

Article

Intelligent Digital Twin Modelling for Hybrid PV-SOFC Power Generation System

Zhimin Guo ¹, Zhiyuan Ye ², Pengcheng Ni ², Can Cao ², Xiaozhao Wei ¹, Jian Zhao ¹ and Xing He ^{3,*}¹ State Grid Henan Electric Power Research Institute, Zhengzhou 450000, China² Anhui Jiyuan Software Co., Ltd., Hefei 230000, China³ Faculty of Electric Power Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

* Correspondence: hexing_hx@126.com

Abstract: Hydrogen (H₂) energy is an ideal non-polluting renewable energy and can achieve long-term energy storage, which can effectively regulate the intermittence and seasonal fluctuation of solar energy. Solid oxide fuel cells (SOFC) can generate electricity from H₂ with only outputs of water, waste heat, and almost no pollution. To solve the power generation instability and discontinuity of solar photovoltaic (PV) systems, a hybrid PV-SOFC power generation system has become one feasible solution. The “digital twin”, which integrates physical systems and information technology, offers a new view to deal with the current problems encountered during smart energy development. In particular, an accurate and reliable system model is the basis for achieving this vision. As core components, the reliable modelling of the PV cells and fuel cells (FCs) is crucial to the whole hybrid PV-SOFC power generation system’s optimal and reliable operation, which is based on the reliable identification of unknown model parameters. Hence, in this study, an artificial rabbits optimization (ARO)-based parameter identification strategy was proposed for the accurate modelling of PV cells and SOFCs, which was then validated on the PV double diode model (DDM) and SOFC electrochemical model under various operation scenarios. The simulation results demonstrated that ARO shows a more desirable performance in optimization accuracy and stability compared to other algorithms. For instance, the root mean square error (RMSE) obtained by ARO are 1.81% and 13.11% smaller than that obtained by ABC and WOA algorithms under the DDM of a PV cell. Meanwhile, for SOFC electrochemical model parameter identification under the 5 kW cell stack dataset, the RMSE obtained by ARO was only 2.72% and 4.88% to that of PSO for the (1 atm, 1173 K) and (3 atm, 1273 K) conditions, respectively. By establishing a digital twin model for PV cells and SOFCs, intelligent operation and management of both can be further achieved.

Keywords: parameter identification; photovoltaic (PV) cell; solid oxide fuel cell (SOFC); hybrid PV-SOFC system; artificial rabbits optimization; digital twin



Citation: Guo, Z.; Ye, Z.; Ni, P.; Cao, C.; Wei, X.; Zhao, J.; He, X. Intelligent Digital Twin Modelling for Hybrid PV-SOFC Power Generation System. *Energies* **2023**, *16*, 2806. <https://doi.org/10.3390/en16062806>

Academic Editor: Idiano D’Adamo

Received: 3 February 2023

Revised: 14 March 2023

Accepted: 15 March 2023

Published: 17 March 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

With the rapid progress of society and the development of different industries, the increasing depletion of traditional energy resources and serious environmental deterioration are bound to promote the exploitation of new energy candidates. To effectively alleviate the pressure on the energy supply chain, changes in the energy structure are imperative, thus renewable and clean energy technologies attract worldwide attention. To further promote a low-carbon lifestyle and energy production structure in China and even the world, China has officially proposed a “dual carbon” target in 2020 [1]. In recent years, the application of renewable energy to cope with climate change and promote energy reform has become the general consensus and concerted action around the world [2]. Among them, solar energy has gained large-scale application thanks to its merits, e.g., abundant storage, clean, zero-emission, low cost, and easy installation. Thus, it is considered as one of the most mature renewable energies to be developed [3]. For PV plants, policy-based

subsidy schemes or tax exemptions are crucial for their large-scale promotion, thus many countries have accordingly introduced relevant subsidy policies. For instance, in China, for distributed PV plants, a full electricity subsidy policy has been implemented. In detail, for distributed PV plants commissioned before 1 January 2018, the national subsidy is implemented in accordance with RMB 0.42/kWh, and for those commissioned after 1 January 2018, the national subsidy standard is implemented in accordance with RMB 0.37/kWh. In addition, distributed PV power generation systems are not required to pay the various funds and surcharges levied with the tariff, as well as system standby capacity charges and other related grid connection service fees for the self-consumption of electricity. For Germany, according to the Annual Tax Act 2022 approved by the German government, Germany will exempt rooftop PV from income tax and the corresponding value added tax from 2023 onwards if it meets the conditions. All the aforementioned initiatives are aimed at promoting the widespread use of PV power generation. However, considering that solar energy also has the disadvantages of power generation instability and discontinuity that are affected by weather, season, and other factors (e.g., night) [4], it is imperative to employ a complement system to photovoltaic (PV) system to enhance the reliability and continuity of electricity generation. As a green power technology of the 21st century, fuel cell (FC) can realize power generation without combustion [5]. FC can generate electricity from hydrogen (H_2) with only the outputs of water, waste heat, and almost no pollution to the environment. At the same time, H_2 energy is an ideal non-polluting renewable energy and can achieve long-term energy storage, which can regulate the intermittence and seasonal fluctuation of solar energy. Therefore, the H_2 energy produced by the electrolysis of the water electrolyzer is stored in a hydrogen storage device [6], which provides a new energy storage method for PV systems.

Meanwhile, a tricky problem of the FC system power generation is to satisfy the demand for H_2 supply. H_2 is a clean and efficient energy carrier used for power generation, however, it is not a free primary energy in nature, thus it is crucial to seek a highly efficient and sustainable solution for its supply. Generally, H_2 is produced through the electrolysis in the water electrolyzer, while its main problem is the quite high energy demand to support this process [6]. Thus, if the FC system can be combined with the PV system, the electrolyzer can be powered by the excess electricity produced by the PV system and H_2 can be produced by water electrolysis. Therefore, a hybrid PV-FC power generation system consisting of the PV system, the electrolyzer, FCs, and hydrogen storage units has become a viable solution [7], which can effectively overcome the intermittent and stochastic nature of power generation from PV systems, as well as the instability of the output power from FCs [8]. In particular, solid oxide FC (SOFC) has been widely used in many areas including portable power supply, distributed power/thermal power system, high-performance power supply, and large-scale power station due to its high energy conversion efficiency and highly flexible fuel requirements [9]. Therefore, this study chooses SOFC as the research object of FC.

This hybrid PV-SOFC power generation system works on the principle that when there is sufficient light, the excess power produced by the PV system is supplied to water electrolysis to produce H_2 in the electrolysis tank and stored in H_2 storage units. When the power supply of the PV system is insufficient, the SOFCs use the stored H_2 to generate electricity [10], enabling efficient use of energy and reducing energy wastage without any pollution. This hybrid system can be used not only as a stand-alone power generation system, but also as a hybrid DC microgrid system in modern power systems to optimize the power supply and energy flow patterns [11]. In general, such hybrid PV-SOFC power generation systems have a wide range of applications that can effectively alleviate the energy crisis and global environmental problems. However, there are many obstacles to the practical application of this hybrid PV-SOFC system, such as unstable energy conversion efficiency. In particular, as the core components of this hybrid PV-SOFC system, the precise modelling of SOFCs and PV cells is of the utmost significance since it is the basis to analyze

and predict the output characteristics of the hybrid system and is the most fundamental step for subsequent performance analysis and state monitoring [12].

In recent years, the rapid advancement of the Internet of Things, 5G communications, artificial intelligence, and automation has provided technical support for the transformation of the energy industry and promoted the information and digital transformation of the energy system [13]. The “digital twin”, which integrates physical systems and information technology, provides new ideas and tools to deal with the current problems faced by the development of smart energy [14]. By establishing a digital twin model for PV cells and SOFCs, intelligent operation and management of both can be achieved. The “digital twin” was firstly used in the aviation sector, and then quickly spread to industrial manufacturing, smart cities, and infrastructure engineering. The core idea is to build a virtual model that can quickly, dynamically, and accurately simulate the whole life cycle of a physical entity based on its physical information and operational data, combined with the theoretical models accumulated in the research field [15]. The “digital twin” models of PV cell and SOFC are the twin of the physical objects of both, receiving data from the physical object in real-time and constantly updating the model to keep it in line with the physical object’s operational state. To realize the digital twin of the PV cell and SOFC models, the models that can reflect the physical reality need to be built, which is also the focus and difficulty of the current research since high reliability and accuracy are required regarding the models. Therefore, this work focused on the accurate and fast identification of unknown model parameters, with the aim of providing a feasible methodology for building a more accurate and reliable “digital twin” model for both.

For PV cells, until now, a variety of PV cell models have been proposed to describe their highly non-linear characteristics to accurately reflect their output current-voltage (I - V) and power-voltage (P - V) characteristics, in which double diode model (DDM) has received the most widespread application thanks to its most proper balance between model complexity and accuracy [16]. For SOFCs, the most representative SOFC model is the electrochemical model [17], which is also investigated in this study. Modelling accuracy depends on the model parameters, which means the reliable model parameter identification is the basis for realizing the “digital twin” of model. Regarding PV and SOFC modelling, the main difficulty is the identification of the unknown parameters of their models.

2. Literature Review

For the parameter identification of PV cells and SOFCs in a hybrid PV-SOFC power generation system, many methods have been developed. First, a systematic survey and analysis of previous research on PV cell parameter identification were conducted in literature [18], which covered and discussed a variety of PV cell modelling and parameter identification methods, which can be broadly classified into analytical, deterministic, and meta-heuristic algorithms, while the first two types of methods have their distinct drawbacks, such as low identification accuracy, high computational effort, strong model dependency, and extreme sensitivity to initial conditions and gradient information. Inspiringly, meta-heuristic algorithms can effectively compensate for the defects with the superiorities of strong flexibility, high accuracy, and insensitivity to gradient information, which is considered as the most ideal method to solve the parameter identification problem. Thus far, many meta-heuristic algorithms are utilized for PV cell parameter identification [16], in which a comprehensive review on meta-heuristic algorithms and related variants which have been applied to PV cell parameter identification was undertaken.

