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High-Performance Technique for Estimating the Unknown Parameters of Photovoltaic Cells and Modules Based on Improved Spider Wasp Optimizer

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Abstract: To better estimate the unknown parameters of the double-diode model, a new optimization technique based on the newly proposed spider wasp optimizer (SWO) is introduced in this study. The performance of SWO was further enhanced by integrating it with a local search strategy to propose a new improved variant called ISWO. This improved variant has a high ability to extensively exploit the solutions surrounding the best-so-far solution in an effort to speed up convergence and produce better results in fewer function evaluations. Using the RTC France solar cell and three PV modules (STM6-40/36, STP6-120/36, and Kyocera KC200GT), ISWO and SWO are evaluated and compared to four well-known metaheuristic optimization methods. The objective values acquired by those algorithms in thirty separate runs are examined using the Wilcoxon rank sum test and a number of performance measures. The experimental findings demonstrate ISWO's exceptional performance for every PV module under consideration.

Keywords: Spider wasp optimizer; Double diode model; Local search strategy; PV modules; Solar systems.

1. Introduction

Recent years have seen a rise in the utilization of renewable energy sources, like fuel energy and solar energy, as a response to climate change and the energy crisis [1]. The use of photovoltaic (PV) systems to convert solar energy plays a crucial role in providing a reliable and affordable renewable alternative energy source [2]. There are several PV models that were presented to model, formulate, and simulate the PV systems. Those models are single diode (SDM) model, double diode (DD) model, and triple diode (TD) model [3]. Those models, unfortunately, have some unknown parameters, where SD model has five unknown parameters, the DD model has seven unknown parameters, and the TD model has nine unknown parameters; those unknown parameters stand as a strict obstacle in front of precise designing the PV modules and solar cells.

Therefore, several studies in the literature tried to present solutions for this problem, termed the parameter estimation problem of PV models. Some of those solutions were based on employing traditional techniques to estimate those unknown parameters. However, those techniques suffer from falling into local minima and low convergence speed, especially since this problem is considered a complicated nonlinear optimization problem, which includes several local optima [3]. Therefore, metaheuristic algorithms have been employed to overcome those shortcomings when tackling this problem. The reason behind using metaheuristics is that they could achieve outstanding outcomes for several optimization problems [4]. In the rest of this section, we will review some of the recently published metaheuristic algorithms for tackling this problem.

Elazab [5] used the grasshopper optimization algorithm (GOA) for the purpose of predicting the parameters of the TD model. The technique was evaluated on two modules, specifically the Kyocera KC200GT and the Solarex MSX-60 PV cells. TLBO was proposed in [6] as a method for searching for near-optimal values for various PV models. The authors discovered that the traditional TLBO still has space for improvement, so they utilized both an elite method and a local search in order to improve both exploration and exploitation capabilities. This newly developed variant of TLBO was termed the simplified TLBO (STLBO). In Table 1, we review several other studies presented recently for this problem.

Table 1. Review of some studies proposed recently for the parameter estimation of PV models.

Year	Algorithm	Objective function	Modelling	References
2023	Improved moth flame algorithms	RMSE	SD model; DD model	[7]
2023	Hybrid grey wolf optimization	RMSE	DD model	[8]
2023	Tree seed algorithm	RMSE	SD model	[9]
2023	Northern Goshawk Optimization algorithm		TD model	[10]
2023	Chaos game optimization algorithm	RMSE	SD model; DD model; TD model	[11]
2023	Artificial hummingbird optimization algorithm	RMSE; Lambert W function; Iterate Newton–Raphson approach	SD model; DD model	[12]
2023	Squirrel search algorithm	RMSE	SD model; DD model	[13]
2023	Growth Optimizer	RMSE	SD model; DD model	[14]
2023	L-SHADE	RMSE	SD model	[15]
2023	Opposition-Based Initialization Particle Swarm Optimization	RMSE	SD model	[16]
2023	Chimp optimization algorithm	RMSE	SD model; DD model; TD model	[17]
2023	Harris Hawks optimization algorithm	RMSE	TD model	[18]
2023	Improved Cheetah Optimizer	RMSE	SD model; DD model	[19]
2023	Amended reptile search algorithm	RMSE	SD model; DD model	[20]

The algorithms presented for this problem still suffer from stagnation into local minima and slow convergence rate. Therefore, in this paper, we propose a new parameter estimation technique based on the spider wasp optimizer (SWO) to better solve this problem. To further improve the performance of SWO, it is integrated with a local search strategy to exploit extensively the solutions around the best-so-far solution in the hope of accelerating the convergence speed for achieving better outcomes in a smaller number of function evaluations; this improved variant of SWO was called ISWO. Both ISWO and SWO are assessed using three PV modules (STM6-40/36, STP6-120/36, and Kyocera KC200GT) and the RTC France solar cell based on the DD model, and compared to four well-established metaheuristic optimization techniques. The objective values obtained by those algorithms in 30 independent times are analyzed in terms of several performance metrics and the Wilcoxon rank sum test. The experimental results expose that ISWO has outstanding performance for all considered PV modules.

