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Maiden Application of Sinh Cosh Optimizer for Parameter Extraction of Photovoltaic Cell Models

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Accurate parameter extraction for PV models is essential for optimizing solar energy systems, with metaheuristic algorithms commonly employed for this purpose. However, existing methods like PSO and ABC often suffer from slow convergence, poor exploration-exploitation balance, and limited precision, especially for complex models such as the three-diode PV model.*

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This study introduces the SCHO for the first time in PV parameter extraction, achieving superior accuracy with consistently low RMSE values across single-, double-, and three-diode models, as well as PV module models. The results highlight its versatility and reliability in diverse PV modeling scenarios.*
- *By leveraging the unique properties of hyperbolic functions and balancing exploration and exploitation phases effectively, the SCHO addresses key limitations of existing methods. It ensures faster convergence, higher stability, and improved parameter optimization for complex PV systems, significantly advancing the field of solar energy research.*

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ABSTRACT

Environmental concerns and climate change have accelerated the worldwide transition to renewable energy sources, with solar power rising to the forefront as a leading contender thanks to its availability, affordability, and relative lack of pollution. To fully realize this potential, it is essential to conduct thorough and accurate modeling of photovoltaic (PV) systems, which requires exact parameter estimations inside PV models. In order to overcome these obstacles, this study is the first of its kind to use the newly created sinh cosh optimizer (SCHO) in parameter estimation. Achieving exact parameter extraction is greatly assisted by the SCHO, a novel metaheuristic approach. As a standard for impartiality and scientific consistency, the study employs the solar cell from RTC France. The four main types of PV systems are the single-diode (SD), double-diode (DD), three-diode (TD), and PV module series. All of these models use the same experimental methodology to include the SCHO in parameter tweaking. With the RTC France solar cell selected for the SD, DD, and TD models and the Photowatt-PWP201 for the PV module model, the SCHO has a solid foundation for evaluation thanks to its prominence in the field. Results from statistical and convergence investigations show that SCHO can reliably estimate current–voltage characteristics with minimal root mean square errors (RMSEs). One further thing that proves it works is how smoothly it converges. Through a comparison with alternative approaches, SCHO is shown to be the best at optimizing the solar PV models' parameters, which means it has the ability to greatly increase solar energy usage.

***Index Terms*—**Metaheuristic algorithms, parameter extraction, photovoltaic (PV) cell models, sinh cosh optimizer (SCHO)

I. INTRODUCTION

A dramatic increase in interest in renewable energy sources has been witnessed in recent years, driven by growing concerns about the impact of traditional fossil fuels such as coal, oil, and gas on the environment and the severity of climate change [1]. Solar energy stands out among these sustainable alternatives since it is abundant, cheap, clean, and everywhere [2]. Photovoltaic (PV) systems are an effective way to tap into this limitless energy source, and accurate modeling is crucial to the system's success [3].

The modeling of PV systems commonly makes use of three well-known PV cell models: the single-diode (SD), double-diode (DD), and more sophisticated three-diode (TD) models. On the other hand, these models include a number of concealed physical characteristics that are not included in the datasheets given by the manufacturer [4]. It is necessary to accurately determine these unknown characteristics for various reasons, including quality assurance, performance evaluation, and the essential function of maximum power point tracking in PV systems [5].

When it comes to the efficient utilization of solar cells and modules and their incorporation into renewable energy systems, having a firm grasp of the criteria that determine their performance is absolutely necessary [6]. When seen in this light, methods of parameter estimation have evolved into indispensable instruments. There is a comprehensive evaluation of recent advancements in optimization strategies for extracting parameters in PV models that can be found in the published literature [7–15]. The studies employed various metaheuristic algorithms to tackle the intricate challenges associated with accurately estimating parameters crucial for optimizing PV system efficiency. For example, the bald eagle search algorithm showcased superior accuracy in SD and DD models, emphasizing its effectiveness in identifying and optimizing PV solar cell parameters [16]. The circle search algorithm addressed the nonlinearity and complexity of the TD model, exhibiting robustness and speed in determining optimal parameters for PV modules [17]. The artificial hummingbird algorithm has emerged as one of the most effective approaches for parameter extraction in various PV models, consistently outperforming alternative methods in terms of precision and accuracy [18]. A significant contribution in this area came from the weighted mean of vectors technique, known as the INFO method, which demonstrated statistical superiority by providing exceptional accuracy and reliability when applied to a wide range of PV cells and modules [19]. The versatility of the INFO method became evident through its successful application to both SD and DD models, further solidifying its potential to drive advancements in solar energy systems by ensuring more efficient parameter extraction [20]. Furthermore, the dandelion optimizer, when integrated with the Newton-Raphson numerical approach, offered distinct advantages not only in terms of accuracy but also in dependability and convergence speed, proving its effectiveness in tackling complex optimization challenges [21]. These developments highlight the continuous evolution of parameter extraction techniques, paving the way for more robust and efficient solutions in solar energy research and implementation.

These studies collectively offer crucial insights into the evolving landscape of optimization techniques for PV parameter extraction, significantly contributing to the development of more efficient and sustainable PV systems. Each method brings unique innovations and advantages, accelerating advancements in renewable energy research. However, despite their benefits, certain approaches face notable challenges, such as slow convergence and limited population diversity, which can hinder performance under certain conditions [22]. Moreover, the inherent randomness in metaheuristic algorithms can occasionally lead to suboptimal convergence rates and stability issues. A major limitation in the current body of research is the predominant focus on parameter estimation for SD and DD models, with minimal attention given to more complex models like the TD model [23].

In response to these gaps, this study takes on the critical challenge of PV model parameter estimation, introducing a novel and highly efficient methodology. Specifically, this paper proposes the sinh cosh optimization (SCHO) method [24], an innovative metaheuristic designed for parameter estimation in PV models. To the best of our knowledge, this is the first research to explore and demonstrate the potential of the SCHO in the context of PV parameter extraction. The SCHO method offers several unique advantages that set it apart from conventional algorithms. First, by harnessing the distinctive mathematical properties of the hyperbolic sine and cosine functions, SCHO facilitates faster convergence toward optimal solutions, which is particularly advantageous in real-time applications where rapid parameter adjustment is essential. Additionally, the SCHO method incorporates a dynamic switching mechanism between exploration and exploitation phases, ensuring a balanced approach that allows for thorough global search (exploration) while also refining local optima (exploitation). This feature helps to prevent premature convergence, a common issue in widely used techniques such as particle swarm optimization (PSO) and atom search optimization (ASO). Moreover, the SCHO consistently achieves lower root mean square error (RMSE) values with smaller standard deviations when compared to traditional algorithms, indicating higher accuracy and reliability. Another notable strength of SCHO is its adaptive weighting mechanism, which introduces variability within the population, thereby enhancing diversity and improving the algorithm's global search capabilities. These features collectively position SCHO as a robust and effective solution for overcoming the limitations observed in previous PV parameter extraction methods.

This research focuses on the RTC France solar cell, examining its performance across SD, DD, and TD models, as well as the Photowatt-PWP201 PV module, which is included as an additional case study. These models are widely used benchmarks in PV research, offering well-documented performance data, which ensures their suitability for validating new optimization algorithms. The RTC France solar cell has been extensively used in the literature for its accuracy in representing typical solar cell behavior, making it a reliable choice for comparison with other methods. Similarly, the Photowatt-PWP201 module provides robust evaluation metrics for PV module modeling, particularly in multi-diode and module parameter estimation studies. These factors make them ideal for evaluating the effectiveness of the SCHO across diverse PV models.

Statistical and convergence analyses were implemented to guarantee that our findings were thoroughly assessed and interpreted. These analyses provided essential insights, enabling us to draw meaningful conclusions about the efficacy of the SCHO in optimizing a variety of solar cell models. The SCHO's experimental results for various model optimizations indicate that parameter estimation is highly precise. The algorithm that has been proposed consistently obtains low RMSE values, which confirms its superior capacity to precisely estimate current–voltage characteristics. Furthermore, the SCHO exhibits seamless and consistent convergence behavior. The method's accuracy in modeling is demonstrated by the firm congruence between the experimental and estimated values, as indicated by the performance metrics. We also conducted a comprehensive statistical comparison of the SCHO's performance with alternative methods [25–37]. This comparison further underscores the competitive advantage of the SCHO in terms of optimization of PV model parameters.

