Parameter estimation based on novel enhanced self-learning particle swarm optimization algorithm with Levy flight for PMSG

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Abstract

A novel parameter estimation method is proposed for the permanent magnet synchronous generator (PMSG), which is implemented by an enhanced self-learning particle swarm optimization algorithm with Levy flight (SLPSO), and the problem of lower parameter estimation precision of standard PSO is obviated. This method injects currents of different intensities into the d-axis in a time-sharing manner to solve the problem of equation under-ranking, and the mathematical model for full-rank parameter estimation is developed. The speed term of PSO is simplified to expedite the convergence of PSO, and a strategy with Chaotic decline for the inertia weight of PSO is adopted to strengthen its ability to jump out of the local optimum. Moreover, the self-learning dense fleeing strategy (SLDF) is proposed where particles perform diffusion learning based on population density information and Levy flight, the evolutionary unitary problem and human intervention in the evolutionary process is averted. Furthermore, the memory tempering annealing algorithm (MTA) and greedy algorithm (GA) is integrated into the algorithm, MTA can facilitate the exploration of potentially better regions, and GA for local optimization enhances the convergence speed and accuracy in late stage of the algorithm. Comparing the proposed method with several existing PSO algorithms through simulation and experiments, the experimental data show that the proposed method can effectively track variable parameters under different working conditions and has better robustness.

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Abstract: A novel parameter estimation method is proposed for the permanent magnet synchronous generator (PMSG), which is implemented by an enhanced self-learning particle swarm optimization algorithm with Levy flight (SLPSO), and the problem of lower parameter estimation precision of standard PSO is obviated. This method injects currents of different intensities into the d-axis in a time-sharing manner to solve the problem of equation under-ranking, and the mathematical model for full-rank parameter estimation is developed. The speed term of PSO is simplified to expedite the convergence of PSO, and a strategy with Chaotic decline for the inertia weight of PSO is adopted to strengthen its ability to jump out of the local optimum. Moreover, the self-learning dense fleeing strategy (SLDF) is proposed where particles perform diffusion learning based on population density information and Levy flight, the evolutionary unitary problem and human intervention in the evolutionary process is averted. Furthermore, the memory tempering annealing algorithm (MTA) and greedy algorithm (GA) is integrated into the algorithm, MTA can facilitate the exploration of potentially better regions, and GA for local optimization enhances the convergence speed and accuracy in late stage of the algorithm. Comparing the proposed method with several existing PSO algorithms through simulation and experiments, the experimental data show that the proposed method can effectively track variable parameters under different working conditions and has better robustness.

Keywords: permanent magnet synchronous generator, particle swarm optimization, self-learning dense fleeing strategy, memory tempering annealing, local optimization.

1 Introduction

Different from fossil fuel, wind energy is a renewable resource with abundant reserves and broad commercial prospects, and it has been widely applied to power generation [1]. Permanent Magnet Synchronous Generator (PMSG) as the core equipment of power generation series, it has higher market acceptance for its better suitability for low wind speed, low energy consumption and lower subsequent maintenance cost. Unfortunately, the parameters of PMSG are different under different operating conditions [4], and this will prevent the controller from working well and may even cause malfunctions, therefore, the precise estimation of the parameters is essential.

Online parameter estimation methods mainly include: extended Kalman filter algorithm [5-6], model reference adaptive system [7-8], least square method [9-10], neural network [11-12], genetic algorithm [13-14], observer-based method [15], etc. In [5-6], the extended Kalman filter method (EKF) is often used to estimate the resistance and flux linkage parameters of the generator, but its computation of matrix is relatively larger and the appropriate Q and R matrices are not easy to choose. In [7-8], the model reference adaptive system (MRAS) was used for parameter estimation, which solves the equation under-ranking problem by fixing one parameter to estimate the other two parameters, and the experiments show that its estimation effect is better, however, it ignores the fact that the parameters of machine are strongly coupled, which also limits its dynamic performance, moreover, the design of adaptive law is complicated. Compared with other methods, the least squares method (LS) in [9-10] has the advantages of better convergence speed and easy realization, but the accuracy and robustness of its parameter estimation are harder to be satisfied. [11-12] used neural network (NN) to estimate the machine parameters. The algorithm has high accuracy, but if the tuning criterion is not implemented properly, the method will fall into a local minimum or overfitting. [13-14] proposed genetic algorithm (GA) to estimate parameters, this method has smaller error, but suffers from premature and computational problems. Moreover, the problem of the equation being under-ranked is ignored. The observer-based method in [15] has better performance in estimating parameters, however, the robustness is not enough when dealing with strongly coupled problems with parameters.

With the measurement data and a suitable objective function, an ideal automatic parameter estimation method is available by the bionic search optimization method. More particularly, the particle swarm optimization (PSO) algorithm benefits from simple implementation, higher search speed, parallel search in the solution space, and is powerful in addressing multi-parameter estimation problems [16-17]. In [18], the PSO was used to estimate the machine parameters, however, the PSO tends to fall into local optimality and cannot estimate all parameters well. The lower precision of PSO parameter estimation is attributed to the fact that its parameters are constant, hence, in [19], by changing the constant inertia weights of PSO to a linear decreasing approach, and experimental results showed better performance.

[20] employed a Gaussian mutation for the extreme values of PSO to enable PSO jumping out of the local optimum and the parameter estimation accuracy was superior. [21] simplified the speed term of PSO to make the convergence speed of PSO better. [22] incorporated simulated annealing algorithm (SA) to PSO, and the result proved that its accuracy is enhanced. The above improvement methods are still difficult to prevent PSO from falling into the local optimum problem. Moreover, there is lack of theoretical basis for evaluating multiple parameters when the equation is under-ranked.

To adress the problem of equation under-ranking and to further improve the performance of PSO parameter estimation, a parameter estimation method based on SLPSO is proposed. The main contributions are summarized as follows:

1) The negative sequence weakening current and i_d = 0 current are injected into the d-axis in time sharing, the same amount of data is collected under the two states, and a mathematical model for full-rank parameter estimation is developed.

