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# Parameter Extraction of PV Solar Cells Using Metaheuristic Methods

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**Abstract**
Due to the increasing crises in energy and environmental factors, the importance of renewable energy is increasing. However, it is gaining importance in developing photovoltaic energy systems. Therefore, great efforts are made to maximize success in accurately modeling PV parameters. Parameter estimation is a complex problem and requires advanced design tools such as optimization techniques because the current voltage (I–V) characteristics of PVs are nonlinear. This study investigates the best technique to estimate the parameters obtained in single-diode and double-diode cases. The Grey Wolf Optimization (GWO), Improved Grey Wolf Optimization (IGWO), Sine Cosine Algorithm (SCA), Whale Optimization Algorithm (WOA), and Multi-Verse Optimizer (MVO) are the algorithms used in this paper. Apart from the literature, this study considers that the PV parameter extraction problem is not just an offline optimization problem but also a real-time optimization issue. The performance of all methods has been compared with experimental data. The lowest error on minimum iteration and highest convergence accuracy have been achieved for offline optimization by using IGWO. The results clearly state that the IGWO is not usable in real-time applications even though IGWO is the best optimizer in offline optimization.

## 1. Introduction

The reasons such as the energy and climate crisis in recent years, the limited use of fossil fuels, acid rain, carbon emission, and negative ozone changes have highlighted the importance of renewable and clean energy. Long-term solutions and research are needed before environmental problems become more serious and irreversible problems. For this reason, renewable energy sources such as the sun [1], water [2], and wind [3] and their sustainable application areas are increasing daily. In addition to the increasing use of clean energy in industry, it is becoming increasingly common in rural and urban areas. This widespread using makes solar systems more and more popular due to their potential advantages, ease of installation, and efficiency.

Solar systems are one of the growing systems in the renewable energy sector. Solar energy systems are one of the most common methods of generating electricity through photovoltaic (PV) modules. Besides, PV systems are preferred due to low pollution, noiseless operation, and widespread distribution. Sunlights are converted into electricity using semiconductor systems [4]. The correct modeling and optimization processes of these systems are the factors that directly affect the efficiency and operating characteristics of the systems.

Photovoltaic systems have nonlinear characteristics depending on variables such as semiconductor material characteristics and environmental factors such as temperature. Therefore, in PV studies, it is essential to compute the correct circuit values to obtain the correct cell characteristics and operate the system efficiently [5]. In recent

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studies on this subject, optimization methods are used seriously as well as numerical methods. The reason for this is that in addition to the values such as open circuit voltage ($V_{oc}$), maximum power ($P_{mpp}$), short circuit current ($I_{sc}$), the current and voltage temperature coefficients ($K_v$; $K_i$) given in the datasheet, the actual circuit parameters used in the system are determined. It is expected to be calculated by the manufacturers. These parameters are photocurrent ($I_{ph}$), the ideality coefficients of diode (n), saturation current ($I_0$), shunt resistance ($R_{sh}$) and series resistance ($R_s$) [6].

Models used to show the behavior characteristics of PV models are single-diode (SDM) and double-diode (DDM) models [7], [8]. In the estimation and optimization processes, there are five values in the SDM and seven values for the DDM [6]. Many methods have been used in finding these parameters and obtaining the optimum parameter values by determining a particular objective function, and studies have been applied on this subject.

Different optimization studies on the PV module have been carried out with different methods in recent studies in the literature. Due to the weaknesses of deterministic methods, optimization algorithms have started to be used to determine unknown values of PV modules in studies. These are maximum power point tracking (MPPT), parameter estimation, maximum efficiency, and minimum cost optimization studies. In [6], the flexible particle swarm optimization (FPSO) based approach is used to extract the values of PV cell models to arrive the maximum power point. It is compared with known methods to demonstrate the proposed adequacy of the approach. In another parameter estimation study [9], the Stochastic Fractal Search (SFS) technique was used. The SFS-based method has been tested for different situations using the SDM and DDM to evaluate its performance. Whippy Harris Hawks Optimization (WHHO) [10] was preferred because of its effectiveness in practical application. According to the literature research, the optimization approaches used to extract the PV parameters are Harmony Search-based Algorithm (HS) [11], Simulated Annealing (SA) [12], Bird Mating Optimizer (BMO) [13], Genetic Algorithm (GA) [14], Teaching Learning Based Optimization (TLBO) [15], [16], Artificial Bee Colony Algorithm (ABC) [17], Mine Blast Algorithm (MBA) [18], Moth–Flame Optimizer (MFO) [19], Whale Optimizer [20], Flower-Pollinating Optimization (FPO) [21], Cat Swarm Optimization (CSO) [22], water cycling optimization [23], Wind Driven Optimization (WDO) [24], Jaya optimization [25], Sunflower Optimization (SFO) [26], Enriched HHO (EHHO) [27], Improved Opposition-Based Whale Optimization Approach (IWOA) [28], Slime Mould Optimization (SMA) [29], Springy whale optimization (SWOA) [30], Bald Eagle Search (BES) Algorithm [31], Improved Marine Predators Algorithm [32], Jellyfish Search Optimizer [33], War Strategy Optimization [34], Improved Honey Badger Algorithms [35], Musical chairs algorithm [36], Honey Badger Algorithm [37], Artificial Ecosystem Optimization Algorithm [38], Tuna Swarm Optimization [39], respectively.

