Power Electronics and Drives
Volume 10(45), 2025 DOI: 10.2478/pead-2025-0003

Power Electronics and Drives

A Hybrid Approach Incorporating WSO-HO and the Newton-Raphson Method to Enhancing Photovoltaic Solar Model Parameters Optimisation

Research paper

Ahmed Jeridi*, Mohamed Hedi Moulahi, Hechmi Khaterchi, Abderrahmen Zaafouri

University of Tunis, National Higher School of Engineers of Tunis (ENSIT), Laboratory of Engineering of Industrial Systems and Renewable Energy (LISIER), 1008 Tunis, Tunisia

Received: 30 August 2024; Accepted: 29 December 2024

Abstract: Accurate parameter estimation is vital for optimising the performance and design of photovoltaic (PV) systems. While metaheuristic algorithms (MHAs) offer promising solutions, they often face challenges such as slow convergence and difficulty balancing exploration and exploitation. This study introduces a novel hybrid approach, WSO-HO, which integrates the strengths of the war strategy optimization (WSO) and Hippopotamus Optimization (HO) algorithms, enhanced by the Newton-Raphson (NR) method, to achieve precise parameter estimation for PV models. The effectiveness of the WSO-HO algorithm was rigorously evaluated through intensive testing on three different solar panels, including the RTC France solar cell using the single diode model (SDM) and the double diode model (DDM), over 30 iterations. Comparative analysis highlights the superior performance of WSO-HO against conventional algorithms, which often struggle with accurately identifying PV model parameters. These promising results demonstrate the significant potential of this hybrid approach to improve parameter optimisation in PV systems, enabling more precise design and enhanced overall system efficiency. Furthermore, the simulation result of the performance of the WSO-HO algorithm was benchmarked against other algorithms reported in the literature, further validating its robustness and effectiveness.

Keywords: *PV system • Newton-Raphson method • WSO-HO algorithms • hybrid meta-heuristic algorithms*

1. Introduction

The requirement for electrical energy has been gaining attention to meet consumption needs due to economic and technical advancements (Alsattar et al., 2020). Achieving energy demand based on oil, coal and gas sources is no longer profitable (Khattar et al., 2019). These are fossil fuels and non-renewable and are finite and unable to meet growing needs. They also present a global warming problem. This calls for a transition to renewable energy sources (El-Khatib et al., 2023; Singh, 2013). Solar energy, being abundant and ubiquitous, offers a promising solution to the energy crisis (Amiri et al., 2024; Farghally et al., 2023). Efficient analysis of solar energy systems requires understanding the characteristics and optimisation of solar cell designs. Various methods have been proposed to optimise these models photovoltaic (PV) system performance often relies on single or dual diode designs, with the latter providing more precise outputs. Accurate parameter estimation is essential to improve efficiency, performance and reliability, enabling systems to better match solar irradiation and enhance economic viability (Jordehi, 2016). As the complexity of the model increases with the addition of diodes, the number of parameters needed to optimise also increases: typically, five for one-diode models and seven for two-diode models. Optimising these parameters is crucial to maximise efficiency under various conditions. In recent work, researchers prefer single diode models

* *Email: ahmed.jeridi@ensit.u-tunis.tn*

Open Access. © 2025 Jeridi et al., published by Sciendo. This is an open access article licensed under the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/).

(SDMs) as the first model. To get closer to the reality of the cell model, they focussed on the double diode models (DDMs) for estimating electrical parameters, using iterative, metaheuristic and analytical methods. However, iterative and analytical methods have limitations, leading to a preference for metaheuristic algorithms (MHAs) due to their precision and fast convergence (Li et al., 2023).

Hybridisation of meta-heuristic algorithms is essential for extracting and identifying parameters of PV systems by combining the strengths of the War Strategy Optimization (WSO) (Ayyarao, T. S. & Kumar, P. P. 2022) and Hippopotamus Optimization (HO) algorithms (Amiri et al., 2024), a new algorithm called WSO-HO has been developed. Integrating the Newton-Raphson (NR) method, simulations and case studies were conducted to evaluate the effectiveness of this approach. These case studies provide representative scenarios for a comparative assessment of different solar PV systems. Experimental results show that optimising SDM and DDM using the WSO-HO algorithm provides increased accuracy in parameter estimation as compared to the original algorithms WSO and HO. The proposed algorithm consistently achieves lower root mean square error (RMSE) values, indicating its superior performance in accurately estimating the (*I, V*) characteristics of SDMs and DDMs. Additionally, the convergence behaviour of the WSO-HO algorithm is faster and smoother than that of the WSO and HO algorithms. In that respect, performance measurements show that estimated and experimental results agree very well; this indicates the suggested approach’s capacity for appropriate modelling. The voltage-power curve (*P, V*) and the current-voltage curves (*I, V*) for the SDM and DDM models optimised with the WSO-HO algorithm closely match the experimental data. Moreover, according to a comparison study, WSO-HO performed better than other recent optimisation techniques. Among the methods considered, WSO-HO allows consistently achieved the lowest RMSE value, demonstrating its effectiveness in fine-tuning the SD Model and DD Model parameters for the RTC France solar cell case study (Ayyarao,T. S. & Kumar, P. P. 2022). To some extent, the performance measurements of the WSO-HO algorithm showed that the estimated values closely matched the actual results from the experiments demonstrating the precise modelling capabilities of the proposed approach. Given that, the voltage-power curve (*P, V*) and current-voltage curve (*I, V*) characterise the SDM and DDM optimised; which using the WSO-HO algorithm closely matched the experimental data. Notably, this approach was compared to other recent optimisation techniques, such as those that combine gradients with a teaching-learning algorithm (Yu et al., 2023). Obviously, the improved butterfly flame enhancement algorithm based on local escape operators is elaborated by Qaraad et al. (2023). Besides, the Crisscross and Nelder-Mead algorithm, the gradient-based optimiser with differential evolution and the sine-cosine algorithm is developed by Yu et al. (2022). The dynamic multi-verse optimiser with leader the least squares chaos game optimisation and the artificial hummingbird optimization (AHO) are presented in Ekinci et al. (2024) and (Bogar, 2023). Some previous works have widely developed such as, the reptile search algorithm with Cauchy mutation and opposition-based learning strategies, adaptive differential evolution with elite learning presented in Fan et al. (2022), the coyote optimization algorithm (Gu et al., 2023), The Hunger Games search with quantum Nelder-Mead (Xu et al., 2022). As well as, in the bald eagle search (Alsattar et al., 2020), tunicate swarm optimization (Nicaire et al., 2021) and the improved tree growth algorithm (Arandian et al., 2022), all authors have highlighted the superior performance of WSO-HO. It consistently achieved the lowest RMSE value among all the methods considered. Similar observations were made for the optimisation of the SD Model and DD Model using the WSO-HO approach, indicating its effectiveness in fine-tuning the parameters of the SDM and DDM for the RTC France solar cell in case study (Jordehi, 2016).

This paper is focussed on hybridisation of different algorithms to offer a compelling solution to address the inherent challenges and complexities of conventional optimisation approaches. By seamlessly integrating the strengths of multiple algorithms, hybridisation improves convergence speed and ensures robustness, adaptability and greater accuracy in parameter extraction for solar PV models. Despite its impressive results and potential, hybridisation still presents some challenges. Our work introduces a pioneering hybrid methodology that combines the WSO algorithm, the HO algorithm and the NR method. This innovative hybrid WSO-HO algorithm is specifically designed to enhance (*P,V*) parameter extraction, leveraging these algorithms’ combined strengths to get higher efficiency, robustness and convergence levels.

Our motivation and contribution are as follows:

The first improvement aims to refine the weight updating mechanism of the WSO algorithm. In the original WSO algorithm, the weights are updated linearly based on the number of iterations without improvement. However, in the modified WSO variant within WSO-HO, the exponent in the weight update formula is increased to 2. This adjustment enhances the exploratory nature of the algorithm, facilitating larger adjustments to the weights over the course of successive iterations. Consequently, the modified WSO algorithm becomes more efficient in exploring various regions of the solution space, thereby reducing the risk of premature convergence to local optima.

