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Smart Collaborative Performance-Induced Parameter Identification Algorithms for Synchronous Reluctance Machine Magnetic Model

Linjie Ren ^{1,2,3,4} , Guobin Lin ⁴, Yuanzhe Zhao ^{1,2,3,4,*} and Zhiming Liao ^{4,*}

¹ Key Laboratory of Road and Traffic Engineering of the State Ministry of Education, Shanghai 201804, China; org0000h@tongji.edu.cn

² Key Laboratory of Rail Infrastructure Durability and System Safety, Tongji University, Shanghai 201804, China

³ College of Transportation Engineering, Tongji University, Shanghai 201804, China

⁴ National Maglev Transportation Engineering R&D Center, Tongji University, Shanghai 201804, China; linguobin@tongji.edu.cn

* Correspondence: zhaoyuanzhe@tongji.edu.cn (Y.Z.); liaozhiming@tongji.edu.cn (Z.L.)

Abstract: In rail transit traction, due to the remarkable energy-saving and low-cost characteristics, synchronous reluctance motors (SynRM) may be a potential substitute for traditional AC motors. However, in the parameter extraction of SynRM nonlinear magnetic model, the accuracy and robustness of the metaheuristic algorithm is restricted by the excessive dependence on fitness evaluation. In this paper, a novel probability-driven smart collaborative performance (SCP) is defined to quantify the comprehensive contribution of candidate solution in current population. With the quantitative results of SCP as feedback information, an algorithm updating mechanism with improved evolutionary quality is established. The allocation of computing resources induced by SCP achieves a good balance between exploration and exploitation. Comprehensive experiment results demonstrate better effectiveness of SCP-induced algorithms to the proposed synchronous reluctance machine magnetic model. Accuracy and robustness of the proposed algorithms are ranked first in the comparison result statistics with other well-known algorithms.

Keywords: rail transit traction; synchronous reluctance machine; nonlinear magnetic model; parameters identification; population evolution mechanism; synergistic optimization

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1. Introduction

The intensification of the greenhouse effect and the nonrenewability of rare earth resources are severe challenges for induction motors (IM) and permanent magnet motors (PM) [1]. The Synchronous Reluctance Motor (SynRM) is the most promising alternative due to its high efficiency and structural robustness [2]. With increasing application of SynRM, novel modeling theories [3] that can closely represent its nonlinear magnetic characteristic have drawn considerable attention in its operation mechanism analysis and high-performance control [4]. Although many magnetic models have been developed based on various nonlinear mapping [5], the physical rationality and parameter accuracy of these models restrict the full utilization of motor performance. Similar to the actual network system [6], the co-energy balance between the d–q axis is the key constraint of modeling. Consequently, a novel magnetic model is established under the constraints of the inherent characteristics. However, there are still some challenges for the proposed model parameter identification, such as local optimal problems caused by the mismatch of special parameters of the algorithm and the multimodality of the objective function.

The SynRM magnetic model is significant for its control and practical application. For many advanced control algorithms, the rationality and accuracy of the model are the foundation [7]. In addition, for intelligent algorithms [8,9] with low model dependence, accurate models help to improve the performance of intelligent control systems. SynRM

modeling technology with both physical consistency and accuracy is a realistic demand and has practical significance. However, the accuracy of the model is still limited by the rationality of the parameter identification algorithm.

Existing research mainly focuses on two types of methods: deterministic and metaheuristic. In [10], least squares (LS) method has been used in the extraction of magnetic model parameters. Suffering from sensitivity to initial solution and dataset noise, the convergence of LS results is unsatisfied and uncertain [11]. As an alternative, metaheuristic algorithms are employed to identify the parameters of various motor models. In [12], a genetic algorithm (GA) was proposed for estimating the parameters of a saturation model using experimental test data under three working conditions. In [13], harmony search (HS) was utilized to identify parameters of a rational function-based inductance model. In [14], two improved particle swarm optimization algorithms (PSO)-based strategies (dynamic PSO and chaos PSO algorithms) are proposed to estimate the parameters of the induction motor model. The direct current, no-load and locked-rotor test results are used for parameter estimation. Other algorithm variants such as self-adaptive differential evolution algorithm (SHDE) [15], dynamic encoding algorithm searches (DEAS) [16], fast parallel co-evolutionary PSO [17] and GA-assisted PSO algorithm [18] are employed to identify the parameters of the motor model. These metaheuristic algorithms have achieved satisfied results in parameter identification of the motor model. However, the multimodality of the problem places more stringent requirements on traditional metaheuristic algorithms.