Nowadays, where renewable energy is essential, the role of photovoltaic (PV) systems in energy production is increasing. However, optimizing accurate parameters is of great value for these systems to work effectively and efficiently. In this context, getting the PV module design with optimized parameters increases energy and minimizes system costs. Extracting this output from the traditional method is complex and time-consuming, so using metaheuristic techniques in this field has great potential.

When the methods and performance evaluations used in studies on obtaining the parameters of PV models in the literature are examined, it is seen that there are still unused methods for obtaining values in SDM and DDM. Moreover, along with the literature, this study investigates the best method for real-time estimation of PV parameters.

This study aims to examine five different metaheuristics to extract the release of PV module design: GWO, IGWO, MVO, WOA, and SCA. Additionally, whether these techniques are suitable for real-time applications will be evaluated within the scope of this study. The main contributions of this study are listed below:

- IGWO was first used to solve SDM (five unknown parameter extraction) and DDM (seven unknown parameter extraction).
- The PV unknown parameter extraction problem is considered a real-time problem.
- For this problem, IGWO, GWO, SCA, WOA, and MVO calculation time is calculated.
- The method that provides the best results in the shortest time is investigated among the five methods.

The rest of the paper has these sections: The SDM and DDM is explained in Section 2. The meta-heuristic methods that are implemented is described in material and methods which is Section 3. Section 4 demonstrates the results and discussion of the optimization data. Section 5 concludes the paper with discussion and future works.

## 2. Problem Formulation

Since PV modules are semiconductor structures, I-V structures are characteristically similar to diodes. Therefore, the parameters are found as different values over time due to the nonlinear characteristic of the PV structure. Therefore, SDM and DDM are the most preferred models in equivalent circuit modeling [40].

### 2.1. Single Diode

Figure 1 shows the equivalent circuit of the SDM. This circuit includes the following circuit elements, respectively: a current source, a diode in parallel with the current source, a semiconductor, and a shunt ($\boldsymbol{R_{sh}}$) and a series ($\boldsymbol{R_s}$) resistor that models the ohmic losses in leakage current [41].

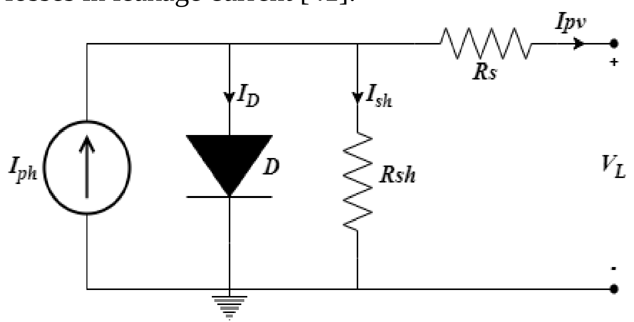


**Figure 1.** Single diode model of PV equivalent circuit.

The output current ($I_{pv}$) can be formulated as in Eq.1 [42]:

$$I_{pv} = I_{ph} - I_D - \left(\frac{V_{pv} + I_{pv}R_s}{R_{sh}}\right) \tag{1}$$

where $V_{pv}$ is the output voltage. The current ($I_D$) flowing through the diode is expressed as in Eq.2 [42]:

$$I_D = I_0\left[exp\left(\frac{V_{pv} + I_{pv}R_s}{V_t\alpha}\right) - 1\right] \tag{2}$$

α is the ideality coefficient of diode. The thermal voltage ($V_t$) used in Eq.2 is calculated as in Eq.3 [42]:

$$V_t = \frac{N_s kT}{\mathrm{q}} \tag{3}$$

where $k$, $q$, and $T$ are the Boltzmann constant, electron charge, and operating temperature, respectively. The photo-generated current ($I_{ph}$) is shown as Eq.4 [42]:

$$I_{ph} = I_{ph-STC} + K_i(T - T_{STC}) \times \left(\frac{G}{G_{STC}}\right) \tag{4}$$

where $T_{STC}$, $I_{ph-STC}$ and $G_{STC}$ are the temperature at standard test condition, photocurrent at standard test condition, and irradiance at standard test condition ($1000W/m^2$), respectively. $I_{ph-STC}$ is calculated as Eq.5 [42]:

$$I_{ph-STC} = I_{sc-STC}\left(\frac{R_s + R_{sh}}{R_s}\right) \tag{5}$$

The reverse saturation current ($I_0$) is calculated as follows [42]:

$$I_0 = \frac{I_{ph-STC} - (V_{oc-STC}/R_{sh})}{exp\left(\frac{V_{oc-STC}}{\alpha V_{t-STC}}\right) - 1} \tag{6}$$

Based on all these calculations, five parameters ($I_{ph}$, $I_0$, α, $R_s$ and $R_{sh}$) requires optimization for the single-diode model.

### 2.2. Double Diode

The SDM does not give good results, especially in low irradiance [37]. Therefore, the DDM is preferred to increase the calculation accuracy. Figure 2 shows the equivalent circuit of DDM. As illustrated in the figure, the first of the two diodes acts as a rectifier and the second account for the current effect from recombination effects. In this way, more precise I-V characteristics are obtained.