To summarize, this work introduces the SCHO method for the first time in literature as a potent and contemporary metaheuristic approach for PV models' parameter estimation, addressing existing gaps in the optimization landscape. The application of the SCHO to the RTC France solar cell and Photowatt-PWP201 PV module showcases its effectiveness in navigating the intricate parameter space of diverse solar cell models, emphasizing its potential for advancing the field of renewable energy. The statistical and convergence analyses provide robust evidence of the SCHO's superior performance, setting it apart from alternative methods. This study contributes a novel methodology to the evolving field of PV parameter optimization, promising enhanced efficiency and sustainability in PV systems.

II. SINH COSH OPTIMIZER

An innovative new metaheuristic algorithm called SCHO uses the hyperbolic trigonometric functions of sinh and cosh [24] to find the best solution. Exploration, exploitation, bounded search, and switching methods are the four most important parts of the SCHO. Like other metaheuristic algorithms, SCHO starts by picking a set of possible answers at random, as shown in (1).

$$X=\begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & x_{1,dim-1} & x_{1,dim} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,dim} \\ \cdots & \cdots & x_{i,j} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & x_{N-1,j} & \cdots & x_{N-1,dim} \\ x_{N,1} & \cdots & x_{N,j} & x_{N,dim-1} & x_{N,dim} \end{bmatrix} \tag{1}$$

In (1), $x_{i,j}$ is the jth point of the ith solution, N is the number of possible solutions, dim is the size of the problem, and X is a set of random possible solutions found by running $= rand\ (N,\ dim) \times (ub - lb) + lb$. In the latter definition, $rand$ is a random number between 0 and 1, and ub and lb are the upper and lower limits, respectively. The SCHO exploration phase is made up of two parts, which are chosen by $T = floor\ (t_{Max}/ct)$, where t_{Max} is the highest number of iterations and ct is the switching coefficient, which is set to 3.6 by default for SCHO. The following description is used for the first part of the exploration.

$$X_{(i,j)}^{t+1}=\begin{cases} X_{(best)}^{(j)}+r_1\times W_1\times X_{(i,j)}^{t}, r_2>0.5 \\ X_{(best)}^{(j)}-r_1\times W_1\times X_{(i,j)}^{t}, r_2<0.5 \end{cases} \tag{2}$$

Here, $X_{(i,j)}^{t+1}$ and $X_{(i,j)}^{t}$ are the jth and ith positions of the ith solution in the next and current iterations, respectively. $X_{(best)}^{(j)}$ is the jth position of the best solution found so far, and r_1 and r_2 are random numbers in the range [0, 1]. In the first exploration phase, W_1 is the weighting coefficient of $X_{(i,j)}^{t}$. It can be written as $W_1 = r_3 \times \alpha_1 \times (\cosh r_4 + 0.388 \times \sinh r_4 - 1)$. In this case, r_3 and r_4 are random numbers between 0 and 1, and $\alpha_1 = 3 \times (-1.3 \times (t/t_{Max}) + 0.45)$. The following position update rule is used in the second part of the exploration.

$$X_{(i,j)}^{t+1}=\begin{cases} X_{(i,j)}^{t}+\left|0.003\times W_2\times X_{best}^{(j)}-X_{(i,j)}^{t}\right|, r_5>0.5 \\ X_{(i,j)}^{t}-\left|0.003\times W_2\times X_{best}^{(j)}-X_{(i,j)}^{t}\right|, r_5<0.5 \end{cases} \tag{3}$$

In the second exploration phase, W_2 is the weighting coefficient of $X_{(i,j)}^{t}$. It is described as $W_2 = r_6 \times \alpha_2$. In this case, r_5 and r_6 are random numbers between 0 and 1, and $\alpha_2 = 2 \times (-(t/t_{Max}) + 0.5)$. The exploitation phase also has two parts, just like the exploration phase. The following definition is used in the first step of exploitation.

$$X_{(i,j)}^{t+1}=\begin{cases} X_{best}^{(j)}+r_7\times W_3\times X_{(i,j)}^{t}, r_8>0.5 \\ X_{best}^{(j)}-r_7\times W_3\times X_{(i,j)}^{t}, r_8<0.5 \end{cases} \tag{4}$$

Here, r_7 and r_8 are random numbers between 0 and 1. In the first step of exploitation, W_3 is the weighting coefficient of $X_{(i,j)}^{t}$. It can be written as $W_3 = r_9 \times \alpha_1 \times (\cosh r_{10} + 0.388 \times \sinh r_{10})$. r_9 and r_{10} are picked at random from the range [0, 1]. The following definition is used to do deep exploitation around the best solution found so far in the second exploitation step:

$$X_{(i,j)}^{t+1}=X_{(i,j)}^{t}+r_{11}\times\frac{\sinh r_{12}}{\cosh r_{12}}\left|W_2\times X_{best}^{(j)}-X_{(i,j)}^{t}\right| \tag{5}$$

where r_{11} and r_{12} are numbers picked at random from the range [0, 1]. This type of search technique is also used in SCHO. For this approach to work, the following form is used:

$$BS_{k+1}=BS_k+floor\left[(t_{Max}-BS_k)/4.6\right] \tag{6}$$

where k is a positive number that starts at 1, and BS_{k+1} and BS_k are the amounts of times the next and current bounded search strategies are run. To move from exploration to exploitation in SCHO, there is a switching process. The following definition is used to describe the switching mechanism employed in the SCHO method.

$$A=\left(10-9\times\left(t/t_{Max}\right)^{\frac{\cosh(t/t_{Max})}{\sinh(t/t_{Max})}}\right)\times r_{13} \tag{7}$$

where r_{13} are random numbers within [0, 1]. For $A > 1$, SCHO performs exploration and for $A < 1$, the exploitation is performed. In light of the description provided so far, Fig. 1 displays a detailed flowchart of the SCHO method.

III. SOLAR PHOTOVOLTAIC SYSTEM'S PROBLEM FORMULATION

A. Model 1: Single Diode

As a simplified but useful mathematical picture of how a PV cell works electrically, the SD model is useful. The idea behind this form is that a SD linked in series with a current source can well represent the PV cell. Even though it is very basic, the SD model does a good job of capturing the most important parts of the PV cell's electrical reaction while still being computationally efficient. The link between a PV cell's current and voltage is shown below in the SD model.

$$I=I_{ph}-I_{sd}\left[e^{\frac{(V+IR_s)}{(nV_t)}}-1\right]-\frac{(V+IR_s)}{R_{sh}} \tag{8}$$

In (8), I represents the PV cell's output current, and V is the voltage across its terminals. The photocurrent generated by the cell when exposed to light is denoted as I_{ph}, while I_{sd} refers to the diode saturation current. R_s and R_{sh} represent the series and shunt resistances of the cell, respectively. The diode ideality factor is given as n, and the thermal voltage V_t is defined as kT/q, where k is Boltzmann's constant, T is the temperature in Kelvin, and q is the elementary charge. Fig. 2 is a conceptual drawing of a solar PV cell using the SD model. It shows a similar circuit to help understand it better.

