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Grasshopper Optimization Algorithms for Parameter Extraction of Solid Oxide Fuel Cells

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The accuracy and reliability of solid oxide fuel cell (SOFC) modeling mainly depend on the precise extraction and optimization of some unknown parameters. However, the SOFC model is a multi-peak, nonlinear, multivariable, and strongly combined system. In the previous decisive optimization methods, it is difficult to achieve satisfactory parameter extraction. Therefore, this article proposes a SOFC parameter extraction method based on the superhuman algorithm and extracts several important parameters of the SOFC model. In addition, the electrochemical model (ECM), which is a typical SOFC model, has also been studied to verify the extraction performance of the glass jump optimization algorithm (GOA) under various working conditions. Simulation results based on MATLAB show that GOA can greatly improve the accuracy, speed, and stability of inferring these unknown parameters through a comprehensive comparison with the particle swarm optimization (PSO) algorithm.

Keywords: parameter extraction, optimization methods, meta-heuristic algorithm, solid oxide fuel cell, electrochemical mode

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INTRODUCTION

Due to insufficient expectations for the adverse effects of highly developed industries, anti-prevention has caused a series of worldwide crises, such as insufficient resources, environmental pollution (Yang et al., 2020; Yang et al., 2021a), and the destruction of the ecosystem. According to the increase in energy demand and the construction of an environmental society, it is important to study alternative energy forms that are different from the previous energy forms. Therefore, the effective use of clean and low-carbon energy such as solar and wind energy has attracted more and more attention (Yang et al., 2021b). Fuel cell (FC) is the fourth-generation technology following water power, fire power, and atomic power. It is being formalized in order to convert chemical energy into electrical energy efficiently and without pollution.

In this context, the market of fuel cells is expanding, and the application of fuel cells in various practical engineering fields is growing. In particular, as a promising member of the FC system, solid oxide fuel cells (SOFCs) have been widely used in military and ship (Yang et al., 2021c), motor vehicle equipment, and other mobile equipment fields (Wei and Stanford, 2019; Buffo et al., 2020; Malfuzi et al., 2020). In addition, as promising environment-friendly power conversion equipment, the performance degradation of SOFC will reduce the life and performance of the battery. Therefore, to establish a correct and reliable SOFC model, technical research related to SOFC modeling analysis and parameter estimation is being carried out. Generally speaking, SOFC models can be divided into three types: electrochemical model (ECM), steady-state model (SSM), and dynamic model. Among them, the feasibility of the electrochemical model has been verified in many studies. Therefore, this article uses an electrochemical model to study the extraction of SOFC parameters (Li et al., 2012). Based on this, some unknown parameters such as air pressure, fuel flow, and battery temperature are very important to ensure the accuracy of modeling (Messaoud et al., 2020).

In addition, the parameter extraction of SOFC is a multivariable and multi-peak nonlinear function optimization problem. In addition, the estimation method based on the data provided by the manufacturer is difficult to meet the engineering requirements, and the impact of each parameter on the model performance is different. Extracting them with traditional methods is a challenging task (Fathy et al., 2020). Therefore, a large number of parameter extraction and optimization methods have been developed and adopted in various models (Zhao et al., 2016). Specifically, the parameter extraction strategy based on the meta-heuristic algorithm has attracted extensive attention because of its superior characteristics. The meta-heuristic algorithm is independent of the system model and has fast convergence speed. Literature research shows various meta-heuristic algorithms, such as chaotic binary shark odor optimizer (CBSSO) algorithm (Isa et al., 2019), bone particle swarm optimization (BPSO) algorithm (Ijaodola et al., 2019), adaptive differential evolution (ADE) algorithm, lunar flame optimization algorithm (MFO) (Wang et al., 2020), hybrid artificial bee colony algorithm (ABC), improved beetle antenna search (IBAS), vortex search algorithm (VSA) (Damo et al., 2019), multivariate optimization (MVO) (Wu et al., 2019a), flower pollination algorithm (FPA), ant optimization algorithm (ALO) (Nassef et al., 2019), gray wolf optimization (GWO), neural network optimization (NNO), and differential evolution (DE) (Masadeh et al., 2017). The overall algorithm can sample all areas of the search space at the same time, so the overall solution can be found simply by using the superhuman algorithm. So far, MHAS has made progress in improving search capabilities and efficiency (Gong et al., 2018). People in the past have conducted a lot of research to solve this problem, but it is worth noting that the accuracy, stability, and robustness of the system still have several shortcomings, which need to be improved (Yang et al., 2016).