This paper's remaining sections are structured as follows: The DD model's mathematical model is discussed in Section 2; in Section 3, we describe the spider wasp optimizer; the proposed algorithm is described in Section 4; Section 5 displays results and discussion; Section 6 discusses conclusion and future work.

2. Double diode model

The double diode (DD) model is offered as an alternative to the single diode (SD) model since the DD model performs better at low irradiance levels [21]. As shown in Fig.1, the DD model includes two diodes: the first diode acts as a rectifier while the other accounts for the current caused by recombination and the influence of non-idealities in the solar cell. The DD model's output current is given by:

$$I = I_{ph} - I_{D1} - I_{D2} - I_{sh} \tag{1}$$

where I_{ph} refers to the current source, and I_{D1} represents the current that flows through the first diode and is given by:

$$I_{D1} = I_{sd1}(exp\left(\frac{V + I * R_s}{n_1 * V_t}\right) - 1) \tag{2}$$

where V is the output voltage, R_s represents the resistance connected in series, n_1 stands for the first ideality factor, and V_t is given by:

$$V_t = \frac{k * T}{q} \tag{3}$$

where k represents the Boltzmann constant, q is the charge of the electron, and T represents the temperature. I_{D2} represents the current that flows through the second diode and given by:

$$I_{D1} = I_{sd2}(exp\left(\frac{V + I * R_s}{n_2 * V_t}\right) - 1) \tag{4}$$

where n_2 stands for the second ideality factor. I_{sh} is given by the following formula:

$$I_{sh} = \frac{V + I * R_s}{R_{sh}} \tag{5}$$

where R_{sh} stands for the shunt resistance. From above, we found that those equations contain seven unknown parameters, namely I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, and n_2, that needs to be accurately estimated to accurately design the solar cell under DDM. The amount of power produced by a solar generation unit that only comprises of one solar cell is not very high at all. Therefore, PV modules connect N_s cells in series so that the output voltage of the PV system can be raised. It is also possible to formulate the PV modules by

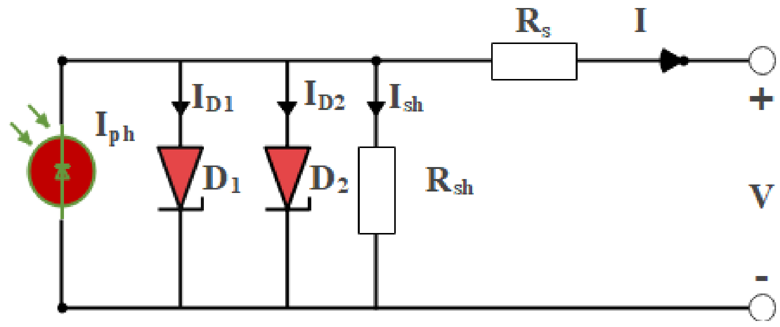


Figure. 1: DDM's Equivalent circuit.

applying the preceding equations, with the one change being that is given by the following equation [22]:

$$V_t = \frac{N_s * k * T}{q} \tag{6}$$

3. Spider wasp optimizer (SWO)

The spider wasp optimizer (SWO) is a new metaheuristic method suggested recently to address continuous optimization issues, such as the parameter estimation of photovoltaic models [23]. The SWO algorithm is based on modeling the three distinct activities of female spider wasps: nesting, hunting, and mating. In the next sections, we'll talk about the mathematical models of these SWO-created behaviors.

3.1. Hunting and nesting behavior

The female spider wasp begins by doing an initial search, known as an "exploration operator," to identify potential prey. When it locates its target, it sends a signal to its exploitation operator to begin closing in and attacking. The mathematical details of these two operators are provided below.

3.1.1. Search stage (Exploration operator)

As noted above, the female spider wasp initiates this operator at the start of the search procedure in order to locate its preferred prey. This behavior can be modeled mathematically using the following expression:

$$\vec{x}_i^{t+1} = \vec{x}_i^t + \mu_1 * (\vec{x}_a^t - \vec{x}_b^t), \tag{7}$$

where $\vec{x}_a^t$ and $\vec{x}_b^t$ are two randomly selected solutions from the current population. The female wasp's steady forward velocity is calculated using an adaptive factor called μ_1, as mathematically defined in the following equation:

$$\mu_1 = |rn| * r_1, \tag{8}$$

where r_1 is a random number between zero and one and rn is a random number drawn from a normal distribution. Prey that falls from the orb may be lost if the female wasps are unable to catch it. To find the lost prey, they employ a different exploring strategy, which is mathematically defined as follows:

$$\vec{x}_i^{t+1} = \vec{x}_c^t + \mu_2 * \left(\vec{L} + \vec{r_2} * \left(\vec{H} - \vec{L}\right)\right), \tag{9}$$

$$\mu_2 = B * \cos(2\pi l), \tag{10}$$

$$B = \frac{1}{1+e^l}, \tag{11}$$

where $\vec{x}_c^t$ is a randomly chosen solution from the current population representing the location of the dropped prey, $\vec{L}$ represents the lower bound, $\vec{U}$ represents the upper bound, $\vec{r_2}$ is a vector including random values generated in the interval [0, 1] and l is a random number between -1 and -2. Finally, the following equation describes the compromise between (4) and (6) that moves the ith solution forward.