In detail, particle swarm optimization (PSO) was applied to extract the solar cell parameters from illuminated current-voltage characteristics for the single and double diode models. An artificial bee colony (ABC) algorithm was devised in reference [19] to accurately identify the solar cells’ parameters, which exhibited a better search capacity to face multi-modal objective functions. An improved whale optimization algorithm (WOA) was developed in reference [20], referred to as IWOA, to accurately extract the parameters of different PV models, in which two prey searching strategies were adopted to effectively

balance the local exploitation and global exploration. For accurate modelling of PV module, an efficient parameter estimation technique named grey wolf optimization (GWO) [21] was developed to estimate the unknown parameters of the PV module. GWO showed high efficiency for parameter estimation of PV module under changing weather conditions. In reference [22], a fuzzy adaptive differential evolution algorithm-based method was developed, in which fuzzy selection strategy and adaptive parameter adjustment strategy were introduced to effectively control the crossover probability and mutation factors to avoid the discrimination into the local optimum while improving the convergence of the algorithm. Recently, an optimization algorithm called the musical chairs algorithm was devised to estimate the unknown parameters of PV cells [23]. The idea behind the use of this algorithm is to have a high number of search agents in the beginning to enhance the exploration and continuously reduce this number to enhance exploitation at the end of optimization and reduce the convergence time.

For FC parameter identification and modelling, there are two main categories [17], namely, traditional approaches and meta-heuristic algorithms. For the traditional methods, the fractional order derivative was adopted to analyze the general electrical characteristic of the dynamic model [24]. In the literature [25], the electrochemical impedance spectroscopy analysis was utilized for the electrochemical and thermodynamic information identification of SOFCs. The real-time estimation of SOFC model parameters in continuous time based on a well-studied FC experimental design was also realized in the literature [26].

For meta-heuristic algorithms, many approaches have been proposed and used to cope with the highly non-linear optimization problem of parameter identification for the SOFC. An improved genetic algorithm for a simplified SOFC electrochemical model was proposed in reference [27], which was based on an adapted encoding and control scheme. An improved Jingqiao adaptive differential evolution algorithm was also developed [28] to achieve fast and reliable SOFC parameter extraction using dynamic vector selection and adaptive cross-rate strategies. A bone particle swarm optimization algorithm was combined with a co-evolutionary framework for both high accuracy and robustness during parameter extraction [29]. In the literature [30], a simplified competitive swarm optimizer that used two simplified optimization strategies significantly improved the overall stability and accuracy. A modified version of grey wolf optimization for SOFC model identification was developed in reference [31], in which two scenarios based on temperature and pressure variations were utilized to show the system reliability. In addition, a Levenberg–Marquardt backpropagation algorithm-based parameter identification technique was proposed in literature [32,33] and applied to fast and precise identification of several unknown parameters for SOFC and PEMFC respectively, which showed satisfactory accuracy, speed, and stability. In reference [34], an extreme learning machine-based method was proposed to extract unknown parameters of SOFC model, in which extreme learning machine is applied to overcome two thorny obstacles (e.g., data shortage and noised data) via predicting additional data and updating noised data.

In this study, a parameter identification strategy based on artificial rabbits optimization (ARO) was designed for the accurate modeling of PV cells and SOFCs, whose contributions are outlined as follows:

1. A hybrid PV-SOFC system as an energy source is proposed to enhance energy utilization efficiency and power generation stability, in which the modelling of PV cells and SOFC is investigated since they are the most critical components in the hybrid system. The utilized ARO based parameter identification strategy can effectively improve both the exploration and exploitation ability, and dynamically adjust the proportion between the exploration and exploitation during iterations, which can effectively improve searching efficiency and avoid being trapped in local optimums;
2. For PV battery parameter identification, DDM benchmark PV battery model is used for verification, upon which the effectiveness of ARO for PV model parameter identification is verified. The simulation results indicate that ARO demonstrates higher accuracy and stability compared with other algorithms;

- For the identification of unknown parameters of SOFC, the representative electrochemical model is used to validate the ARO based parameter identification method under different operating conditions and different datasets. The simulation results show that the ARO can obtain the minimum RMSE and the highest stability under various operating conditions.

The rest of this paper is organized as follows: Section 2 illustrates PV cell and SOFC modelling. ARO based parameter identification method is elaborated in Section 3. Case studies results are presented and analyzed in Section 4. At last, conclusions and perspectives are given in Section 5.

3. Hybrid PV-SOFC System Modelling

This section provides a detailed introduction to the mathematical modelling of the two most core components of the hybrid PV-SOFC system, i.e., the PV cell and SOFC, both of which are modelled based on their basic power generation principles. In detail, the DDM of the PV cell and the electrochemical model of SOFC are discussed, meanwhile, the objective functions for performance evaluation are also presented, respectively.

3.1. PV Cell Modelling

The equivalent model of DDM is illustrated in Figure 1. DDM consists of an ideal constant current source, two diodes D_1 and D_2 , a series resistance R_s , and a shunt resistance R_{sh} . In particular, series resistance represents the total series resistance of material bulk resistance, thin layer resistance, and electrode contact resistance. Meanwhile, shunt resistance is mainly used to characterize the effect of leakage current on edge leakage. Compared with the single diode model (SDM), DDM has a higher precision and can describe and examine I - V and P - V characteristics in a wider range [16].

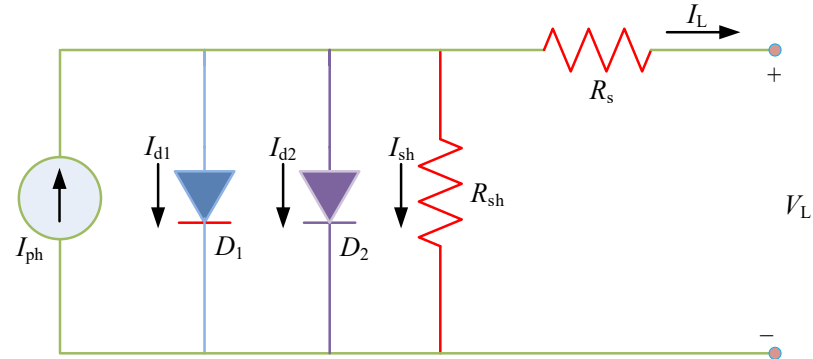


Figure 1. Double diode model.

The output of DDM can be given by [20]:

$$I = I_{ph} - I_{d1} - I_{d2} - I_{sh} \quad (1)$$

where I_{sh} and I_s indicate the current passing through the shunt resistance R_{sh} and series resistance R_s , I_{ph} denotes the photocurrent. In particular, the current I_{d1} and I_{d2} flowing through D_1 and D_2 and I_{sh} are expressed as:

$$I_{d1} = I_{01} \left[\exp \left(\frac{q(V + R_s I)}{a_1 N_s V_T} \right) - 1 \right] \quad (2)$$

$$I_{d2} = I_{02} \left[\exp \left(\frac{q(V + R_s I)}{a_2 N_s V_T} \right) - 1 \right] \quad (3)$$

$$I_{sh} = \frac{V + I R_s}{R_{sh}} \quad (4)$$

where I_{01} and I_{02} indicate the diode saturation current of D_1 and D_2 , a_1 and a_2 are ideality factors of D_1 and D_2 .

In Equations (2) and (3), V_T is given by [35]:

$$V_T = \frac{N_s K T}{q} \quad (5)$$

Hence, the output current of the PV cell based on DDM is presented as [16]:

$$I = I_{ph} - I_{01} \left[\exp \left(\frac{q(V + IR_s)}{a_1 V_T} \right) - 1 \right] - I_{02} \left[\exp \left(\frac{q(V + IR_s)}{a_2 V_T} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \quad (6)$$

According to Equation (6), in total of seven parameters need to be identified in DDM, namely, I_{ph} , I_{01} , I_{02} , R_s , R_{sh} , a_1 , and a_2 .

In order to effectively and quantitatively assess the performance of parameter identification methods, researchers have proposed a variety of evaluation criteria and objective functions. The computed results of the objective function allow for a comparison of the specific performance of different algorithms, thus effectively improving the shortcomings of one specific algorithm. Thus, the proper selection of the objective function is important during the practical application of parameter identification. The root mean square error (RMSE), which is most commonly applied in this problem [36], is selected as the objective function and the error is calculated using the actual and identified values as follows:

$$RMSE(x) = \sqrt{\frac{1}{N} \sum_{k=1}^N (f(V_L, I_L, x))^2} \quad (7)$$

The error functions $f(V_L, I_L, x)$ for DDM is described as:

$$f_{DDM}(V_L, I_L, x) = I_{ph} - I_{01} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_1 k T_{pv}} \right) - 1 \right] - I_{02} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_2 k T_{pv}} \right) - 1 \right] - \frac{V_L + I_L R_s}{R_{sh}} - I_L \quad (8)$$

As can be seen from Equation (8), $RMSE(x)$ should be minimized based on the optimization of the solution vector $x = \{I_{ph}, I_{01}, I_{02}, R_s, R_{sh}, a_1, a_2\}$.