Therefore, this article proposes a grasshopper optimization algorithm (GOA), which is a new intelligent optimization algorithm proposed by S Saremi, S Mirjalili and A Lewiset. It is widely used in parameter optimization and prediction of various models due to its good development ability [20]. In addition, by imitating the variation and crossover process of grasshoppers in nature, the diversity of the population is improved and local optimization is avoided (JemeÏJemei et al., 2008; Wu et al., 2019b). The linear optimization strategy is introduced to speed up the optimization speed and update the individual location with the current optimal location as the target. In addition, the main contributions/innovations of this article can be concluded as follows:

- The electrochemical model of SOFC reflecting the *V-I* data relationship is carefully established, and GOA is proposed to extract several unknown parameters of the SOFC model;
- GOA is used to measure the V-I data of the 5 kW SOFC stack, and comprehensively evaluate and analyze the actual performance of GOA through comprehensive comparison with ALO under various working conditions.
- Finally, the simulation results confirm that GOA can effectively optimize the parameters of the SOFC model through high precision, strong stability, and high convergence speed.

The remaining articles are composed as follows. In Section *Solid Oxide Fuel Cells Modeling*, the mathematical modeling of SOFC and objective function will be explained. In addition, Section *Solid Oxide Fuel Cells Parameter Extraction Based on Glass Jump Optimization Algorithm* also introduces the method of optimizing the model through GOA. Last, in Section *Design of Solid Oxide Fuel Cells Parameter Extraction Based on Glass Jump Optimization Algorithm*, compare the performance of parameter extraction GOA and ALO. Finally, the conclusion is shown in section *Conclusion and Perspectives*.

SOLID OXIDE FUEL CELLS MODELING

The relative principle of the electrochemical mechanism of SOFC is denoted in this section.

Electrochemical Reaction Mechanism

For the establishment of an accurate SOFC model and the improvement of the service life of the battery, the modeling analysis and parameter estimation of SOFC are studied [21]. Generally speaking, the SOFC model can be divided into ECM and SSM. Among them, the electrochemical model is used to study the extraction of SOFC parameters, as illustrated in **Figure 1**, on the left is the physical picture and on the right is the electrochemical reaction process.

The basic generation mechanism inside SOFC is electrochemical reactions, the anode and cathode reaction mechanisms are as follows:

At the anode side

$$H_2 \rightarrow 2H^+ + 2e^-. \tag{1}$$

At the cathode side

$$\frac{1}{2}O_2 + 2H^+ + 2e^- \rightarrow H_2O. \tag{2}$$

Total chemical reaction

$$H_2 + \frac{1}{2}O_2 \rightarrow H_2O. \tag{3}$$

In the anode, H_2 reacts with the catalyst and decomposes into protons and electrons; O_2 reacts with electrons and protons through catalysis to produce water oxygen in the cathode; and H^+ represents the proton; e^- means the electron [22].

Electrochemical Model

This section establishes a voltage characteristic function of electrochemical by

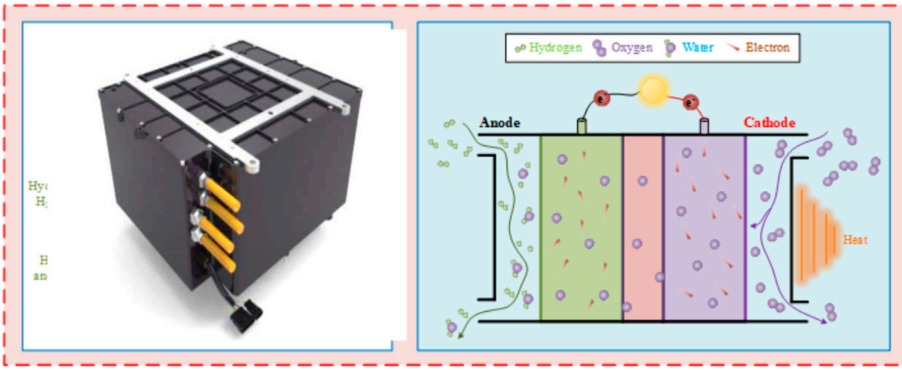

FIGURE 1 | Electrochemical mechanism of SOFC.