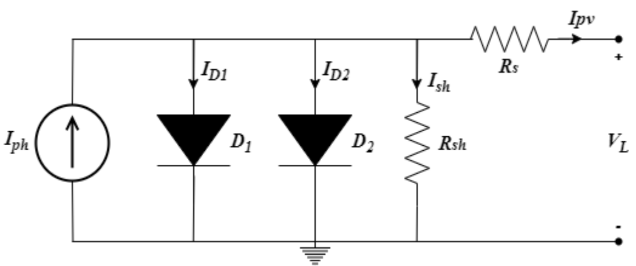


**Figure 2.** DDM of PV equivalent circuit.

The output current of the system ($I_{pv}$) is shown as:

$$I_{pv} = I_{ph} - I_{D1} - I_{D2} - \left(\frac{V_{pv} + I_{pv}R_s}{R_{sh}}\right) \tag{7}$$

Here $I_{D1}$, $I_{D2}$ are diode currents and calculated like Eq.8 and Eq.9:

$$I_{D1} = I_{01}\left[exp\left(\frac{V_{pv} + I_{pv}R_s}{V_t\alpha_1}\right) - 1\right] \quad (8)$$

$$I_{D2} = I_{02}\left[exp\left(\frac{V_{pv} + I_{pv}R_s}{V_t\alpha_2}\right) - 1\right] \quad (9)$$

where $V_t$, $V_{pv}$ are the same in Eq.2. The reverse saturation currents in each diode are calculated as follows:

$$I_{01} = \frac{I_{ph-STC} - (V_{oc-STC}/R_{sh})}{exp\left(\frac{V_{oc-STC}}{\alpha_1 V_{t-STC}}\right) - 1} \quad (10)$$

$$I_{02} = \frac{I_{ph-STC} - (V_{oc-STC}/R_{sh})}{exp\left(\frac{V_{oc-STC}}{\alpha_2 V_{t-STC}}\right) - 1} \quad (11)$$

Based on all these calculations, seven parameters ($I_{ph}$, $I_{01}$, $I_{02}$, $\alpha_1$, $\alpha_2$, $R_s$ and $R_{sh}$) requires optimization for the double-diode model.

### 2.3. Real Time Optimization for PV

The optimization time must be short in the PV panel production process for several reasons. This can both reduce costs and increase production capacity and product quality. The first reason is that PV production consists of certain stages, and correct optimization of each stage can increase the production speed. A rapid optimization process reduces delays on the production line and shortens the overall production time.

The second reason is that the materials used to manufacture solar panels are generally costly. Rapid optimization can minimize material waste, which in turn can reduce costs by optimally optimizing material usage. The third reason is that during the production process, it is essential to control the quality of the panels. Fast optimization processes enable immediate intervention when a production error is detected, thus reducing the number of defective products. Another reason is that solar panel demand may vary depending on technological developments or economic factors. Rapid optimization allows the production process to adapt to such demand changes quickly. Any delay or disruption in the production process can result in additional costs, from energy usage to labor. A fast and effective optimization process can avoid these extra costs.

## 3. Material and Methods

Section 3 discusses the algorithms used in this paper with their mathematical model.

### 3.1. Grey Wolf Optimizer (GWO)

The GWO is a heuristic algorithm developed in 2014 [40]. The hunting behavior of grey wolves inspires the GWO algorithm. They are hierarchically classified into alpha, beta, delta, and omega groups. The alpha team is a dominant species responsible for making decisions such as hunting, sleeping places, and waking time. The beta group, the second layer of the hierarchy, assists the alpha wolves in making decisions and other activities. The delta group and the omega group represent the lowest-ranked grey wolves.

The hunting is a fascinating social behavior of grey wolves alongside the social interactions of wolves. To design GWO, First, we need to define the social hierarchy of wolves. The best, second, third, and worst candidate solutions are alpha, beta, delta, and omega. There are three main parts of the hunting method, the encircling prey, the hunting, and the attacking prey.

The grey wolf can randomly update its position around its hunt using Eq. 12 and 13. The encircling prey can be formulated as below:

$$D = \left|CX_p(t) - X(t)\right| \quad (12)$$

$$X(t+1) = \left|X_p(t) - AD\right| \quad (13)$$

Here, t symbolizes the iteration value, $A$ and $C$ represent the coefficients, $Xp$ the location of the hunt, $X$ the location of an agent. The $A$ and $C$ are calculated as follows:

$$A = |2ar_1 - a| \quad (14)$$

$$C = |2ar_2| \quad (15)$$

The a is the parameter that linearly decreases from 2 to 0 by the iterations. The $r_1$ and $r_2$ are random values in the range of [0, 1].

α, β and δ species of grey wolves have extraordinary hunting abilities. They know the current location of their prey. Therefore, the best three solution candidates are recorded, and the other wolves are allowed to update their locations relative to the positions of the best search wolves using below Eq. 16-18:

$$\begin{aligned} D_a &= |C_1X_a - X| \\ D_\beta &= \left|C_1X_\beta - X\right| \end{aligned} \quad (16)$$

$$D_\delta = |C_1 X_\delta - X|$$

$$\begin{aligned} X_1 &= |X_a - A_1 D_a| \\ X_2 &= |X_\beta - A_2 D_\beta| \\ X_3 &= |X_\delta - A_3 D_\delta| \end{aligned} \quad (17)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (18)$$

At the exploitation (attacking prey) stage, a value is reduced, and therefore the limit of variation of A is reduced. When A has random values in the [-1,1] range, the search agent's next position will be anywhere between its current location and the hunt. Detailed coverage of GWO can be found in [40].