$$\vec{x}_i^{t+1} = \begin{cases} Eq.(7) & r_3 < r_4, \\ Eq.(9) & otherwise, \end{cases} \tag{12}$$

where r_3 and r_4 are two arbitrary numbers between zero and one.

3.1.2. Following and escaping stage (exploration and exploitation operator)

Spider wasps use the following formula to calculate new positions in relation to the spiders in order to capture them at this time:

$$\vec{x}_i^{t+1} = \vec{x}_i^t + C * |2 * \vec{r_5} * \vec{x}_a^t - \vec{x}_i^t|, \tag{13}$$

$$C = \left(2 - 2 * \left(\frac{t}{t_{max}}\right)\right) * r_6, \tag{14}$$

where t and t_{max} stand for the current function evaluation and maximum function evaluation, respectively. $\vec{r_5}$ is a vector that has been given numerical values that range between 0 to 1 and are generated in a random fashion according to the uniform distribution. r_6 is a random numerical value that is created between 0 and 1 according to the uniform distribution. However, there is a possibility that the spiders will escape from the female wasps, therefore the distance between them would gradually expand. The following equation is used in order to simulate this behavior in SWO:

$$\vec{x}_i^{t+1} = \vec{x}_i^t * \vec{vc}, \tag{15}$$

where $\vec{vc}$ is a vector of numerical values that are arbitrarily created between k and $-k$ using the normal distribution. k is produced by applying the following formula:

$$k = 1 - 1 * \left(\frac{t}{t_{max}}\right) \tag{16}$$

The following equation could be used to arrive at an acceptable compromise between (10) and (12):

$$\vec{x}_i^{t+1} = \begin{cases} Eq.(13) & r_3 < r_4 \\ Eq.(15) & otherwise \end{cases}. \tag{17}$$

In SWO, the following equation is used to tradeoff between (12) and (17):

$$\vec{x}_i^{t+1} = \begin{cases} Eq.(12) & p < k \\ Eq.(17) & otherwise \end{cases}' \tag{18}$$

where p is a number picked at random from the range [0, 1] based on the characteristics of the uniform distribution.

3.1.3. Nesting behavior (exploitation operator)

Female wasps pull the broken spider into their nest. Spider wasps can dig and create cells in soil, make mud nests in leaves or rocks, and exploit pre-existing nests or cavities. Spider wasps have many nesting habits, thus SWO uses two equations to model them. The first equation considers drawing the spider to the region with the best spider to create a nest for the immobilized spider and egg over its abdomen, as defined in the following formula:

$$\vec{x}_i^{t+1} = \vec{x}^* + \cos(2\pi l) * (\vec{x}^* - \vec{x}_i^t), \tag{19}$$

where $\vec{x}^*$ denotes the optimal solution obtained so far. The second equation builds the nest in the position of a female spider that is selected randomly from the population. This equation also includes an additional step size, which helps to ensure that no two nests are built in the same position. This equation is mathematically described below:

$$\vec{x}_i^{t+1} = \vec{x}_a^t + \mathrm{r}_3 * |\gamma| * (\vec{x}_a^t - \vec{x}_i^t) + (1 - r_3) * \vec{U} * (\vec{x}_b^t - \vec{x}_c^t), \tag{20}$$

where γ is a random numerical value selected based on the levy flight, and U is a vector consisting of binary values that determine whether or not the additional step size is utilized in the process of updating. Whether or not the additional step size is used can be determined by the following defined factor:

$$\vec{U} = \begin{cases} 1 & \vec{r_4} > \vec{r_5} \\ 0 & otherwise \end{cases}' \tag{21}$$

where $\vec{r_4}$ and $\vec{r_5}$ are two random vectors from a uniform distribution containing numerical values between zero and one. To update each solution during optimization, (16) and (17) are randomly swapped according to the following formula:

$$\vec{x}_i^{t+1} = \begin{cases} Eq.(19) & r_3 < r_4 \\ Eq.(20) & otherwise \end{cases}. \tag{22}$$

At last, during SWO optimization, the following formula is used to swap out the hunting behaviors defined using (18) and the nesting behaviors defined using (21):

$$\vec{x}_i^{t+1} = \begin{cases} Eq.(18) & i < N * k \\ Eq.(22) & otherwise \end{cases} \tag{23}$$

