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An Improved Light Spectrum Optimizer for Parameter Identification of Triple-Diode PV Model

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Abstract: Over the last few decades, researchers have paid attention to finding an effective and efficient metaheuristic algorithm that can determine the ideal parameters for PV models. In this study, to determine the TDM's nine unknown parameters, we will examine the efficacy of a recently proposed metaheuristic algorithm called light spectrum optimizer (LSO). To further enhance the effectiveness of LSO in estimating those unknown parameters, a new improved variant called ILSO is developed. This variant employs LSO in conjunction with two newly developed update systems to improve its exploration and exploitation operators. We compare the best fitness value, worst fitness value, average fitness, standard deviation, and p-value returned by the Wilcoxon rank-sum test obtained by LSO and ILSO to those of three recently published competitors when estimating the nine unknown parameters for the Photowatt-PWP201 module and the RTC France solar cell. The experimental findings show that ILSO is the most efficient.

Keywords: Light spectrum optimizer; Photovoltaic systems; Triple diode model; Newton-Raphson method.

1. Introduction

Solar energy (SE) is widely acknowledged as one of the most prominent examples of currently available renewable energy sources [1]. SE makes it possible to generate electrical power without using any water or fuel, as well as without polluting the surrounding environment. As a direct consequence of this, the ecological equilibrium is preserved. However, there are problems with low photoelectric conversion and correct modeling of photovoltaic (PV) cells in the application of SE in real life [2]. Modeling the PV modules and solar cells requires accurate mathematical models. Therefore, in literature, several mathematical models are typically utilized in the process of analyzing the I-V curve characteristics of SCs. The SDM is the simplest and most used mathematical model, but it does not take into consideration the recombination losses that take place in the depletion area [1]. Therefore, two additional mathematical models, known as the double-diode model and the triple-diode model, were proposed to model the PV modules more accurately.

Each model from those mathematical models has some unknown parameters that have to be accurately estimated to model the SCs correctly. As a result, the solution to this problem is to recast it as an optimization problem. In recent years, deterministic, analytical, and meta-heuristic techniques have been employed in the estimation of those unknown model parameters with a high degree of precision. The analytical approach is based on the investigation of mathematical equations. Although those methods are easy to implement, they have several drawbacks that make them inappropriate for solving this problem [1, 3]. Therefore, some researchers employed deterministic approaches to estimate more accurate outcomes. However, they are highly dependent on the initial values chosen, which makes them prone to falling into local minima and taking a high computational cost to achieve the required outcomes. Meta-heuristic approaches were the only hope for solving this problem, so several studies in the literature employed several meta-heuristic algorithms for solving this problem. Some of those studies will be reviewed in the rest of this section.

In [1], the Harris Hawks optimizer was improved using fractal maps to present a new variant, namely FCHHHO. This variant was applied for estimating the unidentified parameters of RTC France SC and Photowatt-PWP PV modules based on three different PV models. Eltamaly et al. [4] presented the musical chairs algorithm (MCA) to determine the SDM and DDM parameters. The reason behind using MCA is that it begins the optimization process with a large number of search agents in order to improve the quality of the exploration phase. Afterwards, the number of search agents should be gradually decreased in order to improve the quality of the exploitation phase and shorten the amount of time needed for the optimization to converge. Montano et al [5] employed the grasshopper optimization algorithm for estimating the parameters of SDM. This algorithm was compared with two well-established algorithms and assessed using four PV modules.

In [6], the differential evolution adapted using the Linear population size reduction technique was proposed for estimating the unknown parameters of SDM and DDM. Qais et al [7] adapted the transient search optimization (TSO) algorithm to identify the optimal nine parameters of TDM. This was accomplished by minimizing the objective function, which was determined based on the datasheet of PV modules that were tested under standard test circumstances (STC). Also, the results of the proposed TSO were compared with those produced by utilizing various metaheuristic algorithms, and in this regard, the TSO attained the best results. Yadav et al [8] presented the jellyfish optimization (JFO) for estimating the unidentified parameters of SDM. This algorithm was assessed using two PV modules, namely PWP-201 and Soltech-1STH-215P, and compared to two well-common optimization techniques to verify its effectiveness. Several other metaheuristic algorithms were proposed for solving this optimization problem, some of them are the particle swarm optimization [9, 10], war strategy optimization algorithm [11], gravitational search algorithm [12], and Sine-cosine algorithm [13].