### 3.2. Improved Grey Wolf Optimizer (IGWO)

IGWO is designed to minimize the imbalance between the exploration and exploitation of the GWO method. The IGWO algorithm is inspired by the dimension-learning-based-hunting (DLH) wolves in nature.

In the beginning, wolves ($N$: number of agents) are randomly distributed in the search space in the limit of $[l_i, u_j]$.

$$\begin{gathered} X_{ij} = I_j + rand_j\,[0,1](u_j - l_j) \\ i \in [1, N] \quad , \quad j \in [1, D] \end{gathered} \quad (19)$$

$X_i(t) = \{X_{i1}, X_{i2}, \ldots, X_{iD}\}$ represents the $i^{th}$ position in the $t^{th}$ iteration ($D$=dimension). The population is recorded in a matrix with $N$ rows and $D$ columns. In the movement phase, The IGWO computes the next position of the wolf $X_i(t)$. For this computation, IGWO uses the wolf's different neighbors and a randomly selected agent from the matrix. The $R_i(t)$ is indicates the radius between the current location $X_j(t)$ and the location of the candidate $X_{j_{GWO}}(t+1)$. The $R_i(t)$ is computed by Eq. 20.

$$R_i(t) = \big\|\, X_j(t) - X_{j_{GWO}}(t+1) \big\| \quad (20)$$

$$N_i(t) = \big\{ X_j(t) \,|\, D_i(X_j(t), X_j(t)) \leq R_i(t),\ X_j(t) \in Matrix \big\} \quad (21)$$

The $N_i(t)$ is the neighbor of $X_j(t)$. It is calculated by Eq. 21. Here, $D_i$ is the Euclidean interval between $X_j(t)$ and $X_i(t)$.

$$X_{i_{DLH},d}(t+1) = X_{i,d} + rand[0,1](X_{n,d}(t) - X_{r,d}(t)) \quad (22)$$

$X_{i_{DLH},d}(t+1)$ is the new position of DLH based model, calculated using Eq. 23. Here, $n$ is the number of wolves, and $d$ is the dimension.

$$X_i(t+1) = \begin{cases} X_{i_{GWO}}(t+1), & if\ f\left(X_{i_{GWO}}(t+1)\right) < f\left(X_{i_{DLH}}(t+1)\right) \\ X_{i_{DLH}}(t+1), & otherwise \end{cases} \quad (23)$$

Detailed coverage of IGWO can be found in [41].

### 3.3. Multi-Verse Optimizer (MVO)

MVO is an optimization method inspired by multi-verse theory [42]. According to multi-verse theory, it is believed that there is more than one big bang theory [43] that accepts the universe started with a explosion and each explosion causes the birth of a universe [44]. The MVO method considers each solution candidate as a universe. Also, MVO assumes that each parameter in the solution candidate is a member in that universe. The MVO method assigns each solution a value called the inflation rate. The inflation parameter is a value to the fitness function of the solution candidate.

There are three concepts in the MVO method: white holes, black holes, and wormholes. These three concepts are used in order to explore search spaces by MVO. If the inflation rate is high, the white hole probability is high, and the black hole probability is low. The wormholes are used for the random movement of objects toward the best universe.

The white/black hole tunnels are modeled by the roulette wheel mechanism. In each iteration, the universes are ranked according to their inflation parameter, and one is chosen as a white hole. The solution matrix (Universe-$U$) is calculated as Eq. 24:

$$U = \begin{matrix} X_1^1 & \ldots & X_1^d \\ \vdots & \vdots & \vdots \\ X_n^1 & \ldots & X_n^d \end{matrix} \quad (24)$$

where $d$ and $n$ symbolise the amount of variables and universes. $X_i^j$ symbolizes the $j^{th}$ parameter of the $i^{th}$ universe. $Ui$: universe $i$, $NI$: normalized inflation rate.

$$X_i^j = \begin{cases} X_k^j r_1 < NI(Ui) \\ X_k^j r_1 \geq NI(Ui) \end{cases} \quad (25)$$

The random number is symbolized by $r_1$ [0,1]. $X_k^j r_1$ is the solution candidate by the roulette wheel mechanism method.

Wormhole tunnels are assumed to be between a universe and the best universe created to provide local varies for each universe and have a high probability of improving the inflation parameter. The formulation of this mechanism is as follows:

$$X_i^j = \begin{cases} \begin{cases} X_j + TDR\left((ub_j - lb_j)r_4 + lb_j\right) r_3 < 0.5 \\ X_j - TDR\left((ub_j - lb_j)r_4 + lb_j\right) r_3 \geq 0.5 \end{cases} & r_2 < WEP \\ X_i^j & r_2 < WEP \end{cases} \tag{26}$$

$X_j$ shows the $j^{th}$ parameter of the best universe, *TDR* and *WEP* are coefficients, $lb_j$ and $ub_j$ indicate the minimum limit of $j^{th}$ variable $X_i^j$ indicates the $j^{th}$ parameter of $i^{th}$ universe, and $r_2$, $r_3$, and $r_4$ are random values in the range of [0, 1].

$$WEP = min + l\left(\frac{max - min}{L}\right) \tag{27}$$

where *min*=0.2 and *max*=1, *l*=iteration, and *L*= the maximum iteration.

$$TDR = 1 - \left(\frac{l^{1/p}}{L^{1/p}}\right) \tag{28}$$

where p=6 represents the exploitation accuracy. Detailed coverage of MVO can be found in [42].