The second improvement consists of integrating the third phase of the HO algorithm into the hybrid WSO-HO. This phase, renowned for its local search capabilities, strengthens convergence by refining solutions as close as possible to the best current solutions. By iteratively generating new solutions for each soldier using a predefined formula and evaluating their fitness against the objective function, the HO phase enhances the algorithm's ability to navigate complex solution landscapes and converge towards optimal solutions.

The third and final modification integrates a permutation and exchange step between the two WSO algorithms and HO. This additional step diversifies the population by randomly permuting the solution components, thereby promoting deeper exploration of the solution space. By leveraging swap operations, the algorithm mitigates the risk of premature convergence and promotes the exploration of potentially promising solution regions.

Overall, integrating these modifications into the hybrid WSO-HO algorithm provides a sophisticated framework for extracting PV parameters with unprecedented convergence and efficiency. By synergistically combining the strengths of WSO and HO algorithms and incorporating local exploration, exploitation and refinement mechanisms, hybrid WSO-HO presents a robust approach to optimise parameter extraction processes in PV systems. Additionally, integrating the NR method further improves the convergence capabilities of the algorithm, ensuring reliable and precise estimation of the parameters of PV systems.

The remainder of the paper is organised as follows: Section 2 offers a concise examination of single and DDM for solar cells and we introduce the objective function that is used to extract parameters. The optimisation Algorithms, the WSO Algorithm and the HO Algorithm are examined in Sections 3 and 4, respectively, along with the formulation of a modified strategy. Section 5 presents the contributions and innovations made possible by the Modified Algorithm WSO-HO, highlighting its unique characteristics and uses. Section 6 gives the simulation results and parameter optimisation, which displays the results obtained from the modified model. Finally, we give concluding remarks on the hybrid model and the WSO-HO algorithm and outline potential directions for further investigation and study.

2. The PV Cell Modelling and Objective Purpose

2.1. The PV cells modelling

Extensive literature assessments highlight how crucial it is to comprehend the physical characteristics of PV cells in order to create effective models for solar systems. Note that, the SDM and DDM are proposed for a more precise representation and to characterise the behaviour of a solar cell (Qaraad et al., 2023).

The widely used equivalent circuit cell model is the SDM, which is based on basic physical concepts, and it is described by the equivalent circuit given in Figure 1a. Consequently, we have five unidentified parameters in this model that need to be determined (Amiri et al., 2024):

$$I_L = I_{ph} - I_{sd} - I_{Rsh} \tag{1}$$

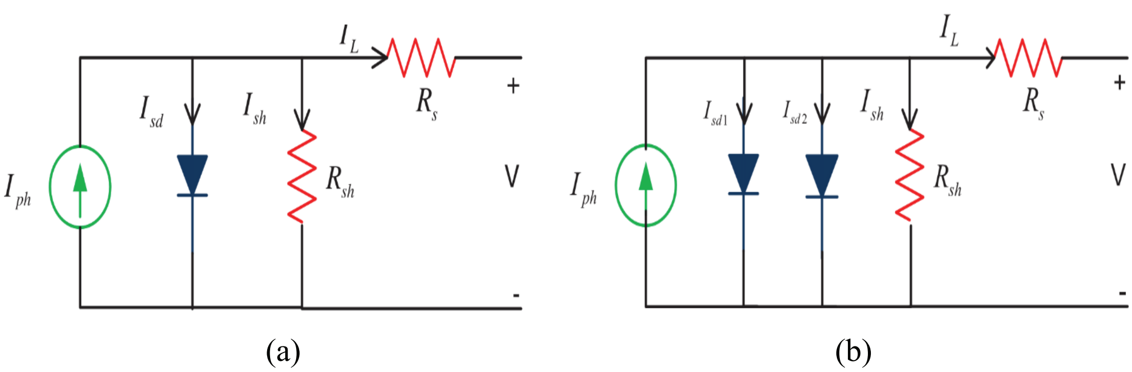


Figure 1. Equivalent circuit cell model. (a) Equivalent circuit of SDM. (b) Equivalent circuit of DDM. DDM, double diode model; SDM, single diode model.

Where I_L is the PV cell load current, I_{ph} is the PV cell photocurrent, and I_{sd} is the reverse saturation current of the diode. Thus, *IRsh* is the shunt resistance current. Therefore, the diode current and the shunt resistance current are defined by Eqs (2) and (3) which refer to Khattar et al. (2019).

$$I_d = I_{sd}\left(e^{\frac{q(V_L + I_L R_S)}{nKT}} - 1\right) \tag{2}$$

$$I_{R_{sh}} = \frac{V_L T + I_L R_S}{R_{sh}} \tag{3}$$

Where: V_L is the output voltage of the PV cell, I_{sd} the diode reverse saturation current, and *k* constant of the Boltzmann. Moreover, *Rs* represents the series resistance, R_{sh} represents the parallel resistance, *q* is the charge of an electron, *n* denotes the diode ideality coefficient and *T* denotes temperature. Substitute Eqs (2) and (3) in Eq. (1), the load current of a PV cell is given by Eq. (4).

$$I_L = I_{ph} - I_{sd}\left(e^{\frac{q(V_L + I_L R_S)}{nKT}} - 1\right) - \frac{V_L T + I_L R_S}{R_{sh}} \tag{4}$$

Five parameters that have not been known (I_{ph}, I_{sd}, R_s, R_{sh}, n) in Eq. (4) must be determined (Amiri et al., 2024). Moreover, the equivalent circuit for DDM can be used to calculate the output current, as illustrated in Figure 1b.

$$I_L = I_{ph} - I_{sd1} - I_{sd2} - I_{Rsh} \tag{5}$$

Applying the identical technique as in the SDM, the PV cell's ultimate output current can be computed using Eq. (6):

$$I_L = I_{ph} - I_{sd1}\left(e^{\frac{q(V_L + I_L R_S)}{n_1 KT}} - 1\right) - I_{sd2}\left(e^{\frac{q(V_L + I_L R_S)}{n_2 KT}} - 1\right) - \frac{V_L T + I_L R_S}{R_{sh}} \tag{6}$$

Note that, I_{sd1} and I_{sd2} are defined as the reverse saturation currents of the diodes D_1 and D_2, respectively. Thus, n_1 and n_2 are the ideality factors of the diodes D_1 and D_2, respectively. It follows that the DDM has seven unknown parameters (*Iph, Isd1, Isd1*, R_S, *Rsh*, n_1, n_2). Obviously, in order to have well-known ones, they need to be estimated (Fan et al., 2022).

2.2. Objective purpose

This study confronts the challenge of parameter optimisation for the PV model. The established formulas are converted into homogeneous forms to overcome the hurdle of unknown parameters as presented in Qaraad et al. (2023). Let's begin by examining the SDM, which can be expressed by the Eqs. (7) and (8):

$$f(V, I, X) = I_{ph} - I_{sd}\left(e^{\frac{q(V_L + I_L R_S)}{nKT}} - 1\right) - \frac{V_L T + I_L R_S}{R_{sh}} \tag{7}$$

$$X = \left(I_{ph},\ I_{sd},\ R_s,\ I_{Rsh},\ n\right) \tag{8}$$

Moreover, examining the DDM model, which can be expressed as follows:

$$X = \left(I_{ph},\ I_{sd1}, I_{sd2}\ R_s,\ I_{Rsh},\ \mathrm{n}_1, \mathrm{n}_2\right) \tag{9}$$

In this study, we use the RMSE as an objective function

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left(i_m^i - i_c^i\left(V_m^i, \mathrm{I}_m^i, X\right)\right)} \tag{10}$$

We can quantify the agreement between the predicted and measured currents using the RMSE. In this context, the expression $I = f(V_m)$ represents the current calculated by our model based on the measured voltage (*Measured*). Note that, I_m is the actual measured current values and N is the total number of data points. The vector X contains the parameters we aim to extract from the PV model. Eq. (6) (Singh, 2013) shows that a lower RMSE signifies a better fit between the modelled and measured current data, indicating a more accurate extraction of the model's parameters. Third, this method combines the hybrid WSO-HO optimization algorithm with the NR method.