The distinguishing feature of metaheuristic algorithms is to construct the optimal population update mechanism. It is a key issue to fully exploit fitness information while maintaining diversity for designing an efficient algorithm. Its essence is the balance of computing resources under multiple dimensions and multiple influencing factors [19]. To improve the population diversity, probability-based attempts have been made. In [20], the probability of fitness evaluation was used to establish more promising searching direction for maintaining diversity. A similar method was adopted to promote exploration ability of differential evolution (DE) in [21]. Through nondominated sorting procedure, diversity information was included in the selection probability, which generated the mutation of the differential evolution (DE) algorithm [22]. However, due to the lack of a unified theory of the collaborative utilization of fitness information and diversity information, traditional metaheuristic algorithms may have defects in solving complex problems. On one hand, searching direction is only guided by fitness, weakening the exploration ability. On the other hand, excessive use of diversity information will weaken exploitation ability. In recent years, smart collaborative (SC) theory has shown outstanding advancement in the modeling [23], resource balancing of complex problems with multiple dimensions and multiple influencing factors. Inspired by the SC theory, the performance of individuals can be modeled from the two dimensions of fitness and diversity through probability.

The parameter estimation of the proposed model is a multimodal problem. There always exists a certain degree of nonlinear noise in the flux linkage data obtained by the experimental method or the finite element analysis (FEA). The multimodality caused by nonlinear noise may make the traditional identification algorithm invalid. Improper specific control parameter selection of many metaheuristic algorithms often results in premature termination. Furthermore, as feedback information for evolution, fitness is over-relied on and diversity information is often ignored. As a result, it may not be possible to obtain the global optimal solution. Hence, developing a competitive metaheuristic algorithm to identify the proposed magnetic model parameters is still a challenging task.

Therefore, we propose a smart collaborative performance (SCP) to quantify the comprehensive performance of individuals in the population through probability. As feedback information, SCP is used to induce the construction of the evolutionary direction of the population. In this way, the fitness and diversity contribution of the candidate solution to current population is introduced in the evolution simultaneously. The candidates with better comprehensive performance are encouraged into new populations, improving the quality of solution in each generation. In addition, the optimal search path update process

is adaptive without additional control parameters. Specifically, three SCP-induced algorithms are proposed to identify the parameters of the SynRM magnetic model accurately and reliably. To evaluate the effectiveness of the proposed algorithms, we compared them with other well-established algorithms on parameter identification problems of the SynRM magnetic model.

The main contributions of this paper can be summarized as follows:

- The SCP-induced algorithms are proposed based on quantified SCP. Interactions among candidate solutions are introduced into the optimal search path updating to promote the related searching ability. To the best of our knowledge, no precedent that employs SCP-induced algorithms to extract the parameters of the SynRM magnetic model has been published or reported publicly;
- As a simple and effective quantitative indicator, SCP is defined to estimate fitness and diversity of candidates uniformly. In addition, the SCP-induced population evolution mechanism is established to select promising candidate solutions in the current population evolution.

The rest of the paper is organized as follows. Section 2 presents the SynRM magnetic model, and the problem formulation of the model. The overview of SCP-induced algorithms is given in Section 3. Experimental results on the multiparameter SynRM magnetic model are shown and analyzed in Section 4. Finally, the conclusions are drawn in Section 5.

2. Problem Formulation

In this section, we propose a novel magnetic model of SynRM. Objective function involved in parameter identification of the propose model is also defined. The proposed model is established under the following hypothesis: (1) The iron loss has been omitted. (2) The stator flux linkages are only dependent on stator currents. (3) The effect of temperature on stator resistance is neglected.

2.1. Modeling of SynRM Magnetic Behaviors

For SynRM, the electromagnetic torque is generated by an anisotropic rotor with a magnetic barrier in the coupled magnetic field. The main rotor topologies are axial lamination (ALA) and transverse lamination (TLA) [24]. The ALA rotor has higher anisotropy. However, its iron loss and processing difficulty are greater than TLA. In general, the internal mechanism of the torque generated by the two rotor structures is the same. Due to the material properties of the rotor, there is inevitably a self-saturation effect in the d - and q -axis magnetic circuits. In addition, due to the sharing of magnetic circuits, there is a cross-coupling effect between the d - and q -axis magnetic linkages. The nonlinear behavior mechanism of the two rotors is the same, and the following general modeling method can be used.

The SynRM magnetic model is characterized by the nonlinear relationships among stator currents (i_s) and flux linkages (ψ_s). The mapping relationship between stator currents and flux linkages in d - q reference frame is expressed by

$$\begin{cases} \psi_d = \psi_d(i_d, i_q) \\ \psi_q = \psi_q(i_d, i_q) \end{cases} \quad (1)$$

where $i_s = (i_d, i_q)^T$, $\psi_s = (\psi_d, \psi_q)^T$ are stator currents and flux linkages, respectively. The subscripts d and q represent d - and q -axis. These nonlinear parameters are determined by the process of electromechanical energy conversion in the machine. The electrical and mechanical systems of the machine are coupled by the magnetic energy (W_m) transformation in the magnetic field. Under the assumption of conservative fields, the energy in the coupled field is conserved. The energy balance equation can be defined as

$$i_s^T u_s = R_s \|i_s\|^2 + \frac{dW_m}{dt} + T_e(i_s)\omega_m \quad (2)$$

where $\mathbf{u}_s = (u_d, u_q)^T$, R_s , T_e (i_s), W_m , ω_m are stator voltages, stator winding resistance, electromagnetic torque, magnetic energy and mechanical velocity of the motor, respectively. The energy conversion in coupled magnetic field is determined by the variation of W_m , which is caused by the change of ψ_s . For convenience, the derivative of W_m can be equivalently expressed by the derivative of comagnetic energy (W_c) as