### 3.4. Whale Optimization Algorithm (WOA)

The WOA approach is inspired by humpback whales (Megaptera novaeangliae) [45]. Megaptera novaeangliae have specific hunting techniques called bubble-net feeding [46]. They prefer to hunt little prey by creating bubbles [47]. There are three main stages in the WOA; encircling prey, spiral bubble-net feeding maneuver, and search for prey.

The WOA algorithm assumes that the optimum value is the prey in the encircling prey stage. Thus, every search agent tries to reach the optimal value by Eq. 29.

$$D = \left|CX_p(t) - X(t)\right| \tag{29}$$

$$X(t+1) = \left|X_p(t) - AD\right| \tag{30}$$

where $X_p$ the location of the best solution candidate, $X(t)$ is the location of a search agent in the $t^{th}$ iteration. The $A$ and $C$ values are coefficients calculated in Eq. 31 and 32, respectively. In these equations, $a$ is the value linearly decreased from 2 to 0, and $r$ is the random value between 0 and 1.

$$A = |2ar_1 - a| \tag{31}$$

$$C = |2ar_2| \tag{32}$$

The second main step of WOA is the bubble net attacking stage, which is an exploitation phase. The humpback whale attacks prey by using a Shrinking encircling mechanism. The shrinking encircling mechanism is mathematically formulated as Eq. 33.

$$\begin{gathered} X(t+1) = D'e^{bl}cos(2\pi l) + X(t), \\ D' = X_p(t) - X(t) \end{gathered} \tag{33}$$

where $b$ indicates the constant value, the $b$ value defines the size of the logarithmic spiral. The $l$ is a random value range of $[-1,1]$. In the WOA, there is a probability of 50% for updating the location of whales. WOA chooses between the shrinking encircling mechanism or the spiral model as Eq. 34. ($p$: random number)

$$X(t+1) = \begin{cases} X_p(t) - AD & if\ p < 0.5 \\ D'e^{bl}\ cos(2\pi l) + X(t) & if\ p \geq 0.5 \end{cases} \tag{34}$$

The last step of WOA is the search for the hunt stage, which is the exploration phase. The WOA explores the search spaces using Eq. 29-30. Detailed coverage of WOA can be found in [45].

### 3.5. Sine Cosine Algorithm (SCA)

The SCA is a metaheuristic method proposed by [48]. Initial, the SCA produces a random set of solutions. Then, according to its objective function value, it chooses the best individual solution as a target for other solutions. Then, each individual in the first population updates their location concerning the best solution using Eq. 35-36.

$$X_i^{t+1} = X_i^T + r_1 \sin r_2 \left|r_3 P_i^t - X_i^T\right| \tag{35}$$

$$X_i^{t+1} = X_i^T + r_1 \cos r_2 \left|r_3 P_i^t - X_i^T\right| \tag{36}$$

where $X_i^T$ is the candidate solution of the population on the $t^{th}$ iteration and $P_i^t$ is the best solution obtained. The $r_1$, $r_2$ and $r_3$ are the random values.

$$X_i^{t+1} = \begin{cases} X_i^T + r_1 \sin r_2 \ |r_3 P_i^t - X_i^T|, r_4 < 0.5 \\ X_i^T + r_1 \cos r_2 \ |r_3 P_i^t - X_i^T|, r_4 \geq 0.5 \end{cases} \quad (37)$$

The parameter $r_1$ determines the updated direction in the gap between or outside the best solution. The $r_2$ parameter determines the update distance based on the best solution. The $r_3$ parameter introduces $a$ random weight to emphasize stochastically ($r_3$ > 1) or lessen ($r_3$ < 1) the impact of the target in defining distance. The parameter $r_4$ switches equally between the sine and cosine values in Eq. 37.

$$r_1 = a - t\ \frac{a}{T} \quad (38)$$

The sine and cosine spacing is reduced during optimization using Eq. 38 to achieve a proper balance between exploration and exploitation in SCA. The $t$, $T$, and $a$ symbolize the current iteration, maximum iteration, and constant. Detailed coverage of SCA can be found in [45], [48].

### 3.5. Sine Cosine Algorithm (SCA)

This section introduces the fitness function and solution clusters for the PV parameter extraction issue. The unknown PV module parameters are computed using a fitness function defined based on the solution cluster. The solution cluster consists of unknown PV module parameters and affects the fitness function value.

There are five parameters in the solution cluster for the SDM $\{I_{ph}, I_0, N_s, R_s, R_{sh}\}$ while double diode cluster $\{I_{ph}, I_1, I_2, N_1, N_2, R_s, R_{sh}\}$ consists of seven parameters. This paper uses an error function to extract the parameters correctly. An error function depicts the difference between the computed and measured data. This paper considers the error function as the fitness function (objective function). The objective function of PV parameter estimation could be described like the mean square error between the computed and measured currents, as shown in Eq. 39. ($N$: number of measured points, $FF$: fitness function)

$$FF = \frac{\sum_{k=1}^{N} \ (I_{measured} - I_{computed})^2}{N} \quad (39)$$

The measured data used in this study is referred from [49].