3.2. SOFC Modelling

As shown in Figure 2, an SOFC mainly consists of the anode, the cathode, and the electrolyte between them [17]. The typical polarization curve of SOFC has three main distinct stages, namely, activation, concentration, and ohmic polarization, as demonstrated in Figure 3. The total chemical reaction process occurring in SOFC is expressed by the following equation.

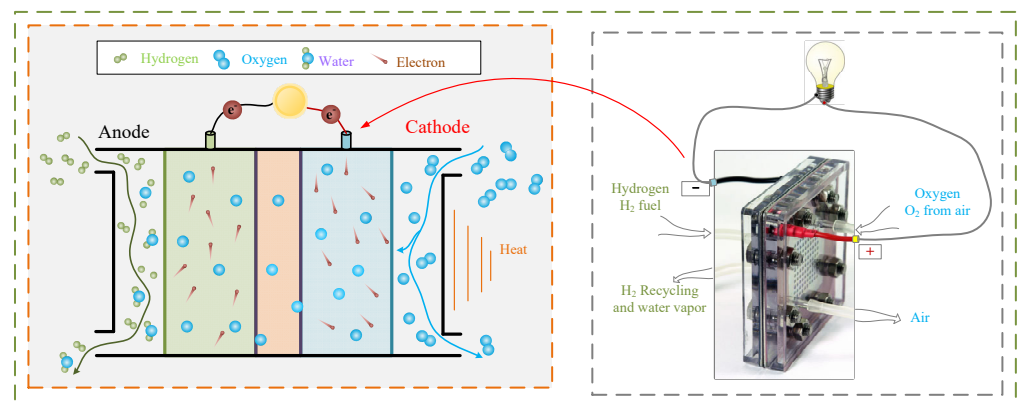


Figure 2. Electrochemical operation mechanism of SOFC [17].

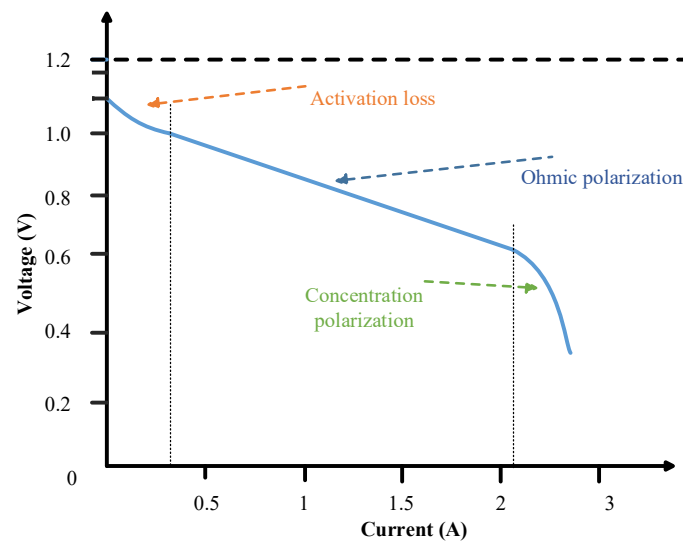


Figure 3. Polarization curve of SOFC.

At anode:



At cathode:



In order to achieve simple and effective control of the SOFC, the electrochemical model is widely used, whose output voltage can be expressed as:

$$V_c = N_{\text{cell}}(E_o - V_{\text{act}} - V_{\text{ohm}} - V_{\text{con}}) \quad (11)$$

where E_o indicates the open circuit voltage; N_{cell} denotes the number of series cells; V_{act} , V_{ohm} , and V_{con} indicate activation voltage loss, ohmic voltage loss, and concentration voltage loss, respectively.

Based on Butler–Volmer equation, the V_{act} can be expressed as:

$$V_{\text{act}} = A \sinh^{-1} \left(\frac{I_{\text{load}}}{2I_{0,a}} \right) + A \sinh^{-1} \left(\frac{I_{\text{load}}}{2I_{0,c}} \right) \quad (12)$$

where A indicates the slope of Tafel line; I_{load} , $I_{0,a}$, and $I_{0,c}$ represent load current density, the exchange current density of anode and cathode, respectively.

Moreover, V_{ohm} can be described by:

$$V_{\text{ohm}} = I_{\text{load}} R_{\text{ohm}} \quad (13)$$

where R_{ohm} denotes the ionic resistance.

Furthermore, V_{con} is described by:

$$V_{\text{con}} = -B \ln \left(1 - \frac{I_{\text{load}}}{I_L} \right) \quad (14)$$

where B indicates a constant; I_L represents the limiting current density.

From Equations (11)–(14), the output of SOFC is described by:

$$\begin{aligned} V_c &= N_{\text{cell}}(E_o - V_{\text{act}} - V_{\text{ohm}} - V_{\text{con}}) \\ &= N_{\text{cell}} \left(E_o - A \sinh^{-1} \left(\frac{I_{\text{load}}}{2I_{0,a}} \right) - A \sinh^{-1} \left(\frac{I_{\text{load}}}{2I_{0,c}} \right) + B \ln \left(1 - \frac{I_{\text{load}}}{I_L} \right) - I_{\text{load}} R_{\text{ohm}} \right) \end{aligned} \quad (15)$$

From Equation (15), electrochemical model has seven unknown parameters (i.e., E_o , A , $I_{0,a}$, $I_{0,c}$, B , I_L , and R_{ohm}), where $I_{0,a} > I_{0,c}$ and $I_L > I_{\text{load}}$.

Similar to PV cell, RMSE is defined as an objective function, calculated as:

$$\text{RMSE}(x) = \sqrt{\frac{1}{N} \sum_{k=1}^N (\text{error}_k)^2} = \sqrt{\frac{1}{N} \sum_{k=1}^N (V_{m,k} - V_{c,k})^2} \quad (16)$$

where $x = \{E_o, A, I_{0,a}, I_{0,c}, B, I_L, R_{ohm}\}$ represents the solution vector, $V_{m,k}$ and $V_{c,k}$ represent the voltage measured and the calculated voltage for the k th time, respectively.

4. Artificial Rabbits Optimization

In this section, the proposed background of the ARO and relevant mathematical models for optimization will be introduced.

4.1. Inspiration

The rabbit is a mammalian, herbivorous vertebrate. In the wild, the rabbit is highly stealthy. When it is stationary, its fur color blends in with the surrounding weeds, which also helps them to avoid enemies. Rabbits stay in low, dry bushes or burrows during the day and come out at night to search for food nearby.

ARO has its origins in the natural rabbit's survival strategies, which mainly contains two aspects: food searching strategy and survival strategy [37]. First, rabbits do not eat the grass near the holes, as the grass grows tall and dense so that the rabbit is less likely to be discovered by enemies and thus will be well protected, so nesting grass is a natural camouflage for rabbits against enemies. Meanwhile, it is also used for food storage, as rabbits will feed on the grass when they cannot find food in the distance. In addition, rabbits have a very wide field of view which is basically used for overhead scanning, thus they can easily search for food in a large searching area. This foraging strategy will be considered as a global exploration during optimization.

Second, there are many natural predators of wild-bred rabbits, including foxes, wild dogs, eagles, and wolves. These natural predators are relatively large, and rabbits tend to hide burrows as a way of avoiding predator attacks when in danger. Rabbits have excellent running ability and are very agile, thus they can stop suddenly in mid-run, and turn sharply to escape pursuit. This survival strategy can effectively increase their chances of survival. This survival strategy will be regarded as the local exploitation during optimization.

4.2. Modelling of ARO

The food searching and hiding strategies of rabbits result in a switch between the two strategies that are adopted in ARO, and related mathematical modelling is demonstrated in this section.

4.2.1. Detour Food Searching Strategy

As mentioned above, although a rabbit is a herbivore, it does not eat the grass around its nest. This is because the grass around a rabbit's nest is used for hiding. They only graze randomly in other areas, not in their own area, and we call this food searching behaviour "detour food searching". In ARO, each rabbit has its own area with grass and burrows, and they tend to visit each other's locations randomly for food searching. As a result, a mathematical model of rabbit meandering foraging is proposed as follows [37]:

$$\vec{v}_i(t+1) = \vec{x}_j(t) + R \cdot (\vec{x}_i(t) - \vec{x}_j(t)) + \text{round}(0.5 \cdot (0.05 + r_1)) \cdot n_1, \quad (17)$$

$$i, j = 1, \dots, n \text{ and } j \neq i$$

$$R = L \cdot c \quad (18)$$

$$L = \left(e - e^{\left(\frac{t-1}{T}\right)^2} \right) \cdot \sin(2\pi r_2) \quad (19)$$

$$c(k) = \begin{cases} 1 & \text{if } k = g(l) \\ 0 & \text{else} \end{cases} \quad k = 1, \dots, d \text{ and } l = 1, \dots, \lceil r_3 \cdot d \rceil \quad (20)$$

$$g = \text{randperm}(d) \quad (21)$$

$$n_1 \sim N(0, 1) \quad (22)$$

where $\vec{v}_i(t+1)$ denotes the candidate position of the i th rabbit at the time $t+1$, $\vec{x}_i(t)$ represents the position of the i th rabbit at the time t , L is the running length which represents the movement pace when performing the detour foraging, while other parameters can be referred to literature [37]. According to Equation (19), the running length L can generate a longer step during the initial iterations, while a shorter step will be generated during the later iterations. In Equation (18), R denotes the running operator which is employed to simulate the running characteristic of rabbits. Figure 4 shows the trajectory of 300 steps of the running operator R in 2-D and 3-D space [37]. From Figure 4, the searching space is probed by a series of sudden turns with the random direction, and with the increase of steps this probe length gradually gets shorter. Taking Figure 4 as an example, the horizontal coordinate x represents the number of iteration steps, and the vertical coordinate y represents the running step length, we can see that as the number of iteration steps x increases, the running length gradually decreases (i.e., the length of the fold lines in each sudden change in the upper right corner of the Figure 4 is obviously shorter than that of the fold lines in the lower left corner).