$$\frac{dW_c}{dt} = \psi_d \frac{di_d}{dt} + \psi_q \frac{di_q}{dt} \quad (3)$$

Due to the conservation of energy, the result is independent of the integral path when W_c in (3) is calculated by curvilinear integration. Thus, the reciprocity condition [5] that W_c needs to satisfy can be presented as

$$\frac{\partial^2 W_c}{\partial i_d \partial i_q} = \frac{\partial^2 W_c}{\partial i_q \partial i_d} \Leftrightarrow \frac{\partial \psi_d}{\partial i_q} = \frac{\partial \psi_q}{\partial i_d} \quad (4)$$

Combine with (3) and (4), the change of stator currents makes the W_c change, and at the same time energy exchange occurs between the d and q axes. This reveals the formation mechanism of nonlinear behavior of SynRM magnetic circuit. The (8) and (9) also indicated that ψ_s is irrotational and W_c is the scalar potential of ψ_s . The divergence of ψ_s can be obtained by Laplacian operation of W_c

$$\nabla^2 W_c = f(i_d, i_q) \quad (5)$$

where $f(i_d, i_q)$ is an unknown function with stator current as the independent variable; (5) is the Poisson's equation of W_c . Obviously, the analytic solution of this equation cannot be obtained directly. As is well known, the general solution often contains Gaussian's function terms. Hence, the nonlinear function based on the Gaussian's function can be used to model W_c . The variation of W_c can be modeled as

$$\Delta W_c = k \left(e^{-W i_d^2} - 1 \right) \left(V_1 i_q^2 - i_q e^{-V i_q} + \kappa_q i_q - e^{-V i_q} \right) \quad (6)$$

where k , W , V_1 , V , κ_q denote the unknown parameter. Combine (3) and (6), the change of W_c with current can also be expressed by flux linkages as

$$\begin{cases} \psi_d(i_d, i_q) = \psi_d(i_d) - \frac{\partial \Delta W_c}{\partial i_d} \\ \psi_q(i_d, i_q) = \psi_q(i_q) - \frac{\partial \Delta W_c}{\partial i_q} \end{cases} \quad (7)$$

where $\psi_d(i_d)$, $\psi_q(i_q)$ are the flux linkages under the effect of self-saturation alone. The second term on the right side of (7) represents the flux linkages under the effect of cross-saturation. Considering the constraints of (7) and reciprocity condition simultaneously, the nonlinear flux linkage model of SynRM can be defined as

$$\begin{cases} \psi_d(i_d, i_q) = \alpha_d (2 - e^{-\gamma_d i_d} - e^{-\gamma_{d1} i_d^2}) + \beta_d i_d \\ \quad - k (2W i_d e^{-W i_d^2}) (V_1 i_q^2 - i_q e^{-V i_q} + \kappa_q i_q - e^{-V i_q}) \\ \psi_q(i_d, i_q) = \alpha_q (2 - e^{-\gamma_q i_q} - e^{-\gamma_{q1} i_q^2}) + \beta_q i_q \\ \quad - k (1 - e^{-W i_d^2}) (2V_1 i_q + V i_q e^{-V i_q} + \kappa_q) \\ \frac{\partial \psi_d(i_d, i_q)}{\partial i_q} = \frac{\partial \psi_q(i_d, i_q)}{\partial i_d} = -k (2W i_d e^{-W i_d^2}) (2V_1 i_q + V i_q e^{-V i_q} + \kappa_q) \end{cases} \quad (8)$$

where $\{\alpha, \gamma, \beta\}$ are non-negative self-saturation coefficients for the d -, and q -axis, and $\{k, W, V, V_1, \kappa_q\}$ are cross-saturation coefficients. The subscripts d and q represent d -axis and q -axis.

2.2. Objective Function

Parameter identification of the model can be transformed into an optimization problem, which aims to minimize the difference between the reference data and simulated data obtained by estimated parameters. Noteworthy, the cross-saturation coefficient must be consistent due to the reciprocity condition. The error functions for the k th flux linkages respect to d - and q -axis, respectively, can be formulated as

$$\begin{cases} f_k^d(\psi_r^d, i_r^d, i_r^q, \mathbf{x}_d) = \alpha_d \left(2 - e^{-\gamma_d i_r^d} - e^{-\gamma_{d1} (i_r^d)^2} \right) + \beta_d i_r^d \\ \quad - k \left(2W i_r^d e^{-W (i_r^d)^2} \right) \left(V_1 (i_r^q)^2 - i_r^q e^{-V (i_r^q)^2} + \kappa_q i_r^q - e^{-V i_r^q} \right) - \psi_r^d \\ \mathbf{x}_d = \{\alpha_d, \gamma_d, \beta_d, k, W, V, V_1, \kappa_d\} \end{cases} \quad (9)$$

$$\begin{cases} f_k^q(\psi_r^q, i_r^d, i_r^q, \mathbf{x}_q) = \alpha_q \left(2 - e^{-\gamma_q i_r^q} - e^{-\gamma_{q1} (i_r^q)^2} \right) + \beta_q i_r^q \\ \quad - k \left(1 - e^{-W (i_r^d)^2} \right) \left(2V i_r^q + V i_r^q e^{-V i_r^q} + \kappa_q \right) - \psi_r^q \\ \mathbf{x}_q = \{\alpha_q, \gamma_q, \beta_q, k, W, V, V_1, \kappa_q\} \end{cases} \quad (10)$$