$$V_c = N_{cell}\left(E_o - V_{act} - V_{ohm} - V_{con}\right), \tag{4}$$

where E_o is defined as the open circuit voltage, N_{cell} is the total number of cells in a SOFC stack, V_{act} is defined as activation voltage drop, V_{ohm} denotes ohmic voltage drop, and V_{con} represents concentration voltage drop.

In addition, voltage loss V_{act} *via* Butler-Volmer equation activation can be described by

$$V_{act} = A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,a}}\right) + A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,c}}\right), \tag{5}$$

where A means the slope of Tafel line, I_{load} is expressed as load current density, $I_{0,a}$ denotes the current density of the anode, and $I_{0,c}$ is defined as the current density of the cathode [22].

Furthermore, ohmic voltage drop V_{ohm} can be defined by

$$V_{ohm} = I_{load}R_{ohm}, \tag{6}$$

where R_{ohm} denotes the ionic resistance.

Finally, concentration voltage drop V_{con} is expressed as follows:

$$V_{con} = -B\ln\left(1 - \frac{I_{load}}{I_L}\right), \tag{7}$$

where B is expressed as a constant and I_L represents the limiting current density.

Subscribe **Eqs 5–7** into **Eq. 4**, the *V-I* relation of SOFC can be summarized by

$$\begin{aligned} V_c &= N_{cell}\left(E_o - V_{act} - V_{ohm} - V_{con}\right), \\ &= N_{cell}\left(E_o - A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,a}}\right) - A\sinh^{-1}\left(\frac{I_{load}}{2I_{0,c}}\right) + B\ln\left(1 - \frac{I_{load}}{I_L}\right) - I_{load}R_{ohm}\right), \end{aligned} \tag{8}$$

It can be seen that seven parameters (i.e., E_o, A, $I_{0,a}$, $I_{0,c}$, B, I_L, and R_{ohm}) need to be extracted in **Eq. 8**.

Fitness Function

The parameter extraction of SOFC is to search optimal parameters to make the experimental data approach to the simulation data accurately [23]. Furthermore, overall root means square error (RMSE) is employed as the fitness function to appraise the efficacy of various algorithms, which can be described by

$$Fitness(x) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(error_k\right)^2} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(V_{m,k} - V_{c,k}\right)^2}, \tag{9}$$

where x is an available solution. It should be noted that N represents the numbers of *I-V* data; $V_{m,k}$ and $V_{c,k}$ are defined as the kth measured voltage and calculated voltage, respectively.

In addition, x denotes the solution vector that can be expressed by $x = [E_o, A, R, B, I_{0,a}, I_{0,c}, I_L]$.

SOLID OXIDE FUEL CELLS PARAMETER EXTRACTION BASED ON GLASS JUMP OPTIMIZATION ALGORITHM

Principle of Glass Jump Optimization Algorithm

The grasshopper optimization algorithm is a novel meta-algorithm for global optimization where the migration and foraging behavior of the grasshopper swarm is mathematically modeled and mimicked to make exploration and exploitation in solution space.

The mathematical model is presented as follows:

$$X_i = S_i + G_i + A_i, \tag{10}$$

where X_i denotes the position of the ith grasshopper, S_i represents the social influence between grasshoppers, G_i defines the gravity factor on the ith grasshopper, and A_i indicates the influence of wind advection on the position of the grasshoppers.