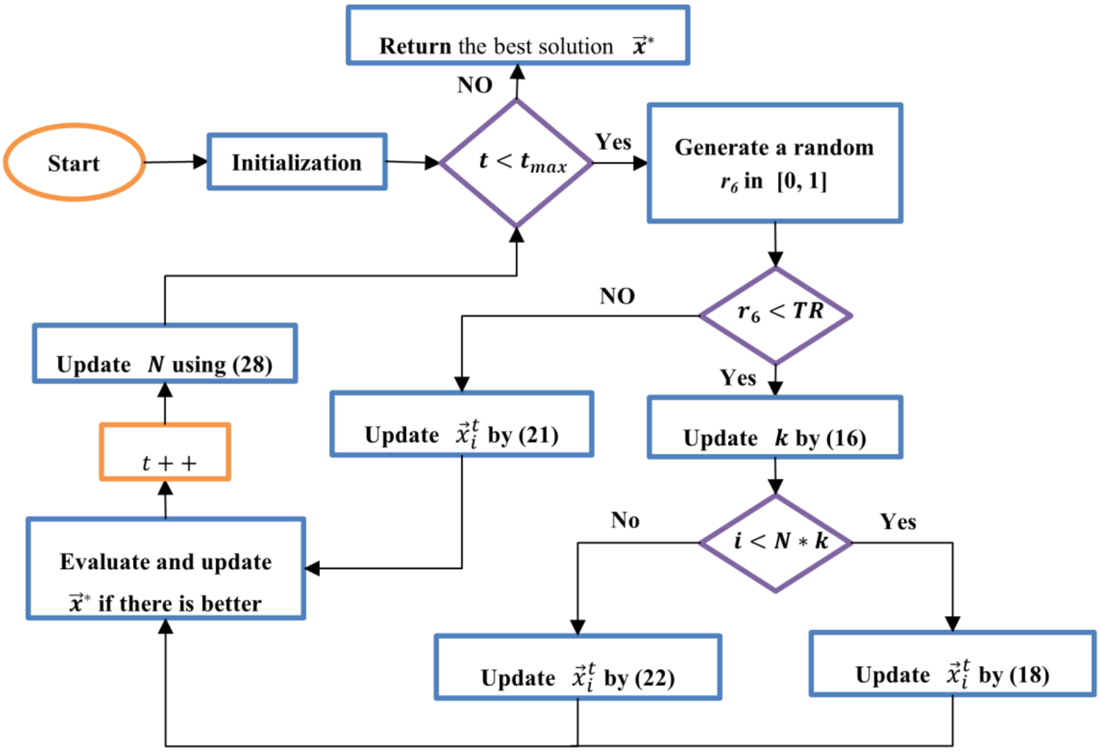


Figure. 2: SWO's Flowchart

3.2. Mating behavior

The method by which SWO creates new solutions or spider wasp eggs is characterized by the following equation:

$$\vec{x}_i^{t+1} = Crossover(\vec{x}_i^t, \vec{x}_m^t, Cr), \quad (24)$$

where $\vec{x}_m^t$ and $\vec{x}_i^t$ are two vectors for the female and male spider wasps, respectively, and Crossover is the uniform crossover operator applied to $\vec{x}_m^t$ and $\vec{x}_i^t$ with a probability, Cr. To identify male spider wasps from females, the following formula is used in SWO:

$$\vec{x}_m^{t+1} = \vec{x}_i^t + \boldsymbol{e}^l * |\beta| * \vec{v}_1 + (1 - \boldsymbol{e}^l) * |\beta_1| * \vec{v}_2, \quad (25)$$

where β and β_1 are two randomly selected numbers from the normal distribution, and $\vec{v}_1$ and $\vec{v}_2$ are two vectors generated by the following formula:

$$\vec{v}_1 = \begin{cases} \vec{x}_a - \vec{x}_i & f(\vec{x}_a) < f(\vec{x}_i) \\ \vec{x}_i - \vec{x}_a & otherwise' \end{cases} \quad (26)$$

$$\vec{v}_2 = \begin{cases} \vec{x}_b - \vec{x}_c & f(\vec{x}_b) < f(\vec{x}_c) \\ \vec{x}_c - \vec{x}_b & otherwise' \end{cases} \quad (27)$$

The factor TR is responsible for the compromise between equations (23) and (24).

3.3. Population reduction and memory saving

The female spider will seal the nest and move on to a more covert position once she has finished laying her eggs on the host's belly. This idea suggests that the female's contribution to the optimization process is complete and that the other wasps may be able to produce better results by doing the remaining function evaluations. To speed up the convergence time of the optimization process, a fraction of the wasps in the population will be removed. This will enhance the number of function evaluations that the surviving wasps may execute. During optimization, the population size is dynamically updated using the following formula:

$$N = N_{min} + (N - N_{min}) \times k, \quad (28)$$

where N is the population size and N_{min} is the smallest population size that will keep the optimization process from getting stuck in local minima. Last but not least, SWO uses a memory preservation technique to pass on each wasp's highest ranking to the next generation. In a nutshell, the new position proposed by each wasp is compared to the existing position, and the latter solution is replaced if it is worse. Finally, the SWO's flowchart is shown in Fig. 2.