Hence, the objective functions defined by root mean square (RMSE) error can be obtained as follows:

$$\text{RMSE}_d(\mathbf{x}_d) = \sqrt{\frac{1}{N} \sum_{k=1}^N f_k^d(\psi_r^d, i_r^d, i_r^q, \mathbf{x}_d)^2} \quad (11)$$

$$\text{RMSE}_q(\mathbf{x}_q) = \sqrt{\frac{1}{N} \sum_{k=1}^N f_k^q(\psi_r^q, i_r^d, i_r^q, \mathbf{x}_q)^2} \quad (12)$$

where $\mathbf{x}$ is the decision variable, N is the sample number, ψ_r, i_r are stator flux linkages and currents in the collected FEA dataset. $\mathbf{x}_d, \mathbf{x}_q$ are the obtained parameter vectors, where $\mathbf{x}_d = [\mathbf{x}_{d1}, \mathbf{x}_c]$, and $\mathbf{x}_q = [\mathbf{x}_{q1}, \mathbf{x}_c]$. $\mathbf{x}_{d1}$ and $\mathbf{x}_{q1}$ are the unique parameters involved in $\mathbf{x}_d$ and $\mathbf{x}_q$, respectively, and $\mathbf{x}_c = [k, W, V, \kappa_d, \kappa_q]$ is the common parameter subvector. Here, the subscripts d and q represent d - and q -axis, respectively. N is the number of reference data.

3. SCP-Induced Parameter Identification Algorithms

In this section, detail of proposed algorithms will be given. First, a new performance indicator named SCP is proposed, which is unified quantification of the fitness and diversity contributions of the candidate solutions in current population. We describe three improved Rao algorithms [25] induced by SCP.

3.1. Smart Collaborative Performance

In general, the performance of the candidate solution is affected from two dimensions, fitness associated with exploitation and diversity related to exploration. In evolution of population, the balance between exploitation and exploration is the key to optimal algorithm design. For the candidate, fitness and diversity information is generated under the influence of evolutionary mechanism. In other words, these two kinds of information can reflect the evolutionary preferences of the current population. Therefore, if a reasonable comprehensive performance quantification standard can be determined, the evolution direction can be influenced through the feedback of quantified indicator. In [21] and [26], fitness and diversity can be calculated by the objective function and the distance between the individual and the surrounding individual, respectively. However, it is impossible to evaluate the overall performance of the corresponding solution through a simple comparison, due to the different properties of the two functions. In addition, even if a comprehensive evaluation method based on these two functions can be found, to quantify the contribution of candidate solutions to the population is still an issue. Inspired by the

collaborative modeling method in [27], an SCP evaluation indicator for the k^{th} candidate solution $\mathbf{x}_k$ is defined as

$$P_s(\mathbf{x}_k, NP) = P_d(\mathbf{x}_k, NP) \cdot c_{k,s} + P_f(\mathbf{x}_k, NP) \cdot (1 - c_{k,s}) \quad (13)$$

where, $P_s(\mathbf{x}_k, NP)$, $P_f(\mathbf{x}_k, NP)$, $P_d(\mathbf{x}_k, NP)$, represent the SCP, fitness performance (FP) and diversity performance (DP) for the candidate expressed in probability, respectively. $c_{k,s}$ is a random number in the range $[0, 1]$, denoting smart collaborative coefficient (SCC). The overall performance of the candidate in the current population is evaluated by SCP. It can be clearly observed that the candidate with better SCP has a larger probability. FP, DP represent the fitness and diversity contributions of the candidate in the current population, respectively. The evolutionary process preference for exploration and exploitation maintenance can be quantified by SCC, which also decided the proportion of FP and DP in SCP evaluation. With the increase of SCC, the preference for diversity increases in SCP. On the contrary, the preference for fitness increases in SCP. Particularly, when $c_{k,s} = 0$ or $c_{k,s} = 1$, SCP degrades into FP or DP. In this situation, SCP only evaluates the performance of the candidate from the perspective of fitness or diversity contribution. If SCP is used as feedback, the performance of the candidate is only affected by exploitation or exploration preference of evolution. As the basis of SCP construction, the quantification process of FP and DP is as follows.

