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# Modified Social Network Search Algorithm Combined with Halley's Method for Parameter Estimation in a Photovoltaic Cell, Module, and Array

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**ABSTRACT**

A significant research focus is how to make photovoltaic (PV) systems operate as efficiently as possible. A sufficient, accurate, and detailed model of the actual PV system is needed in order to get the best performance out of solar panels. More specifically, the parameters of these models are fitted to actual data to determine the correctness of the models. In order to determine the most accurate parameters of a photovoltaic cell, module, and array using actual data, this research suggests a novel method called MSNS-HAL, which combines Halley's method with a modified social network search algorithm. A control parameter with a Gaussian and Cauchy distribution is randomly added to the search space to improve parameter estimation performance and speed up the agents' convergence to the best solution. The best estimate of currents is then determined using Halley's root-finding technique. The proposed model, which has a best root mean square error of $7.1719 \times 10^{-4}$ for the RTC cell, $2.0388 \times 10^{-3}$ for the Photowatt PWP module, and 0.0069 for the experimental field of 18 PV panels, has the highest accuracy when compared to 12 other current optimization approaches.

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## 1. Introduction

The world's energy scarcity has encouraged the development of alternative energy sources, such as solar energy, which is a clean, accessible, and cost-free energy source [1] [2] [3]. The photovoltaic (PV) cell is a crucial component in the production of solar energy [4]. To construct the photovoltaic module, cells are linked either in series or parallel [5]. The photovoltaic array is created by connecting the panels in series and/or parallel to generate the necessary electrical power. A trustworthy and precise model of the cell, module, and the PV array is necessary for the design, prediction, sizing, diagnosis, and maintenance of solar system installations [6] [7] [8]. The literature has defined three distinct models, namely those with one, two, and three diodes. These models have certain characteristics that require precise parameter extraction. The important and difficult task of obtaining these parameters still exists. The optimal PV parameters can be estimated using a variety of techniques developed in the literature, including numerical, analytical, evolutionary, and hybrid techniques. The current-voltage characteristic equation is currently the most appropriate approach for obtaining a PV's parameters because it includes all of the PV's characteristics. The transcendence of this equation results in an optimization issue, making it challenging to solve. Metaheuristics are likely the most effective approaches to address this issue, as they have been shown to be successful in resolving a number of issues in variety of sectors [9], [10].

There are a few publications on parameter estimation of PV systems that have already been published in the literature, which we will briefly cover below.

A.Dehghanzadeh et al [11] proposed the use of Lambert's W function to extract parameters from a photovoltaic model. The model is based on two main ideas: first, the linear component of the PV cell model was identified using Thevenin's theorem, and second the nonlinear component was determined using a piecewise linear function.

In the meantime, Senturk and Eke [12] extracted parameters from a single diode model using a novel empirical relation. The manufacturer's slope of the current-voltage characteristic is used to calculate the initial value of the series resistance empirically. To implement this method, image processing will be necessary to extract information from technical documentation. However, this information may not always be accurate since numerical data for the current-voltage characteristic is generally not provided at the time of purchasing a PV. Analytical procedures work effectively under normal weather conditions, but become ineffective when atmospheric conditions change [6]. Furthermore, findings are significantly less accurate when equations are approximated.

A.K.Tossa et al [13] proposed a new method for accurately simulating a PV module's single diode. The Levenberg Marquardt method forms the basis for implementation of the strategy in the Matlab/Simulink environment. F.Ghani et al [14] utilized a technique that involved examining the current-voltage characteristic. The Newton-Raphson algorithm is used to solve a system of five equations to determine the five parameters of the one-diode model. This algorithm also requires solving the Jacobian matrix, which is complicated by the twenty-five first and second derivative terms. The main drawback of gradient-based methods, such as Newton Raphson, is the need for lengthy convergence calculations, and they may not produce reliable results as the number of parameters to be evaluated increases. Although numerical approaches are successful, their slow convergence does not necessarily guarantee the optimal outcome because they may converge to a local minimum and the initial condition is often difficult to choose [6]. Chauhan and Prakash [15] utilized the penguin emperor optimization technique to estimate the five parameters of a single diode model. Two parameters ($I_{ph}$ and $I_s$) were calculated analytically to shorten the algorithm's execution time. When atmospheric conditions vary, the differential evolution approach is combined with an analytical method by the authors F.D.Mengue et al [16] to estimate the optimal PV parameters. The authors S.Song et al [17] modified the Harris Hawk algorithm with trigonometric persistence to shorten the time spent searching for the global optimum, and the algorithm successfully extracted the best parameters from the one, two, and three-diode models.

D.S. AbdElminaam et al [18] introduced a change to the three-diode concept, where the Heap-based approach is used to estimate a new goal function for each parameter. The bee colony algorithm was combined with a local search method by M.F.Tefek [19] to enhance the fundamental algorithm's exploration capacity.