In this paper, we will investigate the performance of a newly proposed metaheuristic algorithm known as light spectrum optimizer (LSO), for finding the unknown parameters of TDM. In addition, an improved variant of LSO, namely ILSO, is proposed to further improve the performance of LSO for estimating the unknown parameters of the PV module model more accurately. This variant is based on integrating LSO with two newly designed updating schemes to enhance its exploration and exploitation operators. Both

LSO and ILSO are evaluated using the Photowatt-PWP201 module and the RTC France solar cell based on the triple diode model and compared their outcomes to those of three recently published competitors in terms of best fitness value, worst fitness, average fitness, standard deviation, and p-value returned from the Wilcoxon rank-sum test. ILSO, according to the results obtained, is the most effective. In brief, the contributions in this study are:

- Adapting the classical LSO for finding the TDM's parameters
- Improving LSO using two newly proposed updating schemes to better solve this problem
- Assessing ILSO and LSO using the Photowatt-PWP201 module and the RTC France
- The experimental findings show the effectiveness of ILSO over the other competitors.

The following sections of this paper are organized as follows: The mathematical model of the TDM is discussed in Section 2; in Section 3, we describe the light spectrum optimizer and proposed algorithm; in Section 4, findings and their discussion are presented; Section 6 discusses the conclusion and future work.

2. Mathematical description of the problem

Photovoltaic (PV) modules and solar cells are designed according to precise mathematical models to maximize their performance when generating electricity. However, those models have some unknown parameters that might negatively affect their performance if they are not accurately estimated before the design process. There are three different PV models, namely the single diode model, the double diode model (SDM), and the triple diode model (TDM) [14]

. Each of the first two models had some demerits, which were remedied later in the TDM. In this study, we will investigate the performance of one of the recently proposed metaheuristic algorithms for estimating the unknown parameters of TDM and improving the PV modules' performance. However, before that, the rest of this section will go in-depth into the details of the TDM.

1.1. Triple-diode model

The TDM, as defined in Fig. 1, is composed of a photo-current source (I_{ph}), a shunt resistor (R_{sh}), parallel diodes, and series resistance (R_s). The output current of TDM could be computed according to the following equation:

$$I = I_{ph} - \sum_{i}^{3} I_{Di} - I_{sh} \quad (1)$$

where I_{sh} stands for the current in the shunt resistor, symbolized as R_{sh}; I_{ph} stands for the photo-current source; and I_{Di} represents the ith diode's current, which is defined as follows:

$$I_{Di} = I_{sdi}\left(e^{\frac{V+IR_s}{a_i V_t}} - 1\right), \forall\, i \in 1:3, V_t = \frac{kT}{Q} \quad (2)$$

$$I_{sh} = \frac{V + IR_s}{R_{sh}} \quad (3)$$

where I_{sdi} stands for the ith diode's reverse saturation current, a_i stands for the ith diode's ideality factor, V stands for the output voltage, R_s stands for the series resistance, k is the constant of Boltzmann, Q stands for the electron charge, and T stands for the temperature of the solar cell.

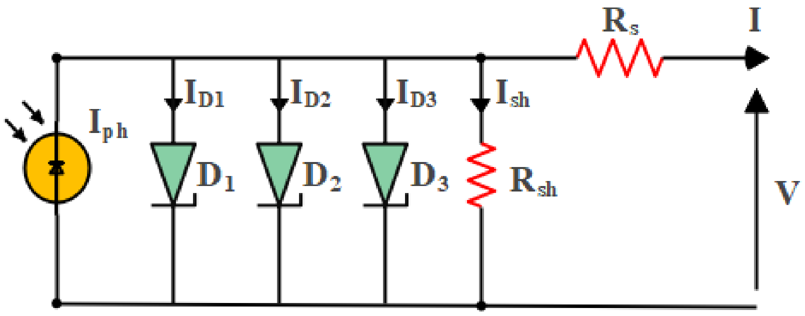


Fig. 1: The TDM's electrical circuit

1.2. Photovoltaic (PV) module

The quantity of power generated by a solar generation unit that consists of a single solar cell is quite low. Therefore, PV modules relate N_s cells in series so that the PV system's output voltage can be increased. It is also possible to formulate the PV modules using the earlier equations, with the exception that $V_t = \frac{N_s kT}{q}$ [15].