The objective function ($f(\mathbf{x}_k)$) is selected as the fitness function ($f_{\text{fitness}}(\mathbf{x}_k)$) for each candidate solution.

$$f_{\text{fitness}}(\mathbf{x}_k) = f(\mathbf{x}_k) \quad (14)$$

Then the candidates are sorted in ascending order of fitness in the population, and probability based on ranking is used to reflect the fitness performance. The ranking and FP of $\mathbf{x}_k$ are presented in (18) and (19), respectively.

$$R_{\text{fitness}}(\mathbf{x}_k, NP) = NP + 1 - i_k, i_k = 1, 2, \dots, NP \quad (15)$$

$$P_{k,f}(\mathbf{x}_k, NP) = \left(\frac{R_{\text{fitness}}(\mathbf{x}_k, NP)}{NP} \right)^2 \quad (16)$$

where i_k represents the fitness ranking of $\mathbf{x}_k$ in the population.

The diversity function based on Euclidean distance between candidates is defined as

$$f_{\text{diversity}}(\mathbf{x}_k) = - \sum_{w=1}^{NP} \|\mathbf{x}_k - \mathbf{x}_w\|, w = 1, 2, \dots, NP \quad (17)$$

Similar to (15) and (16), the diversity ranking and DP are presented as follows.

$$R_{\text{diversity}}(\mathbf{x}_k, NP) = NP + 1 - j_k, j_k = 1, 2, \dots, NP \quad (18)$$

$$P_{k,d}(\mathbf{x}_k, NP) = \left(\frac{R_{\text{diversity}}(\mathbf{x}_k, NP)}{NP} \right)^2 \quad (19)$$

where j_k represents the fitness ranking of $\mathbf{x}_k$ in current population. In (16) and (19), better performance corresponds to larger probability. The overall contribution of the candidates to the population is quantified by the random combination of the probabilities through SCP. As a result, SCP has advantage of theory-driven.

3.2. SCP-Induced Optimal Search Path Update Mechanism

Based on the above calculated probability, evolutionary preferences can be quantified by SCP, and the evolution process is also affected by SCP. As feedback information, SCP only affects the optimal solution search direction update mechanisms. Hence, SCP is used

to modify the three Rao algorithms [25]. Thus, the new update mechanism based on SCP can be defined as

$$x'_{k,v} = x_{k,v} + r_{1,k,v} (x^s_{best,v} - x^s_{worst,v}) \quad (20)$$

$$x'_{k,v} = x_{k,v} + r_{1,k,v} (x^s_{best,v} - x^s_{worst,v}) + r_{2,k,v} \Delta x^s_{kl,v} \quad (21)$$

$$x'_{k,v} = x_{k,v} + r_{1,k,v} (x^s_{best,v} - |x^s_{worst,v}|) + r_{2,k,v} \Delta x^s_{kl,v} \quad (22)$$

where the superscript “s” represents the candidate for quantitative selection based on SCP. Subscripts “best” and “worst” represent the candidates with the largest and smallest SCP in the current population. In the proposed update mechanisms, no additional parameters are introduced. Evolutionary direction is still close to the best candidate solution and away from the worst candidate solution. In addition, Δx_{kl} represents the difference between randomly selected candidates, always greater than zero.

With the introduction of SCP, the evaluation of the merits of the candidates is not only related to their own fitness and diversity, but also related to the current population. In other words, if the FP and DP of the candidates have not changed in the previous search direction update, they will be recalculated before the search direction update. Then, the candidate with a larger P_s is selected in the comparison. The process of calculating Δx^s_{kl} through SCP comparison is proposed in Algorithm 1. If x^s_{best} , x^s_{worst} and Δx^s_{kl} are used as evolutionary guidance, evolutionary preferences will be affected by the inherent randomness of their SCP. This random effect is automatic and does not require additional control parameters, hence the update direction of the candidate solution is expected to be guided into new search regions.

Algorithm 1. SP-based contribution measurement.

```

1: if  $P_s(x_k, NP) \neq P_s(x_l, NP)$  then
2:   if  $P_s(x_k, NP) > P_s(x_l, NP)$  then
3:      $\Delta x^s_{kl} = |x_k| - |x_l|$ 
4:     return  $\Delta x^s_{kl}$ 
5:   else
6:      $\Delta x^s_{kl} = |x_l| - |x_k|$ 
7:     return  $\Delta x^s_{kl}$ 
8:   else
9:     if  $P_d(x_k, NP) \neq P_d(x_l, NP)$  then
10:      if  $P_d(x_k, NP) > P_d(x_l, NP)$  then
11:         $\Delta x^s_{kl} = |x_k| - |x_l|$ 
12:        return  $\Delta x^s_{kl}$ 
13:      else
14:         $\Delta x^s_{kl} = |x_l| - |x_k|$ 
15:        return  $\Delta x^s_{kl}$ 
16:      end if
17:    else
18:      if  $P_f(x_k, NP) \neq P_f(x_l, NP)$  then
19:        if  $P_f(x_k, NP) > P_f(x_l, NP)$  then
20:           $\Delta x^s_{kl} = |x_k| - |x_l|$ 
21:          return  $\Delta x^s_{kl}$ 
22:        else
23:           $\Delta x^s_{kl} = |x_l| - |x_k|$ 
24:          return  $\Delta x^s_{kl}$ 
25:        end while
26:      else
27:         $\Delta x^s_{kl} = 0$ 
28:        return
29:      end if
30:    end if
31:  end if

```

3.3. SCP-Rs Framework

For the proposed update mechanisms, due to the automatic intervention of evolutionary direction, the stagnation and premature convergence in the evolution process are avoided. To inherit the strong exploitation ability of the original Rao algorithms, a new framework combining the original update mechanisms and the modified update mechanism is proposed, named SCP-R algorithms. Corresponding to different update mechanisms, these algorithms are named as SCP-R1, SCP-R2 and SCP-R3. Algorithm 2 gives the pseudo code of SCP-R algorithms, and Figure 1 provides the flow chart.