I.A.Ibrahim et al [20] utilized a hybrid approach to calculate the parameters of a two-diode model. The fruit fly algorithm was used to enhance the exploring capabilities of the wind-driven algorithm to accelerate convergence. Parida and Rout [21] proposed a differential algorithm with a dynamic control parameter. The control component includes crossover and mutation, enabling dynamic fit to optimize the solution. Although metaheuristic algorithms are more effective at solving optimization problems, many of them have drawbacks, such as premature convergence to a local minimum, lengthy execution durations as the search space expands, and solution instability across a number of tests.

In this paper, a novel methodology based on the modified Social Network Search (SNS) algorithm combined with Halley's method (MSNS- HAL) is used to extract the optimal parameters of a photovoltaic cell, module, and array to address the shortcomings indicated above. The Social Network Search (SNS) algorithm mimics how people behave in social networks when they're trying to gain popularity. Like most metaheuristics, the SNS algorithm can occasionally only reach a local minimum. To solve this problem, a perturbation equation is added at random to the search space, enabling the agents to achieve the best outcome. The objective function is then modified to include Halley's approach in order to determine the best-estimated current. The remainder of this essay is structured as follows. The suggested procedure is described in Section 2, and the various outcomes are presented in Section 3. Section 4 completes the drafting.

## 2. Materials and Methods

### 2.1. Problem formulation

The key goal is to precisely estimate the different unknown factors that make up this model in order to derive the mathematical model of a PV cell or module. These various parameters include: $\theta = \left[ I_{Ph}, I_0, n, R_s, R_p \right]$ for the configuration with a single diode (Figure 1) [2], and $\theta = \left[ I_{Ph}, I_{01}, I_{02}, n_1, n_2, R_s, R_p \right]$ for the configuration with two diodes (Figure 2) [2].

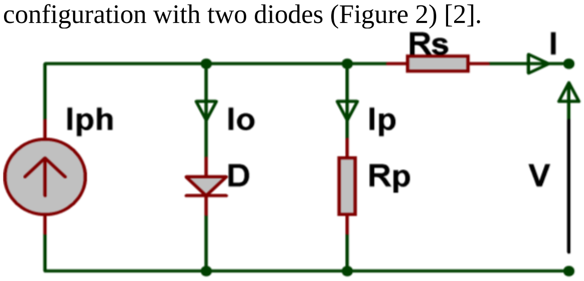



**Figure 1.** One diode PV cell.

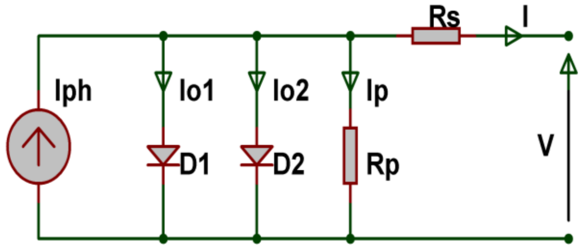



**Figure 2.** Double diode PV cell.

The mean square error is typically used to quantify the objective function defined as the difference between the measured and estimated currents [2], [22], [23], [24] and [25].

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left( I_{mes} - I_{ext} \right)^2} \qquad (1)$$

$N$ : the number of measurement points of the current-voltage characteristic;

$I_{mes}$: the set of points of the experimentally measured current;

$I_{ext}$ : the estimated currents.

In order to have an estimated current-voltage characteristic ($V_i, I_i$) very close to the measured ($V_{mes}, I_{mes}$), the expression of the estimated current for the one-diode model should be defined as follows [2]:

$$I_{i,ext} = I_{ph} - I_0 \left[ \exp\left( \frac{q(V_i + I_{i,ext}.R_s)}{n.k.T} \right) - 1 \right] - \frac{V_i + I_{i,ext}.R_s}{R_p} \qquad (2)$$

Since the non-linearity of equation (2) does not allow for an explicit solution, equation (2) is written as equation (3) below [2]:

$$f(I_{i,ext}) = I_{ph} - I_0 \left[ \exp\left( \frac{q(V_i + I_{i,ext}.R_s)}{n.k.T} \right) - 1 \right] - \frac{V_i + I_{i,ext}.R_s}{R_p} - I_{i,ext} \qquad (3)$$

Where all estimated currents ($I_{i,ext}$) are found by solving the equation

$$f(I_{i,ext}) = 0. \qquad (4)$$

This paper uses the Halley's method to solve equation (4).

### 2.2. The SNS algorithm

#### 2.2.1. Inspiration

The Social Network Search (SNS) algorithm models how users interact with social networks in an effort to gain popularity [2]. The SNS algorithm, like all metaheuristic algorithms, includes a population that symbolizes the opinions of each user in social networks. Each user elevates their standing within the network by exchanging ideas.