TABLE 1 | Extraction procedure of GOA for SOFC parameter extraction.

```
Input measured V-I data;
Initialize GOA parameters;
 Set k=0;
WHILE k ≤ k_max
FOR1 i=1:n
Calculate the fitness of the ith individual using Eq. (10);
END FOR1
Carry out the iteration according to the fitness and algorithm rules;
FOR2 i=1:n
Update ith individual using the global optimal solution and the local optimal solution;
END FOR2
Set k=k+1;
END WHILE
Output the optimal parameters of SOFC
```

Among the above additions, S_i has the greatest influence on the position of the grasshopper. S_i can be described as

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s\left(\left|x_j - x_i\right|\right) \frac{x_j - x_i}{\left|x_j - x_i\right|}, \tag{11}$$

where $|x_j - x_i|$ defines the distance between the ith grasshopper and the jth grasshopper, $s(\cdot)$ is a function to define the degree of social influence, which can be expressed as

$$s(r) = fe^{\frac{-r}{l}} - e^{r}, \tag{12}$$

where f is the intensity of attraction and l denotes the attractive length scale.

Furthermore, the rest of additions G_i and A_i can be calculated as

$$G_i = -ge_g \tag{13}$$

$$A_i = -ue_w, \tag{14}$$

where g is the gravitational constant, e_g denotes a unity vector toward the center of earth, u is a constant drift, and e_w is a unity vector describing the direction of wind.

Besides, for the consideration of coordinating global and local optimization, the substitution of S, G, and A into **Eq. 7** can be improved as follows:

$$X_i = \sum_{j=1, j \neq i}^{N} c \frac{ub_d - lb_d}{2} s\left(\left|x_j - x_i\right|\right) \frac{x_j - x_i}{\left|x_j - x_i\right|} + T_d, \tag{15}$$

where c is the decreasing coefficient to shrink the comfort zone, repulsion zone, and attraction zone, as shown in **Eq. 12**, N is the number of the swarm of grasshopper, ub_d and lb_d are the upper and lower bounds of the function $s(\cdot)$ in solution space, T_d is the best position of grasshopper in d-dimensional space so far. In addition, the influence of gravity is not considered, and it is assumed that the wind direction always points to the optimal solution [24].

$$c = c_{\max} - n\frac{c_{\max} - c_{\min}}{L}, \tag{16}$$

where $c_{max} = 1$, $c_{min} = 0.00004$ in this article, n is the current number of iterations, and L is the largest number of iterations.

General Execution Procedure

In this section, the overall framework of the GOA strategy for extracting SOFC parameters is mainly composed of three parts. First, collect V-I data from the electrochemical model of SOFC under various operating conditions. Next, apply GOA to process the data. Finally, GOA obtains the best SOFC parameters through successive iterations. In addition, **Table 1** also shows the basic steps of the GOA strategy. Among them, the difference between various algorithms is mainly reflected in the retrieval mechanism.

As shown in **Figure 2**, GOA mainly contains several critical operators, including global optimization where the migration and foraging behavior of the grasshopper swarm are mathematically modeled and mimicked to make exploration and exploitation in solution space. Therefore, to find optimal parameters for SOFC, GOA can be directly used to handle the training model.

DESIGN OF SOLID OXIDE FUEL CELL PARAMETER EXTRACTION BASED ON GLASS JUMP OPTIMIZATION ALGORITHM

In this section, GOA is used to extract the unknown parameters of the SOFC model. **Table 2** shows the search range of unknown parameters in the model. Meanwhile, all V-I measurement data are collected from the 5 kW SOFC stack of WCS-SFC MATLAB/SIMULINK. The number and effective area of the stacked series of units are 1,000 cm^2 and 96, respectively.

In this section, the experimental conditions are RH_a = 1 atm, RH_c = 1 atm, T_c = 1,173 K and RH_a = 2 atm, RH_c = 2 atm, T_c = 1,273 K. Through comprehensive comparison, carefully evaluate