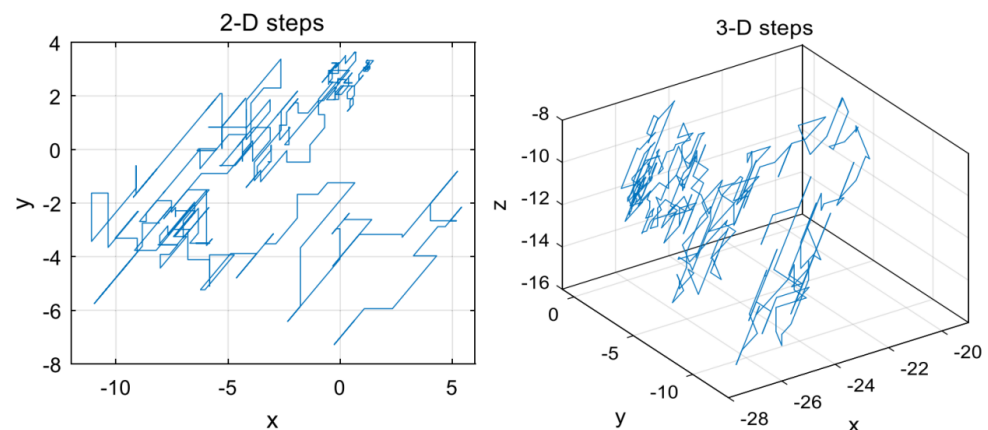


Figure 4. Trajectory of 300 steps of the running operator [37].

Equation (17) suggests that searching individuals perform a random search based on each individual's position. This behaviour allows the rabbit to move to other rabbits' areas. This particular food searching behaviour of rabbits, i.e., visiting others' nests rather than their own, greatly facilitates global exploration and ensures the global searching ability.

4.2.2. Random Hiding Strategy

Rabbit burrowing is a habit evolved by rabbits in order to store food, avoid natural enemies, make a nest and settle down, and reproduce in the long-term harsh living environment in the wild. In ARO, a rabbit digs d burrow and selects one of all the burrows at random as a hiding place to hide in order to avoid being predated. Thus, the i th rabbit's j th burrow is generated based on

$$\vec{b}_{i,j}(t) = \vec{x}_i(t) + H \cdot g \cdot \vec{x}_i(t), \quad i = 1, \dots, n \text{ and } j = 1, \dots, d \quad (23)$$

$$H = \frac{T-t+1}{T} \cdot r_4 \quad (24)$$

$$n_2 \sim N(0, 1) \quad (25)$$

$$g(k) = \begin{cases} 1 & \text{if } k == j \\ 0 & \text{else} \end{cases}, \dots, k = 1, \dots, d \quad (26)$$

where h indicates the hidden parameter that linearly in a randomly perturbed manner during the iterative process. Hence, during the initial stage, burrows are distributed in a larger neighbourhood of the rabbits. This neighbourhood is reduced with iterations increase. To avoid being chased and attacked by the predators, they are declined to randomly select a burrow from their burrows for sheltering, which can be modelled as:

$$\vec{v}_i(t+1) = \vec{x}_i(t) + R \cdot \left(r_4 \cdot \vec{b}_{i,r}(t) - \vec{x}_i(t) \right), i = 1, \dots, n \quad (27)$$

$$g_r(k) = \begin{cases} 1 & \text{if } k == \lceil r_5 \cdot d \rceil \\ 0 & \text{else} \end{cases}, \dots, k = 1, \dots, d \quad (28)$$

$$\vec{b}_{i,r}(t) = \vec{x}_i(t) + H \cdot g_r \cdot \vec{x}_i(t) \quad (29)$$

where $\vec{b}_{i,r}(t)$ denotes a randomly selected burrow, r_4 and r_5 represent two numbers randomly distributed between 0 and 1.

4.2.3. Energy Shrink Strategy

Rabbits tend to search for food in the initial stages of the iteration and often adopt random hiding during later stages of the iteration, which leads to the rabbit's energy to diminish over time. Hence, an energy factor is applied to characterize the transition between global exploration and local exploitation, as follows:

$$A(t) = 4 \left(1 - \frac{t}{T} \right) \ln \frac{1}{r} \quad (30)$$

where r denotes the random number between 0 and 1.

The larger the energy factor, the greater the amount of energy and stamina owned by the rabbit to search for food. The smaller value of the energy factor indicated that the rabbits were less energetic and therefore need to hide randomly. In specific, when $A(t) > 1$, rabbits tend to randomly explore different searching areas for food searching (global exploration); when $A(t) \leq 1$, random hiding occurs (local exploitation), as demonstrated in Figure 5. To sum up, a group of random rabbits (candidate solutions) are generated in the searching space. Then, the rabbit will update its position during iterations, either selected randomly in the group or from its burrows. The energy factor A will decrease increase as iterations increase, upon which the detour food searching behavior will be switched to the hiding behavior.

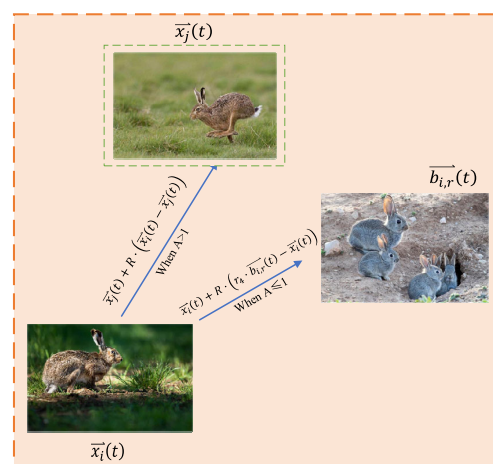


Figure 5. Searching behavior adjustment based on energy factor A .

The ARO algorithm has almost the same amount of performing both detour food searching and random hiding in the iterative process, which contribute significantly to balancing exploration and exploitation. Figure 6 shows the schematic diagram of probability calculation of the detour food searching [37].

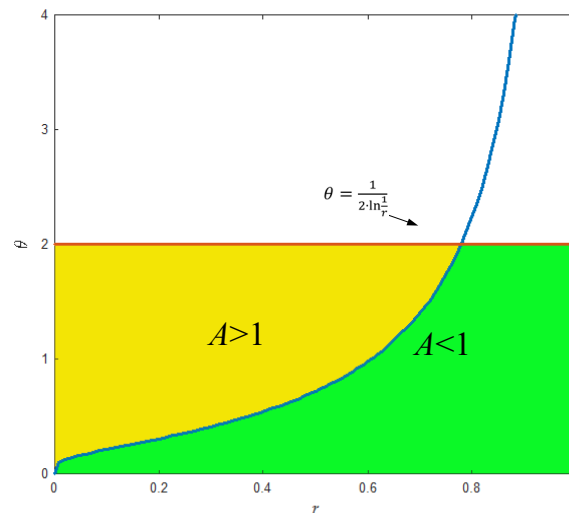


Figure 6. Schematic diagram of probability calculation of detour food searching.

5. Case Studies

In this section, ARO was applied in several PV cells and SOFC models for unknown parameter identification in the MATLAB/SIMULINK testing environment for performance validation. In particular, the DDM benchmark PV cell model was used for PV cell validation. For SOFC parameter identification, the electrochemical model was used for verification. All case studies are undertaken by Matlab 2022a through a personal computer with Intel® Core™i7 CPU at 2.0 GHz and 32 GB of RAM (Santa Clara, CA, USA).

5.1. PV Cell Model Parameter Identification

5.1.1. Design of ARO for PV Cell Parameter Identification

In order to achieve reliable optimization, the optimization variable x_j is limited to the upper limit $x_j^{\max}$ and lower limit $x_j^{\min}$ as follows:

$$x_j^{\min} \leq x_j \leq x_j^{\max}, j = 1, 2, \dots, J \quad (31)$$

where J represents the optimizing variables number.

If an individual rabbit violates Equation (31), it will be randomly reset by:

$$x_j = x_j^{\min} + r_2(x_j^{\max} - x_j^{\min}) \quad (32)$$

where r_2 indicates a number between 0 to 1.

The optimization framework for the identification of PV cell parameters based on ARO is shown in Figure 7. As can be seen in Figure 7, the measured I - V data is considered as input to ARO, and then the optimization procedure will be executed using ARO based on a specific PV cell model, and finally the identified parameters will be the output. For DDM parameter estimation, three meta-heuristic algorithms, namely ABC, WOA, and ARO, are applied to compare and validate the performance of ARO. In this section, the most representative DDM of PV cell is used, and the operating conditions are set to a standard operating environment ($G = 1000 \text{ W/m}^2$ and $T = 33^\circ\text{C}$). 26 sets of experimental I - V data are taken as input, which are acquired from a 57 mm diameter commercial silicon solar cell (R.T.C. France) operating under $G = 1000 \text{ W/m}^2$ and $T = 33^\circ\text{C}$ [20,38], as detailed in Table 1. The maximum iteration number is designed to be 3000, which is found to be

sufficient for convergence after several tests, while all methods were run independently for 30 times and the population size of the algorithms was designed to be 50 to obtain statistical results.

