PMSM parameter identification based on improved PSO

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Abstract. The results of the standard PSO algorithm are easy to fluctuate and the time-varying error is too large. By introducing the strategy of Gaussian decline and Gaussian disturbance, an improved PSO motor parameter identification method is proposed. When the motor parameters change, the improved PSO method can be used to identify the motor parameters faster, more accurate and more stable. The simulation results show that the improved PSO overcomes the recognition results of the standard PSO and improves its recognition accuracy.

1. Introduction
Permanent magnet synchronous motor (PMSM) has been widely used in servo system and other industrial fields due to its advantages of high power density and fast dynamic response. The realization of high-performance PMSM control system depends on accurate motor parameters, but the motor parameters such as stator resistance and inductance are easily affected by temperature, stator current, magnetic saturation and other factors, resulting in the decrease of motor control performance, reliability and system dynamic and static performance. Therefore, in order to obtain a high performance PMSM control system, it is necessary to accurately identify the variation of motor parameters during operation for control. Common identification methods include least square method, extended Kalman filter and neural network method, model reference adaptive identification etc. The least square method is easy to be affected by the external fluctuation, and the extended Coleman filter and neural network algorithm are not easy to be programmed[1].

An improved PMSM multi-parameter identification algorithm based on learning particle swarm optimization (PSO) is proposed to solve the multi-parameter identification problem of permanent magnet synchronous motor (PMSM).In terms of inertia weight, according to the distribution characteristics of Gaussian function, the inertia weight is reduced according to the nonlinear law, and the Gaussian decreasing strategy is adopted. In terms of the convergence rate, namely the particle velocity update, the gaussian disturbance is added to make it continue to search for the optimal population, thus improving the convergence rate and accuracy of PSO algorithm.

2. Motor Mathematical model
In the D-Q rotating coordinate system of the motor, the voltage equation of the permanent magnet synchronous motor can be described as:

\[
\begin{align*}
\dot{u}_d &= R_i + L_d i_d - \omega L_q i_q \\
\dot{u}_q &= R_i + L_q i_q + \omega L_d i_d + \omega \psi_f
\end{align*}
\]

(1)

Where \( u_d, u_q, i_d, i_q \) and \( L_d, L_q \) are D-Q axis voltage, current and inductance. \( R, \omega, \psi_f \) and \( P \) are Stator resistance, electric Angle, permanent magnet flux linkage, differential operator. By further transforming formula (1), we can get:
3. Improved PSO algorithm

3.1. Standard PSO algorithm

Particle Swarm optimization (PSO), proposed by Kennedy and Eberhart in 1995, is a swarm based evolutionary algorithm. The PSO algorithm treats an individual as a "particle" without mass, each particle traveling at a certain speed in the D-dimensional search space[2-3].

Suppose the current position of particle \( i (i = 1,2, \cdots, N) \) is \( X_i = (x_{i1}, x_{i2}, \cdots, x_{id}) \), the current flight speed is \( V_i = (v_{i1}, v_{i2}, \cdots, v_{id}) \), \( p_d \) is the current optimal position of particle \( i \), and \( g_d \) is the optimal position found by all particles in the population. The flight speed of the particle is adjusted according to the flight experience of the particle itself and that of other particles in the crowd. The speed update formula of the standard particle swarm optimization algorithm is as follows:

\[
v_{id} = \omega v_{id} + c_1 r_1 \left( p_{id} - x_{id} \right) + c_2 r_2 \left( g_d - x_{id} \right)
\]

(3)

The position update formula is:

\[
x_{id} = x_{id} + v_{id}
\]

(4)

In the formula (3)(4): \( \omega \) is the inertia weight, which decreases gradually with the evolution process, \( c_1, c_2 \) is the acceleration parameter, \( r_1, r_2 \) is the random number between [0,1].

3.2. Improved PSO algorithm

In the standard PSO algorithm, each particle at the same time to own the best historical experience and the best experience learning, determined by information sharing between the particle individual behavior, the early stage of the algorithm convergence speed, but single period in the late algorithm the inertia weight will affect the precision and convergence of corresponding particles are more likely to fall into local optimum. In view of the above two points, an improved learning particle swarm optimization algorithm is proposed[1].

\[
v_{id} = \omega v_{id} + c_1 r_1 \left( p_{id} - x_{id} \right) + c_2 r_2 \left( g_d - x_{id} \right)
\]

(5)

\[
v_{jd} = \omega v_{jd} + c_1 r_1 \left( p_{jd} - x_{jd} \right) + c_2 r_2 \left( g_d - x_{jd} \right)
\]

(6)

Equations (5) and (6) respectively represent the learning speed of particles with different dimensions. It can be seen that the weight of inertia and \( p_{id}, p_{jd} \) and \( g_d \) will have an impact on the learning speed.
of particles. Therefore, an improved learning particle swarm optimization algorithm is proposed.