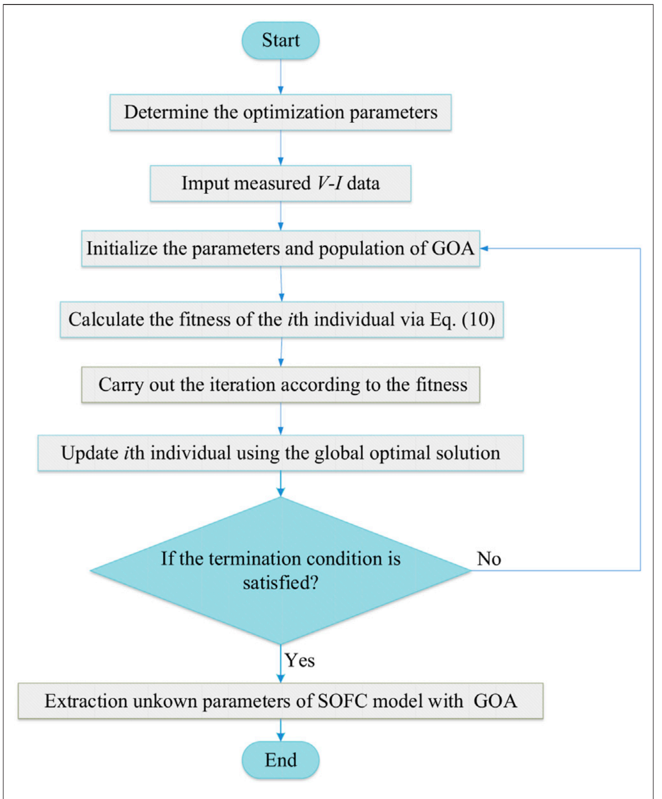

FIGURE 2 | Flowchart of SOFC parameter extraction for GOA.

TABLE 2 | Upper/lower range of seven unknown parameter for SOFC models.

Parameter	E_o (V)	A (V)	R_{ohm} (k$\Omega \cdot$ cm^2)	B (V)	$I_{0,a}$ (mA/cm^2)	$I_{0,c}$ (mA/cm^2)	I_L (mA/cm^2)
Lower bound	0	0	0	0	0	0	0
Upper bound	1.2	1	1	1	30	30	200

TABLE 3 | Statistical results of average RMSE obtained by various algorithms (RH_a = 1 atm, RH_c = 1 atm, T_c = 1,173 K).

Algorithm	ε_1	ε_2	ε_3	ε_4	λ	R_c	b	RMSE
ALO	1.1035	0.0576	0.0000E + 00	0.3875	23.2656	8.3687	200.0000	1.0451E-03
GOA	1.5695	0.1168	0.0000E + 00	0.0925	23.0000	8.9233	200.0000	**4.4297E-04**

Which ελ (λ=1,2,3,4) denotes the semi-empirical coefficients, λ means the water content of proton exchange membrane, λc are the equivalent impedance of a proton membrane and λ is the parametric coefficient.

TABLE 4 | Statistical results of average RMSE obtained by various algorithms (RH_a = 2 atm, RH_c = 2 atm, T_c = 1,273 K).

Algorithm	ε_1	ε_2	ε_3	ε_4	λ	R_c	b	RMSE
ALO	1.1678	0.0906	0.0000E + 00	0.1824	27.4584	11.6574	163.6798	1.1588E-02
GOA	1.1504	0.0832	0.0000E + 00	0.1725	30.0000	10.0929	168.3301	**3.4563E-03**

Which can be find that GOA can get more accurate results.

the parameter extraction performance of ALO and GOA.The experimental conditions are shown in **Table 3** and **Table 4**. Tc represents the operating temperature of the battery, RH_a represents the relative humidity of the anode vapor, and RH_c represents the relative humidity of the cathode vapor.

In addition, in order to obtain a fair and convincing comparison, the two algorithms performed 12 independent runs and obtained statistical results. At the same time, the maximum number of iterations and overall size of all MhA are designed to be 50 and 200, respectively. On the other hand, Matlab 2019a used a personal computer equipped with IntelR CoreTMi7 CPU, 2.0 GHz, and 32 GBAM to conduct all the situation studies.

Case 1 (RH_a = 1 atm, RH_c = 1 atm, T_c = 1,173 K)

When the experimental conditions are RH_a = 1 atm, RH_c = 1 atm, and T_c = 1,173 K, the statistical results of the seven parameters of the SOFC and RMSE electrochemical models obtained by the GOA and ALO algorithms are shown in **Table 3**, which εi (i=1,2,3,4) denotes the semi-empirical coefficients, λ means the water content of proton exchange membrane, Rc are the equivalent impedance of a proton membrane and b is the parametric coefficient; Obviously, the result obtained by RMMSEGOA is much smaller than that of ALO. The RME obtained by ALO is 60.32% smaller than that of GOA. This proves that GOA can greatly enhance the accuracy of SOFC model parameter extraction.