B. Model 2: Double Diode

The DD model is a more advanced way to describe PV cells because it includes more diodes to account for more complex electrical behavior. This improved model adds an extra diode to deal with recombination losses in the PV cell. This makes the model more accurate and complex in representing how PV cells work in the real world. In the DD model, the following equation shows how the current and voltage of a PV cell are related:

$$I=I_{ph}-I_{sd1}\left[e^{\frac{(V+IR_s)}{(n_1V_t)}}-1\right]-I_{sd2}\left[e^{\frac{(V+IR_s)}{(n_2V_t)}}-1\right]-\frac{(V+IR_s)}{R_{sh}} \tag{9}$$

In this text, the main diode's saturation current is represented by I_{sd1}, and the extra diode's saturation current is denoted by I_{sd2}. The main

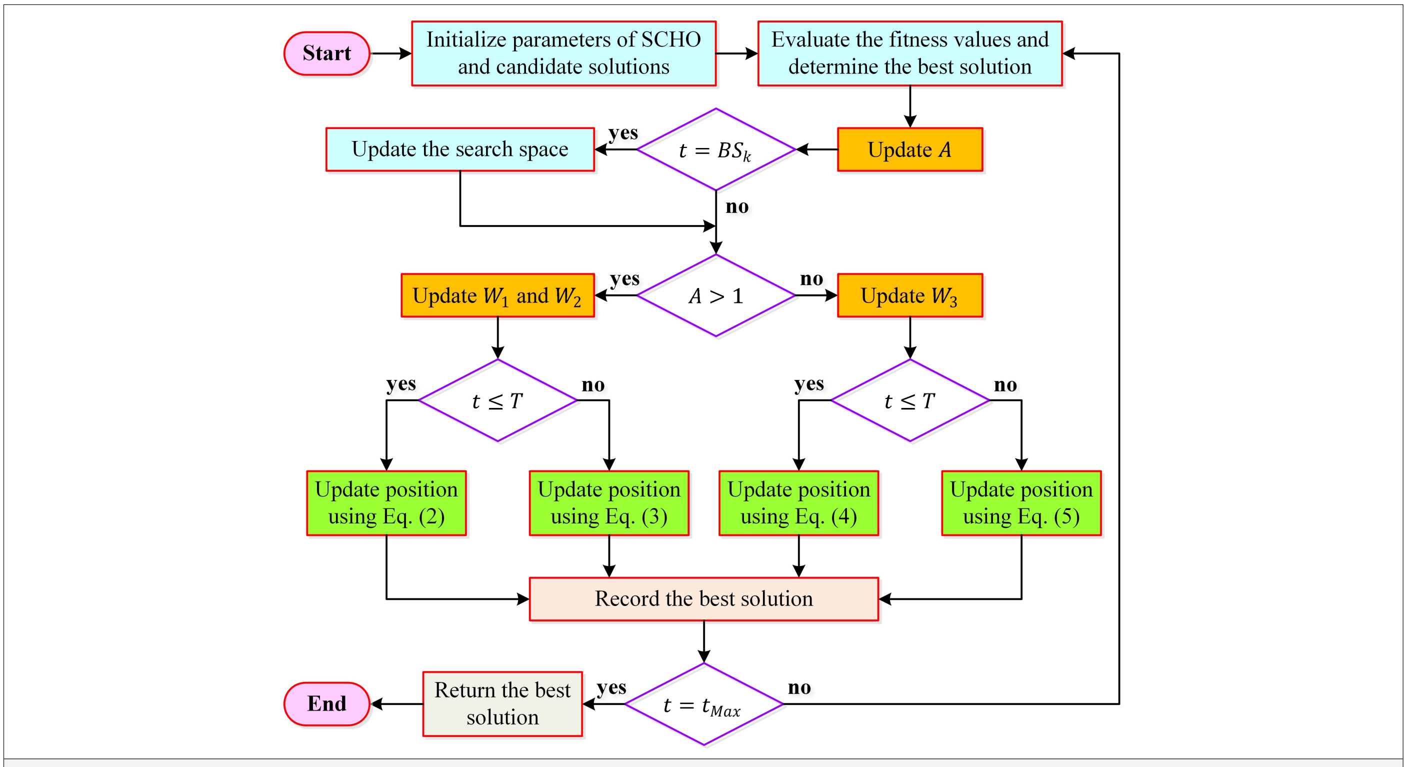

Fig. 1. Flowchart of sinh cosh optimization.

diode's ideality factor is n_1, and the extra diode's ideality factor is n_2. In Fig. 3, the DD model is used to show how a solar PV cell works in theory.

C. Model 3: Three Diode

While the SD and DD models give a better idea of how a PV cell works, the TD model provides a more detailed picture. This model shows that $I = I_{ph} - I_{d}1 - I_{d2} - I_{d3} - I_{sh}$, where I_{d1} denotes the current through the ideal diode, I_{d2} represents the current through the recombination diode, and I_{d3} corresponds to the current flowing through the shunt diode. Given this configuration, the total current in the PV cell within the TD model can be determined by summing the currents from these three diodes.

$$I = I_{ph} - I_{sd1}\left(e^{\frac{V+IR_s}{n_1 V_t}} - 1\right) - I_{sd2}\left(e^{\frac{V+IR_s}{n_2 V_t}} - 1\right) - I_{sd3}\left(e^{\frac{V+IR_s}{n_3 V_t}} - 1\right) - \frac{V+IR_s}{R_{sh}} \quad (10)$$

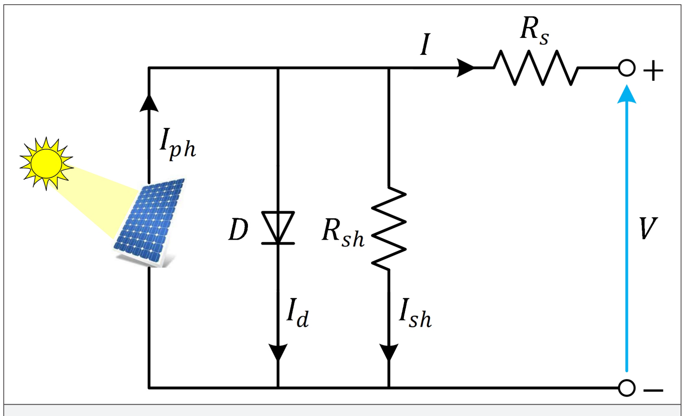

Fig. 2. Equivalent circuit for single-diode model.

In here, the ideality factors of the diodes D_1, D_2, and D_3 are given by n_1, n_2, and n_3, respectively. Using the TD model, Fig. 4 shows the corresponding circuit of a solar PV cell.

D. Model 4: Photovoltaic Module

The PV module model illustrates the relationship between temperature, sunlight exposure, and the module's electrical characteristics. This model assumes that the PV module can be represented by a SD connected in parallel with a current source. The circuit diagram corresponding to this PV module is depicted in Fig. 5. In this configuration, N_p and N_s represent the number of cells connected in parallel and series, respectively. Typically, $N_p = 1$, as most solar cells are arranged in series. Based on this configuration, the following provides a mathematical representation of a PV module.

$$I = I_{ph} - I_{sd}\left[e^{\frac{(V+IR_sN_s)}{(nN_sV_t)}} - 1\right] - \frac{(V+IR_sN_s)}{R_{sh}N_s} \quad (11)$$

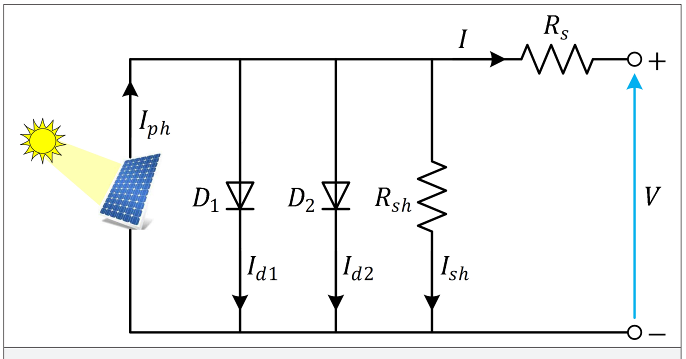

Fig. 3. Equivalent circuit for double-diode model.

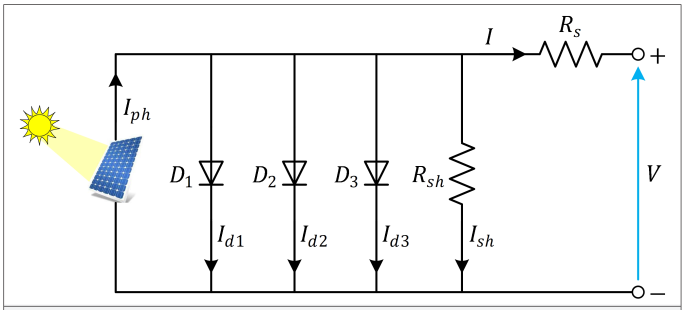

Fig. 4. Equivalent circuit for three-diode model.