### 2.2.2. Principle and model

Four ways [26] in which the perspective of view of one user can be influenced by the point of view of another user:

#### 2.2.2.1. Imitation

This is due to the fact that when one user expresses an idea that is superior to another, others will try to replicate it. This is represented mathematically by the following [26]:

$$Y_{i,New} = Y_j + rand(-1,1).rand(0,1).(Y_j - Y_i) \quad (5)$$

$Y_i$ : is the vector of the viewpoint or position of i^th^ the user

$Y_j$ : is the vector of the viewpoint or position of j^th^ the user

$Y_{i,New}$ :is the new position of user i^th^ in the search space.

#### 2.2.2.2. Conversation

The period of communication with other users during which the best suggestion is chosen is called the conversation. This viewpoint's mathematical model is described by [26]:

$$Y_{i,New} = Y_l + rand(0,1).(Y_j - Y_i).sign(f_i - f_j) \quad (6)$$

$Y_l$ : represents the vector of the problem that is randomly chosen to be discussed.

$sign(f_i - f_j)$: represents the difference in opinion between users

#### 2.2.2.3. Dispute

People can voice their ideas to a group of users during the disagreement phase. This viewpoint's mathematical model is described by [26]:

$$Y_{i,New} = Y_i + rand(0,1).\left(\frac{\sum_t^{Nr} Y_t}{N_r} - \left(1 + round(rand).Y_i\right)\right) \quad (7)$$

$M = \frac{\sum_t^{Nr} Y_t}{N_r}$ : is the average of comments made by other users in the group

AF: $1 + round(rand)$ : is the emphasis a user places on their opinion.

$N_r$ : is the number of users in the group

#### 2.2.2.4. Innovation

This is the ability for a user to share a thought from a novel encounter. This is represented mathematically by the following [26]:

$$Y_{i,New}^d = rand_2.Y_i^d + (1-t).\left(lb_d + rand_1.(ub_d - ld_d)\right) \quad (8)$$

d: is the 10th randomly chosen variable in the interval of decision variables.
lb: is the lower limit of the variable d.
ub: is the upper limit of the variable d.
Users of social networks must abide by established guidelines. These regulations involve abiding by set restrictions. As a result, each viewpoint's boundary is established by:

$$\begin{aligned} y_i &= \min(y_i, ub_i) \\ y_i &= \max(y_i, lb_i) \end{aligned} \quad (9)$$

A user's viewpoint could shift throughout the interaction process. The user might then adopt a novel concept. The following equation will determine a decision once the objective function assesses the value of the new position:

$$Y_i = \begin{cases} Y_i, & f(Y_i) < f(Y_{i,new}) \\ Y_{i,new}, & f(Y_{i,new}) \geq f(Y_i) \end{cases} \quad (10)$$

Before running the algorithm, the initial positions must be generated by the following equation:

$$Y_i = lb + rand(0,1).(ub - lb) \quad (11)$$

One of the four moods imitation, argument, conversation, and innovation is randomly chosen for each iteration of the goal function. The SNS algorithm is described in depth in [26].

### 2.3. Proposed method: The MSNS- HAL algorithm

The SNS method has the same issues with speed, premature convergence, and instability as many metaheuristics. In this work, three ideas have been put up to address these issues: A historical memory function is added, a control parameter is added to the search space using the Gaussian and Cauchy distributions, and Halley's law has been employed to reduce the error between measured and estimated currents.

### 2.3.1. Modification

The search space is spread out by choosing one of the four equations (imitation, discussion, disputation, innovation) at random. We solely used the conservation equation from the original SNS algorithm model in this paper (equation 6). The user's perspective must be better at the end of these interactions by concentrating solely on the dialogue and selecting the user with the best point of view.
Therefore, the conversation's Equation (6) is changed as illustrated below [2]:

$$Y_i = Y_l + rand.(Y_{best} - Y_i).sign(f_i - f_j) - P_i \quad (12)$$

$Y_{best}$ is the vector of the user with the best view after evaluation of the objective function.
**Pi** is the disturbance equation for achieving a better balance between exploration and exploitation. This disturbance equation is defined by:

$$P_i = G_i * (Y_{M1} - Y_{M2}) \quad (13)$$

$G_i$ is a random function generated from the Cauchy distribution.

$$G_i = randch_i(M_{C,ri}, 0.1) \quad (14)$$

With $randch$ the Cauchy distribution, **ri** a random integer between [1 100], $Y_{M1}$ and $Y_{M2}$ are selected candidates in the search space.

### 2.3.2. The Halley's method

Equation (1)'s objective function is a transcendental equation. To prevent this transcendence, several authors assumed that the predicted current was equal to the measured current [27].We have resolved this transcendental issue by including Halley's approach while invoking the goal function in order to obtain optimal values.

#### 2.3.2.1. The method

The Halley's approach is a procedure used in numerical analysis to locate the zero of a function that is twice derivable and has a continuous second derivative.