2) The speed term of PSO is simplified to improve the convergence speed in the later stage. Moreover, the Chaos decreasing strategy is adopted for the inertia weight to strengthen the global search ability.

3) A self-learning dense fleeing strategy (SLDF) based on population density information and Levy flight is designed to allow particles to learn deeply based on population density, The problem of premature algorithmic maturation and human intervention in the evolutionary process is prevented.

4) The memory tempering annealing (MTA) is integrated into the PSO to make it explore potential better areas (exploration), and the greedy algorithm (GA) is also introduced late in the evolution to accelerate the convergence of the algorithm to better regions (excavation). Simulation and experimental results show that the proposed method has better estimation accuracy and precision than other PSO methods.

The remainder of this paper is organized as follows. The full-rank estimation mathematical model is designed in section 2. The principle of proposed method is detail described in section 3. The scheme of parameter estimation and the optimization process and steps are described in section 4. The simulation and experiment results and analysis are given in section 5. Finally, some conclusions are presented in section 6.

2 PMSG model

The voltage equation of PMSG under the d-q coordinate system can be expressed as (1)

$$\begin{cases} u_d = Ri_d + L_d \dfrac{\mathrm{d}i_d}{\mathrm{d}t} - \omega_e L_q i_q \\ u_q = Ri_q + L_q \dfrac{\mathrm{d}i_q}{\mathrm{d}t} + \omega_e (L_d i_d + \psi_m) \end{cases} \tag{1}$$

where R is stator resistance, u_d, u_q, i_d, i_q are the voltages and currents of the d-axis and q-axis, L_d, L_q are the stator inductances of the d-axis and q-axis, ω_e is the electrical angular velocity, ψ_m is permanent magnet flux linkage.

The steady-state voltage equation in the d-q coordinate system is usually expressed as (2)

$$\begin{cases} u_d = Ri_d - \omega_e L_q i_q \\ u_q = Ri_q + \omega_e (L_d i_d + \psi_m) \end{cases} \tag{2}$$

The rank of (2) is 2, which has an under-rank problem in the case of estimating 4 parameters. Most scholars employ the strategy of injecting $i_d \neq 0$ (negative sequence weakening current) and $i_d = 0$ current in the d-axis to solve the under-ranking problem [23]. The injection form is shown in Fig. 1.

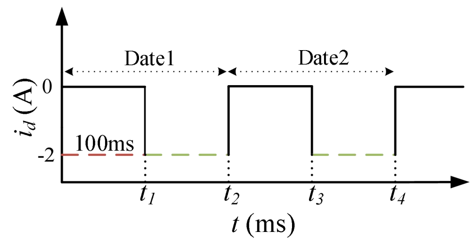


Fig. 1 *Diagram of the injected form*

Collecting the same amount of data under the two states of i_d =0 and i_d = -2 to obtain the 4th-order full-rank discrete equation, which can be expersses as

$$\begin{cases} u_{d0}(k) = -\omega_e(k) L_q i_{q0}(k) \\ u_{q0}(k) = Ri_{q0}(k) + \omega_e(k)\psi_m \\ u_{d1}(k) = Ri_{d1}(k) - \omega_e(k) L_q i_{q1}(k) \\ u_{q1}(k) = Ri_{q1}(k) + \omega_e(k)(L_d i_{d1}(k) + \psi_m) \end{cases} \tag{3}$$

where k is the current number of iterations, $u_{d0}(k)$, $u_{q0}(k)$, $i_{q0}(k)$ and $\omega_e(k)$ are the data sampled for the k-th time in 0-t_1 time in Fig. 1, $u_{d1}(k)$, $u_{q1}(k)$, $i_{d1}(k)$ and $i_{q1}(k)$ are the k-th collected data in t_1- t_2 time.

3 Enhanced self-learning particle swarm optimization algorithm with levy flight

3.1 Simple particle swarm optimization

The principle of PSO is to continuously approach the position with a smaller fitness value to obtain the optimal solution to the problem. The speed and position of the particle is updated in a way that can be expressed as

$$\begin{cases} v_i^{k+1} = wv_i^k + c_1 r_1 (P_{ibest}^k - x_i^k) + c_2 r_2 (P_{gbest}^k - x_i^k) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \tag{4}$$

where v_i and x_i are the velocity and position of particle respectively, P_{ibest} is the best position found by the particle, P_{gbest} is the best position of the particle swarm, r_1 and r_2 are random numbers between 0 and 1, c_1 and c_2 are the acceleration coefficients.

The velocity of particles is too divergent in the late stage of the algorithm will lead to a slow convergence [24], therefore, a simplified particle swarm optimization (SPSO) is proposed, and (4) is simplified as

$$x_i^{k+1} = wx_i^k + c_1 r_1 (P_{ibest}^k - x_i^k) + c_2 r_2 (P_{gbest}^k - x_i^k) \tag{5}$$

3.2 Chaos decreasing strategy

The inertia weight w is an important parameter that affects the performance of SPSO, and tt generally decreases linearly from 0.9 to 0.4, and its expression can be expressed as

$$w = w_{\max} - (w_{\max} - w_{\min})\frac{k}{k_{\max}} \tag{6}$$

where $w_{\max}$ is the initial inertia weight, $w_{\min}$ is the the minimum inertia weight, $k_{\max}$ is the maximum number of iterations.

Larger inertia weights w favor global search, and conversely, smaller one favor local search and convergence. However, the algorithm progressively enhances the capability of local search (linear decreasing strategy) and SPSO is prone to fall into local optimum. Chaotic mappings with the merits of ergodicity and randomness can enhance evolutionary diversity, and the logistic mapping form can be expressed as

$$z = 4 \cdot z(1 - z) \tag{7}$$

where the initial value of z is between (0, 1) and is non-equal to 0, 0.25, 0.5 and 1.

The improved inertia weight update equation can be expressed as

$$w = z \cdot w_{\max} - (w_{\max} - w_{\min})\frac{k}{k_{\max}} \tag{8}$$

This strategy combines the Logistic mapping with the linear decline strategy and the random strategy, which improves the performance of the linear decline strategy and the random strategy, and prevent SPSO from falling into the local optimum.