1.3. Objective function: Root mean squared error (RMSE)

Finding the unknown parameters' values that minimize the discrepancy between experimental and theoretical current data is crucial to the parameter extraction problem's solution. Therefore, the root mean squared error (RMSE), which has been widely used as an objective function (OF) in the literature, is also considered in this study to solve this problem. The mathematical model of this objective function is given by the following formula:

$$Min \quad RMSE = f(\vec{x_i}) = \sqrt{\frac{1}{M} * \sum_{k=1}^{M} (I_m - I_e(V_e, \vec{x_i}))^2} \tag{4}$$

where the measured current is denoted by I_m, and the estimated current is denoted by I_e. The measured data number is denoted by the letter M. $\vec{x_i}$ represents the values obtained by a metaheuristic algorithm for the unknown parameters of TDM. To solve (1), we employ the Newton-Raphson method, with the estimated unknown parameters represented in $\vec{x_i}$, as shown below [16]:

$$I = I - \frac{I}{I'} \tag{5}$$

where I' represents the derivative of I.

3. The proposed light spectrum optimizer

A new meta-heuristic method, known as Light Spectrum Optimizer (LSO), has been presented to take on the challenge of optimizing test functions for a single objective. The meteorological phenomenon that inspired LSO postulates that the colorful rainbow spectrum is produced by light rays reflecting, refracting, and dispersing at different angles as a result of passing through raindrops, with a reflective index ranging from 1.331 as k^{red} and 1.344 as k^{violet}. Each of these rays is a potential solution to the optimization problem. LSO begins by generating N rays, each of which has d dimensions and is first initialized uniformly at random between its upper and lower bounds using the following equation:

$$\vec{x_i} = \vec{L} + (\vec{U} - \vec{L}).\vec{r}, i = 1,2,3, \dots \dots, N \tag{6}$$

where $\vec{x_i}$ is a vector used to hold the ith ray's position. $\vec{\boldsymbol{L}}$ and $\vec{\boldsymbol{U}}$ are two vectors that represent the lower and upper limits of the search space for each dimension in the optimization problem. Similarly to metaheuristic algorithms, LSO's optimization process consists of two phases, which are discussed in detail below: generating new colorful rays (exploration) and dispersing colorful rays (exploitation).

1.4. Generating new colorful ray: Exploration mechanism

The first step in the optimization procedure is to adjust the reflective index between $\boldsymbol{k^{red}}$ and $\boldsymbol{k^{\text{violet}}}$ in the following way:

$$\boldsymbol{k^r = k^{red} + r_1} \times (\boldsymbol{k^{violet} - k^{red}}) \quad (7)$$

where $\boldsymbol{r_1}$ is an arbitrary value between zero and one. A probability between 0 and 1, denoted as $\boldsymbol{p}$, is employed to regulate light ray reflection and refraction, and its value is set at 0.8. However, a randomly generated probability between 0 and 1 called $\boldsymbol{q}$ is employed to control the dispersal of the multicolored rainbow curve. Normal vectors for inner reflection ($\overrightarrow{\boldsymbol{x_{nB}}}$), inner refraction ($\overrightarrow{\boldsymbol{x_{nA}}}$), and outer refraction ($\overrightarrow{\boldsymbol{x_{nC}}}$) are generated successively using the following equations, and these vectors are used to define the orientations of the rainbow spectra throughout the optimization process:

$$\overrightarrow{x_{nA}} = \frac{\overrightarrow{x_r(t)}}{norm\left(\overrightarrow{x_r(t)}\right)} \quad (8)$$

$$\overrightarrow{x_{nB}} = \frac{\overrightarrow{x_p(t)}}{norm\left(\overrightarrow{x_p(t)}\right)} \quad (9)$$

$$\overrightarrow{x_{nC}} = \frac{\overrightarrow{x^*}}{norm\ (\overrightarrow{x^*})} \quad (10)$$

