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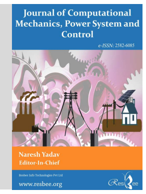


# A Novel Improved Sparrow Search Algorithm for Parameters Extraction in Three-Diode PV Model

**Nitin Pawar**

*Department of Computer Science and Engineering*
*Government Polytechnic, Siddipet, Telangana, India*

**Abstract:** To accommodate the growing adoption of solar power stations, specific electrical modeling of PV cells is essential. Hence, researchers proposed a TDM for accurate PV loss modeling. The greater nonlinearity and characteristics of this TDM.Yet render it a more complicated challenging concept. Thus, it is essential to generate as much power as feasible from both solar as well as wind sources. On the other hand, the majority of the functional aspects of MPPT algorithms used today are unsuitable for the hybrid operation of wind as well as solar energy systems. To derive the nine unknown parameters of the TDM-PV modules, this research demonstrates a unique ESSA strategy. The major goals of this study are to evolve an incredibly specific PV representation that can effectively describe PV systems in the modeling of dynamical energy systems and to evaluate the parameters of TDM using a new optimization technique. The RMSE error between the calculated as well as experimental current of the PV module is taken into account during the formulation of the optimization challenge. The outcomes of ESSA are contrasted with the most current methodologies in the literature to validate the effectiveness ofextracting the parameters of the PV model. The outcomes display that the created method achieves the finestoutput with the least RMSE, mean, and standard deviation.

**Keywords:**Parameter Estimation, TDM, PV, ESSA, Optimization.

***Nomenclature***

| Abbreviation | Description |
|---|---|
| PV | PhotoVoltaic |
| TDM | Three-diode Model |
| MPPT | Maximum Power Point Tracking |
| ESSA | Enhanced Sparrow Search Algorithm |
| RMSi | Root mean squared |
| RMSE | Root Mean Square Error |
| RESs | Renewable Energy Sources |
| SDM | Single Diode Model |
| DDM | Double Diode Model |
| MDDM | modified Double Diode Model |
| STC | Standard Test Conditions |
| NOCT | Normal Operating Cell Temperature |
| HHO | Harris Hawk Optimization |
| I-V | Current-Voltage |
| P-V | Power-Voltage |
| CSA | Circle Search Algorithm |
| COA | Coyote Optimization Algorithm |
| CGO | Chaos Game Optimization |
| IAE | Current Absolute Error |
| PAE | Power Absolute Error |
| MFO | Moth-Flame Optimizer |
| FPA | Flower Pollination Algorithm |
| DEIM | Hybrid Evolutionary Algorithm |
| MBE | Mean Bias Error |
| AEMPP | Absolute Error at the Maximum Power Point |
| LSHADE | linear population size reduction based on Success History Adaptive Differential Evolution |
| INR | Improved Newton Raphson |
| NR | Newton Raphson |


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| | |
|---|---|
| **PGJAYA** | Performance-Guided JAYA Algorithm |
| **CLPSO** | Comprehensive Learning Particle Swarm Optimizer |
| **MLBSA** | Multiple Learning Backtracking Search Algorithm |
| **MRFO** | Manta-Rays Foraging Optimizer |
| **MPALW** | Marine Predator Algorithm with Lambert W function |
| **CPU** | Central Processing Unit |
| **HPO** | Hunter–Prey Optimization |
| **WHO** | Wild Horse Optimizer |
| **I-GWO** | Improved Gray Wolf Optimizer |
| **GWO** | Gray Wolf Optimizer |

# 1. Introduction

Over the past few years, the expansion of endurable RESs has been on active evacuation all over the world because of several severe constituents.This includes an increase in the utilization and rate of fossil fuel and significant concerns in gaining thesafest atmosphere. PV energy is the most well-liked and extensively used RES available today. With the recent cost reductions in PV elements as well as conversion equipment, the PV sector has experienced tremendous economic growth, which has increased the value and effectiveness of this energy source more than other RESs. This demonstrates the extensive efforts put forward to advance the PV sector [9]. Numerous limitations, including solar irradiation, high launching rates, and limited energy conversion, may limit the spread of PV systems despite their exponential growth [10,11]. From the previous context, it is essential to use a precise and trustworthy PV system to explain real behavior under varied weather circumstances [12][6].

Therefore, developing an accurate model that accounts for the impact of boundaries is a key objective [13,14]. Generally, there are numerous numerical representations of PV modules ranging from the most basic called SDM to the most complex one called DDM. Finally the most intricate called MDDM and TDM. Utilizing more detailed models is an important aspect of dealing with increasing the number of large PV installations, especially at low irradiance conditions [15]. These comprehensive methods are also effective in representing the physical behavior of multi-crystalline silicon PV panels as they take the impact of grain borders, carrier replication as well and current leakage into consideration [13-16][5].

SDM is regarded as having a low complexity and extremely tolerable level of accuracy [17] [18]. Since the losses from carrier recombination in the region of depletion are ignored, it is not accurate in the situation of an open circuit voltage with low radiation [19], [20]. The DDM wasoffered to solve this issue. To display the losses caused by recombination, another diode is added. The DDM offers greater precision, but this model wasmore difficult due to a rise in unknown parameters; in the SDM scenario, additional unknown parameters include the ideality factor parameters of the other diode as well as the saturation current [14,20-21]. To deal with low light exposure situations in large PV installations, TDM wasimportant [15]. This model takes into account the unique impacts of boundaries and leakage current [13]. Even though this model can satisfy the majority of the physical requirements for PV solar cells, it is more complicated than SDM and DDM since it must calculate nine parameters [22].

In addition, when the researchers relied on conventional methodologies and the TDM for their research, the results were less precise and took longer to estimate [13]. The unknown parameters of this complex representation should therefore be extracted with more precision and in a shorter amount of time.So a more efficient approach should be suggested. The TDMwas the more complex modelin this article [4]. The general structure of this research is provided below:

- ❖ To estimate the parameters of TDM of PV systems using a novel optimization strategy.
- ❖ To develop a novel optimization named ESSA in such a way as to tune the parameters, such as $I_{dsD1}, I_{dsD2}, I_{dsD3}' I_{spara}, \eta_1, \eta_2, \eta_3, R_{sshunt}, R_{ssries}$.

The following is anoutline of this study's main findings: Section 2covers the features as well as challenges of the conventional techniques. Section 3 details the suggested ESSA, and Section 4emphasizes the results and analysis. Section 5 mentions the advantages and disadvantages. The conclusion is recapitulated in Section 6.