3.3 Self-learning dense fleeing

The organisms will flee from living densities that are too thin, and the population density is expressed as

$$s(i, P_{ibest}) = 1 - \frac{d(i, P_{ibest})}{d_{\max}} \tag{9}$$

where $d(i, P_{ibest})$ represents the Euclidean length from the particle i and the individual extreme, $d_{\max}$ represents the maximum distance between the particle and the extreme.

As the iteration proceeds, the population gradually becomes denser and there is an urgent need to exploit new living spaces. Levy flight is a random search strategy between short-distance flight and stochastic long-distance exploration that obeys the Levy distribution. Levy flight is introduced into the update of SPSO to facilitate its population evolutionary depth, and the Levy flight position update equation is expressed as (10)

$$\begin{cases} X_i^{k+1} = X_i^k + Levy \oplus \alpha \\ Levy = S_l \oplus X_i^k \end{cases} \tag{10}$$

where $\oplus$ represents element-by-element multiplication, α is the step size associated with the scale of the problem of interest, which is a random number in all dimensions of the particle, and it can be expressed as

$$X_i^{k+1} = X_i^k + S_l \oplus X_i^k \oplus random(size(X_i^k)) \tag{11}$$

The step size S_l is calculated as

$$S_l = 0.01 \cdot S \tag{12}$$

where the factor 0.01 comes from L/100, which is the typical step size for walking, where L is the typical length scale, Otherwise, the Levy flight may become too aggressive, which makes the new solution jump out of the optimization-seeking domain (wasting computational power).

The step length S can be calculated by the Mantegna algorithm for random walks, which can be expressed as [25]

$$S = \frac{\mu}{|v|^{\frac{1}{\beta}}} \tag{13}$$

where μ and v follow a Gaussian distribution, which can be expressed as

$$\mu \quad N(0, \sigma_u^2), \qquad v \quad N(0, \sigma_v^2) \tag{14}$$

where

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2})\beta 2^{(\beta-1)/2}} \right\}^{1/\beta} \qquad \sigma_v = 1 \tag{15}$$

where Γ is standard Gamma function.

At higher PSO population density ($s(i, P_{ibest}) > rand()$), Levy flight is better able to facilitate PSO fleeing from areas of lower survival density and protect the evolutionary vitality of the population.

3.4 Global - domain enhancement

Simulated annealing (SA) accepts the position of poor fitness with probability [26]. At temperature T, the fitness values of the original position i and the new position j are f_i and f_j, and the probability of receiving the new position is expressed as

$$P_{ij} = e^{-\frac{f_j - f_i}{T}} \tag{16}$$

When $p_{ij} > rand()$, accept the new position j; otherwise, keep the original position i. The probability of accepting inferior solutions in the early stage of SA is large, and it can jump out of the local optimum.

Increasing the temperature (tempering) when receiving a new solution, and continue to strengthen the search for potential areas. In order to avoid repetition of calculation, the number of tempering should not be too many, it is set to 5 times. Moreover, a memory is set to record the solution with the best fitness value to prevent the forgetfulness of SA.

The above is the memory tempering annealing algorithm (MTA), which contributes to the global exploration of PSO, however, the PSO evolution degenerates to domain search at a later stage (MTA does not accept the difference solution for 5 consecutive times) with limited evolutionary potential, therefore, its replacement by the greedy algorithm (GA) with simple principle and high efficiency of local search at a later stage to enhance the fine exploitation locally.

Moreover, the initial value of GA is the PSO late-seeking optimal value, which is closer to the real value than the random initial value and contributes to better acquisition of the global optimal value.

3.5 The proposed method

A strategy of chaotic decreasing inertia weights is used in SLPSO to enhance the global search capability, and a scatter learning strategy is designed based on the population density to facilitate the particles to explore new lively intervals. Moreover, MTA is introduced to assist the algorithm in exploring potentially better regions, and GA is used to enhance the depth and speed of evolution in the later stages of PSO.

The basic steps of SLPSO are stated as follows

Algorithm: SLPSO

1: Initialize parameters, data sampling and recording as in Fig.1, and obtain initial individual and population extremes.

2: **for** $1 < \mathrm{k} < \mathrm{k}_{\max}$

3: update particle position (x_i) by (5) and evaluate their fitness value ($f(x_i)$).

4: get the fitness difference between the new and the old position Δf (f_j - f_i).

5: **if** $\Delta f<0$ || $\Delta f>0$ && $\exp(-\Delta f/T) > rand()$, the particle enters the new position, and the annealing operation is performed T=CT, or else, keep the original position //T is the initial temperature and C is the coefficient of annealing.

6: **if** Nt < 5, the tempering annealing T=2CT, or else, the local detailed exploitation by GA by inheriting the optimal solution of PSO. // Nt is number of tempering.

7: The inertia weight is chaotically decreasing by utilizing the (8), and obtain the population density ($s(i, P_{ibest})$) by (9).

8: **if** $s(i, P_{ibest})> rand()$, SLDF strategy is initiated to explore new lively areas and enhance population diversity.

9: **if** $f(x_i) < f(P_{ibest})$, update P_{ibest} ($P_{ibest} \leftarrow x_i$).

10: **if** $f(P_{gbest})< f(P_{ibest})$, update P_{gbest} ($P_{gbest} \leftarrow P_{ibest}$).

11: **if** the maximum number of iterations is met, the memory output optimal parameters, or else, continue to iterate.

4 Principle of parameter estimation

The problem of parameter estimation can be transformed into an optimization problem. The basic idea is to continuously adjust the parameters of the adjustable model through SLPSO to minimize the difference between the output of the reference model and the adjustable model. Finally, the optimal solution output by SLPSO is used as the identified parameter. The reference model is expressed as

$$y = h(p, I) \tag{17}$$

where the h function is (3), p is the machine parameters, and p = (R, L_d, L_q, ψ_m), I is the system input, and I= (i_d, i_q, ω_e), y is the system output, and y= (u_d, u_q).