where $\overrightarrow{x_r(t)}$ represents a randomly chosen solution from the population at time t, $\overrightarrow{x_p(t)}$ represents the position of the current ray, and $\overrightarrow{x^*}$ represents the optimal solution obtained even now, and norm(.) represents the normalized vector. The following formula is applied to determine the incident light ray, $\overrightarrow{x_{L0}}$:

$$X_{mean} = \frac{\sum_i^N \overrightarrow{x_i}}{N} \quad (11)$$

$$\overrightarrow{x_{L0}} = \frac{X_{mean}}{norm\ (X_{mean})} \quad (12)$$

where X_{mean} represents the population mean at the current function evaluation. In addition, the vectors of the internally and externally reflected and refracted light rays are calculated as follows:

$$\overrightarrow{x_{L1}} = \frac{1}{k^r}\left[\overrightarrow{x_{L0}} - \overrightarrow{x_{nA}}(\overrightarrow{x_{nA}} \cdot \overrightarrow{x_{L0}})\right] - \overrightarrow{x_{nA}}\left|1 - \frac{1}{(k^r)^2} + \frac{1}{(k^r)^2}(\overrightarrow{x_{nA}} \cdot \overrightarrow{x_{L0}})^2\right|^{\frac{1}{2}} \quad (13)$$

$$\overrightarrow{x_{L2}} = \overrightarrow{x_{L1}} - 2\overrightarrow{x_{nB}}(\overrightarrow{x_{L1}} \cdot \overrightarrow{x_{nB}}) \quad (14)$$

$$\overrightarrow{x_{L3}} = k^r\left[\overrightarrow{x_{L2}} - \overrightarrow{x_{nC}}(\overrightarrow{x_{nC}} \cdot \overrightarrow{x_{L2}})\right] + \overrightarrow{x_{nC}}\left|1 - (k^r)^2 + (k^r)^2(\overrightarrow{x_{nC}} \cdot \overrightarrow{x_{L2}})^2\right|^{\frac{1}{2}} \quad (15)$$

where the inner refracted light ray is represented by $\overrightarrow{x_{L1}}$, the inner reflected light ray is represented by $\overrightarrow{x_{L2}}$, and the outer refracted light ray is represented by $\overrightarrow{x_{L3}}$. After the ray directions have been computed, a random probability between 0 and 1 is assigned to a variable denoted by the symbol p, which is used to determine the formula used for updating the current position of each ray. In particular, at function evaluation $t+1$, the solution is updated according to the following formula if p is less than a randomly generated number in the range [0, 1]:

$$\overrightarrow{x_{t+1}} = \overrightarrow{x_t} + \epsilon RV_1^n GI(\overrightarrow{x_{L1}} - \overrightarrow{x_{L3}}) \times (\overrightarrow{x_{r1}} - \overrightarrow{x_{r2}}) \quad (16)$$

if p is greater than the generated number, the following equation will be used to update the current position of each ray:

$$\overrightarrow{x_{t+1}} = \overrightarrow{x_t} + \epsilon RV_2^n GI(\overrightarrow{x_{L2}} - \overrightarrow{x_{L3}}) \times (\overrightarrow{x_{r3}} - \overrightarrow{x_{r4}}) \quad (17)$$

where $\overrightarrow{x_{r3}}$, $\overrightarrow{x_{r2}}$, $\overrightarrow{x_{r1}}$, and $\overrightarrow{x_{r4}}$ represents four solutions selected at random from the current population. RV_1^n and RV_2^n are both randomly produced vectors. According to (18), the scaling factor ϵ can be determined. GI is a factor that is derived from the inverse incomplete gamma function using the formula (19).

$$\epsilon = a \times RV_3^n \quad (18)$$

where RV_3^n is a vector including random values generated based on the normal distribution, and a is a controlling parameter generated according to (20).

$$GI = a \times r^{-1} \times P^{-1}(a, 1) \quad (19)$$

where r is a uniformly produced random number in the range [0,1] that has been inverted to favor the exploration operator. The inverse incomplete gamma function of the value a is denoted by P^{-1}.

$$\mathrm{a} = \mathrm{RV}_2 \left(1 - \left(\frac{t}{Tmax}\right)\right) \quad (20)$$

where t and $Tmax$ refer to the current and maximum function equations, respectively, and RV_2 is a random value in $[0, 1]$.