4. The proposed improved SWO for parameter estimation

To begin the optimization process, most metaheuristic algorithms generate an initial population that is based on generating N solutions with d dimensions within the search boundary of each dimension. Those solutions are randomly initialized within the search boundary, as defined in the following equation:

$$\vec{x_i} = \vec{L} + \left(\vec{U} - \vec{L}\right) * \vec{r} \tag{29}$$

where $\vec{r}$ is a random vector between 0 and 1. At first, the proposed improved SWO (ISWO) uses these N solutions $\vec{x}_i (i \in N)$, where the number of dimensions d in each solution is equal to seven unknown parameters (I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2) in the DD model to be optimized. Those solutions are initialized using (29) and evaluated using the root mean squared error (RMSE) which is described in the following formula:

$$RMSE = f(\vec{x_i}) = \sqrt{\frac{1}{M} * \sum_{k=1}^{M} \left(I_m - I_e(V_e, \vec{x_i})\right)^2} \tag{30}$$

where I_m refers to the measured current, and I_e is the estimated current. M represents the data point number. $\vec{x_i}$ represents the solutions obtained by ISWO either in the initialization stage or the optimization stage. I_e is solved by $\vec{x_i}$ and the Newton–Raphson method as defined following to achieve more accurate parameters [24]:

$$I = I - \frac{I}{I'} \tag{31}$$

where I' represents the I's first derivative. After evaluating the initial solutions, the optimization process of SWO is started to search for better solutions. Those solutions are also evaluated using (30) and compared with the best solution obtained so far. However, we found that the performance of SWO suffers from slow convergence speed which makes it require a huge number of function evaluations for achieving better outcomes. Therefore, it is improved using a local search strategy to exploit the regions around the best-so-far solution in the hope of improving the exploitation operator of SWO for accelerating the convergence speed. This strategy is mathematically defined as follows:

$$\vec{x}_i^{t+1} = \vec{x}^* + (\mathrm{r}_3 * (1 - r_2) + r_2) * (\vec{x}_a^t - \vec{x}_b^t) + (\mathrm{r}_4 * (1 - r_5) + r_6) * (\vec{x}_c^t - \vec{x}_d^t), \tag{32}$$

where r_2, r_3, r_4, and r_5 are four numbers selected at random between 0 and 1. This strategy is integrated with SWO to propose a new variant with a better exploitation operator; this variant is called improved SWO (ISWO). The pseudocode of this variant is stated in Algorithm 1.

Algorithm 1 The proposed ISWO

Input: *TR*, *Cr*, *N*, N_{min} , t_{max}
Output: $\vec{x}^*$

1. Initialize N solutions, $\vec{x}_i (i = 1,2,3, \dots, N)$, by (29)
2. Evaluating each $\vec{x}_i$ by (30)
3. Extracting the best-so-far solution
4. $t = 1$; //the current function evaluation
5. **while** $(t < t_{max})$
6. r_6: Creating a number at random in the range [0, 1].
7. **if** $(r_6 < TR)$
8. **for** *i=1:N*
9. Updating $\vec{x}_i^{t+1}$ using (23)

Evaluating $\vec{x}_i^{t+1}$ by (30)
Update $\vec{x}^*$ if there is a better solution.
t = t + 1
End for
Else %% Mating Behavior
for *i=1:N*
Updating $\vec{x}_i^{t+1}$ using (24)
Evaluating $\vec{x}_i^{t+1}$ by (30)
Update $\vec{x}^*$ if there is better solution.
t = t + 1
End for
End if
Applying ***Memory Saving***
for *i=1:N* ***%% Applying the local search strategy***
Updating $\vec{x}_i^{t+1}$ using (32)
Evaluating $\vec{x}_i^{t+1}$ by (30)
Update $\vec{x}^*$ if there is better solution.
t = t + 1
End for
Applying ***Memory Saving***
Updating ***N*** by (28)
End while

5. Results and Discussion

In this study, the proposed ISWO is assessed using a well-known solar cell known as RTC France, and three PV modules known as STM6-40/36 (STM), STP6-120/36 (STP), and Kyocera KC200GT (KK). These PV models' characteristics, as defined in [21], are given in Table 2. The upper and lower bounds of each unknown parameter are presented in Table 3. To observe the effectiveness of ISWO, it is compared to several optimization techniques, such as the African vultures optimization algorithm (AVOA) [25], light spectrum optimizer (LSO) [26], RUN [27], gradient-based optimizer (GBO) [28], and classical SWO. t_{max} , N are set to 40,000 and 25, respectively, to ensure a fair comparison, while the other parameters of these algorithms are selected in accordance with the cited articles. All algorithms are implemented in MATLAB R2019a under the same device.