To estimate the parameters of machine, a model with the same structure and adjustable parameters is designed, which can be expressed as

$$\hat{y} = h(\hat{p}, I) \tag{18}$$

where $\hat{p}$ is the adjustable model parameters, and $\hat{p}$ = ($\hat{R}$, $\hat{L}_d$, $\hat{L}_q$ $\hat{\psi}_m$), $\hat{y}$ is the adjustable model output, and $\hat{y}$ = ($\hat{u}_d$, $\hat{u}_q$).

It is necessary to compare the output of the reference model and the adjustable model to accurately estimte the parameters. PSO uses the fitness function to measure the accuracy of the estimation parameters, which can be expressed as

$$\begin{cases} f_1(\hat{L}_q) = \dfrac{1}{\mathrm{k}_{\max}}(u_{d0}(k) - \hat{u}_{d0}(k))^2 \\ f_2(\hat{R}, \hat{\psi}_m) = \dfrac{1}{\mathrm{k}_{\max}}(u_{q0}(k) - \hat{u}_{q0}(k))^2 \\ f_3(\hat{R}, \hat{L}_q) = \dfrac{1}{\mathrm{k}_{\max}}(u_{d1}(k) - \hat{u}_{d1}(k))^2 \\ f_4(\hat{R}, \hat{L}_d, \hat{\psi}_m) = \dfrac{1}{\mathrm{k}_{\max}}(u_{q1}(k) - \hat{u}_{q1}(k))^2 \end{cases} \tag{19}$$

where $\hat{u}_{d0}(k)$, $\hat{u}_{q0}(k)$, $\hat{u}_{d1}(k)$ and $\hat{u}_{q1}(k)$ represent the d-q axis voltages output by the adjustable model.

All parameters are estimated at the same time by (20)

$$\min[f(\hat{p})] = \sum_{i=1}^{4} a_i f_i \tag{20}$$

where a_i is the weighting factor, which are all 0.25 for the estimation parameters are equally important.

The principle block diagram of parameter estimation is shown in Fig. 2.

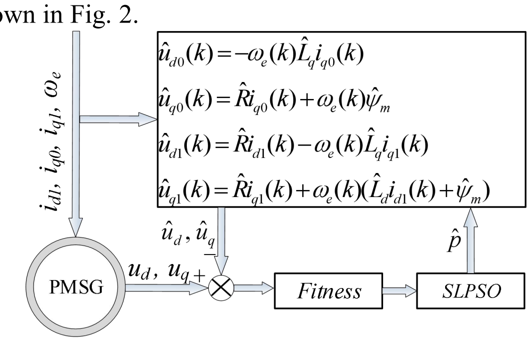


Fig. 2 *Block diagram of parameter identification*

The steps of parameter estimation:

1) Initialize the SLPSO parameters.

2) Collect electrical signals, and obtain the outputs $\hat{u}_{d0}(k)$, $\hat{u}_{q0}(k)$, $\hat{u}_{d1}(k)$ and $\hat{u}_{q1}(k)$ of adjustable model from (18).

3) The initial fitness value f($\hat{p}$ (k)) is obtained from (20).

4) The current individual and group parameter extremes $\hat{p}_i^{pbest}$ and $\hat{p}^{gbest}$ are determined by the fitness value, and the parameter is updated by (5), such as, the update of the $\hat{R}$ can be expressed as

$$\begin{aligned} \hat{R}(k+1) = w\hat{R}_s(k) + c_1 r_1\left[\hat{R}^{pbest} - \hat{R}\ (k)\right] \\ + c_2 r_2\left[\hat{R}^{gbest} - \hat{R}(k)\right] \end{aligned} \tag{21}$$

where $\hat{R}^{pbest}$ and $\hat{R}^{gbest}$ are the individuals and groups optimal values of $\hat{R}$ respectively, and other paremeters update in the same way.

5) The inertia weight is updated by (8), and obtain the population density ($s(i, P_{ibest})$) by (9).

6) Population density is high and the SLDF is initiated, and the

Metropolis principle is used to judge whether to accept new parameters

$$\begin{cases} \Delta f = f(\hat{p}(k+1)) - f(\hat{p}(k)) \\ p = \begin{cases} 1 & \Delta f \le 0 \\ e^{\frac{-\Delta f}{T}} & \Delta f > 0 \end{cases} \end{cases} \tag{22}$$

The p > *rand*(), update the parameter value, and annealing operation is performed, otherwise, keep the original parameter value.

8) Perform tempering annealing or GA optimization operations according to the rules.

9) The maximum number of iterations is reached, the memory output the optimal parameters, otherwise, continue to iteration.

5 Simulation and experimental analysis

5.1 Simulation analysis

To verify the effectiveness of the proposed method, a PMSG vector control system is established in Matlab/simulink as shown in Fig. 3.

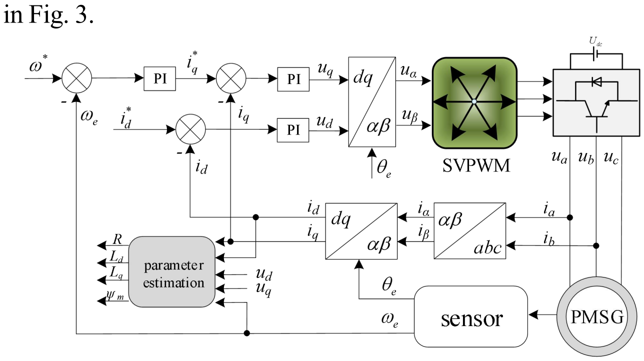


Fig.3 *Vector control system block diagram*

The parameters of generator are shown in Table 1.

Table 1 Generator parameter table

Parameter	Value	Unit
Pole pairs	2	pairs
Resistance	2.875	Ω
Stator d-axis inductance	4.5	mH
Stator q-axis inductance	13.5	mH
Permanent magnet flux	0.17858	Wb
Rated power	1.0	kW
Rated speed	1500	rpm
Rated torque	15	N·m

The parameters of test algorithm are all set as follows: the population number is 20, the number of iterations is the ratio of the running time to the sampling time, the acceleration factor c_1 and c_2 take 1.6, the annealing temperature T and the coefficient C are 1000 and 0.95 respectively, the simulation system runs for 0.2s, system sampling frequency is 10kHz.