1.5. Colorful rays scattering: Exploitation mechanism

This step strengthens the exploitation operator by directing light toward the best-so-far solution, the current solution, and a solution selected randomly from the current solutions. The mathematical model of scattering close to the current position is defined as:

$$\overrightarrow{x_{t+1}} = \overrightarrow{x_t} + RV_3 \times (\overrightarrow{x_{r1}} - \overrightarrow{x_{r2}}) + RV_4^n \times (R < \beta) \times \left(\overrightarrow{x^*} - \overrightarrow{x_t}\right) \quad (21)$$

where RV_3 contains a number that is arbitrarily created between 0 and 1, and RV_4^n is a vector that has been given a random initialization between 0 and 1. The following formula is used to generate rays in a new position for the second phase of the scattering process, and it is applied to both the best solution found to date and the current solution:

$$\overrightarrow{x_{t+1}} = 2 * \cos(\pi \times r_1) \left(\overrightarrow{x^*}\right)\left(\overrightarrow{x_t}\right) \quad (22)$$

where r_1 is a numerical value that was chosen at random from the range 0 to 1. The transition between the first and second stages of the scattering process is carried out in accordance with the following formula, which is based on a predefined probability P_e:

$$\overrightarrow{x_{t+1}} = \begin{cases} (19) & if\ R < P_e \\ (20) & Otherwise \end{cases} \quad (23)$$

where R is a random number between zero and one. In the final stage of scattering, a new solution is generated by combining the current solution with a randomly selected solution from the current solutions according to the following equation:

$$\overrightarrow{x_{t+1}} = \left(\overrightarrow{x_{r1}} + |RV_5| \times (\overrightarrow{x_{r2}} - \overrightarrow{x_{r3}})\right) \times \vec{U} + \left(1 - \vec{U}\right) \times \overrightarrow{x_t} \quad (24)$$

where RV_5 is a normal-distributed random number and $\vec{U}$ is a random vector with values of either 0 or 1. By determining the difference between the objective values of each solution and the best-so-far solution and standardizing this difference in [0, 1], we can tradeoff between (23) and (24). If the difference is less than a random threshold value R_1 between 0 and 1, then (23) is used; otherwise, (24) is carried out, as defined in (25):

$$F' = \left|\frac{F-F_b}{F_b-F_w}\right| \tag{25}$$

$$\overrightarrow{x_{t+1}} = \begin{cases} Eq.(23) & if\ R < P_s\ |\ F' < R_1 \\ Eq.(24) & Otherwise \end{cases} \tag{26}$$

where R and R_1 are numerical values chosen randomly in the interval [0,1]. In this study, LSO is employed to find the unknown parameters of TDM; however, it still has some demerits in terms of convergence speed and local optima avoidance, which motivate us to propose an improved variant, namely improved LSO (ILSO). This variant is based on presenting two newly proposed updating schemes that aid LSO in exploring several regions within the search space. The first scheme is used to strengthen the exploration operator and is mathematically defined as follows:

$$\overrightarrow{x_{t+1}} = \overrightarrow{x_{r1}} + r_2 * (\overrightarrow{x_{r1}} - \overrightarrow{x_{r2}}) + r_3 * (\overrightarrow{x_{r3}} - \overrightarrow{x_{r4}}) \tag{27}$$

where r_2 and r_3 are two numbers selected at random in [0,1], and $\overrightarrow{x_{r4}}$ is a solution randomly chosen from the current population. The second scheme is used to promote the exploitation operator and is mathematically defined as follows:

$$\overrightarrow{x_{t+1}} = (\overrightarrow{x^*} + \overrightarrow{x_t})/2.0 + r_2 * v1 + r_3 * (\overrightarrow{x_{r2}} - \overrightarrow{x_{r3}}) \tag{28}$$

where $v1$ is given by the following equation:

$$\vec{v}_1 = \begin{cases} \vec{x}_{r1} - \vec{x}_t & f(\vec{x}_a) < f(\vec{x}_t) \\ \vec{x}_t - \vec{x}_{r1} & otherwise' \end{cases} \tag{29}$$

Those two schemes are exchanged with each other within the optimization process using the following formula:

$$\overrightarrow{x_{t+1}} = \begin{cases} Eq.(28) & R < 1 - t/Tmax \\ Eq.(27) & otherwise \end{cases} \tag{30}$$

Those schemes are integrated with LSO to improve its performance when tackling the parameter estimation problem of TDM. The steps of ILSO are mathematically listed in Algorithm 1.