## 4. Experiment and Results

Section 4 presents the case studies to evaluate the IGWO based PV parameter extraction model performance. The cases of the SDM and the DDM are investigated. The real measurement data is used to compare the results. The output is explained with graphs and tabular forms.

This study has written all optimization methods on the MATLAB platform. The accuracy of each method has been evaluated with CEC benchmark (Congress of Evolutionary Computation) functions [50]. The simulations have been performed using an I7 7500U Intel 2.7 GHz and 16 GB RAM. Each code has run 25 times to obtain the main results.

### 4.1. Case 1: Single Diode

Figure 3 shows the fitness function graph of the optimization methods for extracting PV values. In addition, it concluded that the IGWO algorithm converges faster than others. The IGWO achieves the best value of 0.0416 in the $15^{th}$ iteration, while the GWO, the second-best method, reaches the best value in the $28^{th}$. Five methods reach the best result (0.0416). Figure 3 shows that the MVO is the worst convergence method for this model. The MVO reaches the best value in about the $375^{th}$ iteration. The SCA and WOA achieve the results on the $140^{th}$ and $105^{th}$ iterations.

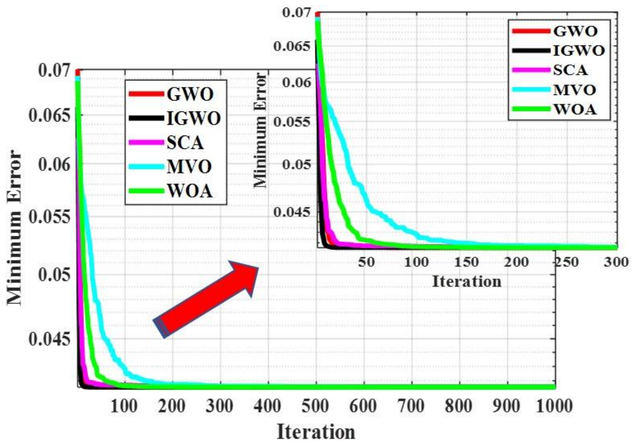


**Figure 3.** The convergence graph for the SDM.

One of the exciting outputs of this study is the computation time results. Figure 4 shows the comparison of the calculation time results of each method. Although Figure 3 clearly shows that the IGWO is the best convergence method among the others, the results of Figure 4 state that The IGWO is the slowest method, with 2.3708 seconds.

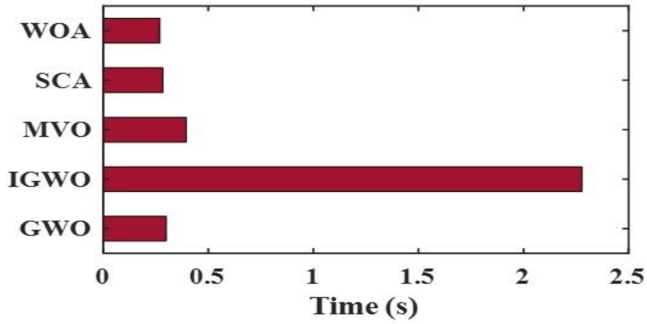


**Figure 4.** The computation time for single diode model.

For real-time optimization analysis, getting the best value in the minimum time [51]. Each algorithm runs with 1000 iterations. One iteration of IGWO spent 2.37 ms time. IGWO reach the best results on the $15^{th}$ iteration, which equals 35,55 ms (15×2.37). If the same calculation is done for GWO, SCA, MVO, and WOA, the results are 9.4977 ms (0.3392×28), 41.6488 ms (0.2228×140), 155.4196 ms (0.4145×375) and 30.0418 ms (0.2861×105), respectively. Thus, in real time, the GWO and WOA solve this problem faster than IGWO.

Figure 5 shows the I-V polarization curve of SDM for further validation of IGWO success. The blue colored curve is the curve of the experiment data gathering from [49]. The red circle represents the IGWO results. It can be concluded from Figure 5 that there is an exact match between the IGWO results and the measurement results in the I-V curve.

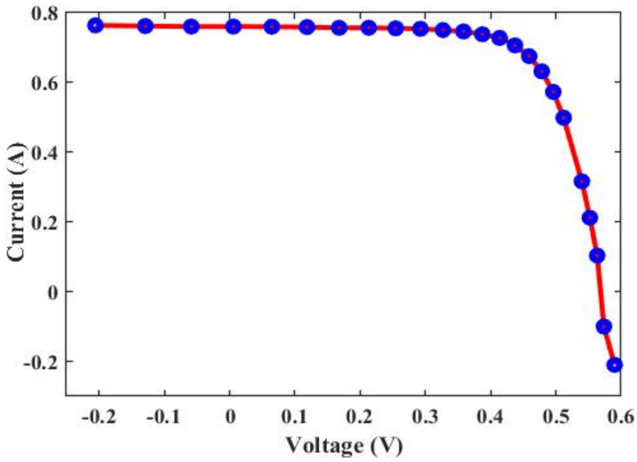


**Figure 5.** The I-V Polarization curve for SDM.

A comparison between the optimal unknown parameter output for the single diode case has been presented for more validation. Table 1 indicates the outputs of five methods that extract the PV parameters for a SDM.