#### 2.3.2.2. Principle

Let's consider the second order of Taylor series

$$f(x) = f(x_n) + f'(x_n)(x - x_n) + \frac{1}{2} f''(x_n)(x - x_n)^2 + \ldots \quad (15)$$

if $x$ is a root of the function $f$ , then this root satisfies $f(x) = 0$.

$$f(x_n) + f'(x_n)(x_{n+1} - x_n) + \frac{1}{2} f''(x_n)(x_{n+1} - x_n)^2 \approx 0 \quad (16)$$

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x) + \frac{1}{2} f''(x_n)\left(x_{n+1} - x_n\right)} \quad (17)$$

Knowing that the newton formula is given by

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x)} \quad (18)$$

The iteration of Halley method is:

$$x_{n+1} = x_n - \frac{f(x_n).f'(x)}{f'(x)^2 - \frac{1}{2} f(x_n).f''(x_n)} \quad (19)$$

$X_n$ Converges to the solution $X_\infty$, and a stopping criterion with precision $\beta$ is therefore defined by:

$$\left| x_{n+1} - x_n \right| \le \beta \quad (20)$$

### 2.3.3. Application of Halley's method for the calculation of the best estimated current

Considering equation 4, the solution of this equation is the estimated current $I_{ext}$ When calling the objective function (Equation 1), the images of the function and the two first derivates are calculated by the following equations (21), (22) and (23):

$$f_i(I_{init}) = I_{ph} - I_0\left[\exp\left(\frac{q(V_i + I_{init}.R_s)}{n.k.T}\right) - 1\right] - \frac{V_i + I_{init}.R_s}{R_p} - I_{init} \quad (21)$$

$$f'(I_{init}) = -\frac{I_0.q.R_s}{n.k.T}\left[\exp\left(\frac{q(V_i + I_{i,ext}.R_s)}{n.k.T}\right)\right] - \frac{R_s}{R_p} - 1 \quad (22)$$

$$f''(I_{init}) = -\left(\frac{I_0.q.R_s}{n.k.T}\right)^2 . \left[\exp\left(\frac{q(V_i + I_{i,ext}.R_s)}{n.k.T}\right)\right] \quad (23)$$

Then the estimated current is iterated by $I_{est}$ from the equation (21):

$$I_{i,est} = I_{init} - \frac{f_i(I_{init}).f_i'(I_{init})}{f_i'(I_{init})^2 - \frac{1}{2} f_i(I_{init}) f_i''(I_{init})} \quad (24)$$

By repeatedly iterating equations (21, 22, 23, and 24) with precision $\beta$, the best estimate current is identified. Figure 3 shows the formula for using Halley's approach to determine the best estimated current. The proposed MSNS- HAL method's pseudocode is displayed in Algorithm 1.

Algorithm 1: Pseudocode of MSNS-HAL algorithm

```
1: Define MSNS-HAL initial parameters
(MaxIter,Nuser, UB,LB)
2: for i=1 to Nuser
3:     Generate initial population    Eq.
(11)
4:      Evaluate objective function   Eq.
(3)
5:   End for
6:   for i=1 to MaxIter
7:      initialise memory parameters
8:      for i=1 to Nuser
9:generate the permutation functio
Eq(13),Eq.(14)
10:       Update the new position     Eq.
(12)
11:       Clamp the new solution      Eq.
(9)
12:       Evaluate objective functi   Eq.
(3)
13:Calculate the best estimated currents
Eq(4), Eq.(21) to q.(24)
14:       Update the best fitness
15:       Update the memory parameter with
Cauchy and Gaussian distribution
16:Select the best position and the best
finest
17:            if  NfBest < f(i)
18:     Update the new position          Eq.
(10)
19:            end if
16:Select the best position and the best
finest
17:            if fBest < precision
18:            end if
19:     end for
20:   end for
```