IV. DEFINITION OF OPTIMIZATION PROBLEM AND IMPLEMENTATION OF SING COSH OPTIMIZER METHOD

The objective function is an integral component of the process of parameter estimation in PV cells. Its purpose is to evaluate the correctness of the estimated parameters by comparing the modeled current–voltage curve with the actual data that was measured. The RMSE is a measure that is frequently utilized for the purpose of measuring the degree of goodness of fit. In accordance with (12), this metric provides a quantitative representation of the average size of the differences that exist between the estimated current (I_{est}) and the experimentally observed current (I_{exp}).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{exp} - I_{est}\right)^2} \tag{12}$$

In this context, N denotes the complete set of data points. Root mean square error offers a thorough evaluation of the total discrepancy between the model and the observed data. In light of the foregoing explanation, Fig. 6 illustrates the schematic diagram of parameter estimation for PV models using the SCHO method.

V. ANALYSIS OF SIMULATION OUTCOMES AND DISCUSSION

This section presents the experimental results and statistical analyses. The RTC France solar cell and the Photowatt-PWP201 PV module are used as case studies. To ensure uniformity and objectivity, a set population size of 40 and a maximum of 500 iterations were applied to all trials. Each case study was also run 25 times to account for any differences that might have occurred during the optimization process. We used the SCHO method to fine-tune the settings for improving the SD, DD, TD, and PV models. This allowed us see how

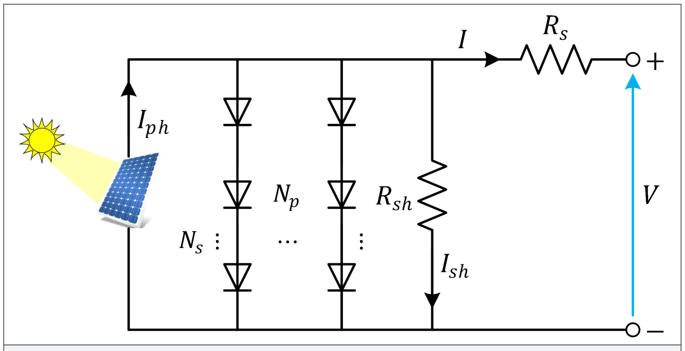

Fig. 5. Equivalent circuit for photovoltaic module model.

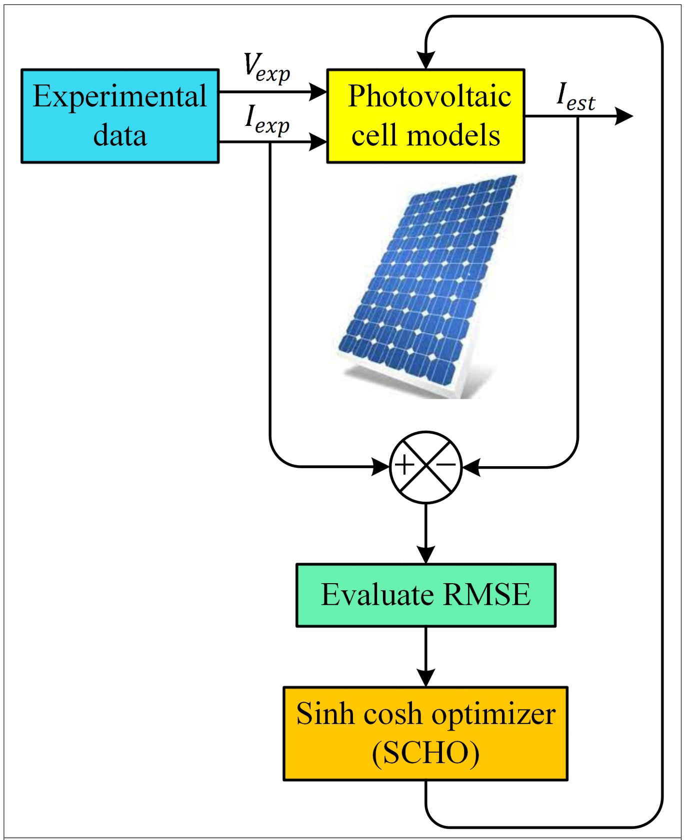

Fig. 6. Schematic diagram of parameter estimation of photovoltaic models via sinh cosh optimizer method.

well it worked with different types of solar cells. The parameter limits for the SD, DD, and TD models are provided in Table I, while Table II describes the limits for the PV model.

A. Simulation Results of Single-Diode Model

This section presents the experimental results of the SD model optimization achieved using the SCHO. Table III provides a summary of the estimated parameters for the SD model, along with the corresponding statistical RMSE value. The results highlight the SCHO's capability to deliver a low RMSE, demonstrating high accuracy in parameter estimation and precise modeling of the current–voltage characteristics for the SD model. Additionally, Figs. 7 and 8 showcase

TABLE I. PARAMETER LIMITS OF SINGLE-DIODE, DOUBLE-DIODE, AND THREE-DIODE MODELS

Parameter	Lower Limit	Upper Limit
I_{ph} (A)	0	1
I_{sd} (μA)	0	1
I_{sd1}, I_{sd2}, I_{sd3} (μA)	0	1
R_s (Ω)	0	0.5
R_{sh} (Ω)	0	100
n	1	2
n_1, n_2, n_3	1	2

TABLE II. PARAMETER LIMITS OF PHOTOVOLTAIC MODULE MODELS

Parameter	Lower Limit	Upper Limit
I_{ph} (A)	0	2
I_{sd} (μA)	0	50
R_s (Ω)	0	2
R_{sh} (Ω)	0	2000
n	1	50

the current-voltage and power–voltage curves for the SD model optimized through SCHO. These figures clearly illustrate that the optimized model effectively captures the solar cell's behavior, as shown by the close match between the curves and the experimental data.

In terms of demonstrating the efficacy of the SCHO for the SD model optimization, a comparative assessment was also performed by using 13 different approaches reported for the SD modeling in the literature. These methods include teaching–learning-based artificial bee colony (TLABC) algorithm [28], slime mould algorithm (SMA) [34], inspired grey wolf (IGWO) [29], gradient-based (GBO) [32], PSO [37], improved learning search (ILSA) [26], generalized oppositional teaching learning (GOTLBO) [27], improved opposition-based whale (OBWOA) [30], comprehensive learning particle swarm (CLPSO) [36], sunflower (SFO) [31], spherical evolution (SE) [33], hybrid multi-group stochastic cooperative particle swarm (HMSCPSO) [25], and ASO [35] algorithms.

The results in Table IV demonstrate that the SCHO method exhibits remarkable performance in the comparison of RMSE results with 13 other optimization algorithms applied to the SD model. Sinh cosh optimizer consistently achieves a minimum, maximum, and mean RMSE of 9.8602E–04, showcasing remarkable stability and uniformity in its outcomes. The exceptionally low standard deviation of 7.1590E–18 further underscores the method's precision, indicating almost negligible variation in results across multiple runs. In comparison to alternative algorithms, SCHO's performance is not only comparable in terms of minimum and mean RMSE values but also stands out for its unparalleled consistency, as reflected in the substantially lower standard deviation.

The efficacy of the SCHO method is particularly noteworthy when considering its consistent and reliable performance in minimizing RMSE, positioning it as a highly promising and dependable approach for SD model optimization in contrast to the other algorithms assessed in this study.

B. Simulation Results of Double-Diode Model

This section presents the experimental results of the DD model optimization performed using the SCHO. Table V provides a summary

TABLE III. ESTIMATED PARAMETERS OF SINGLE-DIODE MODEL WITH SINH COSH OPTIMIZER METHOD

I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	n	RMSE
0.76078	0.32302	0.036377	53.719	1.4812	9.8602E–04

RMSE, root mean square error.