The actual system is disturbed by uncertain factors and there are random errors. Therefore, SLPSO, memory tempering annealing PSO (MTAPSO), simulated annealing PSO (SAPSO) and PSO are tested under different working conditions to independently estimate machine parameters for 10 times, and take the average value as the final output value.

1) Working condition 1

The estimation results and errors in the operating state with the torque of 10N·m and the speed of 1000 r/min are shown in Table 2.

Table 2 The results of parameter estimation under condition 1

Parameter	PSO	SAPSO	MTAPSO	SLPSO
R (Ω)	3.203	3.111	3.005	2.929
Error (%)	11.409	8.209	4.522	1.878
L_d (mH)	4.157	4.350	4.424	4.557
Error (%)	-7.622	-3.333	-1.689	1.289
L_q (mH)	13.255	13.652	13.621	13.592
Error (%)	-1.815	1.126	0.896	0.681
ψ_m (Wb)	0.1703	0.1727	0.1747	0.1759
Error (%)	-4.637	-3.293	-2.173	-1.501
Estimate time (s)	0.068	0.062	0.055	0.045
Fitness value	7.388	5.325	3.310	2.502

2) Working condition 2

Temperature has a great influence on machine parameters, after the test machine runs for a period, its parameters become as: R is 3.1625 Ω, L_d is 4.635 mH, L_q is 14.175 mH, and ψ_m is 0.169651 Wb. The Table 3 is the estimation results and errors under the running state of the torque of 15 N·m and speed of 1500 r/min.

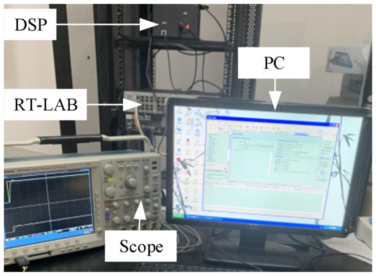
Table 3 The results of parameter estimation under condition 2

Parameter	PSO	SAPSO	MTAPSO	SLPSO
R (Ω)	2.794	2.886	2.990	3.225
Error (%)	-11.653	-8.743	-5.455	1.976
L_d (mH)	4.087	4.304	4.723	4.711
Error (%)	11.823	-7.141	1.899	1.640
L_q (mH)	13.740	14.392	14.355	14.289
Error (%)	-3.069	1.531	1.270	0.804
ψ_m (Wb)	0.1785	0.1757	0.1737	0.1724
Error (%)	5.216	3.566	2.387	1.620
Estimate time (s)	0.076	0.064	0.057	0.046
Fitness value	8.094	5.892	3.681	2.651

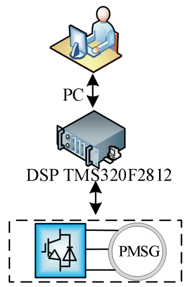
From the data in Tables II and III, we can see that PSO is prone to fall into local optimum when dealing with optimization problems with strongly coupled parameters, and the accuracy is poor (the maximum estimation error is greater than 11%), and its convergence speed is slow. The improved SAPSO, MTAPSO and SLPSO have better accuracy than PSO, and the estimation accuracy of SLPSO is within 2%, which is 3.44% better than MTAPSO and 6.29% better than SAPSO. When the working conditions change, the accuracy of SLPSO is still within 2%, the performance is less affected by external influences, and its robustness is better.

5.2 Experimental verification

This paper uses RT-LAB to implement the hardware in the loop simulation (HILS) of the machine drive system. The RT-LAB experiment platform is shown in Fig. 4. The model of the DSP controller is TMS320F2812, which runs the algorithm, and RT-LAB (OP5600) is used to construct machine and inverter.



(a) Test bench



(b) HILS Configuration

Fig.4 *RT-LAB experiment platform*

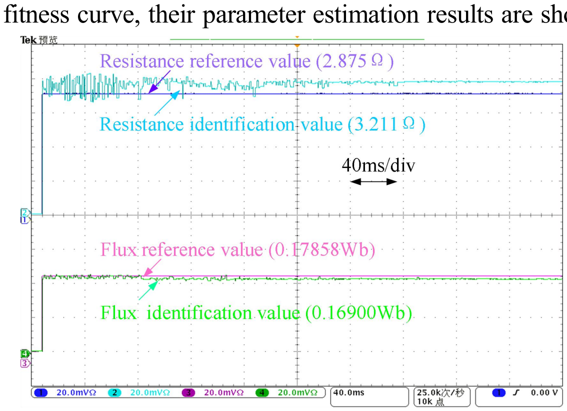
The experimental test conditions are consistent with the simulation.

1) Working condition 1

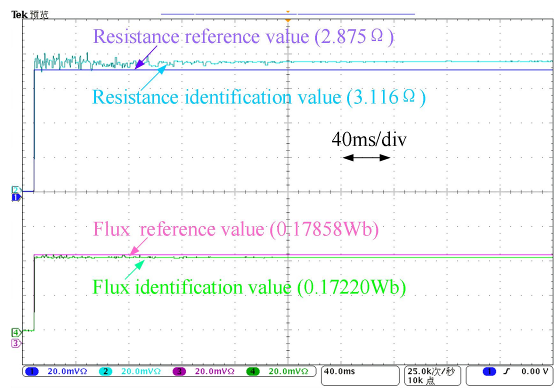
Fig. 5 to Fig. 7 show the results of parameter estimation and the fitness curve, their parameter estimation results are shown in Table 4.