# 2. Literature Survey

## 2.1 Related Works

A combined technique of equation analysis and optimization for the electrical modeling of PV panels based on the datasheet parameters at STC and NOCT conditions was presented by Qais *et al.*[1] in 2020.

To gain an exact simulation of the interior losses of PV modules, TDM was also used. InSTC circumstances, the TDM had9 electrical parameters. In that 4 are determined using derivative equations, while the remaining 5 are determined via the HHO method. The 9 electrical parameters of 2 well-known commercialized PV modules were thus extracted using the recommended approach and these parameters are subsequently contrasted to the parameters of the various methodologies. Moreover, the information gathered under various atmospheric conditions wasutilized to confirm the I-V and P-V features of the suggested approach. Additionally, the suggested technique's absolute current error was compared to that of the other methods, which showed that the suggested approach has a lower error.

In 2022, Qais *et al.* [2] used a powerful algorithm called CSA to accurately simulate the electrical properties of PV panels. The renowned mathematical features of the circle and the perpendicular connection that exists amid its radius as well as tangent line serve as inspiration for the CSA. The nine parameters of the TDM of three economical solar cells are calculated using the CSA and other four algorithms. RMSE of the predicted as well as derived output currents serves as the objective function. The durability and effectiveness of CSA in choosing the best TDM among other approaches were demonstrated by the arithmetical optimization outcome in addition to the divergence curve. To show the CSA's superiority in various circumstances, the predicted I-V curves are shown against the observed I-V curves at varied temperatures and sun irradiation. The CSA-TDM has a lower absolute current error compared to various conventional techniques at maximum voltage.

In 2019, Qais *et al.* [3] suggested an innovative utilization of the metaheuristic COA to derive the nine unknown parameters of the more specific TDM. The main objective of this work is to create themost accurate PV representation for several solar cells. The RMS current error function was effectively minimized using the COA. The COA-based TDM's optimal design factors are quite similar to and compatible with those found using other meta-heuristic optimization techniques. Additionally, under various operating circumstances, the numerical outcomes of the suggested COA-TDM correspond to its experimental findings with no variation.This demonstrates the COA-TDM's efficacy and reliability in producing a precise representation of the solar module. The COA-TDM's outstanding function is a clear indication of both its right design and its merit as a framework based on biological metaheuristics. The COA can thus be used to resolve a variety of Engineering optimization issues in many industrial applications.

A novel utilization of the CGO technique for predicting the TDM's parameters was put forth by Ramadan *et al.*[4] in 2021. The TDM was chosen since it is the most accurate representation of a PV cell. Other current optimization techniques have been contrasted to the CGO results. Through the use of various evaluation criteria, including RMSE values as wellas statistical procedures that additionally calculated IAE as well as PAE values for all of the actual calculated parameters.The findings were compared. The CGO has been used to determine the parameters of the 36 polycrystalline silicon cell PV panel Photowatt-PWP201 for detailed verification. The CGO methodology's results were consistently more accurate than those of other optimization techniques. Furthermore, it responds more quickly.

The parameter extraction procedure of the three evaluated models is based on data acquired in the lab and other data presented in prior research. Allam *et al.* [5] introduced a new optimization approach named MFO in 2016. The result of the recommended technique is compared with the given traditional techniques in the literature, including DEIM and FPA, to confirm its effectiveness. The three algorithms of the chosen models are also subjected to evaluation study under various environmental situations. The outcomes demonstrate that the MFO algorithm gets the best Coefficient of determination and the least RMSE, MBE, and AEMPP. While contrasted to several examined methodologies, MFO also arrives atthe best solution in the quickest amount of time.

In 2021, Ridha *et al.* [6] recommended a novel version of the LSHADE method named ELSHADE-INR by integrating various methodologies contributions.The objective function is toextract the TDM parameters under real environmental conditions. The TDM equation's roots are generally estimated using the ELSHADE-INR.Italso enhances the result's variety as well as promotes rapid convergence. Using actual experimental statistics from 7 different climate conditions, the function of the ELSHADE-INR is contrasted with 2 ELSHADE variations entrenched on traditional NR as well as Lambert W function along with the completely-publicized PGJAYA, CLPSO, MLBSA, MRFO, and MPALW approaches. Comparisons and findings demonstrate the ELSHADE-INR's advantage in terms of precision, durability, CPU execution speed, and reliability.

A novel PV model using HPO and WHO was presented in 2022 by Ramadan *et al.*[7]. With the help of an efficient optimization approach, producer specifications in addition to statistical information.The parameters of solar panels are gained. Simulation findings as well as statistical measures demonstrate the efficacy and the precision of the developed HPO and WHO for parameter derivation of different solar panels under varied operational conditions. The results demonstrate that the best RMSE values for HPO and WHO are 7.56748 and 7.51198, using the records of the R.T.C. France PV module. Furthermore, the statistical findings show that the HPO and WHO algorithms are, respectively, 98.37% and 91.06%

efficient. In addition, there is coherencebetween the datasheet and the approximated models' PV properties.

An application of the enhanced GWOwassuggested by Ramadan *et al.* in 2021 [8] to estimate the parameter values that result in an accurate TDM flawlessly and reliably. The PV TDM wasdesigned to simulate the impact of significant leakage currents and grain boundaries in the PV structure. The I-GWO was being evolved to enhance the original GWO's population, exploration as well and exploitation stability in addition to convergence. I-GWO's effectiveness was contrasted with that of other well-known optimization techniques. I-GWO was assessed using two distinct applications. Actual information from an RTC furnace was used in the first application.While actual data from a polycrystalline PV panel was used in the second. Various assessment standards, the most recent unconditional error as well as numerical assessment for numerous independent runs are all used to contrast the findings.

## 2.2Problem Definition

The Challenges and features of various parameter extraction techniques of three-diode photovoltaic models are shown in Table 1. The HHO methodology [1] was effective and has a reduced error, however, it calculates the dark saturation currents under STC circumstances. CSA [2] was able to achieve reduced absolute current error along with robustness and rapidity. However, it suffers fromoptical and electrical losses within the PV panel. COA-PV is used in [3] that can be used to resolve a variety of Engineering optimization issues in various industrial applications along with the reduction of RMS current error function.However, it extremely reduces dynamic efficiency. The method CGO was introduced in [4],which attains minimal RMSE and the lowest execution period and precision. However, the strategy is highly complex. The MFO method in [5] is precise to provide high efficiency along with the fastest convergence speed over other methods. However, it is unable to strike a balance between exploration as well as exploitation levels. The method termed ELSHADE [6] is robust and stable and can accurately determine the global solution. But, it fails to precisely represent the PV strategy's actual function. The hunter-prey and Wild horse optimizers method introduced in [7] possesses the best values of the objective function but suffers fromlow searching accuracy as well as slow convergence speed. The I-GWO method in [8] is robust and provides improved accuracy. Various drawbacks of this method include less precision, poor local search capabilities,andan unperceptive rate of convergence.