3.2.1. The inertia weight. The performance of the standard PSO algorithm depends largely on the selection of the inertia weight, which is somewhat similar to the temperature in simulated annealing. As the number of iterations increases, the Value of $\omega$ should continuously decrease. Linear decrement strategy is a more general strategy at present. However, at the early stage of iteration, the value of $w$ is relatively large, and the particle swarm will spread over the entire search area at a relatively fast flight speed. After determining the approximate range of the optimal value, if the local search ability of the algorithm is stronger than the global search ability, it requires that the particles can enter into a state with a small value quickly, which will inevitably improve the convergence speed and accuracy of PSO algorithm. Therefore, according to the distribution characteristics of Gaussian function, the inertia weight is reduced in accordance with the nonlinear law. The reduction strategy is as follows:

$$\omega_i = (\omega_{i_1} - \omega_{i_2}) \exp\left[-\frac{k^2}{(e \times \text{MaxNumber})^2}\right] + \omega_{i_2} \quad (7)$$

Where, MaxNumber is the maximum number of iterations, $\omega_{i_1}$ and $\omega_{i_2}$ are the final and initial values of $\omega$ respectively.

3.2.2. Gauss perturbation. If the gaussian decreasing strategy mentioned above is adopted, in the later stage of the algorithm, when $p_{id} \approx g_{id} \approx x_{id}$ occurs, the particle is in a stagnant state and cannot continue to learn; at this time, once the local optimal is reached, the algorithm cannot jump out, resulting in slower convergence rate of the algorithm and even falling into the local optimal. Therefore, only by proper perturbation of the particle extremum in the stagnant state can the particle regain a certain momentum, learn from the new extremum direction, and increase the probability of finding the global optimal solution. Therefore, gauss disturbance factor is introduced to perturb the particles when the algorithm iteration enters the later stage[4].

3.2.3. Improved PSO, particle velocity formula

$$\begin{cases}
    v_{id} = wv_{id} + c_1r_1(p_{id} - x_{id}) + c_2r_2(g_{id} - x_{id}) + x_{id_{max}}f(0,1^2) & g_i < \lambda \\
    v_{id} = wv_{id} + c_1r_1(p_{id} - x_{id}) + c_2r_2(g_{id} - x_{id}) & g_i \geq \lambda
\end{cases} \quad (8)$$

$$g_i = \frac{F_{i}[k] - F_{i}[k-1]}{F_{i}[k-1]} \quad (9)$$

In Equation (8) and (9), $f(0,1^2)$ represents Gaussian disturbance, $F_{i}[k]$ represents individual extremum fitness value at iteration $k$ of the $i$ particle, $g_i$ represents the learning rate of particle fitness, and $\lambda$ is the learning threshold.

4. motor parameter identification

4.1. Principle of motor parameter identification

The current equation of the mathematical model of the motor is transformed into the description of the parameter identification problem, so formula (2) is transformed into:

$$\begin{align*}
    \frac{di_d}{dt} &= -\frac{R}{L_d}i_d + \omega_s \frac{L_e}{L_d} \frac{u_d}{L_d} + \frac{u_d}{L_d} \\
    \frac{di_q}{dt} &= -\frac{R}{L_q}i_q - \omega_s \frac{L_e}{L_q} \frac{u_d - \omega_s v_f}{L_q} \quad (10)
\end{align*}$$

After discretization, the q axis current equation of Equation (10) can be expressed as:
\[ i_q(k) = \theta \hat{i}_q(k-1) + \theta \phi (\omega(k) i_q(k) + \omega(k-1) i_q(k-1)) + \theta \phi [u_q(k) + u_q(k-1)] + \theta \phi [\omega(k) + \omega(k-1)] \] (11)

Where: \( T \) is the adoption period

\[ \theta_{q1} = \frac{-T R + 2 L_q}{T R + 2 L_q}, \quad \theta_{q2} = \frac{-L_q T}{T R + 2 L_q}, \quad \theta_{q3} = \frac{T R}{T R + 2 L_q}, \quad \theta_{q4} = \frac{-T \psi_f}{T R + 2 L_q} \] (12)