Figure 1. The flow diagram of SP-R.

Algorithm 2. Pseudo code of SCP-R algorithm.

```

1: Initialize population size ( $NP$ ) and maximum number of function evaluations ( $Max\_FES$ );
2: Generate the initial population randomly, evaluate the objective function value of each individual;
3:  $FES = NP$ ;
4: While  $FES < Max\_FES$  do
5:   Compute fitness performance  $P_f$  of each individual  $x_k$ ;
6:   Compute diversity performance  $P_d$  of each individual  $x_k$ ;
7:   Identify fitness best individual  $x_{f\_best}$  and fitness worst individual  $x_{f\_worst}$ ;
8:   For  $k = 1$  to  $NP$  do
9:     if  $k = f_{best}$  then
10:      Select the other individual  $x_l$  from population randomly ( $l \neq k$ );
11:       $P_f$  comparison of  $x_k$  and  $x_l$ ;
12:      Modify the best solution by using original Rao;
13:     else
14:      Randomly select  $c_{k,s} \in \{0,1\}$ ;
15:      Compute  $P_s$  each individual according to (13);
16:      Identify  $P_s$  best individual and  $P_s$  worst individual;
17:      Select the other individual  $x_l$  from population randomly ( $l \neq k$ );
18:       $P_s$  comparison of  $x_k$  and  $x_l$  by using Algorithm 1;
19:      Modify candidate solution by using (20), (21) or (22);
20:     end if
21:     Compute  $P_f$  of the updated individual;
22:      $FES = FES + 1$ ;
23:     Accept the new solution if it is better than the old one;
24:   end for
25: End while

```

SCP-R algorithms have simple structure and are free from algorithm-specific parameters. During the operation of the algorithm, evolutionary preferences may be dynamically balanced, which is equivalent to the convergence strength being automatically managed. Different strategies are employed to modify the FP optimal candidate and other candidates, which is equivalent to classifying the candidates in the current population. Considering that there are other optimal candidates nearby, a relatively conservative modification strategy is adopted to search the surrounding region. On the contrary, for the other candidates, more radical modification strategies are employed to improve population diversity as well as exploration capabilities.

4. Experimental Results

4.1. Experiment Setup

To evaluate the performance of the proposed SCP-R algorithms, comparative experiments are carried out with already well established algorithms. These algorithms are the original Rao algorithms [25], Grey Wolf Optimization (GWO) algorithm [28] and Ant Lion Optimization (ALO) algorithm [29]. The proposed model is a dual function model with common parameters. A two-stage experiment is implemented to identify parameters. For the sake of fairness, the parameter configuration of the experiment is the same for different algorithms. The same maximum number of function evaluations (Max_FES) for all algorithms is set to 30,000 in each run. To reduce the statistical error as far as possible, each algorithm is independently conducted 30 times on the problem. The parameter range is fixed in (0.2) to ensure the same search space. In addition, the population size in different stages is set to $NP = 20$ and $NP = 30$. The reference data used in the parameter identification process is the FEA result of a 2 kw-SynRM prototype. The design parameters of the prototype are summarized in Table 1.

Table 1. Parameters of SynRM prototype.

Parameters	Values	Parameters	Values
Rated Power (kw)	2	Rated Voltage (V)	42
Rated Speed (r·min ⁻¹)	1500	Rated Current (A)	35
Rated Torque (N·m)	12.7	Number of pole pairs	2
Stator Resistance (Ω)	0.3	Moment of inertia (kg·m ⁻²)	0.025

4.2. Main Results

4.2.1. Results on q -Axis Flux Linkage Model

For the q -axis flux linkage model, the different algorithms are independently implemented 30 times to obtain its self-saturation and cross-saturation parameters. Because the exact values of the model parameters are unknown, RMSE $_q$ is taken as the standard of accuracy evaluation. The comparison of the best parameter values and the best RMSE among the 30 identification results of different algorithms is given in Table 2. Among them, the best RMSE $_q$ are marked in bold. It can be seen from Table 2 that SCP-R algorithms achieve better accuracy than other algorithms, and SCP-R1, SCP-R2 and SCP-R3 algorithm provide the best RMSE $_q$ value (2.2243×10^{-4}). Although the RMSE $_q$ of some algorithms is very close to the results obtained by SCP-R algorithms, a smaller RMSE $_q$ is conducive to determine the true parameters of the model.

Table 2. Comparison among different algorithms on q -axis flux linkage model.