**Table 1.** The unknown parameter results in the single diode.

| Parameters | GWO | IGWO | MVO | SCA | WOA |
|---|---|---|---|---|---|
| $R_{sh}$ | 1.237515 | 1.236925 | 1.237425 | 1.235133 | 1.236917 |
| $R_s$ | 0.421066 | 0.421976 | 0.140933 | 0.424598 | 0.422377 |
| $\alpha$ | 1.630063 | 1.04896 | 1.99602 | 1.000001 | 1.999988 |
| $I_0$ | 0.605225 | 0.007517 | 0.876953 | 0.00001 | 0.24931 |
| $I_{ph}$ | 0.999276 | 0.999833 | 0.886133 | 0.999999 | 0.999994 |

**Table 2.** Friedman ranking test results for SDM.

| Algorithms | GWO | IGWO | MVO | SCA | WOA |
|---|---|---|---|---|---|
| **Friedman Rankings** | 2 | 1 | 5 | 4 | 3 |

Table 2 shows the Friedman ranking test for SDM. The Friedman rank test is a non-parametric statistical test that compares differences between two or more dependent groups [52]. Table 2 shows that the IGWO algorithm is clearly better than other algorithms regarding convergence ability and accuracy, with IGWO securing first rank, followed by GWO, WOA, SCA, and MVO.

### 4.2. Case 2: Double Diode

Figure 6 shows the convergence graph of the techniques used to extract the DDM parameters. It also shows that the IGWO algorithm has a fast convergence. The IGWO achieves the best value, 0.041569, in the $12^{th}$ iteration. The second best is GWO with the $21^{th}$ iteration. These results are logical because the IGWO is an improved variant of the GWO method and has the advantage of high convergence speed over the original algorithm. The SCA and MVO achieve the best value on $125^{th}$ and $87^{th}$ iterations. Figure 6 demonstrates that the WOA is the worst convergence method for this problem with the $219^{th}$ iteration.

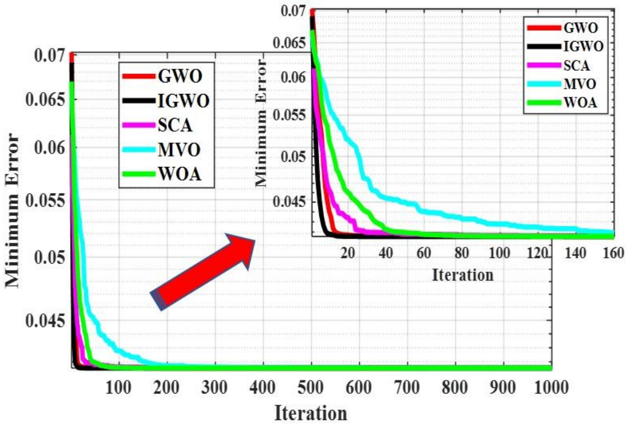


**Figure 6.** The convergence graph for DDM.

According to the computation time outputs, the situation for the DDM is really interesting, like a single-diode model. Figure 7 compares the calculation time results for the DDM. Although the convergence trend in Figure 6 indicates that the IGWO is the best convergence method, the time outputs of Figure 7 state that The IGWO is the slowest method, with 2.7615 seconds.

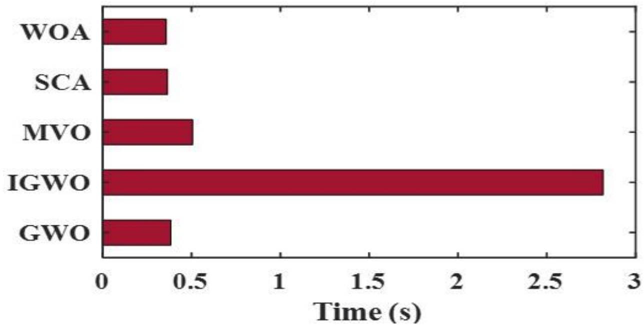


**Figure 7.** The computation time for DDM.

According to the computation time outputs, the situation for the DDM is really interesting, like a single-diode model. Figure 7 compares the calculation time results for the DDM. Although the convergence trend in Figure 6 indicates that the IGWO is the best convergence method, the time outputs of Figure 7 state that The IGWO is the slowest method, with 2.7615 seconds.

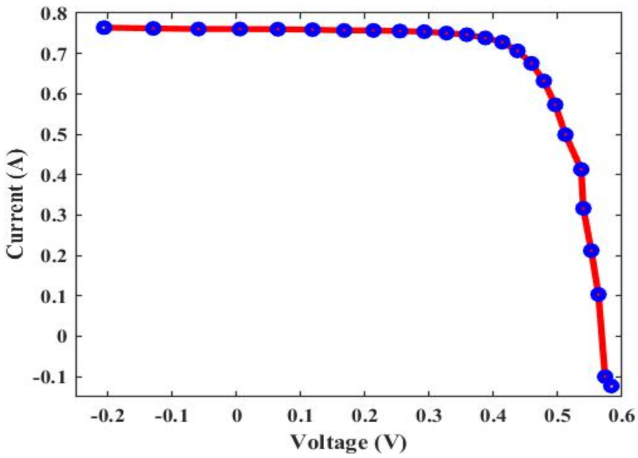


**Figure 8**. The I-V Polarization curve for DDM.

Figure 8 demonstrates the polarization plot of the DDM that emphasizes the success of the IGWO. The blue colored curve is the curve of the experiment data gathering from [49]. The red circle represents the IGWO results. As seen in Figure 7, there is a precise match on the I-V graph between calculated output and measurement results.

