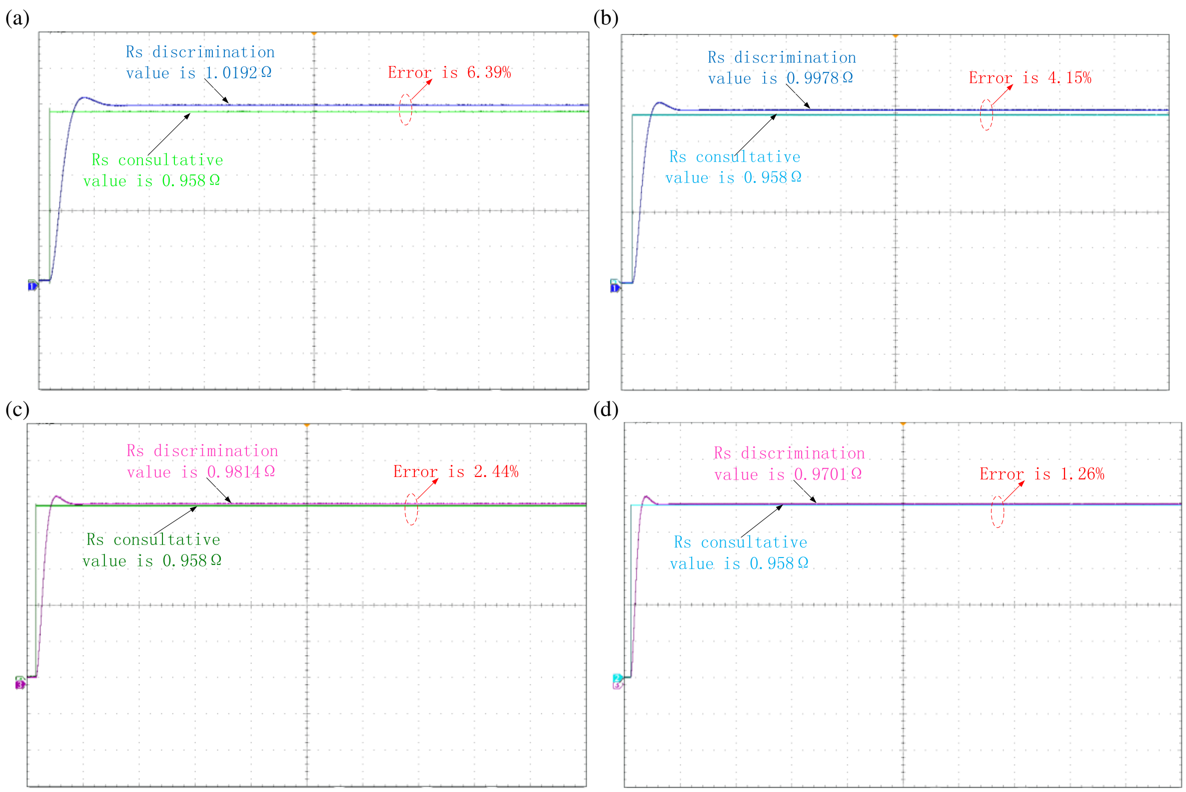

FIGURE 8. Resistance recognition curve. (a) PSO. (b) ALPSO. (c) ALCEPSO. (d) ALCEVPSO.

The identification curves of the electrical parameters are displayed in Figs. 8–10, and the experiments were carried out in the identical circumstances as the simulations. Table 3 shows the experimental results under the selected operating conditions.

Figure 8 shows the plotted resistance recognition curves for each of the four identification methods. The resistance identification result under the ALCEVPSO algorithm is 0.9701 Ω, as illustrated in Fig. 8. The error with the real motor resistance value is 1.26%; under the two algorithms of ALCEPSO and ALPSO, the errors are 2.44% and 4.15%, respectively. ALPSO is shortened by 10 ms, ALCEPSO shortened by 18 ms, and ALCEVPSO shortened by 27 ms, compared to the standard PSO convergence time of 67 ms.

Figure 9 displays the magnetic flux linkage identification diagram. It can be examined in terms of recognition error and convergence time in Fig. 9. The traditional PSO has a 6.9% recognition error and a recognition time of 70 ms. The ALPSO has a 4.21% recognition error and a 59 ms recognition time. The ALCEPSO has a 50 ms recognition time and a 2.62% recognition inaccuracy. The ALCEVPSO exhibits a 41 ms recognition time and a 1.2% recognition error.