***Table 1:*** *Challenges and features of various parameter extraction methodologies of three-diode photovoltaic models*

| Authors | Adapted Scheme | Features | Challenges |
|---|---|---|---|
| **Qais *et al.* [1]** | HHO | Effective<br>Reduced errors | Does not calculate the saturation currents under STC circumstances. |
| **Qais*et al.* [2]** | CSA | Reduced absolute current error<br>Robust and rapidity | Optical as well as electrical losses exist within the PV panel. |
| **Qais*et al.* [3]** | COA-PV | Reduced RMS current error function.<br>Used to resolve a variety of Engineering optimization issues in various industrial applications. | Highly affects dynamic performance |
| **Ramadanet al. [4]** | CGO | Minimal RMSE<br>Lowest execution period<br>High Precision | Highly Complex |
| **Allam *et al.* [5]** | MFO | High Efficiency<br>Precise<br>Fastest Convergence Speed | Unable to strike a balance between exploration as well as exploitation levels. |
| **Ridha *et al.* [6]** | ELSHADE | Robust and Stable<br>Accurately determines the global optimal solution. | Fails to precisely represent the PV strategy's actual function. |
| **Ramadan *et al.* [7]** | HPO + WHO | Best values of the objective function. | Low searching accuracy.<br>Slow Convergence Speed. |
| **Ramadan *et al.*[8]** | I-GWO | Improved accuracy<br>Robust | Less Precision<br>Poor local search capabilities<br>Unperceptive rate of convergence. |

# 3. Proposed Methodology of Parameter Extraction in Three Diode Model

The primary aim of the suggested approach is to develop a novel optimization technique for the extraction of the parameters of TDM.The suggested method constitutes3 major blocks: Application of optimization algorithms, Determination of the objective function, and Mathematical representation of

TDM.The TDM scheme is created based on the PV model for solar panels.It is incredibly accurate and takes all of their losses into account. It has a single current source,3 diodes, and parallel as well as series resistances. The optimization problem can be mathematically formulated based on the RMSE error between the calculated model current and the experimental current of the PV module [3]. An estimator entrenched in a new type of SSA named ESSA, which is inspired by observing the foraging as well as anti-predation characteristics of sparrows. It is used to predict theparameters of the TDM.Figure 1 provides a visual representation of the estimation procedure of the TDM parameters.

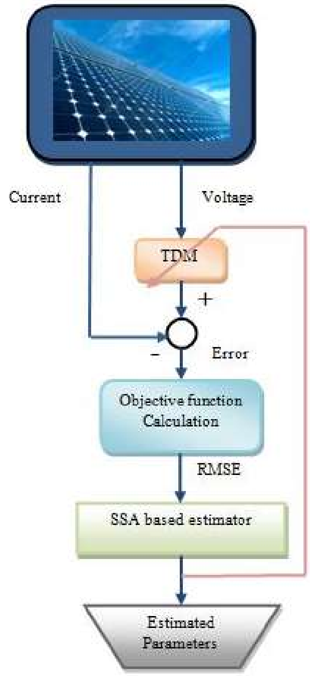



***Fig. 1.*** *Block diagram of parameter estimation using optimization methods*

## 3.1 TDM

Solar module transforms the incident light rays on its plane into electrical current calledphotocurrent $I_{spara}$.Solar panels have relatively low conversion effectiveness. Within the solar panel, there are additional power losses, such as optic as well as electric losses. The electrical losses can be conduction losses in the wires and joint contacts, which areexpressed inseries resistance $R_{sseries}$ . The leakage current between the p-n junction is expressed by shunt resistance $R_{sshunt}$ [2].As shown in Figure. 2, the PV module is illustrated by a photocurrent source, and the losses that occur are denoted by 3 parallel diodes.A shunt resistance together with a series resistor.

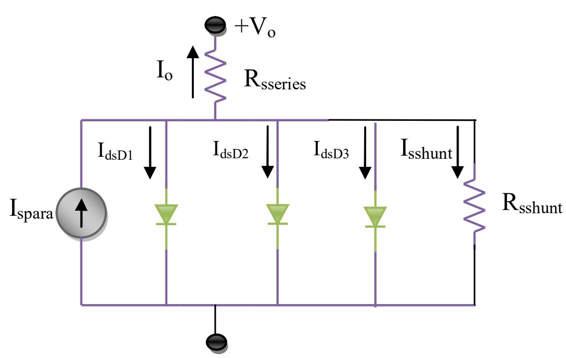



***Fig.2.*** *Circuit diagram of TDM*

In this paper, four parameters $(I_{dsD1}, I_{dsD2}, I_{dsD3}$ and $I_{spara})$ will be computed by mathematical equations, whereas the algorithm will obtain the other five parameters $(\eta_1, \eta_2, \eta_3, R_{sshunt}$ and $R_{ssries})$ [1]. The output current I in (A) of the PV cell can be computed by using Kirchhoff's law and defined by[6],

$$I_o = I_{spara} - I_{dsD1} - I_{dsD2} - I_{dsD3} - I_{sshunt} \quad (1)$$

$$I_o = I_{spara} - I_{dsD1}\left[\exp\left(\frac{q(V_o + R_{sseries}I_o)}{\eta_1 kt_m}\right) - 1\right] - I_{dsD2}\left[\exp\left(\frac{q(V_o + R_{sseries}I_o)}{\eta_2 kt_m}\right) - 1\right] - I_{dsD3}\left[\exp\left(\frac{q(V_o + R_{sseries}I_o)}{\eta_3 kt_m}\right) - 1\right] - \frac{V_o + R_{sseries}I_o}{R_{sshunt}} \tag{2}$$

Equations (1) and (2) describe the total output current (I) of the mathematical model of TDM [8]. So, the TDM will necessitate the withdrawal of 9 variables $I_{dsD1}, I_{dsD2}, I_{dsD3}' I_{spara}, \eta_1, \eta_2, \eta_3, R_{sshunt}, R_{ssries}$ in corresponding items ($Y_1$, $Y_2$, . ., $Y_9$) of the objective function by using the developed ESSA technique.