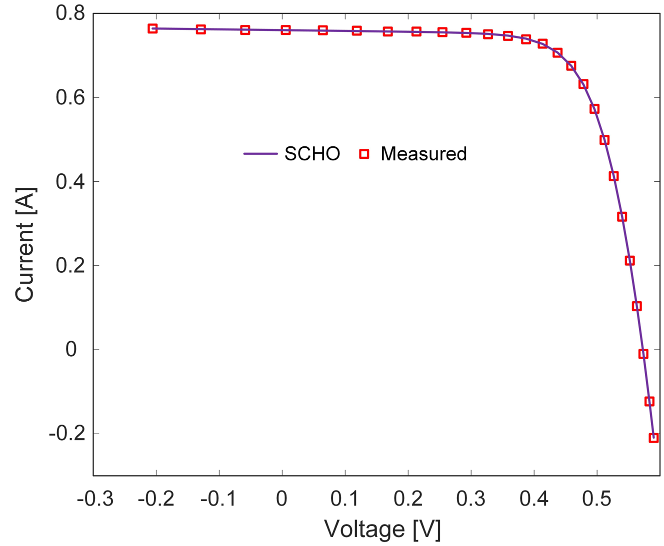

Fig. 7. Current–voltage curve characteristics of single-diode model.

of the estimated parameters for the DD model, along with the corresponding RMSE value. The results highlight the SCHO's capability to achieve a low RMSE and deliver accurate parameter estimation, indicating precise modeling of the current–voltage characteristics for the DD model.

It is also important to note that Figs. 9 and 10 illustrate the current–voltage and power–voltage curves of the DD model that has been tuned with SCHO. The improved model is able to correctly depict the behavior of the solar cell, as evidenced by the fact that the curves and the experimental data are so closely matched with one another. That the model is successful in accomplishing this goal is demonstrated by these figures in a compelling manner.

To further demonstrate the efficacy of the SCHO for the DD model optimization, a comparative assessment was also performed by using 13 different approaches (listed in Table VI) reported for the DD

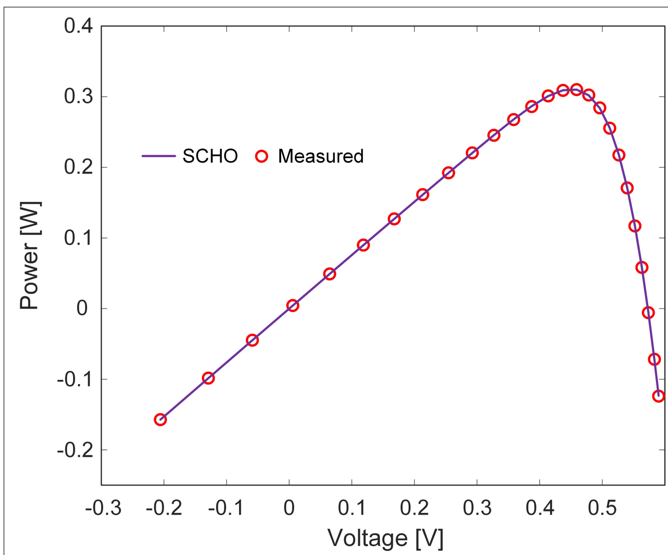

Fig. 8. Power–voltage curve characteristics of single-diode model.

TABLE IV. COMPARISON OF ROOT MEAN SQUARE ERROR RESULTS BETWEEN SINH COSH OPTIMIZER AND 13 DIFFERENT METHODS REPORTED FOR THE SINGLE-DIODE MODEL

Algorithm	Minimum	Maximum	Mean	Standard Deviation
HMSCPSO	**9.8602E–04**	**9.8602E–04**	**9.8602E–04**	5.7282E–15
PSO	1.4385E–03	2.0699E–01	1.8551E–02	3.9068E–02
CLPSO	9.8615E–04	1.1402E–03	1.0047E–03	3.6466E–05
ASO	1.2608E–03	1.4181E–02	3.0480E–03	3.2805E–03
SMA	1.2064E–03	3.8140E–03	1.9438E–03	5.5692E–04
SE	2.4378E–03	2.4430E–03	2.4396E–03	1.5243E–06
GBO	**9.8602E–04**	**9.8602E–04**	**9.8602E–04**	1.0895E–12
SFO	1.0027E–03	9.5160E–03	3.1403E–03	2.0117E–03
OBWOA	9.8960E–04	7.0588E–03	1.9502E–03	1.1035E–03
IGWO	1.6799E–03	4.1120E–02	6.6947E–03	7.4765E–03
TLABC	9.8608E–04	1.0452E–03	9.9642E–04	1.2797E–05
GOTLBO	**9.8602E–04**	**9.8602E–04**	**9.8602E–04**	7.8549E–12
ILSA	9.9977E–04	4.4647E–03	1.3851E–03	6.8799E–04
SCHO	**9.8602E–04**	**9.8602E–04**	**9.8602E–04**	**7.1590E–18**

ASO, atom search optimization; CLPSO, comprehensive learning particle swarm; GBO, gradient-based; GOTLBO, generalized oppositional teaching learning; HMSCPSO, hybrid multi-group stochastic cooperative particle swarm; IGWO, inspired grey wolf; ILSA, improved learning search; OBWOA, improved opposition-based whale optimization; PSO, particle swarm optimization; SE, spherical evolution; SFO, sunflower; SMA, slime mould algorithm; TLABC, teaching–learning-based artificial bee colony.

modeling in the literature. The effectiveness of the SCHO method is evident in its application to the DD model optimization, as demonstrated by the RMSE comparison with 13 other optimization algorithms. Sinh cosh optimizer consistently achieves a minimum, maximum, and mean RMSE of 9.8248E−04, underlining its robust and reliable performance.

The standard deviation, remarkably low at 5.9197E−12, emphasizes the method's precision and stability across multiple runs. In contrast to alternative algorithms, SCHO's performance is not only competitive in terms of minimum and mean RMSE values but also stands out for its exceptionally low standard deviation. This suggests that SCHO provides not only accurate but also highly consistent results, making it a standout choice for optimizing the DD model of a solar cell. The negligible variation in results positions SCHO as a promising and dependable approach for enhancing the accuracy of predictions in the context of the DD solar cell model compared to the other algorithms considered in this study.

C. Simulation Results of Three-Diode Model

This section presents the experimental results of the TD model optimization using the SCHO. Table VII provides a summary of the estimated parameters for the TD model, along with the corresponding RMSE value. The results highlight the SCHO's capability to achieve a low RMSE and deliver accurate parameter estimation, indicating precise modeling of the current–voltage characteristics for the TD model.

Additionally, Figs. 11 and 12 show the current–voltage and power–voltage curves for the TD model optimized with SCHO. Because of the strong agreement between the curves and the experimental data, these figures make it abundantly evident that the optimized model properly captures the behavior of the solar cell. This is shown by the fact that the curves represent the data.

To further demonstrate the efficacy of the SCHO for the TD model optimization, a comparative assessment was also performed by using 13 different approaches (listed in Table VIII) reported for the TD modeling in the literature. The effectiveness of the SCHO method is apparent in its application to the TD solar cell model, as demonstrated by the RMSE comparison with 13 other optimization algorithms. Sinh cosh optimizer consistently achieves a minimum, maximum, and mean RMSE of 9.8248E−04, indicating its robust and reliable performance in minimizing prediction errors for the TD solar

TABLE V. ESTIMATED PARAMETERS OF DOUBLE-DIODE MODEL WITH SINH COSH OPTIMIZER METHOD

I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	RMSE
0.76078	0.22597	0.74935	0.03674	55.485	1.451	2	9.8248E–04

RMSE, root mean square error.