Figure 10 displays the *d*-*q* axis inductive identification curves. ALPSO, ALCEPSO, and ALCEVPSO had recognition errors and convergence times in inductive recognition of 3.454% and 61 ms, 1.88% and 51 ms, and 1.10% and 42 ms, respectively. ALCEVPSO offers the fastest convergence and highest recognition accuracy among the four recognition techniques. This indicates that with the Cauchy Gaussian mixed-variant strategy introduced, the initial population diversity is enriched, and the breadth and depth of the algorithm's search space are guaranteed.

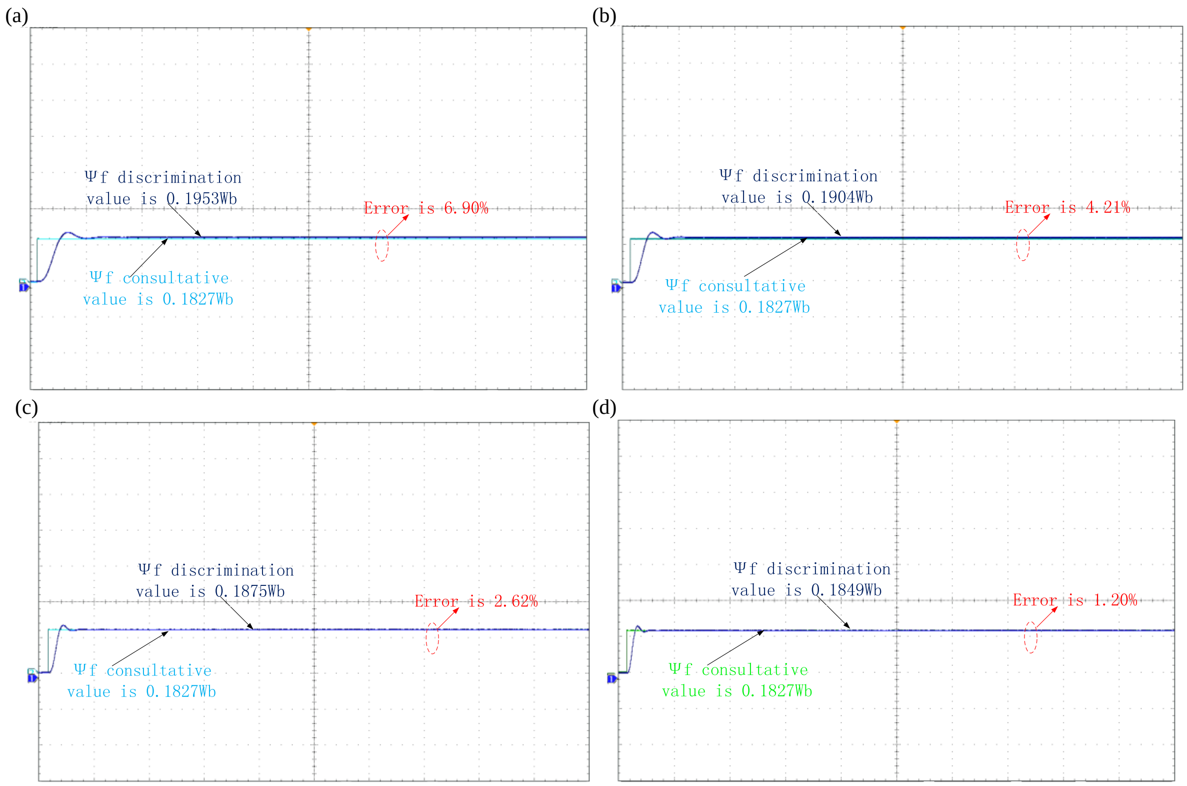

FIGURE 9. Magnet flux linkage recognition curve. (a) PSO. (b) ALPSO. (c) ALCEPSO. (d) ALCEVPSO.