## 3.2 Proposed Optimization Algorithm

By determining the best values for the systems' unknowable parameters, the fundamental goal of PV panel modeling is to reduce the discrepancy betweenexperimental findings as well as obtained data during numerous atmospheric circumstances. The main requirements to apply any optimization algorithm are accomplished by the determination of the vector of solutions (Y), which exhibits the nine unknown parameters of the TDM of PV modules, the search range, and the objective function [23]. The vector of solutions for TDM is realized as the following[4].

$$Y = \left(I_{dsD1}, I_{dsD2}, I_{dsD3}' I_{spara}, \eta_1, \eta_2, \eta_3, R_{sshunt}, R_{ssries}\right) \tag{3}$$

The TDM's parameters for the solar panel are determined using a variety of optimizer methods in this research.It requires the creation of a fitness function. Here, an entirely novel fitness function is introduced to exactly construct the TDM. The current erroris definedas the change between the estimated and measured model currents. It is utilized as the fitness function in the optimization approach [9]. The error function $n_e(V_o, I_o.Y)$ is the variationamong the estimated and the experimental currents and is demonstrated as follows in Eq. (4)

$$n_e(V_o, I_o.Y) = I_o - I_{o-me} \tag{4}$$

Here, the estimated current $I_o$ is determinedby using Eqn. (2) and $I_{o-me}$ denotesthe measured current.The objective function is defined as the RMSE (Y) and is expressed by the following formula[3,5],

$$\text{RMSE}(Y) = \sqrt{\frac{1}{M}\sum_{d=1}^{M} n_e(V_o, I_o, Y)} \tag{5}$$

where, $M$ denotes the number of measured data.

## 3.3 SSA

Research on the foraging, as well as anti-predator features of sparrows, led to the development of a novel type of swarm intelligence optimization tool known as the ESSA. The fundamental principles include:

Sparrows employ two distinct behavioral techniques while foraging: the discoverer and the joiner. The discoverer, who acts as the population's leader, is principally in charge of locating the feeding site and providing accurate directions for the total sparrow population. To obtain food, the joiner frequently goes along with the discoverer's lead. Additionally, some joiners will approach the discoverer with the intention of stealing their food or will graze close by, increasing their predation rate. Every sparrow in the population will exhibit anti-predation behavior when it is put atrisk by a predator or becomes aware of the danger[24].

In the simulation experiment, we need to use computer-generated sparrows to locate prey. The location of sparrows can be described by the matrix below:

$$C = \begin{bmatrix} C_{1,1} & C_{1,2} & \cdots & \cdots & C_{1,Dimen} \\ C_{2,1} & C_{2,2} & \cdots & \cdots & C_{2,Dimen} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ C_{l,1} & C_{l,2} & \cdots & \cdots & C_{l,Dimen} \end{bmatrix} \tag{6}$$

Where$l$ denotes the count of sparrows as well andD$imen$denotes the size of the variables that need to be optimized. Consequently, the following vector can be used to represent the fitness value for all sparrows:

$$K_{sp} = \begin{bmatrix} k([C_{1,1} & C_{1,2} & \cdots & \cdots & C_{1,Dimen} \\ k([C_{2,1} & C_{2,2} & \cdots & \cdots & C_{2,Dimen} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ k([C_{m,1} & C_{m,2} & \cdots & \cdots & C_{n,Dimen} \end{bmatrix} \tag{7}$$

Wherethe value of $K_{sp}$ in each row represents the fitness value of the individual[25].

### 3.4 ESSA

In SSA, the discoverer has an advantage over the joiner in terms of foraging range and priority access to prey. The discoverer typically makes up 10% to 20% of the population. In each iteration, the position update algorithm is as follows[24]:

$$C_{c,d}^{g+1} = \begin{cases} C_{c,d}^{g}.\exp\left(\frac{-c}{\beta Iter_{Maxim}}\right) + Levy(1,1,1.5) & \text{if} J_2 < safe_{thr} \\ C_{c,d}^{g} + S.T + Levy(1,1,1.5) & \text{if} J_2 \geq safe_{thr} \end{cases} \tag{8}$$

Where*g*indicates the existing number of iterations. $C_{c,d}$ indicates the location data of the $c^{th}$ sparrow in the $d^{th}$ dimension. $\beta \in (0,1]$refers to an arbitrary number; S refers to an arbitrary number, which complies with a normal distribution. $T$ denotes a matrix of size 1xd. $J_2 \in [0,1]$and $safe_{thr} \in [0.5,1]$ correspondingly symbolizes the prematurecaveat as well as protectionassessment. $J_2 < safe_{thr}$ signifies no raider is grounded in the foraging region as well as the discoverer iscapable of performing anextensivehunt.On the other hand, $J_2 \geq safe_{thr}$ signifies the presence of the predator in the foraging area.

The Levy distribution encourages enhanced and more efficient search space exploration. Levy flight, a powerful statistical concept, is used by scientists to improve the global exploration capability of several meta-heuristic techniques. Levy flights aid in the discovery of new potential solutions that are distant from the greatest one currently available. A Levy distribution is used to determine the step length in this particular type of random walk. The computations for the Levy flight are as follows:

$$Levy = \frac{0.01 \times a \times \kappa}{|b|^{\frac{1}{\delta}}} \tag{9}$$

where $a$ and $b$ are the 2 normally distributed arbitraryconstants in [0, 1], $\delta$ is a constant assumed to be 1.5 in the present work, and $\kappa$ is determined as:

$$\delta = \left( \frac{T(1+\delta) \times \sin\left(\frac{\pi\delta}{2}\right)}{T\left(\frac{1+\delta}{2}\right) \times \delta \times 2^{\left(\frac{\delta-1}{2}\right)}} \right)^{\frac{1}{\delta}} \tag{10}$$

Where $T(y) = (y-1)!$. The remaining sparrowsexcept the discoverer are all joiners. They update their locations using the following formula[24,25]:

$$C_{c,d}^{g+1} = \begin{cases} S.\exp\frac{\left(C_{worst}^{g} - C_{c,d}^{g}\right)}{u^2} & \text{if } c > 1/2 \\ C_{opl}^{g+1} + \left|C_{c,d}^{g} - C_{opl}^{g+1}\right|.B^{+}.T & \text{otherwise} \end{cases} \tag{11}$$

where $C_{opl}$ indicates the optimal location attained by the producer. $C_{worst}$ denotes the in-progress global worst position. B corresponds to a matrix of 1 × d for which each constituent is arbitrarily allottedto 1 or −1, and $B^{+} = B^{T}(BB^{T})^{-1}$. When $c > l/2$ it suggests that the $c^{th}$ scrounger with the worse fitness value is most likely to be starving[25].We assume the simulation experimentation that these sparrows are conscious of the threat and makeup 10% to 20% of the entire population. These sparrows' beginning placements are generated at random within the population.