To estimate the current for the SDM model, we have the non-linear equation defined by Eq. (11).

$$h(x) = I_{ph} - I_{sd}\left(e^{\frac{q(V_L + I_L R_S)}{nKT}} - 1\right) - \frac{V_L T + I_L R_S}{R_{sh}} - x \tag{11}$$

As well as, for the DDM, the non-linear equation is defined by Eq. (12):

$$k(x) = I_{ph} - I_{sd1}\left(e^{\frac{q(V_L + I_L R_S)}{n_1 KT}} - 1\right) - I_{sd2}\left(e^{\frac{q(V_L + I_L R_S)}{n_2 KT}} - 1\right) - \frac{V_L T + I_L R_S}{R_{sh}} - x \tag{12}$$

To analyse the performance of a photovoltaic (PV) system under various environmental conditions, an accurate mathematical model is essential. The parameters within this model inherently define the system's performance, making their optimization a critical aspect of controlling and improving PV system efficiency. To achieve this, the model outputs are compared with measured data, as shown in Table 1, using the root mean square error (RMSE) as the objective function for optimization (Ayyarao, T. S. & Kumar, P. P. 2022). The study introduces a hybrid methodology, depicted in Figure 2, which integrates a metaheuristic algorithm with the Newton-Raphson (NR) method. The metaheuristic algorithm is employed to identify optimal initial parameters, while the NR method refines these parameters to solve the nonlinear equations with high precision, ensuring an error of less than 1E-4. This combined approach enhances the accuracy and reliability of the PV system model, enabling better performance analysis and optimization under varying environmental conditions.

3. The WSO Algorithm

Drawing inspiration from historical military campaigns, the WSO algorithm mimics the dynamic decision-making process of leaders. Just like a king and commanding officer adjusting tactics based on the battlefield, the WSO algorithm utilises cues to guide its algorithmic soldiers in their search for optimal solutions (Ayyarao, T. S. & Kumar, P. P. 2022).

Table 1. Experimental current (I) and voltage (V) data for RTC France PV cells using SDM and DDM.

Parameter	1	2	3	4	5	6	7	8	9
I (Ampere)	0.764	0.762	0.7605	0.7605	0.76	0.759	0.757	0.7557	0.755
V (Volt)	−0.2057	−0.1291	−0.0588	0.0057	0.0666	0.1183	0.1678	0.2152	0.2618
Parameter	10	11	12	13	14	15	16	17	18
I (Ampere)	0.754	0.7505	0.746	0.7385	0.728	0.706	0.673	0.632	0.573
V (Volt)	0.2924	0.3269	0.385	0.3837	0.4173	0.4573	0.4798	0.4784	0.5119
Parameter	19	20	21	22	23	24	25	26	
I (Ampere)	0.499	0.413	0.316	0.212	0.103	−0.01	−0.123	−0.21	
V (Volt)	0.5319	0.5266	0.3983	0.5321	0.5533	0.5736	0.5833	0.59	

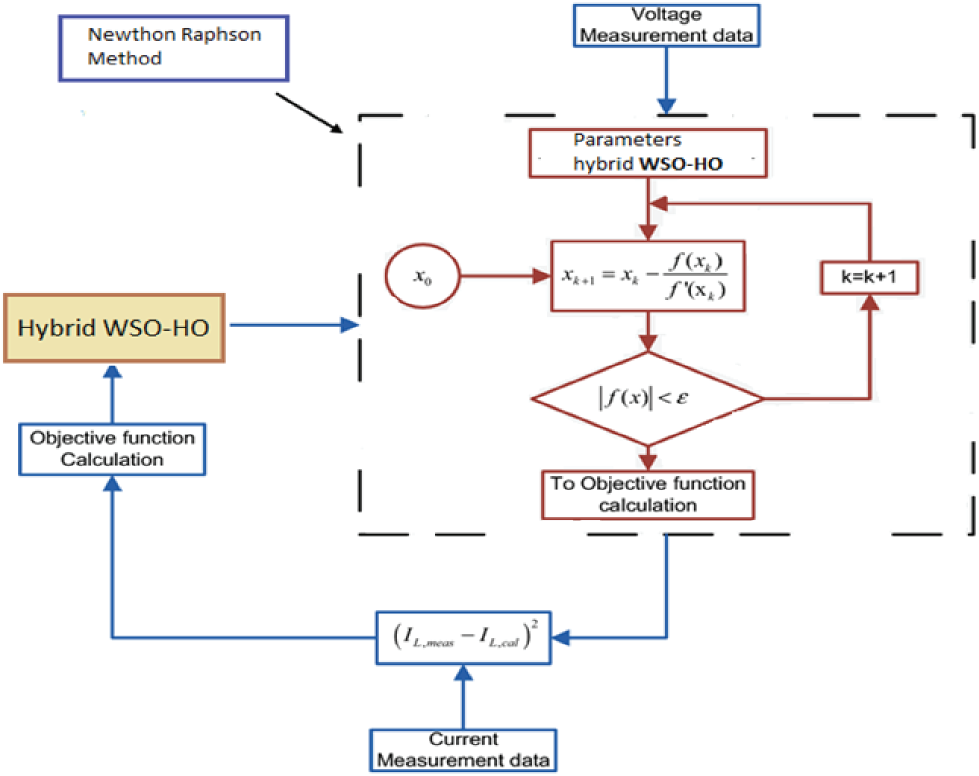


Figure 2. Parameter extraction by integrating Newton-Raphson method with WSO-HO optimization algorithm.

Note that, we present four steps to describe this strategy: The first stage is designated as a Random Attack, and in this stage, the opposing army is attacked by randomly assigned troops to represent algorithmic elements. The strongest individual, similar to the army general, supervises the different units. The second stage is an Attack Strategy; attacking the opposition is this strategy's main objective. The King stands for the optimal result; he is the one who leads the troop. Obviously, when adjusting the algorithm's parameters, the troops dynamically change their position according to the King's and Commander's positions. The third stage is a Signalling by Drums, notably, the King, or the best solution, gives orders to modify the strategy according to the conditions. According to these signals, the soldiers, or algorithmic elements, change strategies and organise their positions. In the fourth stage, owing to Defence Strategy, the primary objective is to protect the King, or retain the optimal solution. Within this framework, a central decision-making unit, analogous to a commander, strategically deploys algorithmic elements to safeguard a superior solution, represented by the King. These elements, akin to troops, meticulously explore the search space, dynamically adapting their search strategies to achieve optimal results in the face of an adversary (the optimisation challenge). The Commander and King functions, which are considered critical, are modelled mathematically in the War Strategy algorithm. Starting with the same weight and rank, the troops represent the algorithmic elements. Further the war goes on, the more their performances determine how much weight and range they have. The king is the soldier who can attack with the greatest force (Ayyarao and Kishore, 2024). Thus, every soldier's position X_i is updated and given by Eq. (13).

$$X_i(t+1) = X_i(t) + 2\rho(C-K) + rand(W_i K - X_i(t)) \tag{13}$$

Where $X_i(t+1)$ is the new increment *position at time* $(t+1)$, X_i *at time* (t) *is the previous position, C is the position of the commander, K is the position of the king, Wi* is the weight and $\rho \in [0,1]$ is the factor used for more flexibility to choose a value depending on the objective function. The soldier returns to the former location, should the attack succeed in the new location (F_n) is lower than in the prior location (F_p) which is given by Eq. (14):

$$X_i(t+1) = X_i(t+1)(F_n \geq F_p) + X_i(t)(F_n < F_p) \tag{14}$$

The soldier's rank (R_i) will be raised if he updates his position successfully given in Eq. (15):

$$R_i = (R_i + 1)(F_n \geq F_p) + R_i(t)(F_n < F_p) \tag{15}$$

The new weight is computed as follows based on the rank indicated by Eq. (16):

$$W_i = W_i\left(1 - \frac{R_i}{\max\_itr}\right)^{\alpha} \tag{16}$$

Where α is weighing factors, which gives a competitive algorithm in this case $\alpha = 1$