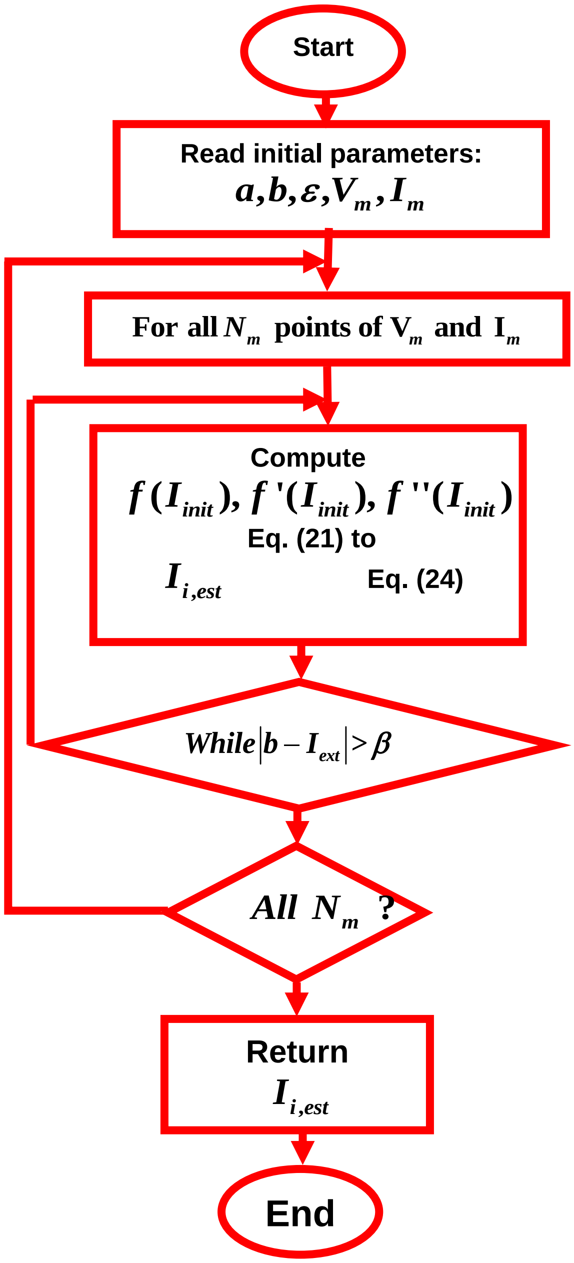



**Figure 3.** Estimated current based on the Halley's method

## 3. Results and Discussion

Three case studies have been put into practice to assess the suggested strategy. The RTC France cell with a two-diode model is the first case; the Photowatt module with a single diode is the second case; and the experimental array with 18 PV modules is the third case. The parameters were the same for each case study to ensure a fair review. There might be a maximum of 1000 iterations; there could be a maximum of 50 users; and there could be a maximum of 10 runs for each scenario.

### 3.1. Case study 1: RTC France PV cell

A test cell that is frequently used in the literature is the RTC France cell. The current-voltage characteristic data is that which is subjected to temperature and irradiation. You can find the manufacturer's and characteristic info in [16].The best outcomes produced by the suggested strategy are displayed in Table 1.On the basis of RMSE, a comparison is also done with [17], [18], [19], [27], [28], [29], [30], [31], [32], and [33].

Table 1 shows that the suggested technique yields the best results, with an RMSE of 7.1719x$10^{-4}$, followed by 7.3255 x $10^{-4}$ for [27], 7.4196x$10^{-4}$ for [28], 7.6300 x $10^{-4}$ for [33], and 7.6499 x $10^{-4}$ for [29], which yields the worst results. We should not forget that the results of these many comparisons are the best ones currently found in the literature.

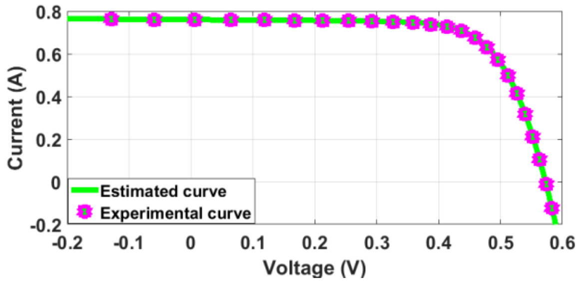



**Figure 4.** Current-voltage characteristic

The parameters obtained from the algorithm were used to plot the current-voltage characteristic in Figure 4. The comparison between the measurement (pink) and the estimate (green) curves shows a good fit, indicating the accuracy of the algorithm. This demonstrates the effectiveness of the method used to estimate the parameters. The results obtained from this method can be relied upon to accurately predict the performance of the PV system. Overall, this approach provides a reliable and efficient way to estimate the parameters of a PV system.

Table 1.Comparison of parameter estimation results in the RTC with literature.

| **Methods** | ***Parameters*** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Iph(A) | Io1(μA) | Io2(μA) | n1 | n2 | Rs(Ω) | Rp(Ω) | *Best RMSE x10$^{-4}$* |
| **Proposed** | **0.7608** | **8.0779** | **0.1342** | **1.4012** | **2.4987** | **0.0380** | **60.9849** | **7.1719** |
| **ADHHO [17]** | 0.76078 | 2.4672 | 3.6648 | 1.4584 | 2.0000 | 0.0366 | 55.09 | 9.8398 |
| **HBO [18]** | 0.7606 | 0.6700 | 0.1970 | 1.9087 | 1.4407 | 0.0368 | 51.6761 | 10.4972 |
| **ABC-Ls [19]** | 0.7608 | 0.2279 | 0.7273 | 1.4518 | 1.9952 | 0.0367 | 53.5381 | 9.8257 |
| **DSO [27]** | 0.7608 | 0.0869 | 2.1772 | 1.3712 | 1.999 | 0.0380 | 58.3713 | 7.3255 |
| **DEDCF [28]** | 0.7608 | 0.06428 | 0.9999 | 1.3577 | 1.7869 | 0.0378 | 56.3793 | 7.4196 |
| **MPA [29]** | 0.7608 | 0.2704 | 0.2676 | 1.9488 | 1.4648 | 0.03667 | 53.5615 | 7.6499 |
| **GAMS [30]** | 0.7607 | 0.2259 | 0.7494 | 1.4510 | 2.0000 | 0.03674 | 55.4854 | 9.8248 |
| **OLGBO [31]** | 7.6078 | 0.74391 | 0.2265 | 2.0000 | 1.4512 | 1.4512 | 55.3151 | 9.8248 |
| **ODGB [32]** | 0.7608 | 02202 | 0.8020 | 1.4489 | 2.0000 | 0.0368 | 55.8326 | 9.8258 |
| **DE [33]** | 0.7605 | 0.4232 | 0.1872 | 1.8757 | 1.4360 | 0.02061 | 51.9345 | 7.6300 |