So:

\[ R = \frac{1 - \theta_{q1}}{2 \theta_{q3}}, \quad L_d = -\frac{\theta_{q3}}{\theta_{q3}}, \quad L_q = \frac{1 + \theta_{q1} T}{4 \theta_{q3} \theta_{q3}}, \quad \psi_f = -\frac{\theta_{q4}}{\theta_{q3}} \] (13)

4.2. Improved PSO identification parameters

Based on the above derivation, the q axis current tracking function can be established as follows:

\[ \hat{i}_q(k) = \hat{\theta} \hat{i}_q(k-1) + \hat{\theta} \phi [\omega(k) i_q(k) + \omega(k-1) i_q(k-1)] + \hat{\theta} \phi [u_q(k) + u_q(k-1)] + \hat{\theta} \phi [\omega(k) + \omega(k-1)] \] (14)

where \( \hat{\theta}_{q1}, \hat{\theta}_{q2}, \hat{\theta}_{q3}, \hat{\theta}_{q4} \) is the estimate of \( \theta_{q1}, \theta_{q2}, \theta_{q3}, \theta_{q4} \).

Then, according to formula (6), the objective function of the system can be established as shown in formula (15) below. At this point, the parameter identification problem of the motor system is converted to the problem of obtaining the minimum coefficient of formula (15) based on the improved particle swarm optimization algorithm.

\[ J(\theta) = \sum_{k=0}^{K-1} \| i_q(k) - \hat{i}_q(k) \|^2 / t \] (15)

According to the improved PSO algorithm, the minimum parameters of the above formula can be iteratively calculated, and the motor parameters can be reversely calculated by formula (10) and Formula (13) according to the identified parameters.

4.3. Algorithm design

According to the state equation of PMSM in the synchronous rotation coordinate system and combined with the improved PSO, the following functions can be constructed as the fitness function of the algorithm[5-6]:

\[ F_n[i] = (\sum_{i=1}^{N} [i_q(k) - \hat{i}_q(k)])^2 / t \] (16)

Where, \( \hat{i}_q(k) \) is equation (14), and \( t \) is the number of iterations.

The calculation steps of the improved PSO algorithm are as follows:

Step 1: Collect and save the data of the motor during operation for a period of time: \( i_q, L_d, L_q, \) and \( \psi_f \) and set the maximum number of iterations \( t_{max} \).

Step 2: Set the range of the identified parameters \( R, L_d, L_q \) and \( \psi_f \), initialize the position and velocity of N particles, initialize the relevant parameters, and set the maximum number of iterations \( t_{max} \).

Step 3: Calculate the fitness value of each particle \( F_n[i] \).

Step 4: According to \( i_q(k), i_d(k), u_q(k), \omega(k), p_{id}(k) \) and \( g_{di}(k) \) are calculated, and fitness value
of each particle is compared with \( p_{iD}(k) \) and \( g_{iD}(k) \), so as to update \( p_{iD}(k) \) and \( g_{iD}(k) \);

Step 5: Calculate the weight and update the position and speed of each example according to Equation (7), (8) and (9);

Step 6: Judge whether the fitness value of \( A \) in this iteration is less than the set threshold, then output \( A \) and exit the algorithm; Otherwise, repeat steps 3-6.

5. The simulation verification

Figure 2 is the simulation model established based on MATLAB.

5.1. Parameter step change identification

The identification curve of parameter step change is as follows: the given resistance value changes in step at 1s, \( L_d \) change in step at 2s, and \( L_q \) change at 3s.

5.2. Parameter time-varying identification

The identification curve of time-varying parameters is as follows: the given resistance value changes at 1s, \( L_d \) changes at 2s, and \( L_q \) changes at 3s.
5.3. Results & Discussion
It can be seen from the figure that, compared with the standard PSO algorithm, the improved PSO algorithm has the advantage of being able to track the parameters quickly and meet the identification requirements with less fluctuation when the parameters change in step or time-varying jump due to external reasons. The disadvantage is that the calculation process is complex and the requirement for the control unit is relatively high.

6. Conclusions
Using the performance of the PSO algorithm, the gaussian nonlinear law decreasing strategy is introduced to calculate the inertia weight, and the Gaussian disturbance in the PSO algorithm's particle velocity updating formula is added to make the particle search more efficient. The improved algorithm is applied to identify the electrical parameters of PMSM. The experimental results show that the proposed algorithm can solve the multi-parameter coupling problem in PMSM parameter identification and accurately identify the stator resistance, DQ axis inductance and other parameters.

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