The locations of the King, the commander of the army and an arbitrary soldier serve as the basis for the position update in the second strategy presented in Eq. (17):

$$X_i(t+1) = X_i(t) + 2\rho(K - X_{rand}(t)) + rand.W_i(C - X_i(t)) \tag{17}$$

4. Hippopotamus Optimization Algorithm (HOA)

The Hippopotamus Optimization Algorithm (HO) is a meta-heuristic optimisation algorithm inspired by the behaviour of hippopotamuses in their natural environment. The algorithm simulates the movement and interactions of hippopotamuses in a river or pond, as well as their defence mechanisms against predators (Amiri et al., 2024). Obviously, there are three phases for this algorithm. In phase one, the hippopotamuses' position is updated in the river or pond, in this step the hippopotamuses move around the river or pond in search of food. They are attracted to the dominant hippopotamus position (*DHp*) and to the mean position of a random group of hippopotamuses (*MG*). Note that, I_1 and I_2 are integers between 1 and 2 which are described by Eqs (18) and (19).

$$X_{p1}(i,:) = X(i,:) + rand(1,1).(DHp - I_1 X(i,:)) \tag{18}$$

$$X_{p2}(i,:) = X(i,:) + A.(DHp - I_2 MG) \tag{19}$$

Phase two is hippopotamus defence against predators and in this phase, the hippopotamuses defend themselves against predators by moving away from them. They use different strategies depending on their fitness compared to the predator as described by Amiri et al. (2024), which is represented by Eq. (20).

$$X_{p3}(i,:) = RL(i,:).predator + \left(\frac{b}{c - d\cos(2\pi g)}\right).\left(\frac{1}{\text{distanceLeader}}\right) \tag{20}$$

Where X_{p3} is a hippopotamus position which was faced to predator $c \in [1,1.5]$ is a uniform random, $b \in [2,4]$ is a uniform random, $distanceLeader \in [2,3]$ is a uniform random number, *RL* is a random vector with a Levy distribution, utilised for sudden changes in the predator's position during an attack on the hippopotamus, $g \in [-1,1]$ represents a uniform random number.

In phase three, the Hippopotamus escapes from the Predator. The hippopotamuses that are being chased by predators try to escape by moving in random directions, as described by Eq. (21).

$$X_{p4}(i,:) = X(i,:) + rand(1,1).(LO_{LOCAL} + D(HI_{LOCAL} - LO_{LOCAL})) \tag{21}$$

where: LO_{LOCAL}, HI_{LOCAL} denote the lower and upper bounds of the *j-th* decision variable, respectively and

$X_{p1}(i,:)$ is the i-th hippotamus's new location in phase 1.
$X_{p2}(i,:)$ is the i-th hippotamus's new location in phase 2.
$X_{p3}(i,:)$ is the i-th hippotamus's new location in phase 3.
$X_{p4}(i,:)$ is the i-th hippotamus's new location in phase 4.
$X(i,:)$ is the current position of the i-th hippopotamus.

5. New Hybrid Approach

5.1. WSO-HO algorithm hybridisation

The hybrid algorithm is given by incorporating the War Strategy Optimization Algorithm (WSO) with Hippopotamus Optimization Algorithm (HO). The new hybrid approach is a meta-heuristic optimisation Algorithm that combines the strengths of two distinct algorithms. This combination aims to exploit the advantages of each algorithm and overcome their individual limitations. So, the WSO-HO hybrid algorithm is a combination of the WSO and HO. Three modifications have been made to the WSO-HO hybrid algorithm to improve its performance for the extraction of PV parameters. The first modification is to the WSO algorithm. In the original WSO algorithm, the weights of the soldiers are updated using the following Eq. (22):

$$W_1(i) = 1 \times W_1(i) \times \left(1 - \frac{Wg(i)}{Max\_iter}\right) \tag{22}$$

Where $W_1(i)$ is the weight for the i-th soldier, $Wg(i)$ is the number of iterations that the *i-th* soldier has not improved its fitness, and *Max_iter* is the maximum number of iterations. The modified WSO algorithm in the hybrid WSO-HO algorithm updates the weights W_1 using the following Eq. (23):

$$W_1(i) = 1 \times W_1(i) \times \left(1 - \frac{Wg(i)}{Max\_iter}\right)^2 \tag{23}$$

In the original WSO algorithm, the exponent is 1, while in the modified WSO algorithm in WSO-HO, the exponent is 2. This change makes the modified WSO algorithm more explorative than the original WSO algorithm. This is because the weights W_1 are decreased by a larger amount each iteration in the modified WSO algorithm. This encourages the algorithm to explore new areas of the search space and to avoid getting stuck in a local optimum.

The second modification consists of adding the third step of HO to this hybrid. This step of the HO algorithm is a local search phase which helps to improve the convergence of this algorithm, which is presented in Figure 3. However, this step is added to the WSO-HO hybrid algorithm to further improve its performance. The third phase of the HO algorithm works by generating a new solution $X_{p4}(i)$ for each soldier (*i*) using the Eq. (24):

$$X_{p4}(i,:) = \begin{cases} X(i,:) + D \times rand(1,1) \times (HI_{LOCAL} - LO_{LOCAL}) \\ X(i,:) - D \times rand(1,1) \times (HI_{LOCAL} - LO_{LOCAL}) \end{cases} \tag{24}$$

Where X *(i,:)* is the current solution for soldier *i*, and note that the search space's lower and upper bounds are denoted by LO_{LOCAL} and HI_{LOCAL}, respectively, *D* is a vector random variables, and *rand (1, 1)* is generator random number between 0 and 1. The new solution X_{p4} (*i*) is then evaluated using the objective function (*fobj*). The existing solution is substituted with the new solution, when the new solution proves to be greater. The third step of the WSO-HO algorithm modification introduces a permutation and swap step after the HO phase. Obviously, this modification is considered to enhance the optimisation process. This step begins with the random permutation of population indices, followed by the permutation of solution components to generate new configurations. Each new configuration is then evaluated for its fitness and if a new fitness value is better than the current best value, it replaces the old one. This process helps to diversify the population and avoid premature convergence, thus improving the algorithm's robustness and efficiency, which is presented in Figure 4. Experimental results show a significant improvement in fitness values compared to traditional methods, highlighting the effectiveness of this permutation-based optimisation approach in complex solution spaces.

5.2. WSO-HO algorithm hybridisation with NR

The hybridisation approach described here combines the WSO-HO algorithm with the NR method to improve the accuracy of parameter extraction for PV cells, as outlined in Algorithm 2 (Figure 5). The process begins with the collection of voltage and current measurements from PV cells, which serve as critical reference data. These measurements are essential for calculating error metrics and evaluating the performance of the solutions generated by the algorithms.