Table 4 The experimental results of parameter estimation under condition 1

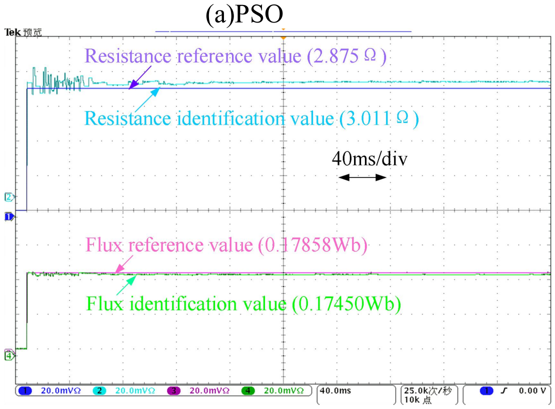
Parameter	PSO	SAPSO	MTAPSO	SLPSO
R (Ω)	3.211	3.116	3.011	2.930
Error (%)	11.687	8.383	4.730	1.913
L_d (mH)	4.152	4.347	4.579	4.558
Error (%)	-7.733	-3.400	1.756	1.289
L_q (mH)	13.251	13.653	13.628	13.593
Error (%)	-1.844	1.133	0.948	0.689
ψ_m (Wb)	0.1690	0.1720	0.1745	0.1759
Error (%)	-5.365	-3.685	-2.285	-1.501
Estimate time (s)	0.390	0.380	0.370	0.260
Fitness value	7.423	5.337	3.319	2.504



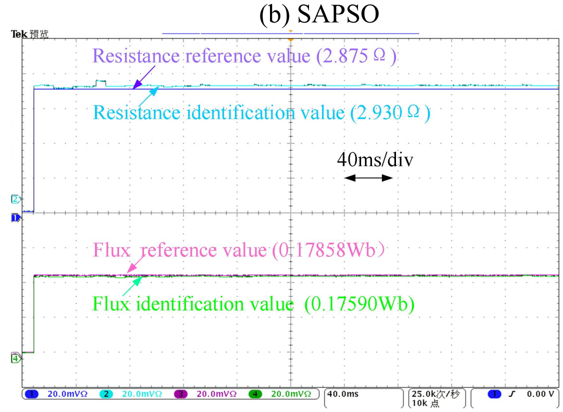
(a)PSO



(b) SAPSO



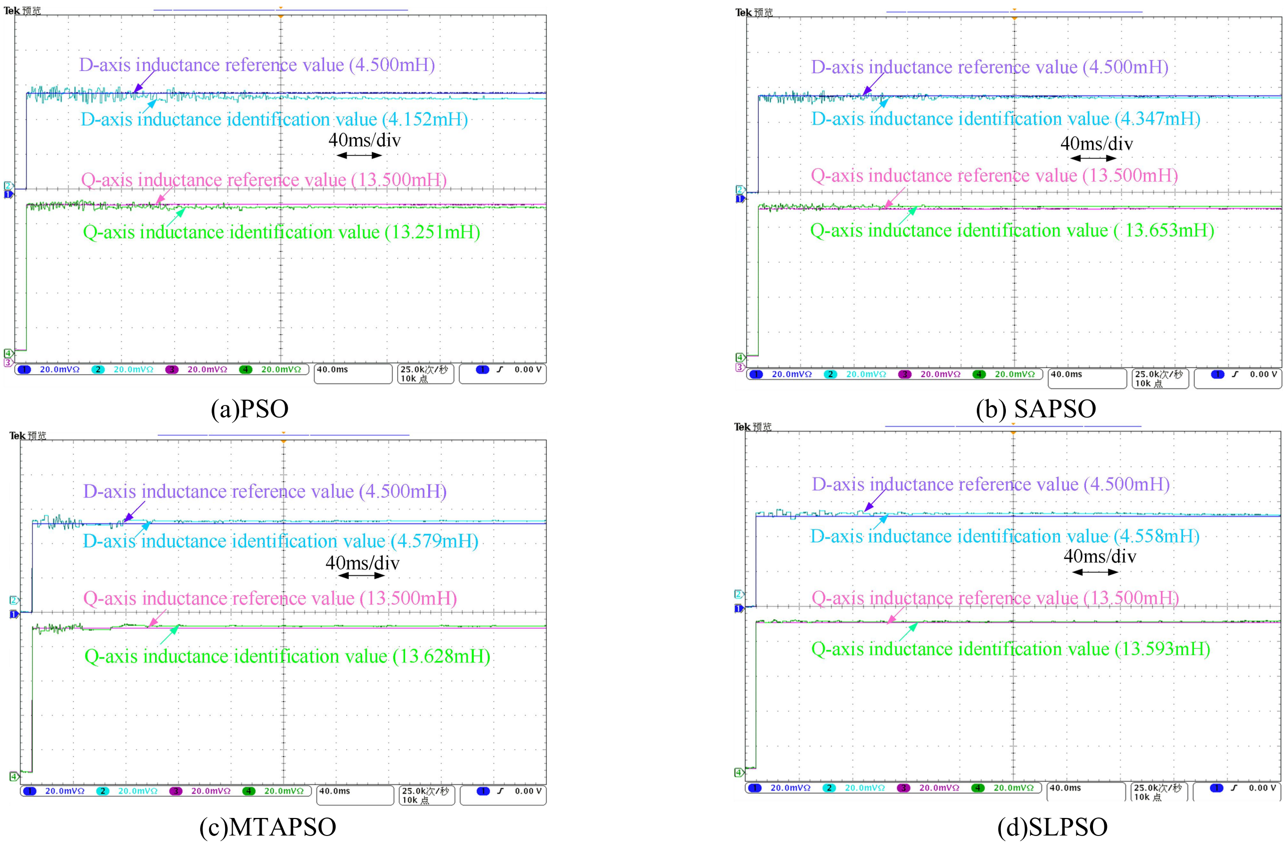
(c)MTAPSO



(d)SLPSO

Fig.5. *Parameter estimation results of R and ψ_m under condition 1.*

The estimation curve of R and the ψ_m by PSO is close to stable at 390ms, and its estimation value of R deviates from the true value by nearly 11.7%, the SAPSO estimation curve stabilizes within 8.5% of the true value at 380ms, and the MTAPSO stabilizes at 4.8% of the true value at 370ms. Compared with the other three methods, the convergence speed of the SLPSO estimation curve is faster, and its estimation error is within 2% at 260ms, moreover, its estimation error is 1.913%, which is 0.6, 0.77 and 0.84 times smaller than that of MTAPSO, SAPSO and PSO, respectively, demonstrating that the proposed method has favorable global self-decoupling ability in dealing with the strongly coupled parameter problem.