**Table 3.** The unknown parameter results in the double diode.

| Parameters | GWO | IGWO | MVO | SCA | WOA |
|---|---|---|---|---|---|
| $R_{sh}$ | 1.237112 | 1.237378 | 1.237186 | 1.255711 | 1.237312 |
| $R_s$ | 0.111071 | 0.002382 | 0.238979 | 0.00001 | 0.422831 |
| $\alpha_1$ | 1.212469 | 1.995611 | 1.996953 | 1.676885 | 1.77301 |
| $\alpha_2$ | 1.200126 | 1.992697 | 1.887299 | 1.984556 | 1.111419 |
| $I_{01}$ | 0.122898 | 0.093894 | 0.700794 | 0.00001 | 0.024884 |
| $I_{02}$ | 0.000523 | 0.008832 | 0.640783 | 0.62012 | 0.14825 |
| $I_{ph}$ | 0.874122 | 0.830082 | 0.92585 | 0.826977 | 0.99999 |

**Table 4.** Friedman ranking test results for DDM.

| Algorithms | GWO | IGWO | MVO | SCA | WOA |
|---|---|---|---|---|---|
| **Friedman Rankings** | 2 | 1 | 3 | 4 | 5 |

For validation, the comparison between the unknown parameters obtained from methods for the double diode case has been presented for more validation. Table 3 shows the output of all methods used to extract the PV parameters for a DDM.

The Friedman ranking test for DDM is given Table 4. According to the ranking results on Table 4, the IGWO algorithm performs better than other methods regarding convergence ability and accuracy, with IGWO securing first rank, followed by GWO, MVO, MVO, and WOA.

### 4.3. An Overview of The Results

The SDM and DDM results show that different optimization algorithms have unique advantages and limitations for this application. IGWO offers rapid convergence for both SDM and DDM. The fast convergence ability of IGWO maybe because this algorithm is an improved version of GWO. As an improved algorithm, IGWO can explore the search space more effectively. Although IGWO offers fast convergence for both SDM and DDM, it is the slowest in computation time. IGWO tends to approach the best result by doing more detailed research.

On the other hand, the fact that GWO has good performance for both SDM and DDM shows that this algorithm's basic features and structure are quite suitable for the nature of the PV parameter extraction problem. SCA and MVO may offer better results in DDM than SDM because the convergence process of these algorithms may be more conducive to investigating different combinations of parameters in a more complex model. The fact that WOA performs lower than other methods may suggest that the algorithm does not have an optimal search and convergence process for this particular problem set.

## 5. Conclusion and Discussion

In this paper, five different meta-heuristic optimization techniques have been implemented to extract PV module design parameters. These methods include GWO, IGWO, MVO, WOA), and SCA. These algorithms have been implemented in the SDM case and the DDM case. An error function has been used to calculate the difference between the computed and measured current values. Different from the literature, the unknown parameter estimation is not just considered an offline optimization problem but also a real-time optimization problem in which the calculation time matters. Thus, the computation times for each method used in this paper are calculated. The inferences obtained from the study can be listed as follows;

1) The IGWO, GWO, SCA, MVO, and WOA algorithms can successfully extract PV module design parameters. The fitness function results can be given as proof of this inference.
2) For offline optimization, the IGWO is more successful than the other system in both cases, SDM and DDM. The convergence trends in Figure 3 and Figure 6 can be proven. In SDM, IGWO reaches 0.0416 in the $15^{th}$ iteration, and in DDM, it comes to 0.041569 in the $12^{th}$ iteration, supporting this claim.
3) The unknown PV parameters extraction problem is an offline optimization issue. However, if we want a real solution for the solar PV industry, it needs to be real-time optimization solved quickly. The computed time results are really interesting. The IGWO, the most successful method, is also the slowest among the five methods. The GWO, SCA, and WOA methods are more usable for real-time application. Figure 4 and Figure 7 can be given as proof.
4) The IGWO is used for the five unknown SDM parameter estimation and the seven unknown DDM parameter estimation issues for the first time in the literature. This study provided the first literature contribution in this field, with IGWO's successful results of 0.0416 for SDM and 0.041569 for DDM. The success of IGWO for these problems has been shown with this study for the first time.

The limitation of this paper is that this study was conducted only on a specific set of PV module design parameters. This study assumes that the mathematical modeling used fully reflected PV module structures. For future work, we will try the solve optimum parameters for the three-diode / four-diode model. Also, we will run this problem with other heuristic based optimization methods.

### Contributions of the authors

SAC: Conceptualization,Methodology, Software, Validation, Analysis,Visualization, Writing,
SK: Conceptualization,Methodology, Software, Validation,Visualization, Investigation,Writing.

### Conflict of Interest Statement

There is no conflict of interest between the authors.

### Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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