$$C_{c,d}^{g+1} = \begin{cases} \left( C_{best}^{g} + \psi \left| C_{c,d}^{g} - C_{best}^{g} \right| \right) & \text{if} \quad h_c > h_g \\ C_{c,d}^{g} + M\left( \dfrac{C_{c,d}^{g} - C_{worst}^{g}}{(h_u - h_w) + \varepsilon} \right) & \text{if} \quad h_c = h_g \end{cases} \tag{12}$$

Where $C_{best}$ is the current global ideal spot. $\psi$ denotes the step volumemanagingfactor with a mean value of 0 along with a variance of 1. M∈ [−1, 1] is anarbitrary constant. Here $h_c$ represents the estimation of the current sparrow's fitness. The current global best and worst fitness values are $hg$ and $hw$ respectively. $\varepsilon$ is the lowest factor to prevent zero-division errors. For simplicity, when $h_c > h_g$, it represents that the sparrow is at the border of the assembly. $C_{best}$denotes the position of the middle of the population and is securein the region. The condition $h_c = h_g$ shows that the sparrowsare attentivetothe threat. Mindindicateshow the sparrow travels. The main steps of the ESSA can be condensed into the pseudo code provided in Algorithm 1 depending on the idealization and viability of the aforementioned model. The flowchart of the proposed ESSA model is shown in Figure 3.

**Algorithm1:** Pseudocode of ESSA

| ESSA Algorithm |
|---|
| Input: |
| W:Maximum number of iterations |
| $n_p$ : Total count of producer |
| $n_s$ : count of sparrows that notice threat |
| $F_2$: Alert level |
| m: Total count of sparrows |
| Set the parameters necessary for the initialization of the population of m sparrows. |
| Output: $C_{best}, h_g$ . |
| 1.While (z<W) |
| 2.Determine the current best as well as worst individuals by ranking the fitness values. |
| 3. $J_2 = \text{rand}(1)$ |
| 4.for $c = 1 : n_p$ |
| 5. Upgrade the sparrow's position using Eqn (8) |
| 6.end for |
| 7.for $c = (n_p + 1) : 1$ |
| 8. Upgrade the sparrow's position using Eqn (11) |
| 9.end for |
| 10.for $c = 1 : n_s$ |
| 11. Upgrade the sparrow's position using Eqn (12) |
| 12. End for |
| 13.Obtain the bestposition. |
| 14.Update it if the new location is superior tothe previous one |
| 15. $g = g + 1$ |
| 16.End while |
| 17.Return $C_{best}, h_g$ |

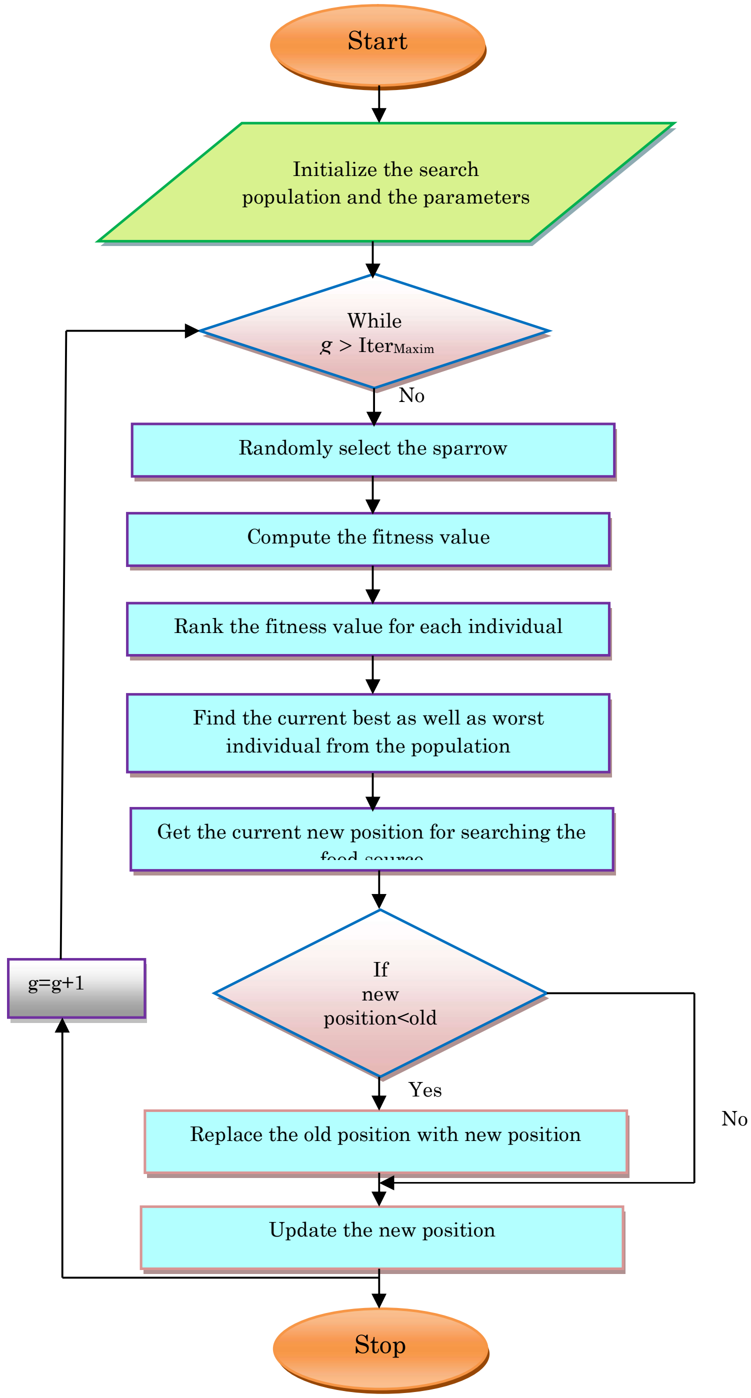



***Fig. 3.*** *Flow chart of proposed ESSA Algorithm*

## 4. Results and Discussion

The suggested methodology is used to estimate the electrical parameters of two well-known commercial PV cells (Canadian Solar Inc.'s CS6K-255P and Dow Chemical's DPS-10-1000). In the suggested method models, the PV panels usethe STC and NOCT datasheet characteristics, where these datasheet values are provided by the majority of PV producers.The developedESSA technique isused to reduce the objective function by producing $\eta_1, \eta_2, \eta_3 . R_{sshunt}$ and $R_{sseries}$. The total number of iterations permitted is 30.