Table 2: Characteristics of solar cell and PV modules

Characteristics	KK	STM	STP	RTC
$P_m[W]$	200	25.5	102	0.31
$V_m[V]$	26.3	16.98	14.93	0.459
$I_m[A]$	7.61	1.5	6.83	0.6755
$V_{oc}[V]$	32.9	21.02	19.21	0.5736
$I_{SC}[A]$	8.21	1.663	7.48	0.7605
N_s	54	36	36	1
K_i	0.0318	-0.00065	0.00065	0.000387
K_v	-0.123	-0.00346	-0.003466	-0.003739

Table 3: Upper bound and lower bound of unknown parameters

Parameter	$\vec{L}$	$\vec{U}$

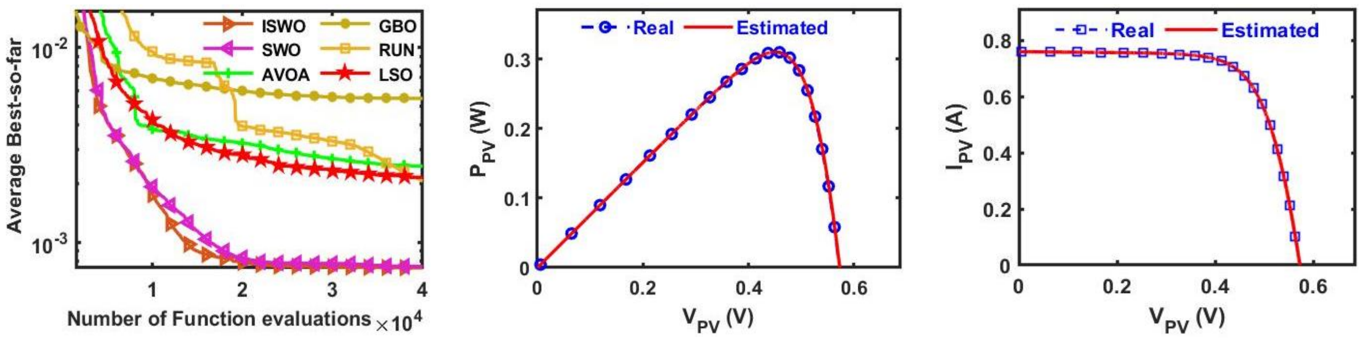
$I_{ph}(A)$	$0.9I_{SC}$	$1.1I_{SC}$
$I_{sdi}(A), i \in 1:2$	$1\ nA$	$10\ \mu A$
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	500
$a1$	1	2
$a2$	1.2	2

5.1. RTC France

To collect the statistical data presented in Table 4 (Best, average (Avg), worst (Wrst), Friedman mean rank (F-rank), and standard deviation (SD)), for this solar cell, all algorithms are executed 30 independent times. Using the Wilcoxon rank-sum test, we can assess whether or not ISWO differs significantly from the other algorithms by looking at the p-value. If the p-value is less than 5%, then there is a difference. According to this table, ISWO could be better than all algorithms for all considered performance metrics. In addition, its outcomes are significantly different, as shown in the p-value column presented in this table. Fig. 3(a) shows that ISWO converges faster than all the compared algorithms; Figs. 3(b) and (c) show that the parameters of ISWO could generate consistent I-V and P-V curves with those generated under the measured data.

Table 4: Comparison among algorithms over DDM-based RTC France

Algorithms	*Best*	*Wrst*	*Avg*	*SD*	*F-rank*	*p-value*
ISWO	7.32648E-04	7.50983E-04	7.37540E-04	4.07801E-06	1.10	
SWO	7.32648E-04	7.72723E-04	7.49563E-04	1.09958E-05	2.07	2.7829E-07
AVOA	8.24308E-04	5.70239E-03	2.45739E-03	1.10198E-03	5.00	3.0199E-11
GBO	7.39344E-04	6.94424E-02	5.46518E-03	1.73930E-02	3.17	4.1997E-10
RUN	7.85314E-04	4.28320E-03	2.06421E-03	1.16173E-03	4.73	3.0199E-11
LSO	1.04082E-03	3.02446E-03	2.14766E-03	4.50612E-04	4.93	3.0199E-11



a) b) c)