Algorithm	Self-Saturation Coefficients				Cross-Saturation Coefficients					RMSE q
	α_q	β_q	γ_q	γ_{q1}	k	W	V	V_1	κ_q	
SCP-R1	0.0072	1.0324	0.1233	7.8240×10^{-4}	0.0216	0.0020	0.0114	0.2633	0.0758	2.2243×10^{-4}
SCP-R2	0.0072	1.0324	0.1233	7.8240×10^{-4}	0.0216	0.0020	0.0114	0.2633	0.0758	2.2243×10^{-4}
SCP-R3	0.0072	1.0324	0.1233	7.8240×10^{-4}	0.0216	0.0020	0.0114	0.2633	0.0758	2.2243×10^{-4}
Rao-1	0.0071	1.0297	0.1238	7.8393×10^{-4}	0.0215	0.0020	0.0115	0.2633	0.0751	2.2443×10^{-4}
Rao-2	0.0079	0.2632	0.6453	7.0144×10^{-4}	0.0215	0.0020	0.0115	0.2633	0.0751	5.8524×10^{-4}
Rao-3	0.0072	1.6691	0.0597	7.6864×10^{-4}	0.0042	0.0016	0	2.0000	2.0000	7.0207×10^{-4}
GWO	0.0071	1.0610	0.1251	7.8437×10^{-4}	0.0198	0.0021	0.0112	0.2685	0.1083	2.3034×10^{-4}
ALO	0.0140	0.0014	0.3133	7.7888×10^{-4}	0.0197	0.0033	0.0109	0.2151	0.0041	6.9356×10^{-4}

4.2.2. Results on d -Axis Flux Linkage Model

When d -axis model parameters are extracted, the best cross-saturation coefficients are applied to the identification of the parameters of the model. Thus, there are only four parameters to be identified. The best estimated parameters and the best RMSE $_d$ of different algorithms are listed in Table 3. The SCP-R algorithms also provide the best RMSE $_d$ value (4.0815×10^{-4}) among all compared algorithms.

To illustrate the excellent results of the identification results, the absolute error rate (AER) between the estimated value and the FEA value is shown in Figure 2. Obviously, the estimated value of flux linkages in the entire current range is highly consistent with its FEA value. In terms of AER, except for the very few points on the edge of the model where the AER is close to 4%, the AER at other contrast points does not exceed 1%.

Table 3. Comparison among different algorithms on d -axis flux linkage model.

Algorithm	Self-Saturation Coefficients				RMSE d
	α_d	β_d	γ_d	γ_{d1}	
SCP-R1	0.0615	0.1498	0.0100	0.0013	4.0815×10^{-4}
SCP-R2	0.0615	0.1498	0.0100	0.0013	4.0815×10^{-4}
SCP-R3	0.0615	0.1498	0.0100	0.0013	4.0815×10^{-4}
Rao-1	0.0615	0.1500	0.00995	0.0013	4.0866×10^{-4}
Rao-2	0.0616	0.1497	0.0100	0.0013	4.0821×10^{-4}
Rao-3	0.0615	0.1498	0.0100	0.0013	4.0817×10^{-4}
GWO	0.0615	0.1498	0.0100	0.0013	4.0818×10^{-4}
ALO	0.0623	0.1484	0.0098	0.0013	4.2398×10^{-4}

Figure 2. (a) Mismatch of d -axis flux linkage, estimated value vs finite element analysis (FEA) value; (b) Mismatch of q -axis flux linkage, estimated value vs FEA value.

4.3. Results Discussion

4.3.1. Robustness of SCP-R Algorithms

To further evaluate the robustness of the proposed algorithms. Analysis based on RMSE statistics is implemented. The statistical results of the parameter identification of the dual function model by the different algorithms that run 30 times independently are given in Table 4. The results of the algorithms involved are calculated according to the best RMSE (B), worst RMSE (W), average RMSE (M), and standard deviation RMSE (SD). For each model, the best result in the corresponding algorithm is indicated in bold.

In terms of average accuracy and robustness, it can be observed from Table 4 that the overall performance of the proposed SCP-R algorithms is better than other algorithms. For the q -axis flux linkage model, the best M (2.5142×10^{-4}) and best SD (8.2501×10^{-4}) are provided by the proposed SCP-R1 algorithm. Specifically, the SCP-R3 algorithm with excellent SD (3.7124×10^{-19}) is far more robust than other algorithms. The distribution characteristics of the results of 30 independent runs of the different algorithms are presented in Figure 3 using box plots. The distribution range of the parameter identification results also demonstrates the superiority of the proposed SCP-R algorithms. Similarly, the results distribution corresponding to the SCP-R3 algorithm is the most concentrated. Obviously, the proposed SCP-R has better performance on searching accuracy and reliability for solving the parameters identification problems of the SynRM magnetic model, and its performance is competitive in contrast with all compared algorithms.

Table 4. Statistical results of root mean square (RMSE) of different algorithms for Synchronous Reluctance Motor (SynRM) magnetic model (30,000 function evaluations).