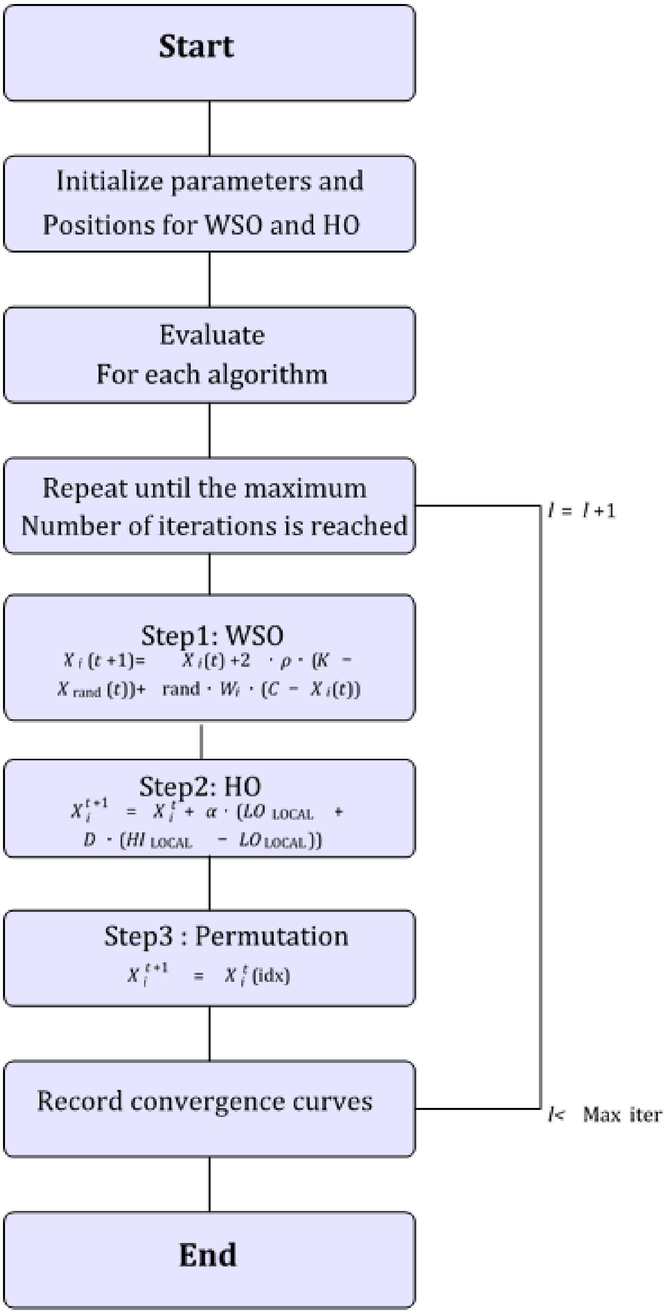


Figure 3. Flow Chart of Hybrid WSO-HO Algorithm.

The initialisation phase leverages the WSO-HO algorithm. The first stage, driven by the WSO component, explores the solution space extensively to identify initial parameter estimates. This exploration phase is pivotal, as it provides a comprehensive understanding of the potential solution landscape. The subsequent stage utilises the HO component, which refines these initial estimates by concentrating on local optimisation. This targeted exploitation of the local search space enhances the accuracy of parameter estimates by zeroing in on the most promising regions.

After the WSO-HO algorithm delivers optimised values, the NR method is applied to further fine-tune these estimates. In each iteration, the NR formula updates the parameter estimates by computing the function value and its derivative. A specific convergence criterion is evaluated to determine if the estimates have stabilised. Upon achieving convergence, the objective function is computed to assess the solution's quality by measuring the

Algorithm 1. Hybrid WSO-HO Algorithm.

Input:

SearchAgents, Max_iterations, lb, ub, dim, fobj

Output:

Best_score, Best_pos, Convergence_curve, **HO**_curve1.

For (iter = 1) to Max_iterations:

1. **For** (i = 1) to SearchAgents:

- Update the position of solution (i) using the **WSO** rules in the new position has a better fitness

then

- Update the current position and fitness of solution (i)

- **If** the new position has a better fitness than King:

- Update King

2. Update the weight factor (W_1) of solution (i)

3. Update the Convergence_curve with the fitness of King

4. **For** (i = 1) to Search Agents:

- Perturb the position of solution (i) using the **HO** rules if the new position has a better fitness **then**

- Update the current position and fitness of solution (i)

- **If** the new position has a better fitness than King:

- Update King

5. Update the **HO**_curve with the fitness of King

6. **For** (i = 1) to SearchAgents:

- Generate a random index for permutation (idx = rand (1, pop_size)

- Permute the components of the solution \(X(i) = X(i) \gets X(idx))

- Evaluate the new solution (fitness(i) = fobj(X(i))) if (fitness(i) King_fit)

- (King_fit = fitness(i)); King (gets X(i))

Return:

Best_score, Best_pos, Convergence_curve, **HO**_curve

Figure 4. Hybridization WSO-HO Algorithm.

discrepancy between the observed and calculated values based on the current estimates. If the objective function fails to meet the pre-defined precision threshold, the parameters are reinitialised using the WSO-HO algorithm and the entire process is repeated. This iterative procedure continues until the optimal solution is identified, ensuring the final parameter estimates are both precise and reliable.Overall, this hybridisation strategy effectively integrates the broad exploration capabilities of WSO, the localised refinement of HO and the iterative precision of the NR method. This robust framework achieves high accuracy in parameter optimisation, making it particularly suitable for PV applications.

Algorithm 2. Hybrid WSO-HO algorithm with NR for parameter estimation.

Input:

Voltage measurement data (V), current measurement data (I), convergence threshold (Gamma), maximum number of iterations (N_{max})

Output:

Optimized parameter estimates (x*)

Procedure: **WSO-HO-Newton-Raphson**

1. Step 1: Initialization with **WSO**

- Generate an initial set of candidate parameters using the WSO algorithm.
- Evaluate the candidate parameters using the data (V) and (I).
- Select the best parameters found by **WSO** to serve as the starting point for **HO**.

2. Step 2: Refinement with **HO**

- Refine the initial parameters with the HO algorithm to obtain (x_0).
- Check the quality of (x_0) by computing the mean square error.
- Proceed to the next step with (x_0) as the initial estimate for Newton-Raphson.

3. Step 3: Local Optimization with Newton-Raphson

- Initialize (k = 0).
- While (not converged) and (k < N_{max}):
- Compute the update (x_{k + 1} = x_k - frac{g(x_k)} {g'(x_k)}), where (g(x) \) is the function to minimize.
- If (|x_{k + 1} - x_k| < epsilon)

then

- Convergence achieved: Set (x* = x_{k + 1}) and exit.
- Else
- Update (k = k + 1) and continue the iteration.
- End while.

4. Step 4: Objective Function Calculation

- Compute the final objective function error = (I_{L,meas} - I_{L,cal})^2).
- Return (x*), the optimized parameters.

End the procedure

Figure 5. Hybrid WSO-HO Algorithm with NR method. NR, Newton-Raphson.

6. Simulation Results and Parameter Optimisation

In the following, we investigate the SDM and the DDM parameter extraction performance of the hybrid algorithm WSO-HO. The data utilised in this study came from an experimental setup using a 57 mm-diameter commercial silicon solar cell (R.T.C. France) that was running at 25°C and 1000 W/m^2 of solar radiation (Arandian et al., 2022). Table 2 displays the parameter combinations of the WSO-HO algorithm used for SDM and DDM. Different numbers of parameters must be extracted for each model: five for SDM and seven for DDM. Setting the bounds for each parameter and so establishing the search space of the algorithm is a necessary step before starting the optimisation

Table 2. The boundaries of extracted PV parameters for SDM and DDM

Parameter	Lower bound	Upper bound
I_{ph} (A)	0	1
I_{sd}, I_{sd1}, I_{sd2}, (μA)	0	1
R_s (Ω)	0	1
R_{sh} (Ω)	0	100
n, n_1, n_2	1	2

DDM, double diode model; PV, photovoltaic; SDM, single diode model.

process. Numerous studies (Amiri et al., 2024) have used these limitations, which guarantee the consistency and dependability of the analysis.

To ensure consistency, Matlab Simulink has simulated the WSO-HO algorithm thirty times (El-Khatib et al., 2023). A variety of solar cell models' parameters are extracted using optimisation algorithms. The NR method is used to simulate the objective function that these techniques require in order to evaluate potential solutions. Bounded spaces are used to construct optimisation problems. Notably, Table 1 lists these boundaries. Previous studies (Green, 1982; Villalva et al., 2009) indicate that these parameters and their bounds ensure that simulations realistically represent the operational capabilities of solar cells, enabling engineers and researchers to optimise PV systems.

6.1. Results using the single-diode model

In this section, we present the experimental results of optimising the SDM using the proposed WSO-HO hybrid approach. Additionally, we compare the performance of our approach with other recent optimisation algorithms of PV solar cell models (Huang et al., 2020). Table 2 presents the estimated parameters of the SDM obtained using WSO-HO, WSO, HO (Ayyarao and Kumar, 2022), the Gazelle optimization algorithm (GOA) and Gazelle optimization- Nelder–Mead algorithms (GOANM). The results reveal that the WSO-HO algorithm achieves higher accuracy in parameter estimation compared to WSO, HO, GOA and GOANM (Ekinci et al., 2024).