Algorithm 1: The steps of ILSO

Input: N, $Tmax$

Initializing N solutions using Eq. (6)
While $(t< Tmax)$
for *each* i *solution*
Evaluate each $\overrightarrow{x_{t+1}^i}$ according to Eq. (4)
Update $\overrightarrow{x^*}$ if $\overrightarrow{x_{t+1}^i}$ is better
$t = t + 1$
Compute $\overrightarrow{x_{nA}}$, $\overrightarrow{x_{nB}}$,&$\overrightarrow{x_{nC}}$
Compute $\overrightarrow{x_{L0}}$, $\overrightarrow{x_{L1}}$,$\overrightarrow{x_{L2}}$, &$\overrightarrow{x_{L3}}$
Update k^r
Update GI, ϵ, and a
Generate randomly p, q in the range (0, 1)

if $p \leq q$
  Compute $\overrightarrow{x_{t+1}^{i}}$ by Eq. (16)
Else
  Compute $\overrightarrow{x_{t+1}^{i}}$ by Eq. (17)
end if
Evaluate each $\overrightarrow{x_{t+1}^{i}}$ according to Eq. (4)
Update $\overrightarrow{x^{*}}$ if $\overrightarrow{x_{t+1}^{i}}$ is better
$t = t + 1$
Update using Eq. (26)
end for
for each i solution
  Evaluate each $\overrightarrow{x_{t+1}^{i}}$ according to Eq. (4)
  Update $\overrightarrow{x^{*}}$ if $\overrightarrow{x_{t+1}^{i}}$ is better
  $t = t + 1$
  Compute $\overrightarrow{x_{t+1}^{i}}$ by Eq. (30)
end for
end while
Return $\overrightarrow{x^{*}}$

4. Results and Discussions

In this section, the performance of ILSO and LSO is compared to three competitors, namely the artificial gorilla troops optimizer (GTO) [17], the pelican optimization algorithm (POA) [18], and the dandelion optimizer (DO) [19], when estimating the unknown parameters of the Photowatt-PWP201 module and the RTC France solar cell based on the triple diode model. The properties of this solar cell and PV module are described in Table 1. The lower bound and upper bound of each unknown parameter are listed below:

$$0.9I_{SC} \leq I_{ph}(A) \leq 1.1I_{SC}$$
$$1\ nA \leq I_{sdi}(A) \leq 10\ \mu A, \forall i \in 1{:}3$$
$$0 \leq R_s(\Omega) \leq 0.5$$
$$0 \leq R_{sh}(\Omega) \leq 500$$
$$1 \leq a1 \leq 2$$
$$1.2 \leq a2 \leq 2$$
$$1.4 \leq a3 \leq 2$$

Regarding the parameters of the proposed algorithms and rival optimizers, they are all set as recommended in the cited papers, with the exception of $Tmax$ and N, which are assigned values of 35000 and 30, respectively. To ensure a fair comparison. All algorithms are implemented in MATLAB over the same device.

Table 1: Properties of RTC France and Photowatt-PWP201module

Characteristics	$P_m[W]$	$V_m[V]$	$I_m[A]$	$V_{oc}[V]$	$I_{SC}[A]$	N_s	K_i	K_v
RTC France	0.31	0.459	0.6755	0.5736	0.7605	1	0.000387	-0.003739
Photowatt-PWP201	11.5	12.649	0.912	16.7785	1.0317	36	0.0008	-0.0725

1.6. RTC France solar cell

Table 2 presents the outcomes of four performance metrics, namely best fitness (best), average fitness (average), worst fitness value (worst), standard deviation (STD), and p-value returned from the Wilcoxon rank-sum test, which are obtained by various algorithms when estimating the unknown parameters of the RTC France based on TDM. Those outcomes are obtained after running each optimizer 25 independent times. This table discloses that ILSO could achieve more accurate outcomes than all the compared algorithms for all performance metrics. In addition, the outcomes of ILSO are significantly different, as shown in the p-value row in this table. To further show the effectiveness of ILSO, the convergence curve analysis and multiple comparison test are employed and depicted in Figs. 2(a) and (b), respectively. Those figures confirm the effectiveness of ILSO over all the other competitors. Finally, the I-V curve and P-V curve obtained by ILSO and measured data for the RTC France solar cell are presented in Figs. 2(c) and (d).