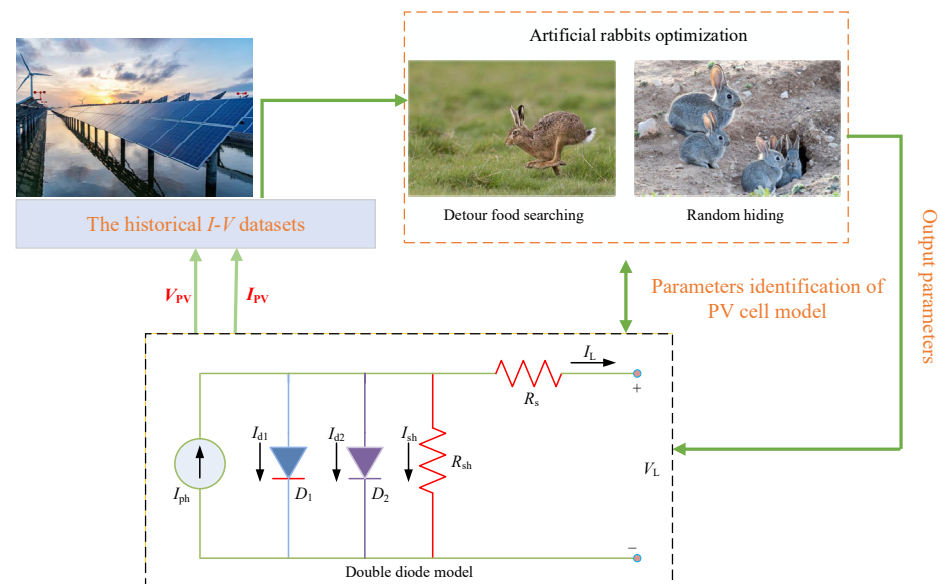


Figure 7. ARO based parameter identification framework.

Table 1. Benchmark *I-V* dataset.

<i>I-V</i> Data	1	2	3	4	5	6	7	8	9	10	11	12	13
V_L (V)	−0.2057	−0.1291	−0.0588	0.0057	0.0646	0.1185	0.1678	0.2132	0.2545	0.2924	0.3269	0.3585	0.3873
I_L (A)	0.7640	0.7620	0.7605	0.7605	0.7600	0.7590	0.7570	0.7570	0.7555	0.7540	0.7505	0.7465	0.7385
<i>I-V</i> Data	14	15	16	17	18	19	20	21	22	23	24	25	26
V_L (V)	0.4137	0.4373	0.4590	0.4784	0.4960	0.5119	0.5265	0.5398	0.5521	0.5633	0.5736	0.5833	0.5900
I_L (A)	0.7280	0.7065	0.6755	0.6320	0.5730	0.4990	0.4130	0.3165	0.2120	0.1035	−0.0100	−0.1230	−0.2100

5.1.2. Validation on DDM

As tabulated in Table 2, the optimal parameter identification results and RMSE of three algorithms under DDM are demonstrated, which shows that ARO can obtain the smallest RMSE, followed by ABC and WOA, which indicates that ARO has the highest parameter identification accuracy. For example, the RMSE obtained by ARO are 1.81% and 13.11% smaller than that obtained by ABC and WOA algorithms. Moreover, by returning the extracted parameters to the DDM, the simulated data of ARO are in very good agreement with the actual data almost in all data points as shown in Table 2 and Figure 8.

Table 2. Parameter identification results obtained by various algorithms under DDM.

Algorithm	I_{ph} (A)	I_{01} (μ A)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{02} (μ A)	a_2	RMSE
ABC	0.7604	0.5450	0.0372	52.0978	1.8104	0.1511	1.4196	1.0037×10^{-3}
WOA	0.7603	0.5333	0.0358	71.7116	1.6921	0.1502	1.4360	1.1342×10^{-3}
ARO	0.7608	0.2256	0.0366	54.6219	2.0000	0.2162	1.4516	9.8554×10^{-4}

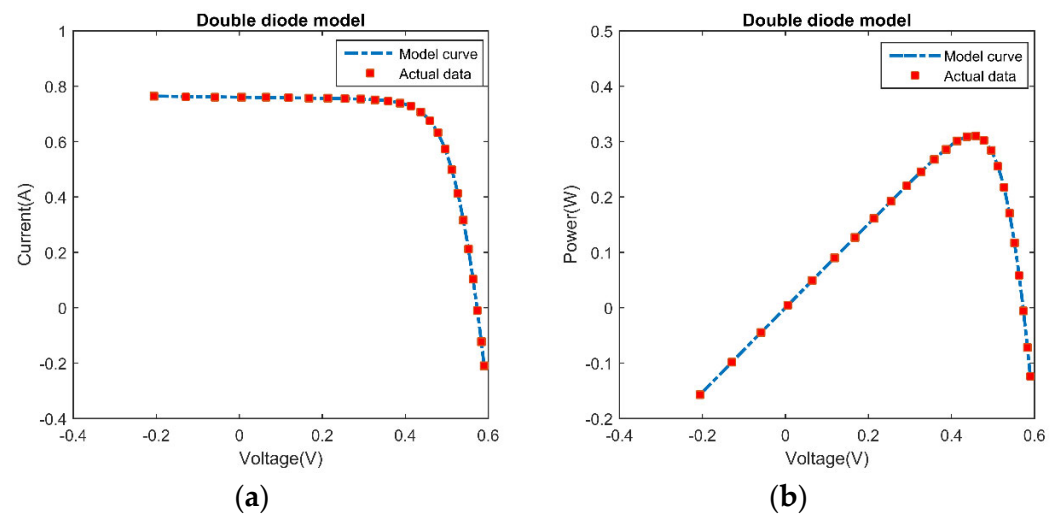


Figure 8. Output I - V and P - V curves obtained by ARO: (a) I - V curve; and (b) P - V curve.

The output I - V and P - V curves obtained by ARO are illustrated in Figure 8. The actual data are acquired from the experiment conducted in literature [38] published in 1986, where a 57 mm diameter commercial silicon solar cell (R.T.C. France) operating under $G = 1000 \text{ W/m}^2$ at $T = 33 \text{ }^\circ\text{C}$, with a CBM 8096 microcomputer acting as the controller. Figure 8 demonstrates that the simulated output curves acquired by ARO are basically the same as original actual curves, which can intuitively reflect its high fitting accuracy.

Convergence speed and stability are both important criteria for measuring the performance of an optimization method. The convergence curves of the RMSE of WOA, ABC, and ARO for DDM are demonstrated in Figure 9. Although WOA and ABC converge quickly in the beginning stage, on the other hand, they also easily stagnate quickly and suffer from prematurity, leading to low-quality local optimums. However, ARO tends to have a higher quality global optimum and a more stable convergence process due to its adaptive adjustment between global exploration and local exploitation throughout the iteration, thus avoiding falling into a local optimum.

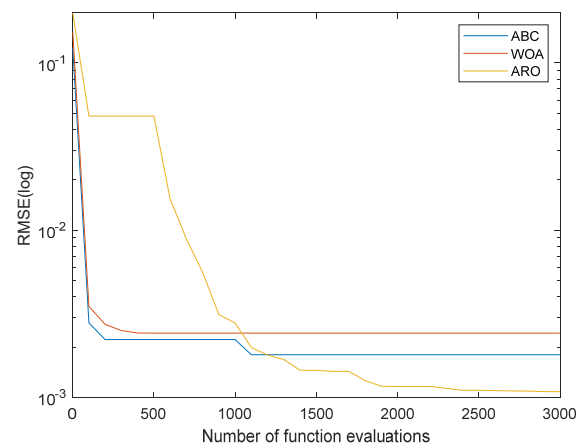


Figure 9. Convergence curves obtained by various algorithms for DDM.

Figure 10 shows the boxplots for the various algorithms under DDM, visualizing the distribution of RMSE results over 30 independent runs by different methods. ARO algorithm has the smallest upper and lower RMSE bound intervals of all the algorithms, with no outliers exist. This demonstrates that the ARO algorithm is able to achieve high convergence stability and high optimization accuracy for the problem of DDM parameter identification.

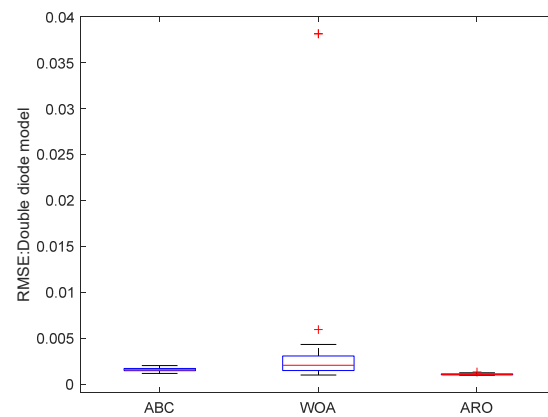


Figure 10. Boxplot graph obtained by various algorithms.

5.2. SOFC Model Parameter Identification

In this section, ARO was adopted for the complex optimization problem of SOFC parameter identification, which is typically highly non-linear with multiple constraints. This section evaluated the performance of ARO, GWO, and PSO based on two different V - I datasets under the electrochemical model, respectively. One set of data was collected from a battery stack consisting of 79 cells, as shown in Figure 11.

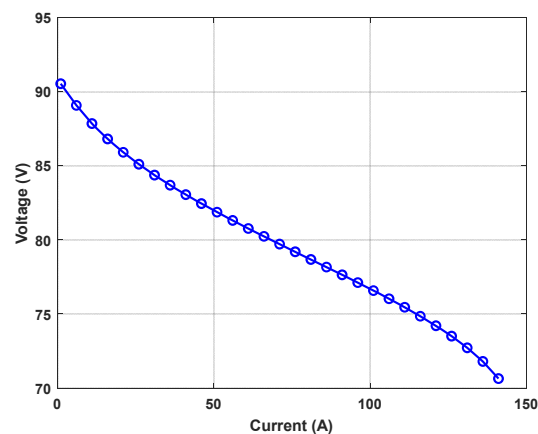


Figure 11. Datasets for validation for electrochemical model.