### 3.2. Case study 2: Photowatt PWP PV module

The current-voltage characteristic data for this model's 11.5W panel was collected during periods of high irradiation and low temperature. You can find the manufacturers and characteristic info in [17]. The MSNS-HAL algorithm's top parameters are displayed in Table 2 as results. A RMSE of 2.0388x$10^{-3}$ was found.

A comparison with other recently published approaches, including [15], [17], [19], [27], [28], [29], [30], [31], [32], [33]and [34], has been carried out in Table2. With a value of 2.0388 x $10^{-3}$, the MSNS- HAL algorithm clearly has the best optimal when compared to the best recently suggested algorithms, which have optimum values of 2.0399 and 2.0467. Additionally, it should be noted that the results of the original SNS algorithm are substantially worse than those of the suggested technique, coming in at 2.4242x$10^{-3}$.

In Figure 5, we have the convergence curves of the initial SNS algorithm and the MSNS- HAL algorithm.

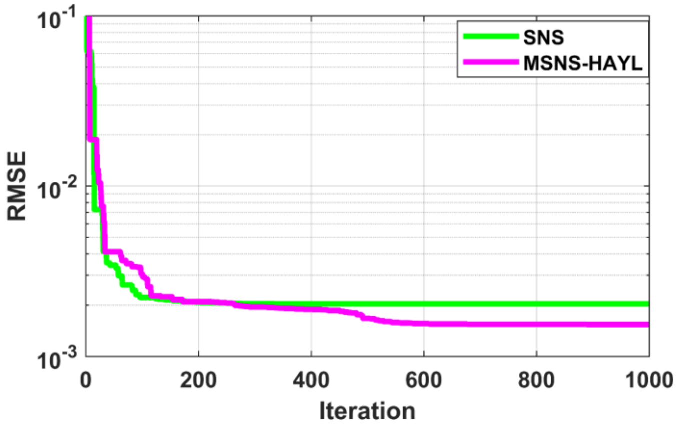



**Figure 5.** Convergence curves

The presented graph shows that the convergence curve of the MSNS-HAL algorithm reaches its minimum before the six-hundredth iteration, which illustrates the speed of convergence of the algorithm. Clearly, the MSNS-HAL algorithm reached its maximum at $2.0388x10^{-3}$, while the basic SNS algorithm only reached a local minimum of $2.4242x10^{-3}$. This difference in performance between the two algorithms is significant and demonstrates the effectiveness of the MSNS-HAL algorithm. The speed of convergence of the MSNS-HAL algorithm is an important advantage for real-time applications. The results obtained confirm the relevance of using the MSNS-HAL algorithm for parameter estimation.

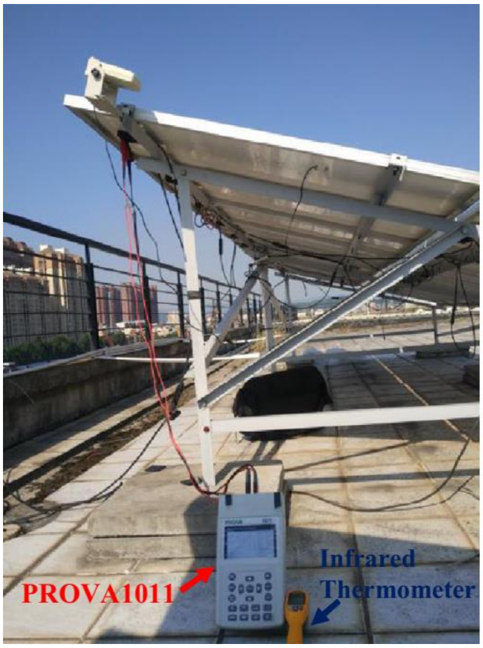
### 3.3. Case study 3: 18 PV experimental field