Figure 3A shows the convergence of ALO and GOA. This shows that GOA can achieve lower errors. In particular, it is difficult for ALO to converge, and it is difficult to obtain the best solution with high quality. Therefore, it can be seen that GOA has gradually discovered high-quality solutions with high convergence stability and high search efficiency.

Figure 3B also shows the RMMSE box whiskers obtained by ALO and GOA. This reflects the RMSE distribution achieved by ALO and GOA in 12 runs. Obviously, the distribution range and upper and lower limits of GOA are smaller than ALO. In addition, it can effectively reduce the deviation value of RMMSE obtained by GOA. Therefore, it can also effectively verify that GOA can more accurately extract the unknown parameters of the SOFC model.

Besides, the average RMSE obtained by ALO and GOA are shown in **Figure 3C**, which shows that GAO can acquire a smaller average RMSE. Besides, RMSE obtained by GOA is 54.68% smaller than that of ALO, which verifies that GOA can effectively enhance the accuracy of parameter extraction. There is no doubt that GOA can effectively find more appreciate unknown parameters.

Last, **Figure 3D** describes *V-I* curves via ALO and GOA under RH_a = 1 atm, RH_c = 1 atm, T_c = 1,173 K experimental conditions. It can easily see that data *via* GOA are highly matched up with measure data; the result effectively reflects that GOA has superior performance for SOFC parameter extraction.

Case Two (RH_a = 2 atm, RH_c = 2 atm, T_c = 1,273 K)

Table 4 shows the model parameters and RME of ALO and GOA under the experimental conditions of RH_a = 2 atm, RH_c = 2 atm, T_c = 1,273 K, indicating that GOA can effectively improve the calculation accuracy. For example, the RME obtained by GOA is 69.23% lower than that of ALO. Therefore, GOA has a stable global search function. While considering reliability and speed accuracy, ideal results can be obtained.