(a)PSO (b) SAPSO

(c)MTAPSO (d)SLPSO

Fig.6. *Parameter estimation results of L_d and L_q under condition 1.*

It can be seen from Fig. 6 that the inductance estimation curve of PSO fluctuates greatly, and its error is 4.5% higher than that of SAPSO. The inductance estimation accuracy of MTAPSO is 1.5% higher than that of SAPSO. The exploration domain of SLPSO with inertial weight chaotic decreasing strategy is broader, which makes it better to escape from local optimum, and the final estimation accuracy of inductance remains within 1.3%.

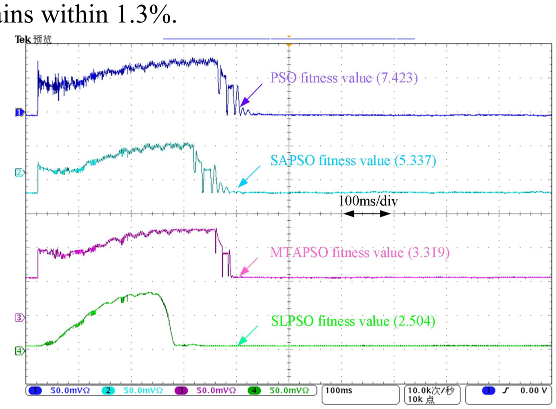


Fig.7. The curve of fitness function under condition 1.

It can be seen from Fig. 7 that PSO falls into a local optimum, which causes its fitness value curve to converge to 7.388 at 390ms. The fitness values of SAPSO and MTAPSO are smaller than PSO, which are 5.337 and 3.319 respectively. MTAPSO stabilizes at 370ms, and SLPSO converges to 2.504 in 260ms, which shows that SLPSO has better accuracy and convergence speed than other methods.

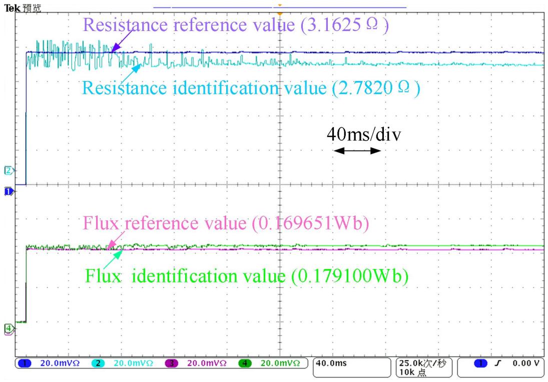
2) Working condition 2

Fig. 8 to Fig. 10 show the results of parameter estimation and the fitness curve under condition 2, and their parameter estimation results are shown in Table 5.

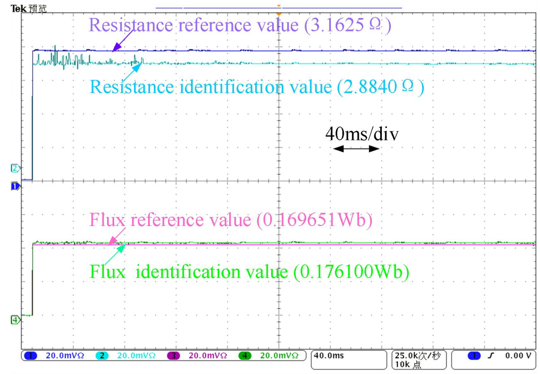
Table 5 The experimental results of parameter estimation under condition 2

Parameter	PSO	SAPSO	MTAPSO	SLPSO
R (Ω)	2.782	2.884	2.977	3.225
Error (%)	-12.032	-8.806	-5.866	1.976
L_d (mH)	4.082	4.387	4.725	4.713
Error (%)	11.931	-5.351	-1.942	1.683
L_q (mH)	13.701	14.408	14.373	14.290
Error (%)	-3.344	1.644	1.397	0.811
ψ_m (Wb)	0.1791	0.1761	0.1743	0.1724
Error (%)	5.570	3.801	2.740	1.620
Estimate time (s)	0.48	0.42	0.380	0.260
Fitness value	8.318	5.990	3.747	2.657

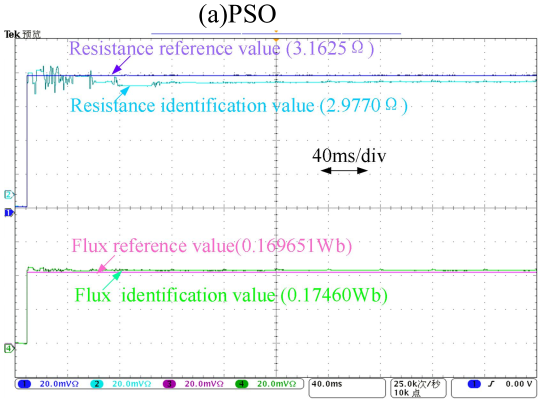
Fig. 8 shows the estimation curves of R and ψ_m by the four algorithms when the machine parameters and operating conditions change. The estimation curve of PSO fluctuates greatly, and its error exceeds 12%. The curves of SAPSO, MTAPSO, and SLPSO also fluctuate. SLPSO has a smaller fluctuation, which is only 0.095% higher than that under working condition 1, and the estimation accuracy is maintained better than other methods.