## 4.1 Electrical Parameter Analysis

Tables 2 and 3 provide a list of the 9 electrical characteristics of the TDM PV for the dow chemical DPS-10-1000(Case 1) and Canadian Solar Inc-CS6K-255P(Case 2) PV modules that were attained using the suggested approach and the ESSA methodology.

***Table 2:*** *Electrical characteristics of dow chemical DPS-10-1000 PV module's TDPV model at STC circumstances*

| | GWO | FF | SSA | PROP |
|---|---|---|---|---|
| $I_{spara}$ | 8.153 | 8.236545 | 8.2152 | 8.26526 |
| $I_{dsD1}$ | 1.421e-8 | 1.86325e-8 | 2.523642e-8 | 1.025631e-15 |
| $I_{dsD2}$ | 4.236e-9 | 3.2633e-10 | 2.36542e-10 | 1.15243e-7 |
| $I_{dsD3}$ | 1.3256e-10 | 3.26423e-10 | 4.32562e-10 | 4.93562-20 |
| $\eta_1$ | 1.236 | 1.526 | 1.325 | 1.0245 |
| $\eta_2$ | 1.325 | 1.5682 | 1.154 | 1.8442 |
| $\eta_3$ | 1.254 | 1.145 | 1.475 | 1.3253 |
| $R_{sseries}$ | 0.2235 | 0.14523 | 0.3562 | 0.256412 |
| $R_{sshunt}$ | 523.021 | 423.1 | 506.2 | 4125.3 |

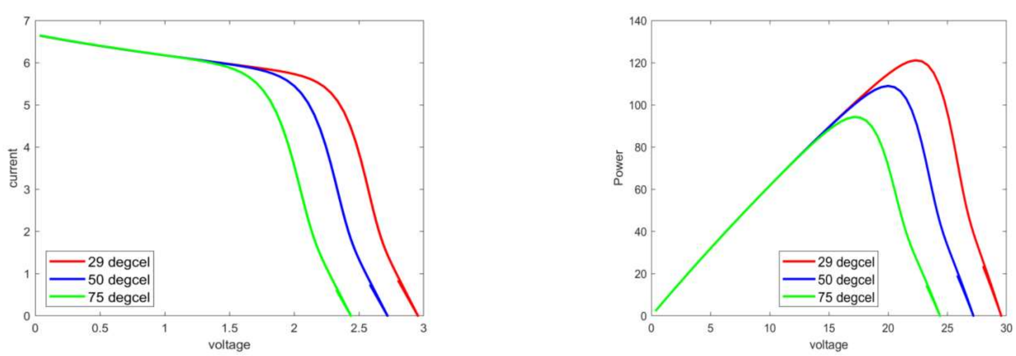
***Table 3:*** *Electrical characteristics of Canadian Solar Inc-CS6K-255P PV module's TDPV model at STC conditions*

| | GWO | FF | SSA | PROP |
|---|---|---|---|---|
| $I_{spara}$ | 8.23 | 9.23 | 9.653 | 9.1254 |
| $I_{dsD1}$ | 6.213e-6 | 1.2351e-11 | 1.32566e-12 | 4.332551e-20 |
| $I_{dsD2}$ | 3.15624e-6 | 1.10e-11 | 2.325e-6 | 1.11e-10 |
| $I_{dsD3}$ | 1.362e-12 | 6.32e-10 | 5.147e-9 | 3.25e-6 |
| $\eta_1$ | 1.235 | 1.524 | 1.325 | 1.623 |
| $\eta_2$ | 1.523 | 2.31 | 2.125 | 1.57 |
| $\eta_3$ | 1.41 | 1.548 | 1.14 | 1.69 |
| $R_{sseries}$ | 0.1475 | 0.04251 | 0.2325 | 0.2012 |
| $R_{sshunt}$ | 800 | 2.302e3 | 1.325e5 | 685.23 |

These electrical properties are compared to those discovered by other techniques. The electrical parameters for the dow chemical DPS-10-1000 and Canadian Solar Inc-CS6K-255P modules are compared with the corresponding GWO, FF, and SSA values. Additionally, by comparing the acquired data with a plot of the I-V and P-V characteristics of the dow chemical DPS-10-1000 and the Canadian solar Inc-CS6K-255P under different atmospheric conditions, the usefulness of the suggested approach is confirmed.

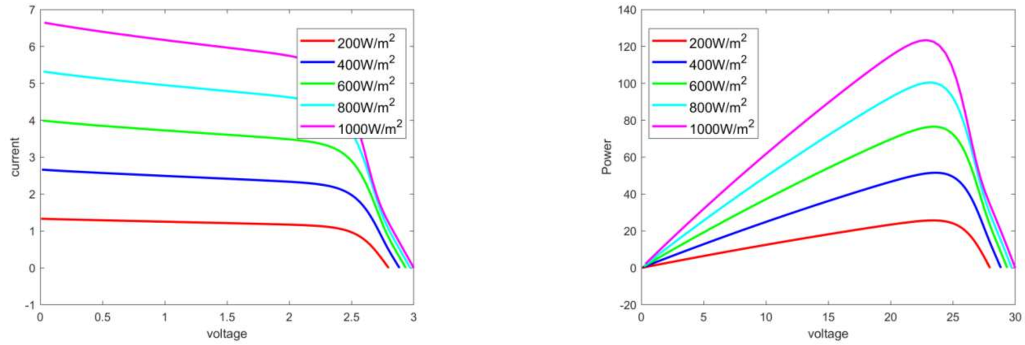
**Case 1:**

The I-V and P-V characteristics of the suggested methodology are shown for the Dow Chemical DPS-10-1000 PV panel and contrasted with the calculated statistics under various temperature settings, as shown in Figure. 4.




a) IV temperature characteristics b) PV temperature characteristics

***Fig.4.*** *Temperature characteristics of dow chemical DPS-10-1000*



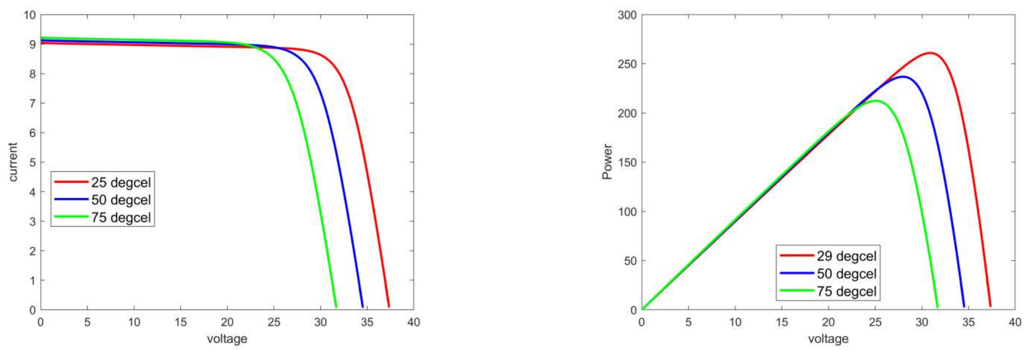

a) IV characteristics b) PV characteristics

***Fig. 5.*** *Radiation intensity characteristics of dow chemical DPS-10-1000*

Additionally, as shown in Figure5, the I-V and P-V characteristics of the proposed technique are shown and are contrasted with the actual data at various radiation intensities (1000, 800, 600, and 400 W/m2). These figures show that the outcomes produced by the proposed ESSA technique are comparable to the measured data under various functioning situations.