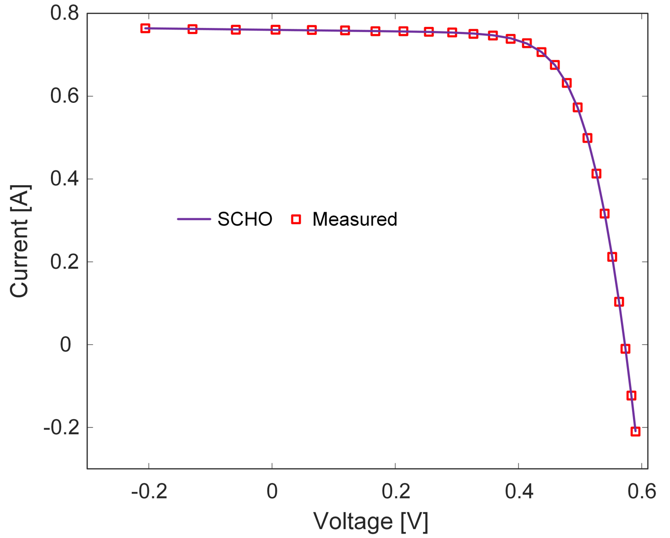

Fig. 9. Current–voltage curve characteristics of double-diode model.

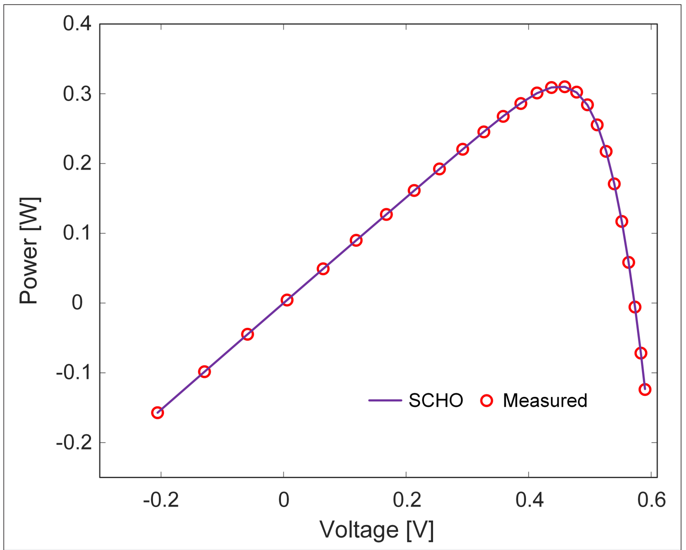

Fig. 10. Power–voltage curve characteristics of double-diode model.

TABLE VI. COMPARISON OF RMSE RESULTS BETWEEN SINH COSH OPTIMIZER AND 13 DIFFERENT METHODS REPORTED FOR DOUBLE-DIODE MODEL

Algorithm	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
HMSCPSO	9.8249E−04	9.8768E−04	9.8521E−04	1.2717E−06
PSO	9.8286E−04	4.3495E−02	1.4217E−02	1.7652E−02
CLPSO	9.8608E−04	1.7587E−03	1.0631E−03	1.5193E−04
ASO	9.9236E−04	1.1281E−02	3.3761E−03	2.3006E−03
SMA	1.0477E−03	4.5841E−03	2.0125E−03	6.1928E−04
SE	9.9891E−04	2.4435E−03	1.9864E−03	4.3562E−04
GBO	9.8250E−04	1.3397E−03	1.0093E−03	8.9548E−05
SFO	1.1743E−03	2.5992E−02	5.3534E−03	6.2657E−03
OBWOA	1.1088E−03	4.0192E−03	2.0414E−03	6.5149E−04
IGWO	1.9197E−03	4.2447E−02	6.0593E−03	7.3472E−03
TLABC	9.8644E−04	2.4480E−03	1.0897E−03	2.8773E−04
GOTLBO	9.8262E−04	9.8691E−04	9.8471E−04	1.2777E−06
ILSA	1.0051E−03	6.4631E−03	2.0371E−03	1.2283E−03
SCHO	**9.8248E−04**	**9.8248E−04**	**9.8248E−04**	**5.9197E−12**

ASO, atom search optimization; CLPSO, comprehensive learning particle swarm; GBO, gradient-based; GOTLBO, generalized oppositional teaching learning; HMSCPSO, hybrid multi-group stochastic cooperative particle swarm; IGWO, inspired grey wolf; ILSA, improved learning search; OBWOA, improved opposition-based whale; PSO, particle swarm optimization; SE, spherical evolution; SFO, sunflower; SME, slime mould algorithm; TLABC, teaching–learning-based artificial bee colony.

TABLE VII. ESTIMATED PARAMETERS OF THREE DIODE MODEL WITH SINH COSH OPTIMIZER METHOD

I_{ph} **(A)**	I_{sd1} **(μA)**	I_{sd2} **(μA)**	I_{sd3} **(μA)**	R_s **(Ω)**	R_{sh} **(Ω)**	n_1	n_2	n_3	**RMSE**
0.76078	0.22597	0.74935	5.2416E−13	0.03674	55.485	1.451	2	1.672	9.8248E−04

RMSE, root mean square error.

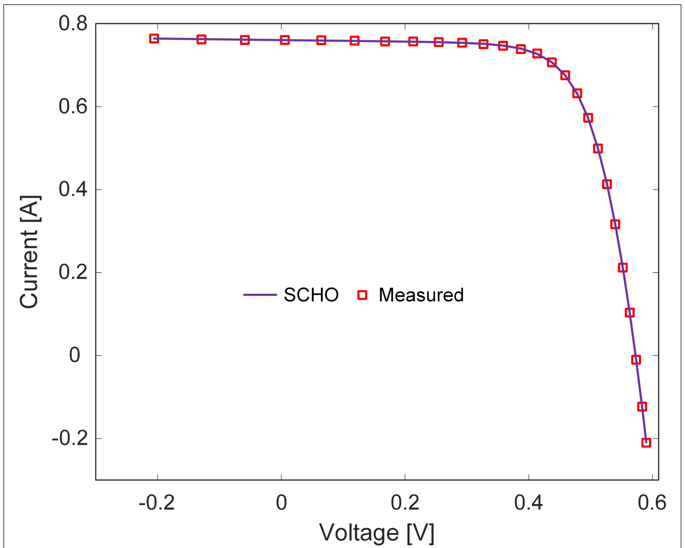

Fig. 11. Current–voltage curve characteristics of three-diode model.

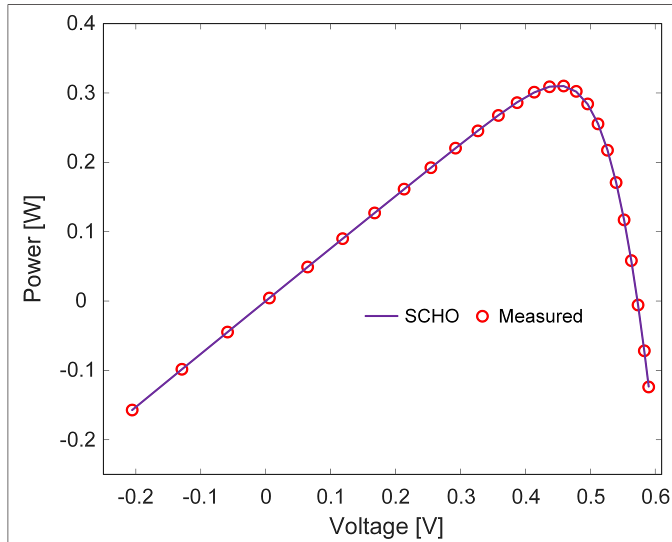

Fig. 12. Power–voltage curve characteristics of three-diode model.

cell model. The slightly higher standard deviation, at 2.5371E–09, still underscores the method's precision and stability across multiple runs. In comparison to alternative algorithms, SCHO's performance is competitive in terms of minimum and mean RMSE values, with the standard deviation remaining impressively low. This suggests that SCHO not only delivers accurate results but also maintains a high level of consistency, making it a strong contender for optimizing the TD model. The negligible variation in results further supports the reliability of SCHO in enhancing prediction accuracy for the TD model, positioning it as a promising and dependable optimization approach compared to the other algorithms considered in this study.