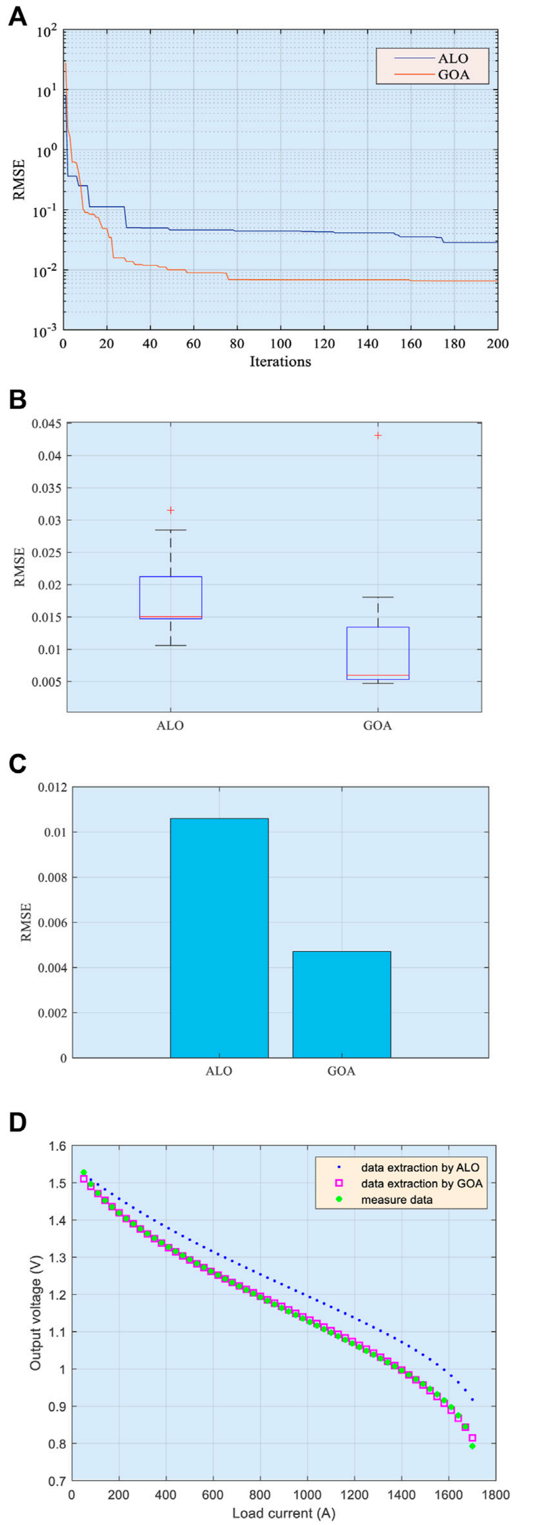

FIGURE 3 | (A) Convergence curves of ALO and GOA; **(B)** Boxplot of RMSE obtained by ALO and GOA; **(C)** average RMSE of ALO and GOA; **(D)** comparison between ALO and GOA.

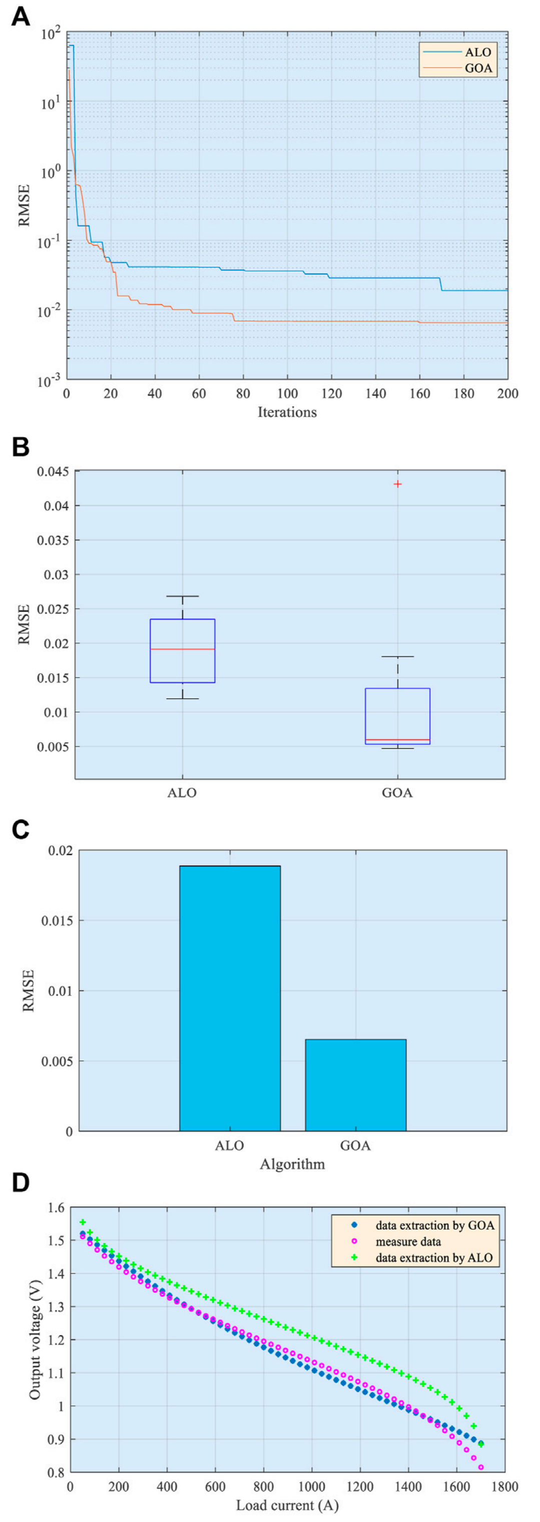

FIGURE 4 | (A) Convergence curves of ALO and GOA; **(B)** Boxplot of RMSE obtained by ALO and GOA; **(C)** average RMSE of ALO and GOA; **(D)** comparison between ALO and GOA.