At the same time, another dataset was selected from a 5 kW cell stack in WCS-SOFC MATLAB/SIMULINK consisting of 96 cells operating under various operating scenarios [39,40], as shown in Figure 12. Tables 3 and 4 show the dataset size and the parameters range, respectively.

Table 3. The size of dataset.

Datasets for Validation		Datasets for 5 kW Cell Stack			
Electrochemical model	(1 atm, 1173 K)	(1 atm, 1273 K)	(3 atm, 1173 K)	(3 atm, 1273 K)	
34	69	69	65	65	

Table 4. The range of unknown parameters.

Electrochemical Model							
Parameters	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 limit	0	0	0	0	0	0	0
Upper limit	1.2	1	1	1	30	30	200

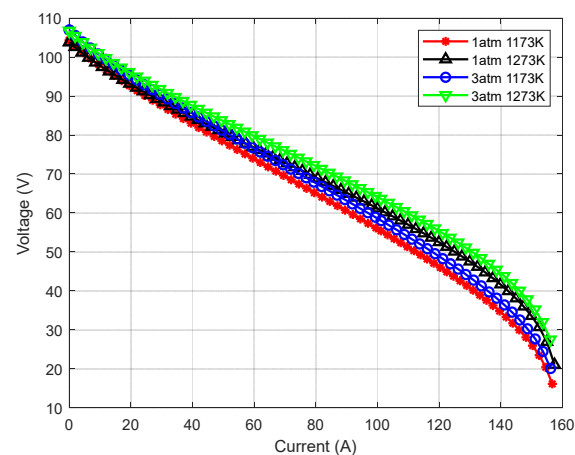


Figure 12. Datasets for 5 kW cell stack under various operating scenarios.

5.2.1. Validation of ARO

This subsection uses the first aforementioned dataset, and the seven unknown parameters of the electrochemical model are set to $[E_0, A, R_{ohm}, B, I_{0,a}, I_{0,c}, I_L] = [1.15, 0.02, 0.0004, 0.03, 12, 4, 152]$.

The identification parameters results are illustrated in Table 5 along with the RMSE, in which the RMSE values can give a direct and clear indication of the optimization accuracy. As shown in Table 5, ARO identifies the unknown parameters in a largest similarity to the real measurement data. ARO also achieves the smallest RMSE compared to other algorithms, e.g., the RMSE value achieved by ARO is only 8.67% and 20.23% to that of GWO and PSO. It verifies ARO achieves parameter estimation of the electrochemical model with the highest accuracy.

Table 5. Identification results of various algorithms.

Algorithms	Identified Parameters							RMSE
	E_0	A	R	B	$I_{0,a}$	$I_{0,c}$	I_L	
Actual value	1.1500	0.0200	0.0004	0.0300	12.0000	4.0000	152.0000	0
GWO	1.1479	0.0298	0.0000	0.0453	20.2558	6.2900	157.4983	4.9882×10^{-4}
PSO	1.1495	0.0316	0.0000	0.0457	30	5.4398	158.0896	2.1379×10^{-4}
ARO	1.1498	0.0284	0.0002	0.0338	30	4.7907	153.2175	4.3264×10^{-5}

Meanwhile, Figure 13 demonstrates the boxplot and convergence graphs of various methods under 100 independent runs. Figure 13a illustrates the RMSE results distribution of different algorithms, it can be verified that ARO owns the smallest distribution range with minimal lower and upper bounds. Figure 13b also proves that ARO has a more stable convergence process and higher convergence precision.

5.2.2. Verification on a 5 kW Cell Stack

The effectiveness of ARO was verified on a 5 kW cell stack here. Furthermore, the estimated results under four various operating scenarios are shown in Table 6, which demonstrates that the identification results of ARO can obtain the smallest RMSE under all operating scenarios compared with GWO and PSO. For example, the RMSE obtained by ARO is only 2.72% and 4.88% to that of PSO for the (1 atm, 1173 K) and (3 atm, 1273 K) conditions, respectively.

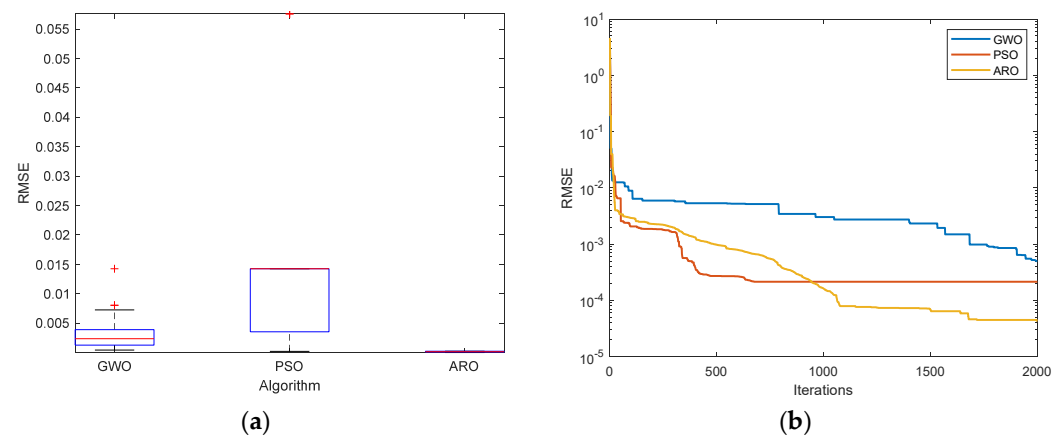


Figure 13. Boxplot and convergence graphs of various algorithms: (a) boxplot; and (b) convergence graph.

Table 6. Identification results of various algorithms for 5 kW cell stack dataset.

Conditions	Algorithm	Identified Parameters							RMSE
		E_o	A	R_{ohm}	B	$I_{0,a}$	$I_{0,c}$	I_L	
(1 atm, 1173 K)	GWO	1.0850	0.0807	0.0007	0.1641	28.2084	13.3625	167.6413	4.1991×10^{-3}
	PSO	1.086896591	0.0561	0	0.3998	30	6.7940	200	8.9389×10^{-3}
	ARO	1.0861	0.0286	0.0030	0.0753	29.9587	4.6816	160.1067	2.4342×10^{-4}
(1 atm, 1273 K)	GWO	1.0820	0.0571	3.73×10^{-8}	0.2488	19.5695	8.6351	178.3767	3.9708×10^{-3}
	PSO	1.0821	0.0449	0	0.0366	30	5.2947	200	6.247×10^{-3}
	ARO	1.0812	0.0283	0.0023	0.0849	29.4272	4.21366	160.3749	2.2096×10^{-4}
(3 atm, 1173 K)	GWO	1.1149	0.0609	0	0.0351	22.1903	8.4946	193.5037	4.5549×10^{-3}
	PSO	1.1122	0.0547	0	0.0388	12.4485	12.4485	200	4.8315×10^{-3}
	ARO	1.1140	0.0295	0.0030	0.0775	29.9881	4.8380	160.3771	3.2846×10^{-4}
(3 atm, 1273 K)	GWO	1.1032	0.1143	0	0.1332	29.5083	25.8728	163.5788	3.3413×10^{-3}
	PSO	1.1112	0.0362	0	0.3744	8.1947	8.1947	200	5.7429×10^{-3}
	ARO	1.1120	0.0288	0.0023	0.0854	29.9999	4.1656	160.3958	2.8078×10^{-4}

In addition, Figure 14 shows the boxplots for the various algorithms under different running conditions, which illustrates the RMSE distribution for each algorithm over 20 runs. It is clear that the ARO achieved the smallest range of RMSE distributions under various conditions, and also yielded the smallest lower and upper bounds on RMSE. This validates that ARO can effectively boost convergence stability and identification accuracy.

In addition, Figure 15 depicts convergence curves of different algorithms under various operating scenarios, in which ARO can converge to the minimum RMSE value under all four testing scenarios. In contrast, although PSO also converges quickly in the beginning stage, it stagnates quickly and suffers from prematurity. GWO can converge continuously throughout the whole evolutionary process, while it struggles to obtain high-quality optimal solutions in all scenarios. The convergence result indicated that ARO is able to break the adsorption of local minima and find a more desirable searching direction. Namely, it shows a more stable convergence tendency and achieves higher quality solutions in all scenarios due to its strong exploration mechanism.