D. Statistical Performance Validation of Sinh Cosh Optimization Method

The statistical performance of the SCHO method is assessed across three distinct solar cell models. The analysis, presented in Table IX, showcases the remarkable efficacy of the SCHO method in minimizing

TABLE VIII. COMPARISON OF ROOT MEAN SQUARE ERROR RESULTS BETWEEN SINH COSH OPTIMIZER AND 13 DIFFERENT METHODS REPORTED FOR THREE-DIODE MODEL

Algorithm	Minimum	Maximum	Mean	Standard Deviation
HMSCPSO	9.8249E–04	9.8875E–04	9.8449E–04	1.7012E–06
PSO	9.8867E–04	2.2286E–01	3.1565E–02	4.9226E–02
CLPSO	9.8718E–04	1.6584E–03	1.0626E–03	1.3945E–04
ASO	1.5422E–03	1.4815E–02	3.8224E–03	2.7252E–03
SMA	9.8790E–04	4.7632E–03	2.0641E–03	7.3098E–04
SE	1.0384E–03	2.5241E–03	1.7261E–03	4.7103E–04
GBO	9.8252E–04	1.3008E–03	1.0101E–03	6.5732E–05
SFO	1.0480E–03	9.3214E–03	3.7184E–03	2.0384E–03
OBWOA	1.0370E–03	3.7377E–03	2.4524E–03	8.0763E–04
IGWO	1.8593E–03	5.8416E–02	6.9433E–03	1.0136E–02
TLABC	9.8916E–04	2.3912E–03	1.1365E–03	2.9090E–04
GOTLBO	9.8290E–04	9.9154E–04	9.8513E–04	2.0857E–06
ILSA	1.0906E–03	2.9440E–02	3.7149E–03	5.1369E–03
SCHO	**9.8248E–04**	**9.8249E–04**	**9.8248E–04**	**2.5371E–09**

ASO, atom search optimization; CLPSO, comprehensive learning particle swarm; GBO, gradient-based; GOTLBO, generalized oppositional teaching learning; HMSCPSO, hybrid multi-group stochastic cooperative particle swarm; IGWO, inspired grey wolf; ILSA, improved learning search; OBWOA, improved opposition-based whale optimization; PSO, particle swarm optimization; SE, spherical evolution; SFO, sunflower; SMA, slime mould algorithm; TLABC, teaching–learning-based artificial bee colony.

TABLE IX. STATISTICAL PERFORMANCE OF SINH COSH OPTIMIZER FOR SINGLE-DIODE, DOUBLE-DIODE, AND THREE-DIODE MODELS

Model Type	Minimum	Maximum	Mean	Standard Deviation
SD	9.8602E–04	9.8602E–04	9.8602E–04	**7.1590E–18**
DD	**9.8248E–04**	**9.8248E–04**	**9.8248E–04**	5.9197E–12
TD	**9.8248E–04**	9.8249E–04	9.8248E–04	2.5371E–09

DD, double diode; SD, single diode; TD, three diode.

RMSE for each model type. For the SD model, SCHO consistently achieves a minimum, maximum, and mean RMSE of 9.8602E–04, underscoring its exceptional stability and precision, as evidenced by the remarkably low standard deviation of 7.1590E–18. In the context of the DD solar cell model, SCHO demonstrates a similarly impressive performance, maintaining a uniform minimum, maximum, and mean RMSE of 9.8248E–04. The standard deviation, standing at 5.9197E–12, highlights the method's precision and reliability across multiple runs. Extending its effectiveness to the TD model, SCHO showcases consistent performance with a minimum, maximum, and mean RMSE of 9.8248E–04 to 9.8249E–04. The standard deviation, though slightly higher at 2.5371E–09, remains impressively low, emphasizing the method's reliability and accuracy. The results from Table IX collectively affirm the efficacy of the SCHO method in optimizing various solar cell models, indicating its robustness and precision across different complexities, from SD to TD models. The consistently low RMSE values and minimal standard deviations underscore the reliability and stability of SCHO, making it a promising optimization method for a diverse range of solar cell configurations.

E. Convergence Curves of Sinh Cosh Optimizer Method

The convergence performance of SCHO across the SD, DD, and TD models for RMSE optimization is evaluated in this section. The SCHO demonstrates an impressive ability to consistently converge toward the lowest RMSE values achieved across the SD, DD, and TD models. Fig. 13 depicts the convergence behavior of SCHO.

Notably, it demonstrates swift convergence toward the lowest RMSE value for each model, achieved in earlier iterations for DD and TD models compared to the SD model. Such behavior underscores SCHO's efficiency in fine-tuning the DD and TD model parameters. This finding emphasizes the algorithm's capacity to adjust its convergence behavior based on the complexities of various models, ensuring effective and efficient optimization.

F. Simulation Results of Photovoltaic Model

The experimental results of the PV model optimization of the Photowatt-PWP201 PV module obtained via utilization of the SCHO are presented in this section. Table X summarizes the estimated parameters of the PV model obtained via SCHO. The respective table additionally reports the statistical RMSE value as well. The results highlight the SCHO's capability to produce low RMSE values and ensure high accuracy in parameter estimation, demonstrating its precision in modeling the current–voltage characteristics of the PV model.

Furthermore, the current–voltage and power–voltage curves of the PV model that was optimized using the SCHO are presented here, as can be seen in Figs. 14 and 15. These figures provide evidence

TABLE X. ESTIMATED PARAMETERS OF PHOTOVOLTAIC MODULE MODEL WITH SINH COSH OPTIMIZER METHOD

I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	n	RMSE
1.0305	3.4823	1.2013	981.98	48.643	2.42507E–03

RMSE, room mean square error.

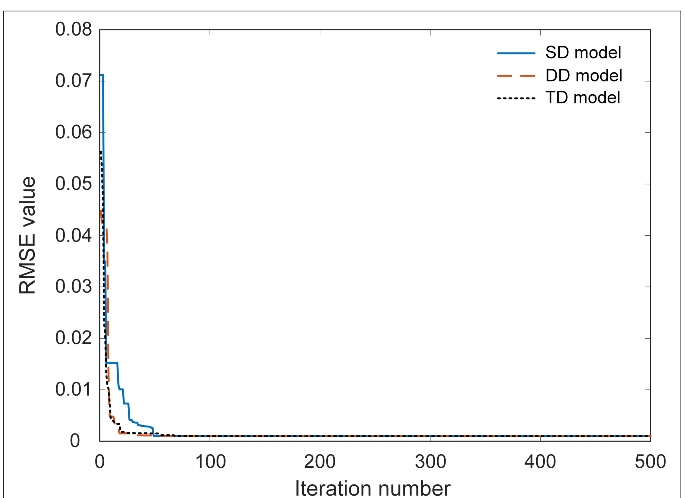

Fig. 13. Change of root mean square error objective functions for single-diode, double-diode, and three-diode models.

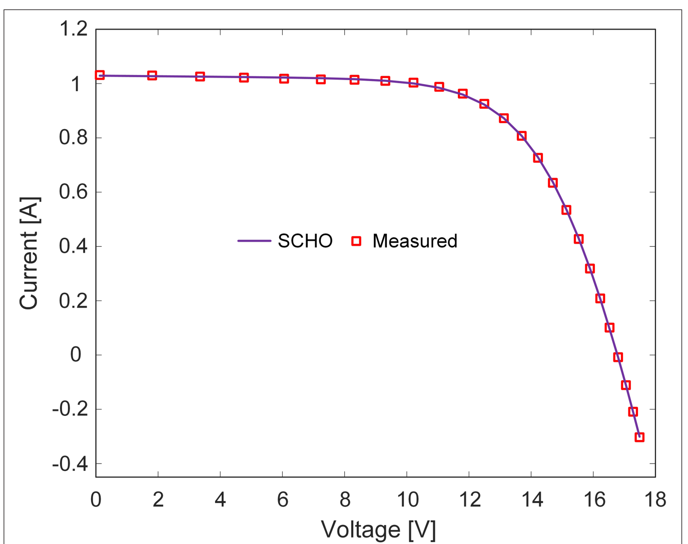

Fig. 14. Current–voltage curve characteristics of photovoltaic module model.