This underscores the superior performance of the proposed WSO-HO approach in fine-tuning the SDM parameters (Ekinci et al., 2024). To further evaluate the performance of the WSO-HO algorithm, Table 3 presents statistical RMSE values obtained for the SDM using both HO and WSO (Alsattar et al., 2020). The results consistently show that the WSO-HO algorithm achieves lower RMSE values compared to WSO, HO, GOA and GOANM. This indicates that the proposed WSO-HO approach can accurately estimate the (I-V) and (P-V) characteristics of the SDM, resulting in better model performance.

The convergence behaviour of the WSO-HO, WSO and HO algorithms during the SDM optimisation process are presented in Figure 6a,b (Arandian et al., 2022). These figures demonstrate that the WSO-HO algorithm converges to a stable solution more rapidly and exhibits smoother convergence behaviour compared to WSO and HO. This further confirms the effectiveness of the proposed WSO-HO approach. The results show close agreement between experimental and estimated values, indicating the precise modelling capabilities of WSO-HO (Ekinci et al., 2024). Additionally, Figure 6a,b respectively illustrate the (I-V) and (P-V) curve characteristics of the optimised SDM using the WSO-HO algorithm. Figure 7a,b demonstrates that the optimised model accurately captures the behaviour of the solar cell, with curves closely matching experimental data.

Table 3 comprehensively compares the estimated parameters and RMSE values for the SDM obtained using the WSO-HO algorithm with other approaches such as WSO and HO, as well as other recent optimisation algorithms including Chaotic Capuchin Neural Network with Gaussian Bare-bones Optimization (CCNMGBO), improved multi-objective fitness optimized by Levy (IMFOL), randomized teaching-learning-based optimization (RTLBO), Dynamic Levy Mutated Vortex Optimization (DLMVO) and others. The results highlight the superior performance of GOANM, as it achieves the lowest RMSE value among all compared methods. This underscores the importance of the proposed GOANM algorithm in accurately modelling the behaviour of the RTC France solar cell (Arandian et al., 2022). In summary, the experimental results consistently demonstrate that WSO-HO outperforms other optimisation approaches, as evidenced by its accurate parameter estimation, low RMSE values, rapid convergence and close alignment with experimental data. These findings highlight the significance and effectiveness of WSO-HO in SDM optimisation for PV solar systems, particularly for the RTC France solar cell case study.

Table 3. The SDM parameters estimated at the best RMSE

Algorithm	*Iph* (A)	*Isd*1(μA)	*Rs* (Ω)	*Rsh* (Ω)	*n*	RMSE
WSO-HO	0.76079	0.31069	0.036547	52.8899	1.4773	7.729856E-04
WSO	0.76078	0.31069	0.03654	52.889	1.47727	7.730056E-04
HO	0.76774	0.54060	0.03164	19.31912	1.53746	8.753850E-04
GOANM (Amiri et al., 2024)	0.76079	0.31069	0.036547	52.8899	1.4773	7.729900E-04
GOA (Amiri et al., 2024)	0.76070	0.34001	0.036182	55.7021	1.4864	7.870400E-04
IMFOL (Qaraad et al., 2023)	0.76078	0.32302	0.036377	53.7186	1.4812	9.860200E-04
RTLBO (Yu et al., 2023)	0.76078	0.32302	0.036377	53.7185	1.4812	9.860200E-04
DLMVO (Ekinci et al., 2024)	0.7608	0.3230	0.0364	53.7185	1.4812	9.860200E-04
OBL-RSACM (Li et al., 2023)	0.76080	0.32203	0.03643	53.3521	1.4812	9.845200E-04
AHO (Bogar, 2023)	0.76079	0.31086	0.036540	52.8595	1.2155	7.730600E-04
PSOCS (Fan et al., 2022)	0.76078	0.32302	0.036377	53.7185	1.4812	9.860200E-04
ELADE (Gu et al., 2023)	0.76077	0.30839	0.036555	52.8267	1.4765	7.754700E-04
ILSA (Huang et al., 2020)	0.76077	0.32302	0.036377	53.7185	1.4812	9.860200E-04
IHGS (Xu et al., 2022)	0.76078	0.32302	0.0364	53.7178	1.4812	9.860200E-04
BES (Alsattar et al., 2020)	0.7607	0.3230	0.0364	53.7185	1.4812	9.860200E-04
DE (Yu et al., 2022)	0.7607	0.3209	0.0363	54.1134	1.4709	7.769200E-04
BES (Nicaire et al., 2021)	0.7683	0.3262	0.0367	54.2557	1.4958	9.860000E-04
ITSA (Arandian et al., 2022)	0.7606	0.3298	0.0363	56.5694	1.4832	9.933900E-04

AHO, artificial hummingbird optimization; DLMVO, Dynamic Levy Mutated Vortex Optimization; ILSA, Improved Learning Search Algorithm, GOA, Gazelle optimization algorithm; GOANM, Gazelle optimization- Nelder–Mead algorithms; IMFOL, improved multi-objective fitness optimised by Levy; RMSE, root mean square error; RTLBO, randomized teaching-learning-based optimization; SDM, single diode model; TSA, tunicate swarm algorithm; ELADE, Elite Learning Adaptive Differential Evolution, PSOCS, Particle Swarm Optimization and Cuckoo Search; BES, Bald Eagle Search algorithm; CGO-LS, Chaos Game Optimization-Least Squares algorithm; DE, Differential Evolution algorithm; ELADE, Elite Learning Adaptive Differential Evolution; IHGS, Improved Hunger Games Search; ISCA: Improved Sine Cosine Algorithm; ITSA, Improved Tunicate Swarm Algorithm; PSOCS, Particle Swarm Optimization with Cuckoo Search algorithm; RTC France solar cell, a standard silicon solar cell used for PV model validation an parameter extraction.

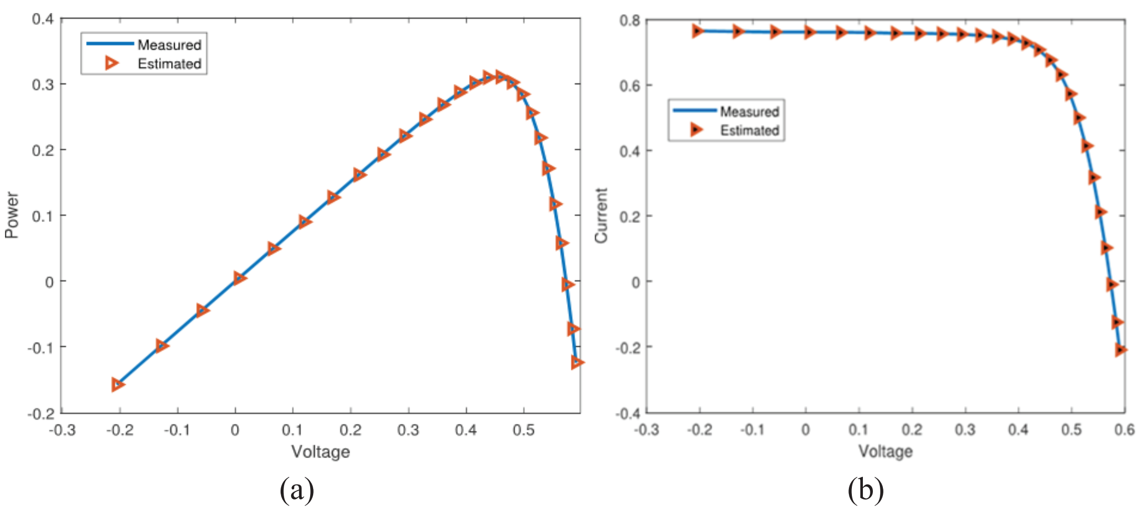
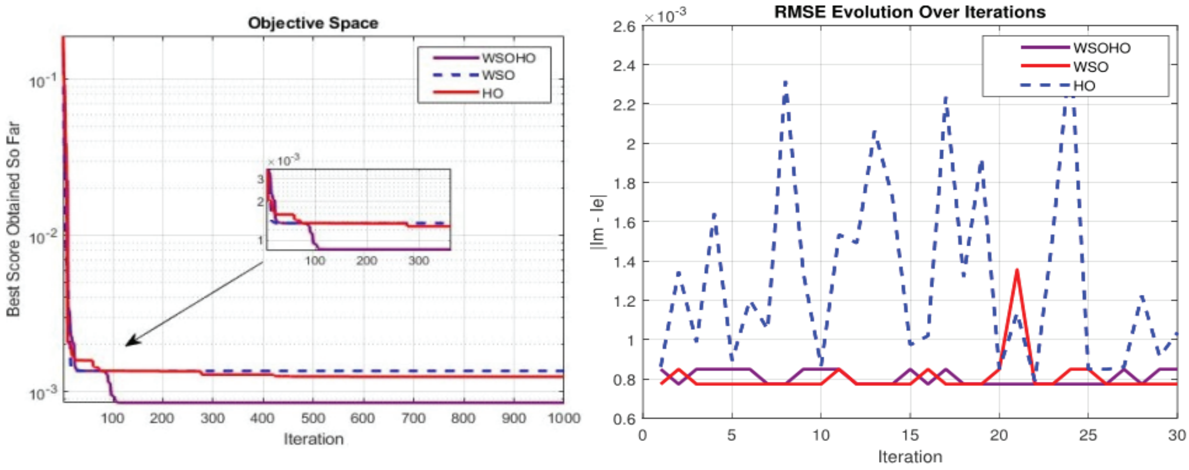