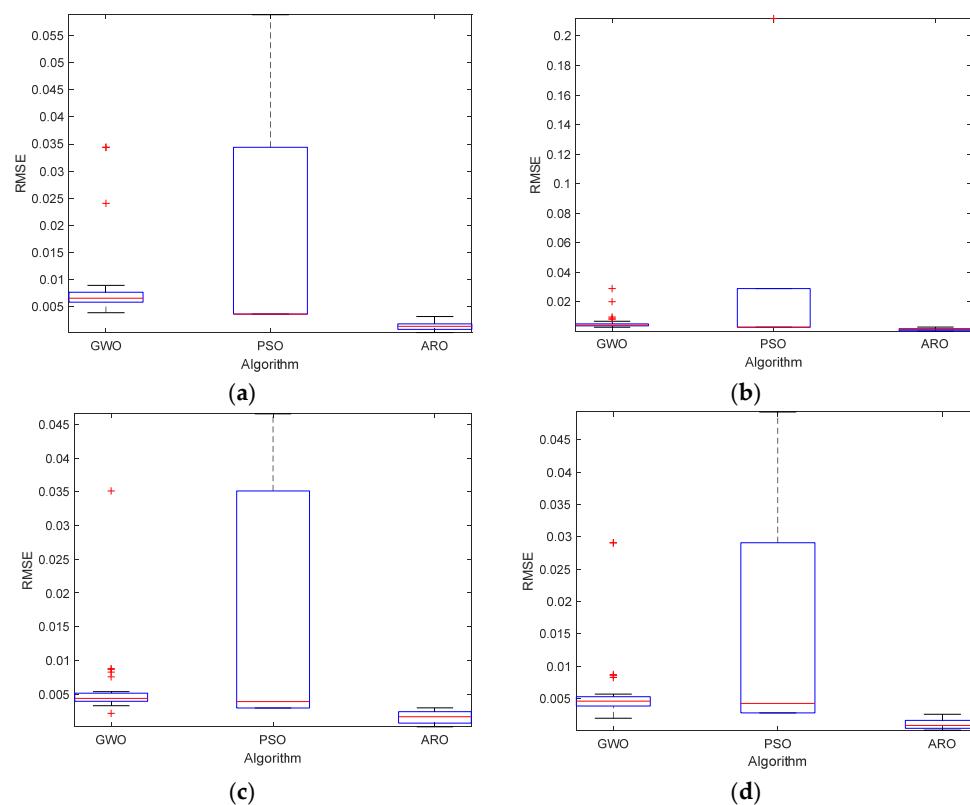


Figure 14. Boxplot of different algorithms at various environmental conditions: (a) 1 atm, 1173 K; (b) 1 atm, 1273 K; (c) 3 atm, 1173 K; and (d) 3 atm, 1273 K.

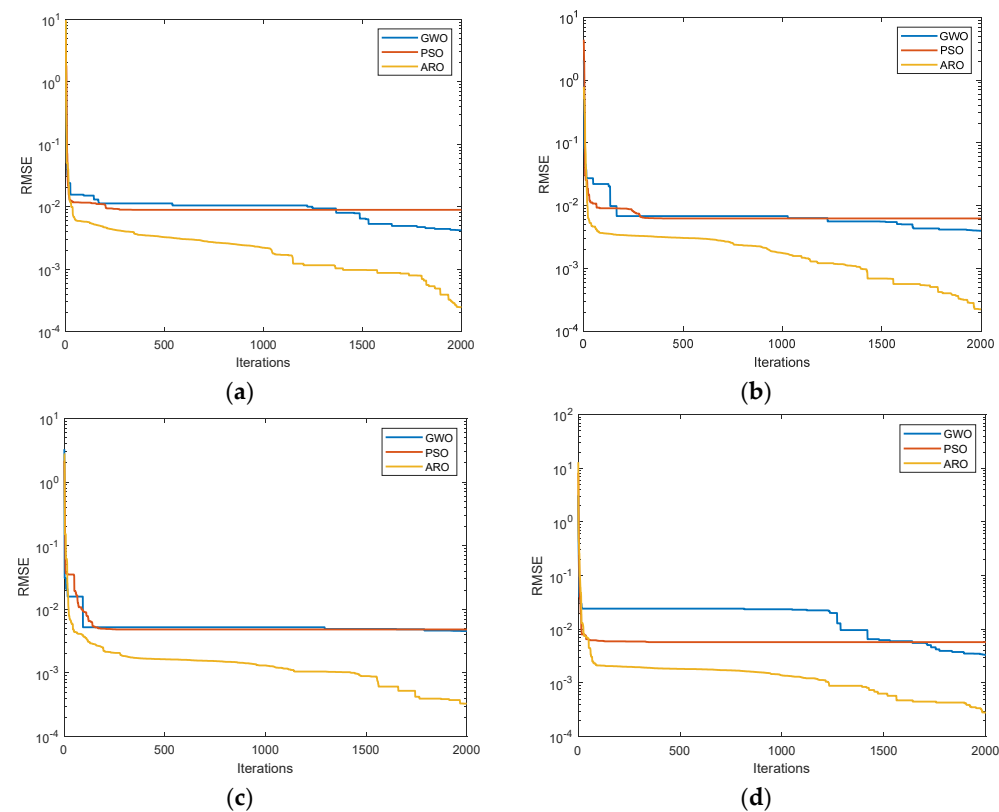


Figure 15. Convergence graphs of different algorithms at various environmental conditions: (a) 1 atm, 1173 K; (b) 1 atm, 1273 K; (c) 3 atm, 1173 K; and (d) 3 atm, 1273 K.

6. Conclusions and Perspectives

This paper took the two core components of a hybrid PV-SOFC system, i.e., the PV cell and the SOFC as the research focus with the aim of reliably identifying the unknown parameters in their models and thus achieving accurate modelling, the main contributions of which are outlined as:

1. To deal with parameters identification of the PV cell and SOFC models, this paper applied an ARO based intelligent parameter identification strategy to achieve accurate modelling of both models. The aim was to provide a feasible method for building a more accurate and reliable “digital twin” model of this hybrid power generation system, and ultimately to achieve a highly automated, intelligent, and low-carbon system operation and management system;
2. The proposed ARO-based parameter identification strategy improves the convergence speed and optimization accuracy by designing a dynamic searching mechanism to regulate the searching behaviour during the iterations, i.e., detour foraging and random hiding, so as to better balance global exploration and local exploitation;
3. ARO was applied for parameters estimation for the DDM model of PV cells and the electrochemical model of SOFC, and its effectiveness was fully verified. The simulation results indicated that ARO show higher accuracy and stability in comparison with other algorithms. For instance, for parameter identification of SOFC electrochemical model under the first dataset, the RMSE value achieved by ARO was only 8.67% and 20.23% to that of GWO and PSO. Meanwhile, the convergence curves of the RMSE obtained by different algorithms also proved that ARO acquires a higher quality global optimum and shows a more stable convergence process.

Overall, this study also has some limitations, for instance, the limited diversity of PV cell models and SOFC models are utilized for verification. In addition, all the case studies were only tested under the ideal laboratory simulation environment rather than practical operation conditions. Meanwhile, only the core components of the hybrid PV-SOFC system were studied instead of all components. Therefore, follow-up research is necessary, and future research will focus on the following three areas:

1. For PV cells and SOFC parameter identification, more types of cell models can be applied for validation. Meanwhile, the ability to perform parameter identification online and in real time can be further developed;
2. Future validation of the SOFC models considering degradation mechanisms can bring higher engineering value in terms of health condition monitoring, and fault detection and diagnosis;
3. The research focus of the digital twin includes the creation of digital twin models, physical information fusion, and service applications. This paper focused on the study of building accurate and reliable digital twin models of core components in the hybrid PV-SOFC system. Therefore, further research is required for the digital twin model of the whole system in its entirety and for the application of the methods proposed in this paper in the areas of optimal design, optimal operation, and fault diagnosis.

Author Contributions: Z.G.: writing the original draft and editing. Z.Y., P.N. and C.C.: conceptualization. X.W., J.Z. and X.H.: visualization and contributed to the discussion of the topic. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the science and technology project from State Grid Corporation of China: Research on Digital Twin-based Management and Interaction Technology for Efficient Collaboration of County Energy Internet, grant number (5700-20224202A-1-1-ZN).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Abbreviation

ABC	artificial bee colony
ARO	artificial rabbits optimization
DDM	double diode mode
FC	fuel cell
GWO	grey wolf optimization
H ₂	hydrogen
I-V	current-voltage
PSO	particle swarm optimization
PV	photovoltaic
P-V	power-voltage
RMSE	root mean square error
WOA	whale optimization algorithm
SDM	single diode model
SOFC	solid oxide fuel cell

Variables

a_1	the ideality factors of D_1
a_2	the ideality factors of D_2
$q = 1.6 \times 10^{-19} \text{C}$	the electron charge
N_s	the number of series connected PV cells in the PV panel
V_t	the junction thermal voltage
A	the slope of Tafel line
E_o	the open circuit voltage
N_{cell}	the number of series cells
I_{01}	the diode saturation current of D_1
I_{02}	the diode saturation current of D_2
$I_{0,a}$	the exchange current density of anode
$I_{0,c}$	the exchange current density of cathode
I_{d1}	the current flowing through D_1
I_{d2}	the current flowing through D_2
I_{load}	the load current density
I_L	the limiting current density
I_{ph}	the photocurrent
I_s	the current passing through the series resistance
I_{sh}	the current passing through the shunt resistance
V_{act}	the activation voltage loss
$V_{c,k}$	the voltage calculated voltage for the k th time
V_{con}	the concentration voltage loss
$V_{m,k}$	the voltage measured for the k th time
V_{ohm}	the ohmic voltage loss

References

- Huang, R.; Zhang, S.; Wang, P. Key areas and pathways for carbon emissions reduction in Beijing for the “Dual Carbon” targets. *Energy Policy* **2022**, *164*, 112873. [\[CrossRef\]](#)
- Zhang, G.; Shi, Y.; Maleki, A.; Rosen, M.A. Optimal location and size of a grid-independent solar/hydrogen system for rural areas using an efficient heuristic approach. *Renew. Energy* **2020**, *156*, 1203–1214. [\[CrossRef\]](#)
- Verbois, H.; Huva, R.; Rusydi, A.; Walsh, W. Solar irradiance forecasting in the tropics using numerical weather prediction and statistical learning. *Sol. Energy* **2018**, *162*, 265–277. [\[CrossRef\]](#)
- Awasthi, A.; Shukla, A.K.; SR, M.M.; Dondariya, C.; Shukla, K.N.; Porwal, D.; Richhariya, G. Review on sun tracking technology in solar PV system. *Energy Rep.* **2020**, *6*, 392–405. [\[CrossRef\]](#)
- Ahmad, M.Z.; Ahmad, S.H.; Chen, R.S.; Ismail, A.F.; Hazan, R.; Baharuddin, N.A. Review on recent advancement in cathode material for lower and intermediate temperature solid oxide fuel cells application. *Int. J. Hydrog. Energy* **2022**, *47*, 1103–1120. [\[CrossRef\]](#)
- Yang, B.; Wang, J.; Yu, L.; Shu, H.; Yu, T.; Zhang, X.; Sun, L. A critical survey on proton exchange membrane fuel cell parameter estimation using meta-heuristic algorithms. *J. Clean. Prod.* **2020**, *265*, 121660. [\[CrossRef\]](#)
- Fathy, A.; Yousri, D.; Alanazi, T.; Rezk, H. Minimum hydrogen consumption-based control strategy of fuel cell/PV/battery/super-capacitor hybrid system using recent approach-based parasitism-predation algorithm. *Energy* **2021**, *225*, 120316. [\[CrossRef\]](#)