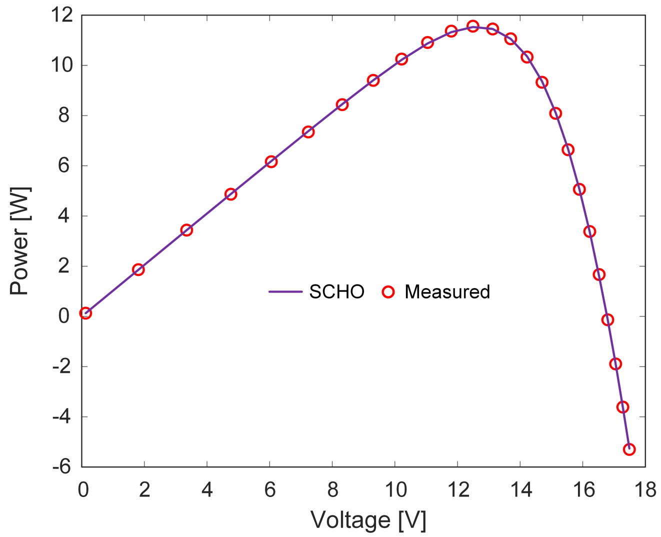

Fig. 15. Power–voltage curve characteristics of photovoltaic module model.

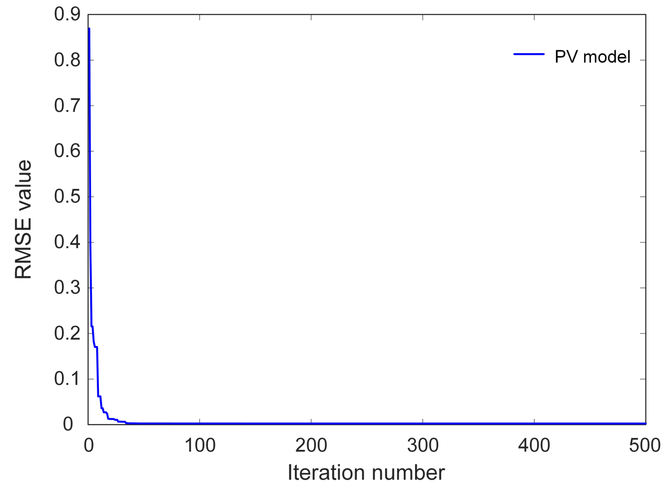

Fig. 16. Change of root mean square error objective function for photovoltaic module model.

that the model has been successfully optimized by proving that the optimized model accurately captures the behavior of the PV module to a satisfactory degree. The fact that the model has been effectively optimized is made plainly clear by this. The fact that the curves are so well-aligned with the experimental data is proof that the model has been tuned in the proper manner. A clear illustration of this is provided by the fact that the curves are in agreement with the data.

To further demonstrate the efficacy of the SCHO for the PV module model optimization, a comparative assessment was also performed by using 13 different approaches (listed in Table XI) reported for the PV module modeling in the literature. The effectiveness of the SCHO method is apparent in its application to the PV module model, as demonstrated by the RMSE comparison with 13 other optimization algorithms. Sinh cosh optimizer consistently achieves a minimum, maximum, and mean RMSE of 2.42507E–03, indicating its robust and reliable performance in minimizing prediction errors for the PV module model.

TABLE XI. COMPARISON ROOT MEAN SQUARE ERROR RESULTS BETWEEN SINH COSH OPTIMIZER AND 13 METHODS FOR PHOTOVOLTAIC MODULE MODEL

Algorithm	Minimum	Maximum	Mean	Standard Deviation
HMSCPSO	2.4251E–03	2.4251E–03	2.4251E–03	1.0163E–13
PSO	2.5960E–03	3.1526E–01	9.5950E–02	1.1586E–01
CLPSO	2.4252E–03	2.4404E–03	2.4297E–03	4.2654E–06
ASO	3.0963E–02	8.5895E+00	1.8985E+00	2.2757E+00
SMA	2.5056E–03	2.5820E–02	3.3705E–03	4.2402E–03
SE	2.4318E–03	4.2870E–02	7.6165E–03	8.6671E–03
GBO	2.4251E–03	2.4251E–03	2.4251E–03	1.0812E–11
SFO	2.4426E–03	5.9764E–02	2.3963E–02	1.7439E–02
OBWOA	2.4326E–03	7.2608E–03	3.0451E–03	1.1361E–03
IGWO	2.6728E–03	2.7434E–01	8.5910E–02	1.2545E–01
TLABC	2.4252E–03	2.7563E–03	2.5305E–03	9.3960E–05
GOTLBO	2.4251E–03	2.7425E–01	2.0547E–02	6.8964E–02
ILSA	2.4308E–03	3.4786E–03	2.6102E–03	1.7788E–04
SCHO	**2.42507E–03**	**2.42507E–03**	**2.42507E–03**	**1.4383E–15**

ASO, atom search optimization; CLPSO, comprehensive learning particle swarm; GBO, gradient-based; GOTLBO, generalized oppositional teaching learning; HMSCPSO, hybrid multi-group stochastic cooperative particle swarm; IGWO, inspired grey wolf; ILSA, improved learning search; OBWOA, improved opposition-based whale optimization; PSO, particle swarm optimization; SE, spherical evolution; SFO, sunflower; SMA, slime mould algorithm; TLABC, teaching–learning-based artificial bee colony.

The convergence performance of SCHO across the PV module model for RMSE optimization is also evaluated in this study. Fig. 16 depicts the convergence behavior of SCHO. As demonstrated in the latter figure, SCHO exhibits a remarkable capability to converge toward the low RMSE value, underscoring SCHO's efficiency in fine-tuning the parameters of the PV module model.

VI. CONCLUSION

Recognizing the critical importance of accurate modeling in optimizing solar energy systems, this study has tackled the significant task of parameter estimation in PV models. Improving solar energy usage is highly dependent on accurately characterizing PV systems, which in turn relies on estimating hidden parameters in these models. To our knowledge, this is the first publication to provide the SCHO approach as a novel and potent metaheuristic tool for PV model parameter estimation. All of the study's results point to the SCHO technique as an excellent way to get precise parameters for PV models. As a means of maintaining uniformity and impartiality, the research centered on the Photowatt-PWP201 PV module and the RTC France solar cell. Parameter tuning for the SD, DD, TD, and PV solar cell models was executed with the SCHO approach in a smooth manner by utilizing a common experimental framework. We used statistical analysis and examined convergence behavior to evaluate the data thoroughly. When compared to more conventional algorithms such as PSO, ASO, and SMA, the experimental findings show that SCHO routinely achieves faster and more accurate convergence. For example, SCHO attains an RMSE of 9.8602E−04 for the SD model, which is much lower than other approaches' standard deviations (7.1590E−18 vs. PSO's 3.9068E−02), suggesting that SCHO performs more consistently across several trials. When compared to other approaches, SCHO's smooth convergence curves across all models show that it can quickly and accurately fine-tune parameters, making it a promising contender for real-time optimization in solar systems.

Beyond the achievements presented in this work, the SCHO method holds significant potential for future applications. Its ability to rapidly converge and produce low-error estimates makes it a promising candidate for real-time parameter tuning in adaptive solar energy systems. Additionally, the method could be integrated into hybrid renewable energy systems, where multiple energy sources need optimization in dynamic environments. Moreover, the SCHO's robustness in different PV models indicates its broader applicability across various renewable energy domains, including wind energy systems and battery storage optimizations, where accurate parameter estimation is critical. Future work could explore extending the SCHO method to handle multi-objective optimization problems [38–41], allowing for the simultaneous optimization of efficiency, cost, and sustainability.

Availability of Data and Materials: The data that support the findings of this study are available on request from the corresponding author.

Peer-review: Externally peer-reviewed.

Declaration of Interests: The author has no conflict of interest to declare.

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