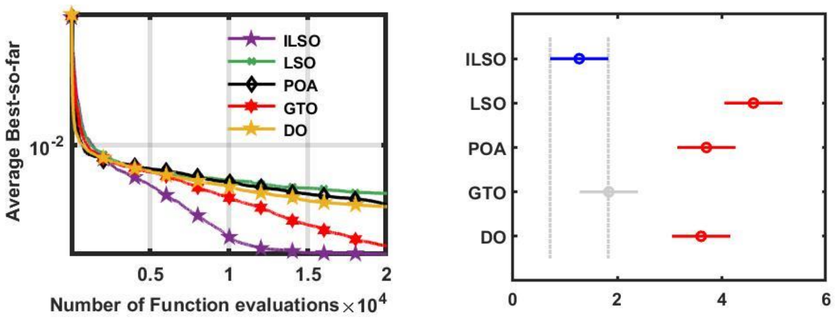
Table 2: Performance analysis over RTC France over the TDM

Algorithms	*ILSO*	*LSO*	*POA*	*GTO*	*DO*
Best	**7.515103E-04**	2.170131E-03	7.794266E-04	7.517423E-04	8.096134E-04
Worst	**1.695653E-03**	4.670947E-03	4.715392E-03	2.630616E-03	4.087969E-03
Average	**8.021100E-04**	3.266317E-03	2.501136E-03	9.702419E-04	2.411337E-03
STD	**1.691133E-04**	6.789619E-04	9.169341E-04	4.511328E-04	9.196907E-04
p-value		**3.019859E-11**	**1.205668E-10**	**3.005888E-04**	**6.065757E-11**

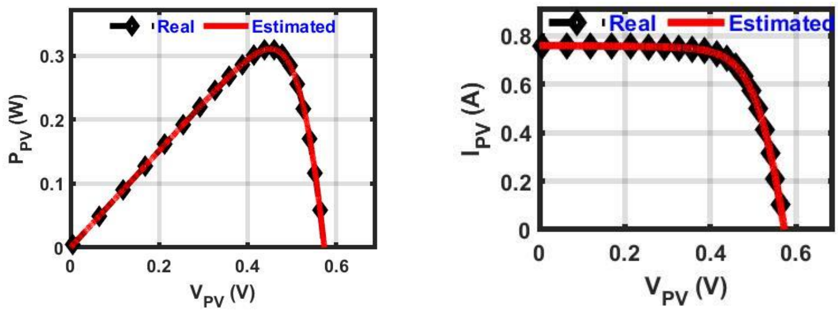
***Bold** indicates the best result.

1.7. Photowatt-PWP201 module

Table 3 displays the results of four considered performance metrics and the p-value returned from the Wilcoxon rank-sum test. The outcomes of these metrics are obtained by various algorithms within 30 independent times when attempting to estimate the unknown parameters of the Photowatt-PWP201 module based on TDM. This table reveals that ILSO was capable of achieving more accurate results than any of the other algorithms that were compared for each and every performance metric. The p-value row in this table demonstrates that there is a statistically significant difference between the results of ILSO and the other groups. The convergence curve analysis and the multiple comparison test are used, and they are illustrated in Figs. 3(a) and (b), respectively. These are used to further demonstrate the usefulness of ILSO. These figures provide more evidence that ILSO is more effective than any of its other rivals. In conclusion, the I-V curve and the P-V curve generated by ILSO as well as the observed data for the Photowatt-PWP201 module are displayed in Figs. 3(c) and (d), respectively.



a) b)



c) d)

Fig. 2: Performance analysis over RTC France: (a) Convergence curve; b) Multiple comparison test; c) P-V curve; d) I-V curve.