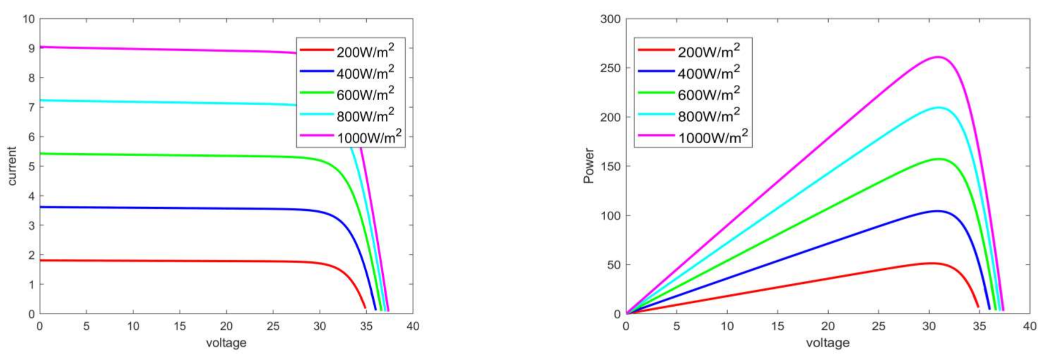
**Case 2:**

For the Canadian solar Inc-CS6K-255P panel, the I-V and P-V characteristics of the proposed method are plotted as well as contrasted with the calculated statistics under constant various temperature conditions, as established in Figure. 6.




a)IV temperature characteristics b)PV temperature characteristics

***Fig. 6.*** *Temperature characteristics of Canadian Solar Inc-CS6K-255P*

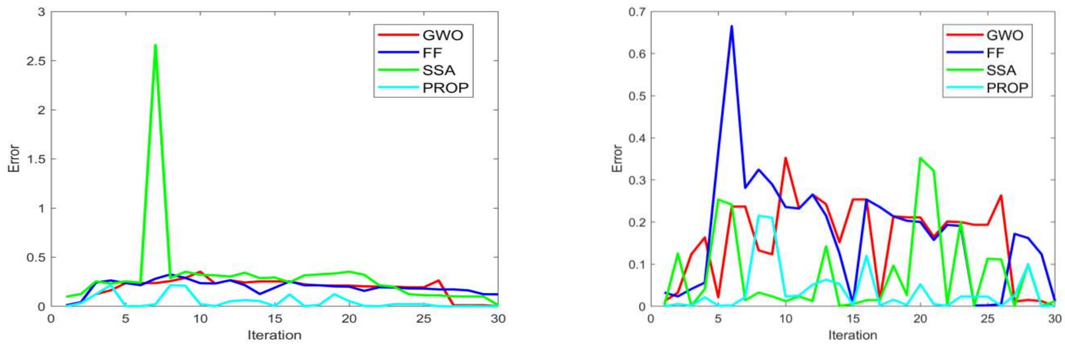



a)IV characteristics b)PV characteristics

***Fig. 7.*** *Radiation intensity characteristics of Canadian Solar Inc-CS6K-255P*

Additionally, as shown in Figure7, the I-V and P-V characteristics of the suggested approach are plotted and contrasted with the information obtained at various radiation intensities (1000, 800, 600, and 400 W/m²).Thesefigures show that the outcomes produced by the developed ESSA methodology are comparable to the calculatedstatistics under various operating situations. Additionally, the current and voltage of both solar modules under various ecological settings are evaluated. Additionally, the proposed approach is validated using the total current error among the measured current and the calculated current with the help of the suggested approach.

### 4.2Error Analysis




a) For dow chemical DPS-10-1000 b) For Canadian Solar Inc-CS6K-255P

***Fig. 8.*** *Total error of PV current*

As shown in Figure. 8, the total inaccuracy of currents for the dow chemical DPS-10-1000panelis compared with GWO, FF,and SSA methods. Similar comparisons are made between the total current error of the developed technique attained by GWO, FF, and SSA for the Canadian Solar Inc.-CS6K-255P panel as in Figure. 8.b. The suggested technique significantly reduced absolute error because of the utilization of the objective function's largest variable, especially in the knee area (maximum power region), The comparison methods employed calculatedstatistics to mold the PV modules. According to the optimization and analysis results, the ESSA method has some benefits, including the capacity to resolve challenging nonlinear issues, quick convergence to the optimal solution, and straightforward computation.

## 5. Advantages and Disadvantages

**Advantages**

- Reduced absolute error because of the utilization of the objective function's largest variable, especially in the knee area (maximum power region).
- Has the capacity to resolve challenging nonlinear issues.
- Quick convergence to the optimal solution.
- Straightforward computation.

**Disadvantages**

- Doesn’t supports online monitoring of solar panels

## 6. Conclusion

This study explored the parameter estimation of TDM PV systems to estimate more specific parameters for the PV model.It has a significant financial impact on PV system manufacture.It is possible to obtain the PV panel's nine TDM parameters. Utilizing ESSA technology and other comparisons,to verify the validity of the suggested TDM. The estimated and measured I-V and P-V curves are then compared to validate the TDMs' accuracy. The absolute difference among the predicted as well as calculated currents was lowest for the TDM based on the ESSA. Finally, they are examined under numerous environmental settings, with their predicted output currents contrasted with calculated output currents, to show the superiority of the computed TDMs. The simulation results show that the ESSA-entrenched TDM is resilient under a range of ecological circumstances. Future investigations will focus on the online monitoring of solar panels using the anticipated ESAA-entrenched TDM.