Figure 6. Curves with the measured and estimated data. (a) (P, V) data for SDM. (b) (I, V) data for SDM. SDM, single diode model.

Figure 8 illustrates the convergence and robustness curves for various optimisation algorithms applied to the SDM. Among these, the hybrid WSO-HO algorithm demonstrates superior performance, achieving optimal scores rapidly in the early iterations. This efficiency underscores its ability to explore the search space effectively. In contrast, other algorithms such as AHO (Bogar, 2023), mountaineering team-based optimization (MTBO), whale optimization algorithm (WOA), tunicate swarm algorithm (TSA) (Arandian et al., 2022), sine cosine algorithm (SCA) and grey wolf optimizer (GWO) exhibit slower convergence rates. Their relative inefficiency in reaching lower scores early on may limit their practical applicability. For this comparison, the optimisation algorithms were selected based on established studies in the literature. All simulations utilised the NR method, maintaining identical temperature



(a) (b)

Figure 7. Convergence and robustness curves for SDM. (a) Curves convergence (b) Curves robustness. SDM, single diode model.

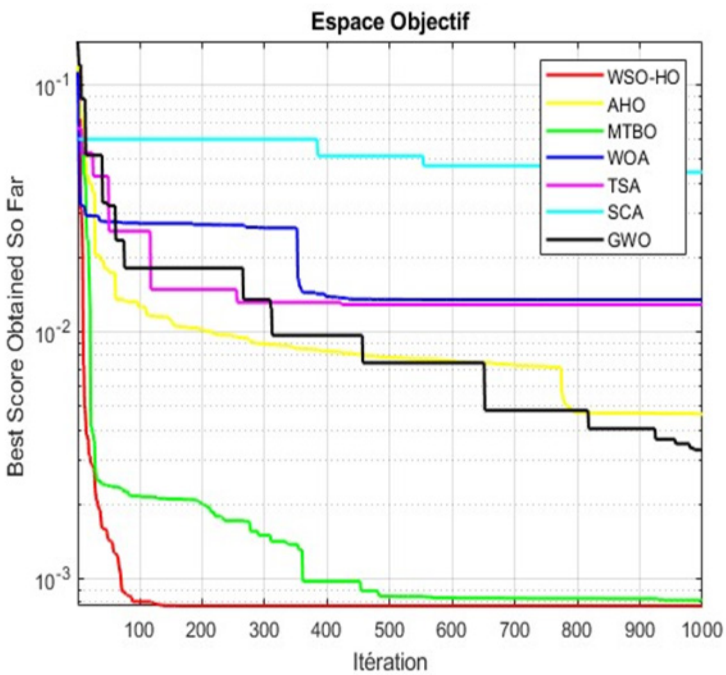


Figure 8. Convergence and Robustness Curves of Optimization Algorithms Applied to the SDM.

conditions and the same current and voltage data extracted from RTC France cells. This analysis highlights the robustness and reliability of the WSO-HO algorithm. It not only achieves superior scores but also demonstrates consistent performance across a wide range of iterations, making it a preferred choice for optimising PV models.

7. Results Using the Double-diode Model

In this section, we present the experimental results of optimising the double-diode model using the proposed WSO-HO approach (Xu et al., 2022). We also compare the performance of this approach with other recent optimisation algorithms for PV solar cell models. To further evaluate the effectiveness of the WSO-HO algorithm, Table 4

Table 4. The DDM Parameters Estimated at the best RMSE

Algorithm	*Iph* (A)	*Isd*1 (μA)	*Isd*2 (μA)	*Rs* (Ω)	*Rsh* (Ω)	*n*1	*n*2	RMSE
WSO-HO	0.760805	0.0854343	0.9991529	0.0376485	56.0775146	1.37756104	1.81810675	7.42069103E-04
WSO	0.760804	0.069334	0.884680	0.0376813	55.918552	1.3648682	1.7688404	7.4378257E-04
HO	0.7607879	0.3106909	0.3106909	0.0365467	52.8899092	1.47727164	1.47727160	8.55885e-04
GOANM [Amiri, H.H et al., 2024]	0.76081	0.11624	0.9768	0.037459	55.7298	1.3994	1.8597	7.4339E-04
GOA [Amiri, H.H et al., 2024]	0.76079	0.19704	0.4356	0.03688	54.2616	1.4417	1.8186	7.5810E-04
IMFOL [Qaraad, M. et al., 2023]	0.76078	0.76632	0.2251	0.036731	55.6567	2.0000	1.4508	9.8252E-04
RTLBO [Yu, X. et al., 2023]	0.76078	0.22597	0.7494	0.03674	55.4855	1.4510	2.0000	9.8248E-04
DLMVO [Ekinci,S., et al., 2024]	0.7608	0.7493	0.2260	0.0367	55.4854	2.0000	1.4510	9.8248E-04
OBL-RSACM [Li, J. et al., 2023]	0.76033	0.39986	0.2677	0.03669	56.0102	1.4151	2.0000	9.8237E-04
AHO [Bogar,E., 2023]	0.76078	0.27988	0.2768	0.036530	54.2856	1.9563	1.4682	9.8401E-04
PSOCS [Fan, Y., et al., 2022]	0.76078	0.22598	0.7493	0.036740	55.4855	1.4510	2.0000	9.8248E-04
ELADE [Gu, Z. et al., 2023]	0.76072	0.24468	0.3802	0.036927	53.5130	1.4564	1.9899	7.6480E-04
ILSA [Huang, T., et al., 2020]	0.76078	0.50569	0.2557	0.036609	54.9246	2.0000	1.4614	9.8270E-04
IHGS [Xu, B., et al., 2022]	0.76078	0.74935	0.2260	0.03674	55.48542	2.0000	1.45102	9.8248E-04
BES [Alsattar, H. A., et al., 2020]	0.7608	0.2259	0.7493	0.0367	55.4854	1.4510	2.0000	9.8248E-04
DE [Yu, S., 2022]	0.7605	0.42322	0.1873	0.02061	51.9345	1.8758	1.4360	7.6300E-04
ITSA [Nicaire, N. F., et al., 2021]	0.7608	0.9731	0.1679	0.0369	53.8368	1.9213	1.4281	9.82E-04

WSO, HO, GOANM and GOA. AHO, artificial hummingbird optimization; DDM, double diode model; DLMVO, Dynamic Levy Mutated Vortex Optimization; GOA, Gazelle optimization algorithm; GOANM, Gazelle optimization- Nelder–Mead algorithms; IMFOL, improved multi-objective fitness optimized by Levy; RMSE, root mean square error; RTLBO, randomized teaching-learning-based optimization; TSA, tunicate swarm algorithm.