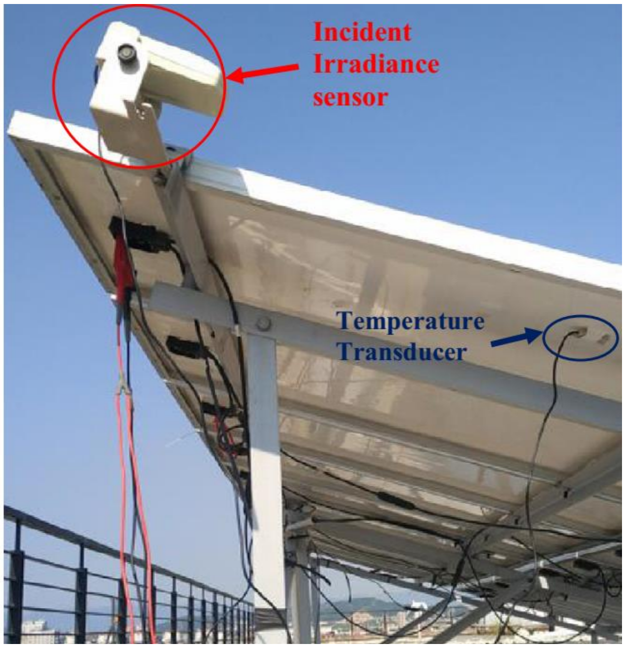
We used the MSNS- HAL algorithm to extract the five model parameters from a diode of the PV field of the experimental platform in Figure 6 at various temperatures and irradiances in order to validate the algorithm's validity.

Table 2.Comparison of parameter estimation results in the PWP with literature.

| **Methods** | ***Parameters*** | | | | | |
|---|---|---|---|---|---|---|
| | Iph(A) | Io(µA) | n | Rs(Ω) | Rp(Ω) | *Best RMSE x $10^{-3}$* |
| **Proposed** | **1.0323** | **2.4937** | **47.3299** | **1.2406** | **747.9467** | **2.0388** |
| **NEPO [15]** | NA | NA | 48.4720 | 1.1720 | 982.4500 | 2.2000 |
| **ADHHO [17]** | 1.0304 | 3.5062 | 48.6690 | 1.2007 | 999.4300 | 2.4252 |
| **ABC-Ls [19]** | 1.0305 | 3.4742 | 48.6338 | 1.2016 | 984.1798 | 2.4250 |
| **DSO [27]** | 1.0323 | 2.4965 | 1.3148 | 1.2405 | 748.3230 | 2.0399 |
| **DEDCF [28]** | 1.0314 | 2.6380 | 47.5980 | 1.2356 | 821.6413 | 2.0529 |
| **MPA [29]** | 1.0323 | 2.5127 | 1.3689 | 1.2392 | 744.7016 | 2.0467 |
| **GAMS [30]** | 1.0320 | 3.2681 | 1.3445 | 1.2062 | 828.2928 | 2.4426 |
| **OLGBO [31]** | 1.0305 | 3.48226 | 4.8642 | 1.20127 | 981.9830 | 2.4250 |
| **ODGB [32]** | 1.0305 | 3.4769 | 48.6369 | 1.2014 | 980.5942 | 2.4115 |
| **DE [33]** | 1.0314 | 2.6380 | 1.3139 | 0.0343 | 22.8238 | 2.0529 |
| **FB-LLSEM [34]** | 1.0315 | 3.1436 | 1.3411 | 1.2181 | 858.4100 | 2.1321 |
| **EPO[15]** | 1.031 | 0.2090 | 48.4720 | 1.1720 | 982.450 | 2.2000 |


a) Experimental of 18 PV array




b) I-V sensor c) Incident irradiance and temperature sensor

**Figure 6.** Experimental platform

Details of the parameters of this experimental field are available in [35]. The best extracted parameters and atmospheric conditions of the PV field are given in Table 3.

Table 3. Results of the experimental platform of 18 PV array

| **Operating condition** | | | **Best parameters** | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Irradiance (w/m²)** | Temperature (°C) | **Algorithms** | *Iph(A)* | *Io(μA)* | *n* | *Rs(Ω)* | *Rp(Ω)* | *Best RMSE* |
| **553** | 41.4 | **MSNS - HAL** | **10.0076** | **0.005976** | **5.99754** | **2.6917** | **360.6267** | **0.0254** |
| | | ABC-TRR[31] | 10.00 | 0.0057 | 215.87 | 2.699 | 368.2 | 0.0580 |
| **511** | 52.5 | **MSNS - HAL** | **9.2413** | **0.0098** | **6.1851** | **2.5401** | **412.1607** | **0.02213** |
| | | ABC-TRR[31] | 8.00124 | 0.01276 | 6.46768 | 2.54568 | 426.17692 | 0.0580 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **442** | 36.7 | **MSNS - HAL** | **8.0012** | **1.2604** | **6.3684** | **2.5506** | **426.4955** | **0.0166** |
| | | ABC-TRR[31] | 8.00 | 0.0099 | 230.29 | 2.568 | 419.8 | 0.0313 |
| **390** | 35.9 | **MSNS - HAL** | **7.0612** | **0.0036** | **6.0254** | **2.6665** | **487.4974** | **0.0128** |
| | | ABC-TRR[31] | 7.06 | 0.0057 | 225.77 | 2.630 | 515.5 | 0.0291 |
| **333** | 32.4 | **MSNS - HAL** | **6.0219** | **0.0024** | **6.1708** | **2.6608** | **561.7872** | **0.0097** |
| | | ABC-TRR[31] | 6.02 | 0.0034 | 225.75 | 2.634 | 580.2 | 0.0182 |
| **281** | 30.3 | **MSNS - HAL** | **5.0859** | **0.0022** | **6.2488** | **2.6531** | **603.3562** | **0.0069** |
| | | ABC-TRR[31] | 5.08 | 0.0032 | 228.83 | 2.620 | 621.8 | 0.0134 |

This Table confirms the accuracy of the MSNS-HAL algorithm in predicting the parameters when the PVs are subjected to various temperature and irradiance circumstances by showing that the order of magnitude of the RMSEs is lower than in the reference study [35]. The curves of the experimental measurements and the estimated curves of the PV array's current-voltage characteristic are presented in Figure 7.