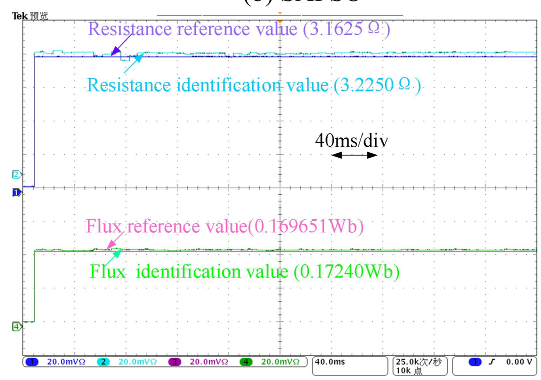
(a)PSO



(b) SAPSO

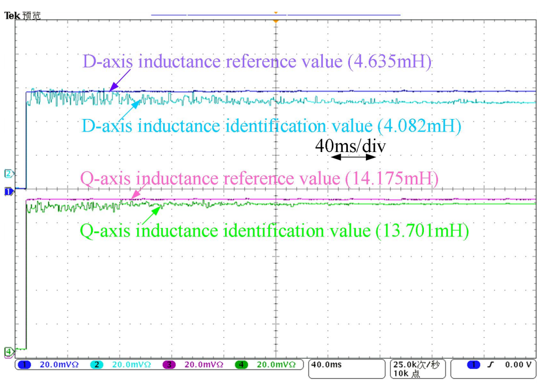


(c)MTAPSO

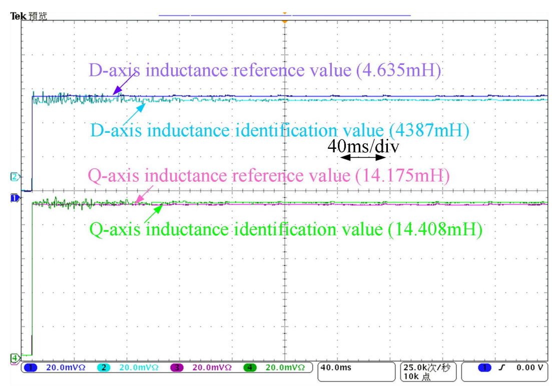


(d)SLPSO

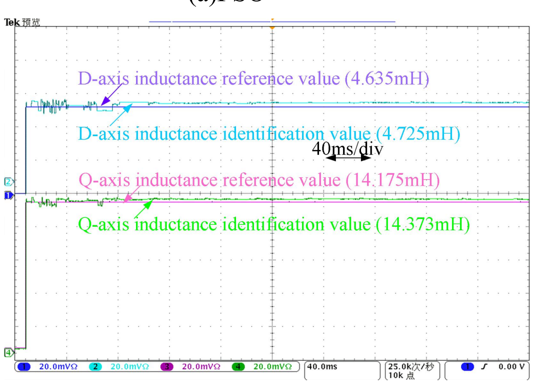
Fig.8. Parameter estimation results of R and ψ_m under condition 2.



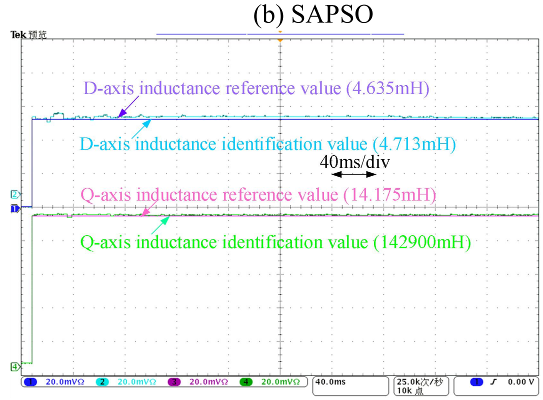
(a)PSO



(b) SAPSO



(c)MTAPSO



(d)SLPSO

Fig.9. Parameter estimation results of L_d and L_q under condition 2.

Fig. 9 shows the estimation curves of inductance by the four algorithms. Changes in working conditions and parameters cause the system to fluctuate. PSO is greatly affected, the parameter estimation accuracy of inductance is reduced by 4.2%, the accuracy of the optimized SAPSO, MTAPSO and SLPSO are reduced by 1.95%, 0.45% and 0.39% respectively. The accuracy of SLPSO decreases relatively lower, and its error remains within 2%.

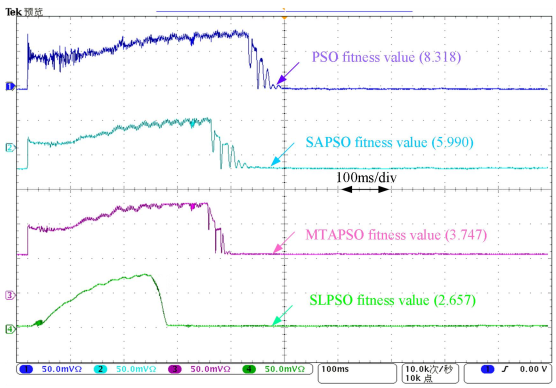


Fig.10. The curve of fitness function under condition 2.

It can be seen from Fig. 10 that the fitness value curve of PSO fluctuates greatly under the condition of increased disturbance. SAPSO and MTAPSO have joined SA, the estimation accuracy has been improved, and the accuracy of MTAPSO with tempering and memory is better than SAPSO. The fitness value of SLPSO with SLDF and global - domain enhancement strategy is smaller than other methods, which shows that its estimation accuracy and speed are better, and changes in working conditions have little effect on it.

As a conclusion, the accuracy and speed of the parameter estimation of PSO are less satisfactory. The estimation accuracy of SAPSO and MTAPSO is better than that of PSO. Moreover, the estimation accuracy and speed of the SLPSO proposed in this paper are better than the other three schemes, and it exhibits good robustness in the case of changing working conditions and parameters.

6 Conclusion

To overcome the issue that estimated equation is under-ranked and PSO is vulnerable to local optimum, a novel parameter estimation method for machine in SLPSO is proposed. The following conclusions are drawn from the analysis of the experimental results under different scenarios.

1) The full-rank estimation equation is obtained by injecting i_d=0 and negative-sequence weak magnetic currents in a time-sharing manner, and the potential problem of divergence is avoided for the optimal solution.

2) The chaotic inertia weight is used to facilitate SLPSO to explore potentially better regions, and the SLDF based on population density information and Levy flight is designed, and the algorithm can adaptively perform deep learning or exploitation operations to avoid population monotony and the necessity of human intervention.

3) A global - domain enhancement strategy is devised, i.e., MTA as a tool to facilitate the algorithm in enhancing deep learning and guaranteeing eco-activity, and GA for accelerating the algorithm in fine-grained mining and guaranteeing better convergence to better confidence intervals.

4) It is still able to estimate the parameters well under different parameters and working conditions, and its estimation accuracy is controlled at more than 98%, the requirements of high-performance controllers and fault detection demands can be better fulfilled.

7 Acknowledgments

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