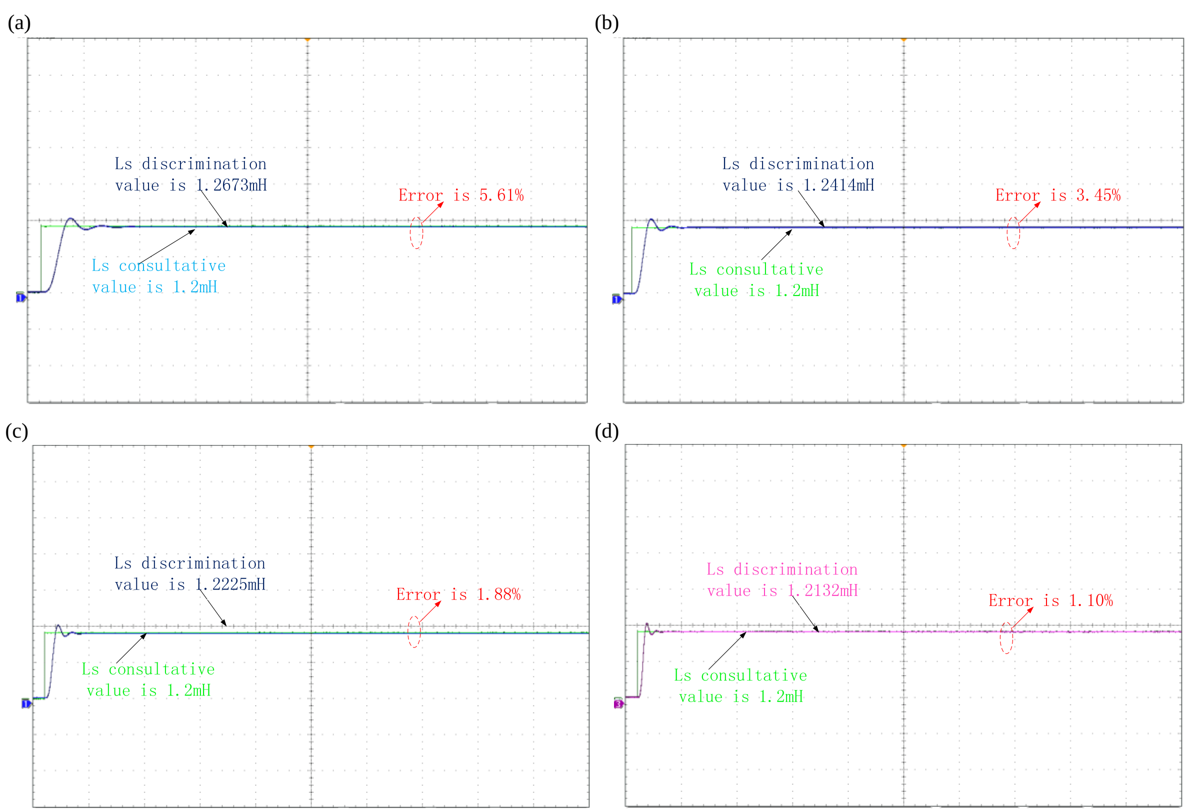

FIGURE 10. D-q axis inductance recognition curve. (a) PSO. (b) ALPSO. (c) ALCEPSO. (d) ALCEVPSO.

Table 3 displays the experimental findings for the four recognition techniques. From Table 3, it is easy to conclude that among the four proposed methods, ALCEVPSO has the highest recognition accuracy, the smallest error with the system benchmark, the shortest convergence time, and the best recognition effect. In addition, compared with the traditional PSO algo-

TABLE 3. Experimental results of motor parameter identification.

Parameter	PSO	ALPSO	ALCEPSO	ALCEVPSO
Stator resistance/Ω	1.0192	0.9978	0.9814	0.9701
Error/%	6.39%	4.15%	2.44%	1.26%
Stator d-axis and q-axis inductance/mH	1.2673	1.2414	1.2225	1.2132
Error/%	5.61%	3.45%	1.88%	1.10%
magnet flux linkage/Wb	0.1953	0.1904	0.1875	0.1849
Error/%	6.90%	4.21%	2.62%	1.2%

rithm, its maximum error is 5.75 times that of ALCEVPSO, which solves the problem of low recognition accuracy, and the convergence time is shortened.

6. CONCLUSION

In traditional particle swarm algorithms, the problems that the algorithms tend to fall into local optima and low identification accuracy cannot be avoided. In order to solve this problem, in this paper, an Adaptive Learning Co-Evolutionary Variational Particle Swarm Optimization (ALCEVPSO) algorithm is proposed and used to identify the electrical parameters of PMSWG. By theoretical basis and experimental analysis, the following conclusions are derived:

1) By using the ALCEVPSO method proposed in this paper, the parameter values of resistance, magnet flux linkage, and quadrature and direct axis inductance of PMSWG can be recognized online in real time.

2) ALCEVPSO has better parameter identification ability, and the identification error does not exceed 1.3%. In addition, the convergence rate of the algorithm is 40 ms/s, and both the convergence rate and parameter accuracy are better than those of ALCEPSO and ALPSO identification methods.

ACKNOWLEDGEMENT

This work was supported by the Scientific Research Fund of Hunan Provincial Education Department under Grant Number 23B1017, Natural Science Foundation of Hunan Province of China under Grant Number 2022JJ50094.

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