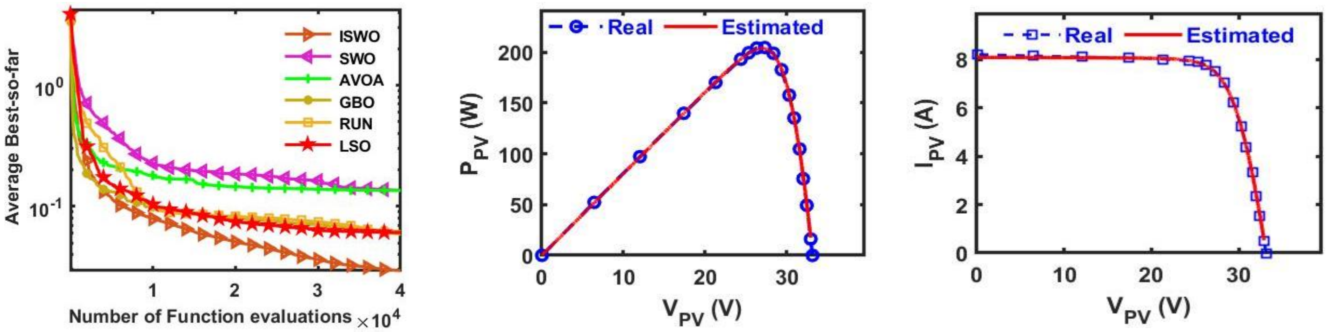
Figure. 3: Comparison among algorithms when estimating the unknown parameters of DDM based on RTC France: a) Convergence curve; b) P-V curve; c) I-V curve.

5.2. KK module

All algorithms are run 30 times in a row to compute (Best, Avg, Wrst, F-rank, and SD) for this PV module, and present them in Table 5. This table suggests that ISWO may have the best overall performance of any algorithm. The p-value column in this table further demonstrates the vast dissimilarity between the ISWO outcomes and those of the rival optimizers. In Fig. 4(a), we can see that ISWO converges more quickly than any of the other rival algorithms; in Figs. 4(b) and (c), we can see that ISWO's parameters can produce I-V and P-V curves that are compatible with those produced under the measured data.

Table 5: Comparison among algorithms over DDM-based KK module

Algorithms	*Best*	*Wrst*	*Avg*	*SD*	*F-rank*	*p-value*
ISWO	2.82117E-02	3.66776E-02	2.94687E-02	2.02154E-03	1.10	
SWO	2.82141E-02	4.56896E-01	1.35828E-01	1.80216E-01	3.00	2.6641E-09
AVOA	3.74544E-02	4.57603E-01	1.35055E-01	1.47326E-01	5.23	3.0199E-11
GBO	3.37116E-02	4.56896E-01	6.19611E-02	7.51918E-02	3.53	4.5043E-11
RUN	2.96735E-02	9.85216E-02	5.88377E-02	1.85134E-02	3.87	8.1527E-11
LSO	3.98071E-02	8.66341E-02	6.07863E-02	1.51501E-02	4.27	3.0199E-11



a) b) c)

Figure.4: Comparison among algorithms when estimating the unknown parameters of DDM based on KK module: a) Convergence curve; b) P-V curve; c) I-V curve.

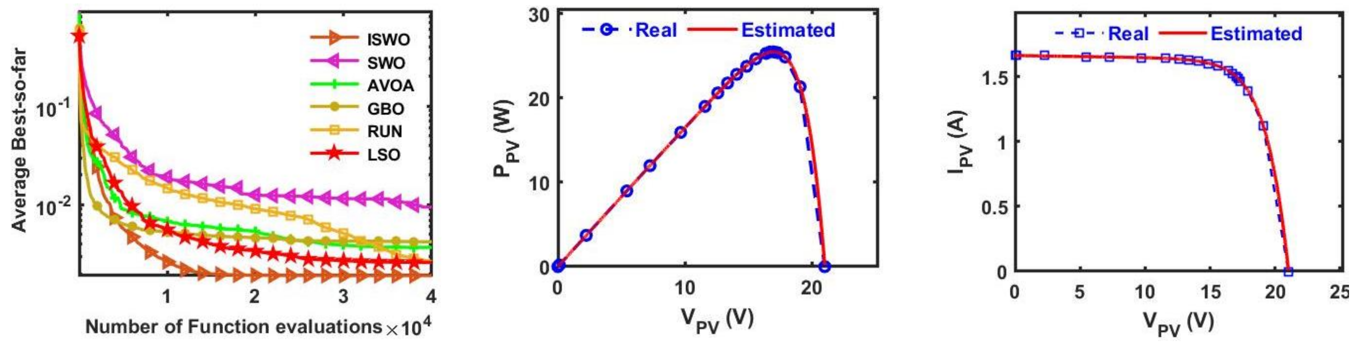
5.3. STM module

Table 6 displays the analysis of 30 independent times of each algorithm represented in the Best, Avg, Wrst, F-rank, and SD for this PV module. Based on this data, ISWO appears to have the highest possible overall performance. This table's p-value column provides further evidence of the dramatic contrast between ISWO results and those obtained using competing optimizers. The speed with which ISWO converges is illustrated in Fig. 5(a), while the ability of ISWO's parameters to generate I-V and P-V curves that are consistent with those generated under the measured data is demonstrated in Figs. 5(b) and (c).