8. Ghaffari, A.; Askarzadeh, A. Design optimization of a hybrid system subject to reliability level and renewable energy penetration. *Energy* **2020**, *193*, 116754. [\[CrossRef\]](#)
9. Singh, M.; Zappa, D.; Comini, E. Solid oxide fuel cell: Decade of progress, future perspectives and challenges. *Int. J. Hydrog. Energy* **2021**, *46*, 27643–27674. [\[CrossRef\]](#)
10. Melzi, B.; Kefif, N.; El Haj Assad, M. Modelling and optimal design of hybrid power system photovoltaic/solid oxide fuel cell for a mediterranean City. *Energy Eng.* **2021**, *118*, 1767–1781. [\[CrossRef\]](#)
11. Siti Khodijah, A.; Shiba, M.; Obara, S.Y. Design of compensation battery for tidal power-photovoltaics-SOFC microgrids in Ternate and Pulau-Tidore Islands. *Int. J. Energy Res.* **2021**, *45*, 2100–2115. [\[CrossRef\]](#)
12. Wang, J.; Yang, B.; Li, D.; Zeng, C.; Chen, Y.; Guo, Z.; Yu, T. Photovoltaic cell parameter estimation based on improved equilibrium optimizer algorithm. *Energy Convers. Manag.* **2021**, *236*, 114051. [\[CrossRef\]](#)
13. He, X.; Ai, Q.; Qiu, R.C.; Huang, W.; Piao, L.; Liu, H. A big data architecture design for smart grids based on random matrix theory. *IEEE Trans. Smart Grid* **2015**, *8*, 674–686. [\[CrossRef\]](#)
14. Grieves, M. Digital twin: Manufacturing excellence through virtual factory replication. *White Pap.* **2017**. [\[CrossRef\]](#)
15. Singh, M.; Srivastava, R.; Fuenmayor, E.; Kuts, V.; Qiao, Y.; Murray, N.; Devine, D. Applications of Digital Twin across industries: A review. *Appl. Sci.* **2022**, *12*, 5727. [\[CrossRef\]](#)
16. Yang, B.; Wang, J.; Zhang, X.; Yu, T.; Yao, W.; Shu, H.; Sun, L. Comprehensive overview of meta-heuristic algorithm applications on PV cell parameter identification. *Energy Convers. Manag.* **2020**, *208*, 112595. [\[CrossRef\]](#)
17. Yang, B.; Wang, J.; Zhang, M.; Shu, H.; Yu, T.; Zhang, X.; Sun, L. A state-of-the-art survey of solid oxide fuel cell parameter identification: Modelling, methodology, and perspectives. *Energy Convers. Manag.* **2020**, *213*, 112856. [\[CrossRef\]](#)
18. Abbassi, R.; Abbassi, A.; Jemli, M.; Chebbi, S. Identification of unknown parameters of solar cell models: A comprehensive overview of available approaches. *Renew. Sustain. Energy Rev.* **2018**, *90*, 453–474. [\[CrossRef\]](#)
19. Oliva, D.; Cuevas, E.; Pajares, G. Parameter identification of solar cells using artificial bee colony optimization. *Energy* **2014**, *72*, 93–102. [\[CrossRef\]](#)
20. Xiong, G.; Zhang, J.; Shi, D.; He, Y. Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm. *Energy Convers. Manag.* **2018**, *174*, 388–405. [\[CrossRef\]](#)
21. Nayak, B.; Mohapatra, A.; Mohanty, K.B. Parameter estimation of single diode PV module based on GWO algorithm. *Renew. Energy Focus* **2019**, *30*, 1–12. [\[CrossRef\]](#)
22. Dang, J.; Wang, G.; Xia, C.; Jia, R.; Li, P. Research on the parameter identification of PV module based on fuzzy adaptive differential evolution algorithm. *Energy Rep.* **2022**, *8*, 12081–12091. [\[CrossRef\]](#)
23. Eltamaly, A.M. Musical chairs algorithm for parameters estimation of PV cells. *Sol. Energy* **2022**, *241*, 601–620. [\[CrossRef\]](#)
24. Cao, H.; Deng, Z.; Li, X.; Yang, J.; Qin, Y. Dynamic modeling of electrical characteristics of solid oxide fuel cells using fractional derivatives. *Int. J. Hydrog. Energy* **2010**, *35*, 1749–1758. [\[CrossRef\]](#)
25. Caliendo, P.; Nakajo, A.; Diethelm, S. Model-assisted identification of solid oxide cell elementary processes by electrochemical impedance spectroscopy measurements. *J. Power Sources* **2019**, *436*, 226838. [\[CrossRef\]](#)
26. Jayasankar, B.R.; Huang, B.; Ben-Zvi, A. Receding horizon experiment design with application in sofc parameter estimation. *IFAC Proc. Vol.* **2010**, *43*, 541–546. [\[CrossRef\]](#)
27. Yang, J.; Li, X.; Jiang, J.H.; Jian, L.; Zhao, L.; Jiang, J.G.; Xu, L.H. Parameter optimization for tubular solid oxide fuel cell stack based on the dynamic model and an improved genetic algorithm. *Int. J. Hydrog. Energy* **2011**, *36*, 6160–6174. [\[CrossRef\]](#)
28. Gong, W.; Cai, Z.; Yang, J.; Li, X.; Jian, L. Parameter identification of an SOFC model with an efficient, adaptive differential evolution algorithm. *Int. J. Hydrog. Energy* **2014**, *39*, 5083–5096. [\[CrossRef\]](#)
29. Jiang, B.; Wang, N.; Wang, L. Parameter identification for solid oxide fuel cells using cooperative barebone particle swarm optimization with hybrid learning. *Int. J. Hydrog. Energy* **2014**, *39*, 532–542. [\[CrossRef\]](#)
30. Wei, Y.; Stanford, R.J. Parameter identification of solid oxide fuel cell by Chaotic Binary Shark Smell Optimization method. *Energy* **2019**, *188*, 115770. [\[CrossRef\]](#)
31. Yang, B.; Chen, Y.; Guo, Z.; Wang, J.; Zeng, C.; Li, D.; Zhang, X. Levenberg-Marquardt backpropagation algorithm for parameter identification of solid oxide fuel cells. *Int. J. Energy Res.* **2021**, *45*, 17903–17923. [\[CrossRef\]](#)
32. Yang, B.; Zeng, C.; Wang, L.; Guo, Y.; Chen, G.; Guo, Z.; Zhu, J. Parameter identification of proton exchange membrane fuel cell via Levenberg-Marquardt backpropagation algorithm. *Int. J. Hydrog. Energy* **2021**, *46*, 22998–23012. [\[CrossRef\]](#)
33. Yang, B.; Guo, Z.; Yang, Y.; Chen, Y.; Zhang, R.; Su, K.; Zhang, X. Extreme learning machine based meta-heuristic algorithms for parameter extraction of solid oxide fuel cells. *Appl. Energy* **2021**, *303*, 117630. [\[CrossRef\]](#)
34. Wang, J.; Xu, Y.P.; She, C.; Xu, P.; Bagal, H.A. Optimal parameter identification of SOFC model using modified gray wolf optimization algorithm. *Energy* **2022**, *240*, 122800. [\[CrossRef\]](#)
35. Jordehi, A.R. Parameter estimation of solar photovoltaic (PV) cells: A review. *Renew. Sustain. Energy Rev.* **2016**, *61*, 354–371. [\[CrossRef\]](#)
36. Muangkote, N.; Sunat, K.; Chiewchanwattana, S.; Kaiwinit, S. An advanced onlooker-ranking-based adaptive differential evolution to extract the parameters of solar cell models. *Renew. Energy* **2019**, *134*, 1129–1147. [\[CrossRef\]](#)
37. Wang, L.; Cao, Q.; Zhang, Z.; Mirjalili, S.; Zhao, W. Artificial rabbits optimization: A new bio-inspired meta-heuristic algorithm for solving engineering optimization problems. *Eng. Appl. Artif. Intell.* **2022**, *114*, 105082. [\[CrossRef\]](#)

38. Easwarakhanthan, T.; Bottin, J.; Bouhouch, I.; Boutrit, C. Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers. *Int. J. Sol. Energy* **1986**, *4*, 1–12. [[CrossRef](#)]
39. Hagan, M.T.; Demuth, H.B.; Beale, M.H. *Neural Network Design*; PWS Publishing Co.: Boston, MA, USA, 2002.
40. Yang, B.; Li, D.Y.; Zeng, C.Y.; Chen, Y.J.; Guo, Z.X.; Wang, J.B.; Shu, H.C.; Yu, T.; Zhu, J.W. Parameter extraction of PEMFC via Bayesian regularization neural network based meta-heuristic algorithms. *Energy* **2021**, *228*, 120592. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.