Figure 4A shows the convergence of ALO and GOA, indicating that GOA can obtain a lower RMMSE. Furthermore, GOA can obtain a lower RMSE than ALO. At the same time, compared with ALO, GOA requires less than 20 iterations to converge to a lower RMSE. Which can be find that GOA can get more accurate results.

Moreover, the boxplots of RMSE obtained by ALO and GOA under the second experiment condition are shown in **Figure 4B**, which indicate the distribution of the results obtained by ALO and GOA in 12 runs. In addition, it can be seen that the upper/lower bound sand distribution range of GOA is smaller than that of ALO. It can effectively verify that the GOA can simultaneously enhance convergence stability and searching ability.

Besides, **Figure 4C** shows the average RMSE obtained by ALO and GOA; it shows that the two algorithms can find global optimum more easily. On this basis, GOA can more accurately and stably determine the best values of these unknown parameters. For example, the average RMSE obtained by GOA is 69.23% lower than ALO under the second experiment condition.

Finally, **Figure 4D** describes the *V-I* curves based on measurement data and extraction data *via* GOA under RH_a = 2 atm, RH_c = 2 atm, T_c = 1,173 K experimental condition. Therefore, the results show that the data extracted by GOA are highly matched with the measured data, which effectively reflects the superiority of GOA in SOFC parameter extraction.

CONCLUSION AND PERSPECTIVES

In order to improve the accurate and efficient parameter extraction of the SOFC electrochemical model, a parameter extraction strategy of the SOFC model based on GOA is proposed. On this basis, the following three main contributions/novelties can be drawn:

- GOA is applied to enhance parameter extraction accuracy of SOFC electrochemical model;
- Case studies demonstrate that GOA can considerably acquire high accuracy, great robustness, and fast convergence of SOFC parameter extraction compared with ALO. In particular, RMSE obtained by ALO is 60.32 and 69.23% smaller than that of GOA under different experiment conditions, which verifies that GOA can effectively improve the accuracy of parameter extraction.
- By imitating the variation and crossover process of grasshoppers in nature, the diversity of the population is improved and local optimization is avoided, and the linear optimization strategy is introduced to speed up the optimization speed and update the individual location with the current optimal location as the target.

Future studies will be undertaken in the following two aspects:

- Using GOA for the parameter extraction of SOFC is a promising optimization method, which provides a new method for effectively improving solution quality with a more reliable fitness function of SOFC parameters extraction. Therefore, it may be applied to parameter extraction of more complex models and even other FCs;
- The proposed method is only evaluated in simulation conditions. Hence, its practical performance using actual experimental data will be tested in the next step.
- In addition, when the relevant parameters and external characteristics of the fuel cell are known, GOA can also be used in the research of PEM parameter extraction.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

XA: writing the original draft and editing. YY: conceptualization. HX: visualization and contributed to the discussion of the topic.

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GLOSSARY

Variables

A slope of Tafel line
V_c SOFC's output voltage, V
E_o Nernst potential, V
V_{act} activation voltage loss, V
V_{ohm} ohmic voltage loss, V
V_{con} concentration voltage loss, V
I_L limiting current density (mA/cm^2)
I_{load} load current density (mA/cm^2)
$I_{0,a}$ anode exchange current density (mA/cm^2)
$I_{0,c}$ cathode exchange current density (mA/cm^2)
I_0 exchange current density (mA/cm^2)
R_{ohm} ionic resistance ($k\Omega \cdot cm^2$)
ABC artificial bee colony
IBAS improved beetle antenna search
DE differential evolution
ALO ant lion optimizationant optimization algorithm
CBSSO chaotic binary shark smell optimization
BPSO bone particle swarm optimization
DNM dynastic model
ECM electrochemical model
GOA grasshopper optimization algorithm
ALO ant lion optimizationant optimization algorithm
GA genetic algorithm
GWO gray wolf optimization
IADE improved adaptive differential evolution
MhA meta-heuristic algorithm
MVO multivariate optimization
PSO particle swarm optimization
PEMFC proton exchange membrane fuel cell
RMSE root mean square error
SECM simple electrochemical model
SOFC solid oxide fuel cell
SSM steady-state model
V-I voltage-current