Table 6: Comparison among algorithms over DDM-based STM module

Algorithms	*Best*	*Wrst*	*Avg*	*SD*	*F-rank*	*p-value*
ISWO	1.67466E-03	5.00373E-03	1.91424E-03	8.39859E-04	1.67	
SWO	1.68581E-03	7.48355E-02	9.46206E-03	2.22983E-02	2.63	2.0523E-03
AVOA	1.71041E-03	1.13256E-02	3.69549E-03	1.97573E-03	5.10	2.4386E-09
GBO	1.67633E-03	7.48355E-02	4.21444E-03	1.33404E-02	2.53	2.0523E-03
RUN	1.72082E-03	4.69906E-03	2.65942E-03	7.74663E-04	4.43	8.4848E-09
LSO	1.77518E-03	3.88648E-03	2.60276E-03	4.81170E-04	4.63	8.4848E-09

*__Bold__ refers to the best result.



a) b) c)

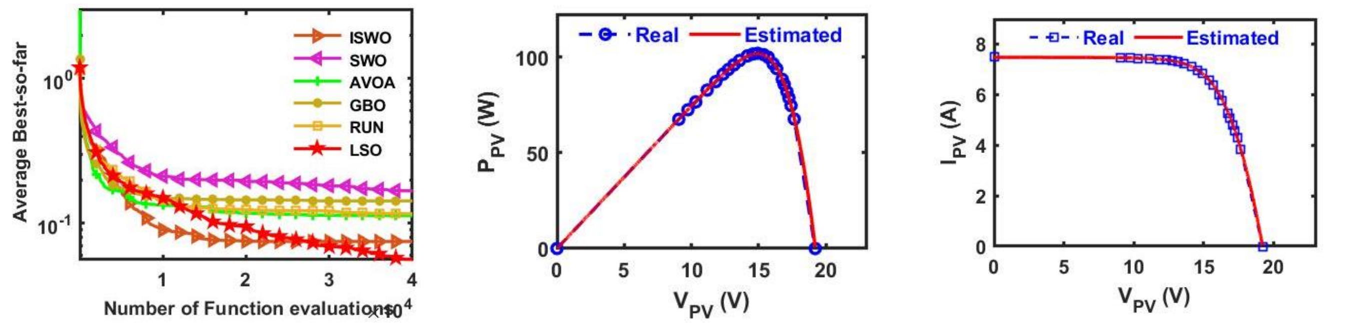
Figure.5: Comparison among algorithms when estimating the unknown parameters of DDM based on STM module: a) Convergence curve; b) P-V curve; c) I-V curve.

5.4. STP module

Table 6 shows the results of the Best, Avg, Wrst, F-rank, and SD analyses of 30 replicated runs of each algorithm for this PV module. ISWO appears to have the best potential overall performance based on these results. The p-value column in this table further demonstrates the striking difference between ISWO and alternative optimizers' outputs. Fig. 6(a) shows how quickly ISWO converges, while Figs. 6(b) and (c) show how ISWO's parameters can produce I-V and P-V curves that are consistent with those produced under the measured data.

Table 7: Comparison among algorithms over DDM-based STP module

Algorithms	*Best*	*Wrst*	*Avg*	*SD*	*F-rank*	*p-value*
ISWO	1.37983E-02	2.17188E-01	7.48197E-02	9.47955E-02	1.90	
SWO	1.39487E-02	2.17188E-01	1.66661E-01	8.60334E-02	4.00	5.0619E-08
AVOA	1.40418E-02	2.57218E-01	1.12779E-01	1.12444E-01	4.00	1.1635E-05
GBO	1.37983E-02	2.17188E-01	1.42740E-01	9.95169E-02	3.87	1.4715E-06
RUN	1.39121E-02	2.18558E-01	1.16401E-01	1.02661E-01	3.90	3.3117E-06
LSO	1.46570E-02	2.20647E-01	5.60676E-02	6.34974E-02	3.33	3.4957E-03



a) b) c)

Figure. 6: Comparison among algorithms when estimating the unknown parameters of DDM based on STP module: a) Convergence curve; b) P-V curve; c) I-V curve.

6. Conclusions

Using the recently developed spider wasp optimizer (SWO), this research introduces a novel optimization strategy for improving parameter estimation in the double-diode model. In order to further increase SWO's performance, a new variation dubbed ISWO was proposed. ISWO is based on combining SWO with a local search technique to hasten convergence and yield superior outcomes with fewer function evaluations. Four popular metaheuristic optimization techniques are compared to ISWO and SWO using the RTC France solar cell and three PV modules (STM6-40/36, STP6-120/36, and Kyocera KC200GT). By employing the Wilcoxon rank sum test and other performance metrics, we compare the objective values those algorithms have obtained throughout 30 independent runs. The experimental results show that ISWO performs exceptionally well in comparison to every other PV module. In the future, this local search strategy will be employed with some of the other metaheuristic algorithms to further investigate their performance. In addition, ISWO will be applied to solving several other optimization problems, such as the DNA fragment assembly problem, the 0-1 knapsack problem, and the multidimensional knapsack problem.

Supplementary Materials

Not applicable.

Author Contributions

The authors contributed equally to this work.

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This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Data Availability Statement

All data used to support the findings of this study are available upon request.

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