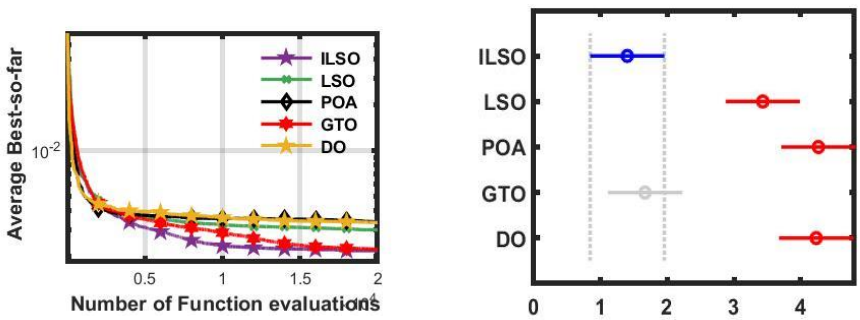
Table 3: Performance analysis over Photowatt-PWP201 module over the TDM

Algorithms	*ILSO*	*LSO*	*POA*	*GTO*	*DO*
Best	**2.050660E-03**	2.389523E-03	2.612456E-03	2.050674E-03	2.388104E-03
Worst	**2.533591E-03**	3.679760E-03	4.246695E-03	2.671222E-03	5.167893E-03
Average	**2.179462E-03**	2.990192E-03	3.352704E-03	2.222857E-03	3.343317E-03
STD	**2.814545E-04**	3.021238E-04	3.691542E-04	2.130525E-04	5.477742E-04
p-value		**2.227269E-09**	**9.918629E-11**	**1.114256E-03**	**1.776908E-10**

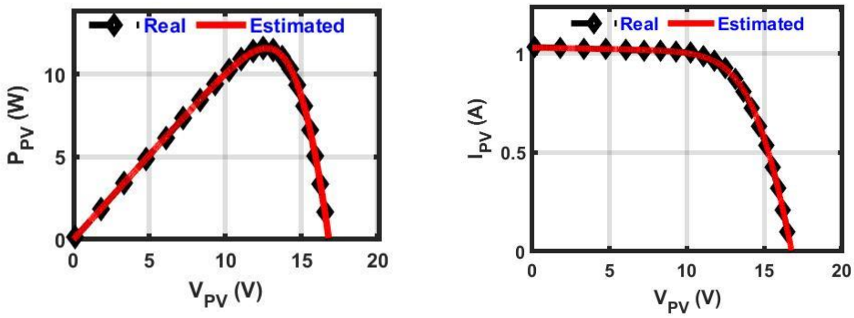
***Bold** indicates the best result.

5. Conclusions

Researchers have focused their efforts over the course of the most recent few decades on locating a metaheuristic that is effective and efficient for establishing the appropriate parameters for PV models. Therefore, in this study, we will investigate the performance of a recently introduced metaheuristic algorithm known as the light spectrum optimizer (LSO), with the goal of determining the nine undetermined parameters of the TDM. In addition, an improved variant of LSO known as ILSO has been developed in order to further boost the effectiveness of the algorithm in estimating those unknown characteristics. This variant makes use of LSO in conjunction with two update systems for the purpose of enhancing its exploration and exploitation operators, both LSO and ILSO are employed to estimate the nine parameters for the Photowatt-PWP201 module and the RTC France solar cell, and LSO and ILSO's results are compared to those of three recently published competitors in terms of best fitness value, worst fitness value, average fitness, standard



a) b)



c) d)

Fig. 3: Performance analysis over Photowatt-PWP201 module: (a) Convergence curve; b) Multiple comparison test; c) P-V curve; d) I-V curve.

deviation, and p-value returned by the Wilcoxon rank-sum test. According to the results of the experiments, ILSO is the method with the highest efficiency. The proposed ILSO will be evaluated in the future using a variety of other optimization problems, such as the 0-1 knapsack problem, feature selection, task scheduling problem in cloud and fog computing, path planning problem for UAVs, and multiobjective optimization problem.

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Ethical approval

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.

Informed Consent Statement

Not applicable.

Data Availability Statement

All data supporting the findings of this study are included within the paper.

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