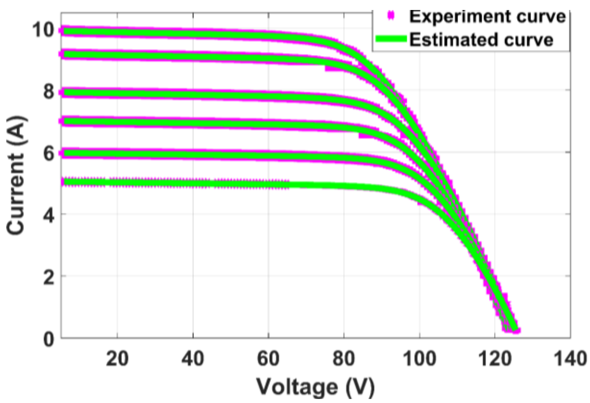



**Figure 7.** I-V characteristic of PV array (GL100) at different Temperature.

It can also be observed in the curves of Figure 7 the goodness of fit between the experimental and the estimated curves: this shows us the accuracy of the results obtained. Indeed, Figure 7 presents the curves of experimental measurements as well as the estimated curves of the current-voltage characteristic of the PV network. We can also observe on these curves the quality of the fit between the experimental and estimated curves. This demonstrates the accuracy of the results obtained. The experimental and estimated curves allow visualizing the performance of the PV network. The comparison between the experimental and estimated curves validates the method used for parameter estimation. The results obtained are therefore reliable and accurate.

## 4. Conclusions

The best internal parameters of a photovoltaic cell, module, and array were determined by using a novel methodology in this research called MSNS-HAL, which is based on the modified Social Network Search (SNS) algorithm mixed with Halley's method. The Social Network Search (SNS) algorithm mimics how people behave in social networks when they're trying to gain popularity. Three methods were used for the SNS algorithm modification. First, a control parameter was added at random using Gaussian and Cauchy distributions, and then a historical memory function was added. The Halley's approach was applied while calling the goal function to improve the precision of the most recent best estimations. Three separate systems: a PV cell, a PV panel, and an 18 PV array were used to put the concept into practice. With an RMSE of $7.1719 \times 10^{-4}$ for the PV cell and $2.0388 \times 10^{-3}$ for the PV module, the various results obtained on the one hand, and comparisons with other methods in the literature on the other hand, demonstrate that the proposed method is significantly better than all other methods in the literature. The results of the experimental PV array with 18 panels further show the algorithm's robustness when panels are exposed to various environmental conditions. Convergence curves reaching the optimal before the five hundredth iterations also show the algorithm's speed. However, despite a very good convergence with an error of $7.1719 \times 10^{-4}$ for the PV cell, $2.0388 \times 10^{-3}$ for the PV module, and $6.9000 \times 10^{-4}$ for the experiment in the worst-case scenario in terms of irradiance ($281 w/m^2$), it took at least 500 iterations to achieve good convergence. This remains the main limitation of our work. Future work can be extended to improve the chosen method to achieve faster convergence of results, meaning fewer iterations to achieve the best possible result.

**Nomenclature**

| | |
|---|---|
| $AF$ | Emphasis a user places on their opinion |
| $Gi$ | Random function generated from the Cauchy distribution |
| $I_0$ | Saturation currents |
| $I_{ext}$ | The estimated currents |
| $I_{mes}$ | The set of points of the experimentally measured current |
| $I_{ph}$ | Photocurrent |
| $M$ | Average of comments made by other users in the group |
| $N$ | The number of measurement points of the current-voltage characteristic |
| $n$ | Ideality factors |
| $N_r$ | Number of users in the group |
| $P_i$ | Disturbance equation |
| $RMSE$ | Mean square error |
| $R_P$ | Parallel resistance |
| $R_S$ | Series resistance |
| $Y_{Best}$ | Vector of the user with the best view after evaluation of the objective function |
| $Y_i$ | Vector of the viewpoint or position of ith the user |
| $Yi,_{New}$ | New position of user ith in the search space |
| $Y_J$ | Vector of the viewpoint or position of jth the user |
| $Y_l$ | Vector of the problem that is randomly chosen to be discussed |
| $Y_{M\,1,2}$ | Selected candidates in the search space |

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