## Compliance with Ethical Standards

**Conflicts of interest:** Authors declared that they have no conflict of interest.

**Human participants:** The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

## References

[1] Qais, H. Mohammed, H. M. Hasanien and S. Alghuwainem, "Parameters extraction of three-diode photovoltaic model using computation and Harris Hawks optimization," Energy, Vol. 195, pp. 117040, 2020.
[2] Qais, H. Mohammed, H. M. Hasanien, S. Alghuwainem, K. H. Loo, M. A. Elgendy and R. A. Turky, "Accurate Three-Diode model estimation of Photovoltaic modules using a novel circle search algorithm," Ain Shams Engineering Journal, Vol. 13, No. 3, pp. 101824, 2022.
[3] Qais, H. Mohammed, H. M. Hasanien, S. Alghuwainem and A. S. Nouh, "Coyote optimization algorithm for parameters extraction of three-diode photovoltaic models of photovoltaic modules," Energy, Vol. 187, pp. 116001, 2019.
[4] Ramadan, Abdelhady, S. Kamel, M. M. Hussein and M. H. Hassan, "A new application of chaos game optimization algorithm for parameters extraction of three diode photovoltaic model," IEEE Access, Vol. 9, pp. 51582-51594, 2021.
[5] Allam, Dalia, D. A. Yousri and M. B. Eteiba, "Parameters extraction of the three diode model for the multi-crystalline solar cell/module using Moth-Flame Optimization Algorithm," Energy Conversion and Management, Vol. 123, pp. 535-548, 2016.
[6] Ridha, H. Mohammed, H. Hizam, C. Gomes, A. A. Heidari, H. Chen, M. Ahmadipour, D. H. Muhsen and M. Alghrairi, "Parameters extraction of three diode photovoltaic models using boosted LSHADE algorithm and Newton Raphson method," Energy, Vol. 224, pp. 120136, 2021.
[7] Ramadan, A. Husam, B. Khan and A. A. Z. Diab, "Accurate parameters estimation of three diode model of photovoltaic modules using hunter–prey and wild horse optimizers," IEEE Access, Vol. 10, pp. 87435-87453, 2022.
[8] Ramadan, Abd-ElHady, S. Kamel, T. Khurshaid, S. R. Oh and S. B. Rhee, "Parameter extraction of three diode solar photovoltaic model using improved grey wolf optimizer," Sustainability, Vol. 13, No. 12, pp. 6963, 2021.
[9] Soliman, A. Mahmoud, H. M. Hasanien, R. A. Turky and S. M. Muyeen, "Hybrid African vultures–grey wolf optimizer approach for electrical parameters extraction of solar panel models," Energy Reports, Vol. 8, pp. 14888-14900, 2022.
[10] Ridha, H. Mohammed, C. Gomes, H. Hazim and M. Ahmadipour, "Sizing and implementing off-grid stand-alone photovoltaic/battery systems based on multi-objective optimization and techno-economic (MADE) analysis," Energy, Vol. 207, pp. 118163, 2020.
[11] Ridha, H. Mohammed, C. Gomes, H. Hizam, M. Ahmadipour, A. A. Heidari and H. Chen, "Multi-objective optimization and multi-criteria decision-making methods for optimal design of standalone photovoltaic system: A comprehensive review," Renewable and Sustainable Energy Reviews, Vol. 135, pp. 110202, 2021.
[12] Yu, Kunjie, B. Qu, C. Yue, S. Ge, X. Chen and J. Liang, "A performance-guided JAYA algorithm for parameters identification of photovoltaic cell and module," Applied Energy, Vol. 237, pp. 241-257, 2019.
[13] Nishioka, Kensuke, N. Sakitani, Y. Uraoka and T. Fuyuki, "Analysis of multicrystalline silicon solar cells by modified 3-diode equivalent circuit model taking leakage current through periphery into consideration," Solar energy materials and solar cells, Vol. 91, No. 13, pp. 1222-1227, 2007.
[14] A. Kassis and M. Saad, "Analysis of multi-crystalline silicon solar cells at low illumination levels using a modified two-diode model," Solar Energy Materials and Solar Cells, Vol. 94, No. 12, pp. 2108-2112, 2010.
[15] Chin, V. Jack, Z. Salam and K. Ishaque, "Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review," Applied Energy, Vol. 154, pp. 500-519, 2015.
[16] Brano, V. Lo and G. Ciulla, "An efficient analytical approach for obtaining a five parameters model of photovoltaic modules using only reference data," Applied Energy, Vol. 111, pp. 894-903, 2013.
[17] Mahmoud, Yousef and E. F. El-Saadany, "A photovoltaic model with reduced computational time," IEEE transactions on industrial electronics, Vol. 62, No. 6, pp. 3534-3544, 2014.
[18] Hasanien, M. Hany, "Shuffled frog leaping algorithm for photovoltaic model identification," IEEE Transactions on Sustainable Energy, Vol. 6, No. 2, 509-515, 2015.
[19] Lim, L. H. Idris, Z. Ye, J. Ye, D. Yang and H. Du, "A linear identification of diode models from single $ I $–$ V $ characteristics of PV panels," IEEE Transactions on Industrial Electronics, Vol. 62, No. 7, pp. 4181-4193, 2015.
[20] Shannan, N. M. A. Alrahim, N. Z. Yahaya and B. Singh, "Single-diode model and two-diode model of PV modules: A comparison," In 2013 IEEE international conference on control system, computing and engineering, pp. 210-214, 2013.
[21] Gupta, Sudhanshu, H. Tiwari, M. Fozdar and V. Chandna, "Development of a two diode model for photovoltaic modules suitable for use in simulation studies," In 2012 Asia-Pacific Power and Energy Engineering Conference, pp. 1-4, 2012.
[22] Elazab, S. Omnia, H. M. Hasanien, M. A. Elgendy and A. M. Abdeen, "Parameters estimation of single-and multiple-diode photovoltaic model using whale optimisation algorithm," IET Renewable Power Generation, Vol. 12, No. 15, pp. 1755-1761, 2018.

[23] D. F. Alam, D. A. Yousri and M. B. Eteiba, "Flower pollination algorithm based solar PV parameter estimation," Energy Conversion and Management, Vol. 101, pp. 410-422, 2015.
[24] Marmouh, Soufiane, M. Boutoubat and L. Mokrani, "Performance and power quality improvement based on DC-bus voltage regulation of a stand-alone hybrid energy system," Electric Power Systems Research, Vol. 163, pp. 73-84, 2018.
[25] Xue, Jiankai and B. Shen, "A novel swarm intelligence optimization approach: sparrow search algorithm," Systems science & control engineering, Vol. 8, No. 1, pp. 22-34, 2020.