Model	Population Size	Algorithm	RMSE			
			B	M	W	SD
<i>q</i> -axis flux linkage model	<i>NP</i> = 20	SCP-R1	2.2243×10^{-4}	2.5142×10^{-4}	5.6827×10^{-4}	8.2501×10^{-4}
		SCP-R2	2.2243×10^{-4}	3.2947×10^{-4}	0.0022	3.7615×10^{-4}
		SCP-R3	2.2243×10^{-4}	2.7336×10^{-4}	0.0011	1.7291×10^{-4}
		Rao-1	2.2243×10^{-4}	0.0017	0.0238	0.0043
		Rao-2	5.8524×10^{-4}	0.0053	0.0238	0.0074
		Rao-3	7.0207×10^{-4}	0.0073	0.0238	0.0093
		GWO	2.3034×10^{-4}	0.0018	0.0050	0.0012
		ALO	6.9356×10^{-4}	0.0022	0.0049	0.0010
<i>d</i> -axis flux linkage model	<i>NP</i> = 30	SCP-R1	4.0815×10^{-4}	4.0815×10^{-4}	4.0815×10^{-4}	6.4849×10^{-12}
		SCP-R2	4.0815×10^{-4}	4.3181×10^{-4}	8.7509×10^{-4}	6.2187×10^{-10}
		SCP-R3	4.0815×10^{-4}	4.0815×10^{-4}	4.0815×10^{-4}	3.7124×10^{-19}
		Rao-1	4.0866×10^{-4}	0.0010	0.0034	0.0014
		Rao-2	4.0821×10^{-4}	0.0028	0.0232	0.0041
		Rao-3	4.0817×10^{-4}	0.0023	0.0034	0.0012
		GWO	4.0818×10^{-4}	0.0029	0.0232	0.0056
		ALO	4.2398×10^{-4}	0.0032	0.0180	0.0017

Figure 3. Best RMSE boxplot over 30 runs of different algorithms for SynRM magnetic model (a) Statistical results of RMSE_d (b) Statistical results of RMSE_q.

4.3.2. Discussion on Optimal Solution Search Path Update Mechanism of SCP-R

In order to demonstrate the effectiveness of the proposed SCP-R framework, comparative experiments for two variants of SCP-R algorithms are implemented in this subsection. The algorithms are obtained by modifying the optimal search path mechanism of the SCP-R algorithms. For the mechanism of the SCP-R2 algorithm, the interaction between the current candidate and the randomly selected candidate does not depend on SCP (denoted as M-SCP-R2). Similarly, the modification to the SCP-R3 algorithm is denoted as M-SCP-R3. Note that the SCP independent SCP-R1 algorithm will degenerate to the original Rao-1. The comparison of these two algorithms has been implemented in the previous subsections. The statistical results of the two variants are presented in Table 5. For each model, the values shown in bold in Table 5 indicate the comparatively better results of the respective algorithms. In terms of average accuracy and robustness, it can be clearly observed from Table 5 that the overall performance of the proposed SCP-R algorithms is better than the other variants. The obvious difference between the results of the SCP-R algorithm and the corresponding variants indicates that the SCP-R framework is beneficial to optimize the original optimal solution update path mechanism. In summary, the excellent performance

of the SCP-R algorithms verifies that the SCP-R-framework-based optimal solution search path update has achieved appropriate balance between exploration and exploitation.

Table 5. Statistical results of RMSE of different SCP-R algorithms for SynRM magnetic model (30,000 function evaluations).

Model	Population Size	Algorithm	RMSE			
			B	M	W	SD
<i>q</i> -axis flux linkage model	<i>NP</i> = 20	SCP-R2	2.2243×10^{-4}	3.2947×10^{-4}	0.0022	3.7615×10^{-4}
		M-SCP-R2	2.2243×10^{-4}	0.0097	0.2617	0.0476
		SCP-R3	2.2243×10^{-4}	2.7336×10^{-4}	0.0011	1.7291×10^{-4}
		M-SCP-R3	2.2243×10^{-4}	0.0034	0.0722	0.0131
<i>d</i> -axis flux linkage model	<i>NP</i> = 30	SCP-R2	4.0815×10^{-4}	4.3181×10^{-4}	8.7509×10^{-4}	6.2187×10^{-10}
		M-SCP-R2	0.0111	0.0112	0.0113	8.0570×10^{-5}
		SCP-R3	4.0815×10^{-4}	4.0815×10^{-4}	4.0815×10^{-4}	3.7124×10^{-19}
		M-SCP-R3	0.0111	0.0112	0.0113	6.6143×10^{-5}

5. Conclusions

In this paper, SCP-R algorithms for the SynRM magnetic model parameter identification are proposed, which focuses on establishing a quantitative method for overall performance of candidates in current population. By implementing the SCP-based quantification framework, fitness and diversity information of candidates are uniformly employed for evolutionary guidance. A good balance between exploration and exploitation can be achieved. Experiment results further demonstrated that SCP-R algorithms perform better in terms of accuracy and reliability when compared with other well-established algorithms. Therefore, combining the SCP-based contribution measurement together with the proposed SCP-R framework may further improve the SynRM magnetic model parameter identification performance.

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