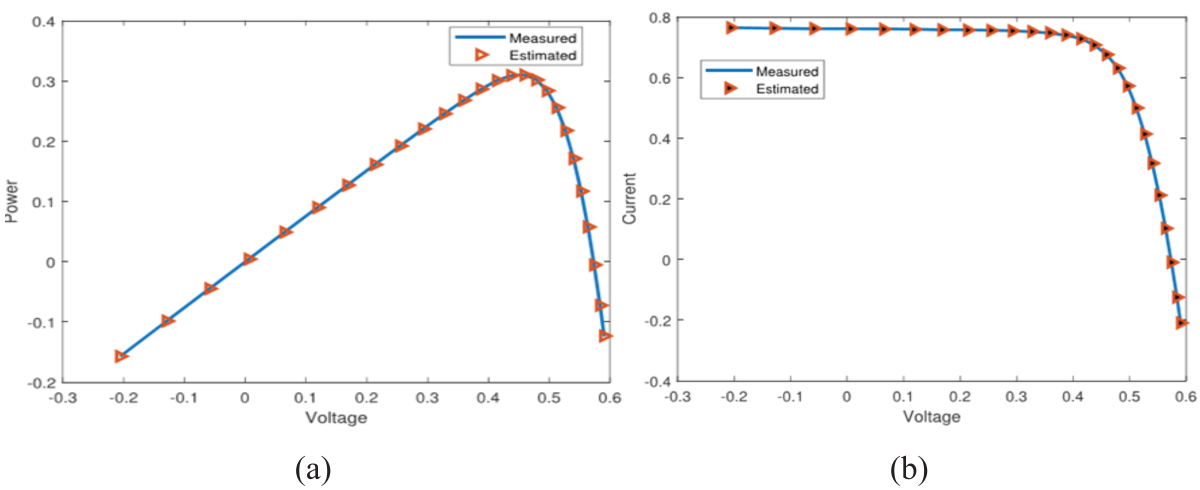
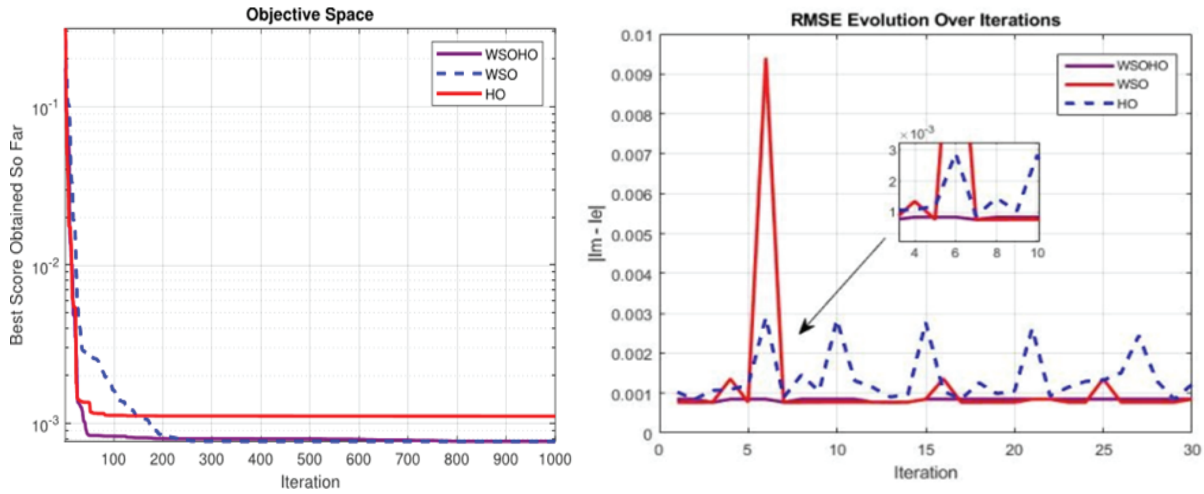


Figure 9. Curves with the measured and estimated data. (a) Curves (P, V) for DDM. (b) Curves (I, V) for DDM. DDM, double diode model.

presents the RMSE statistical values obtained for the double-diode model using both WSO and HO. The results clearly indicate that the WSO-HO algorithm consistently achieves lower RMSE values compared to WSO, HO, GOANM and GOA. AHO, artificial hummingbird optimization; DDM, double diode model; DLMVO, Dynamic Levy Mutated Vortex Optimization; GOA, Gazelle optimization algorithm; GOANM, Gazelle optimization- Nelder–Mead algorithms; IMFOL, improved multi-objective fitness optimized by Levy; RMSE, root mean square error; RTLBO, randomized teaching-learning-based optimization; TSA, tunicate swarm algorithm.

Figure 9 a,b illustrates the (P-V) and (I-V) characteristics of the optimised DDM achieved using the WSO-HO algorithm. The close alignment of the curves with experimental data confirms the model's ability to accurately represent the behaviour of the solar cell. This underscores the effectiveness of the WSO-HO approach in enhancing the DDM's performance and reliability.

Figure 10a,b clearly demonstrates that the WSO-HO algorithm converges to a stable solution more rapidly and exhibits smoother convergence behaviour compared to WSO and HO. This highlights the efficiency and



(a) (b)

Figure 10. Convergence and robustness curves for DDM. (a) Curves convergence (b) Curves robustness. DDM, double diode model.

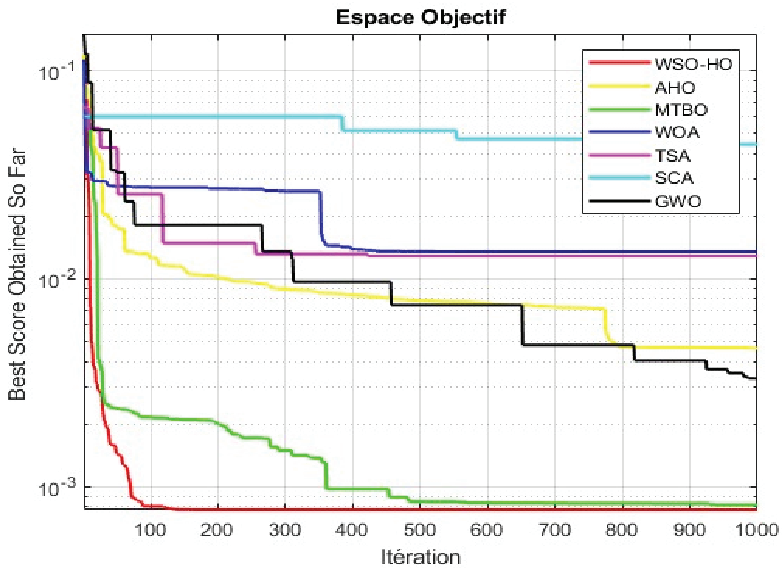


Figure 11. Convergence and Robustness Curves of Optimisation Algorithms Applied to the DDM. DDM, double diode model.

effectiveness of the proposed WSO-HO approach (Jeridi et al., 2024), Using performance indicators such as mean, standard deviation and range (Min, Max), Table 3 provides the performance metrics of the WSO-HO algorithm applied to the DDM for the RTC France solar cell case study (Fan et al., 2022). The results reveal a strong agreement between estimated and experimental values, confirming the algorithm's precise modelling capabilities. Table 3 comprehensively compares the estimated parameters and RMSE values achieved with WSO-HO against recent optimisation techniques, including CCNMGBO, IMFOL, RTLBO, DLMVO, OBL-RSACM, CGO-LS, AHO, PSOCS, ELADE, COA, SDGBO, IHGS, BES, DE, ITSA and TSA. The findings indicate that WSO-HO outperforms these methods by consistently achieving the lowest RMSE value, underscoring its superior accuracy in modelling the RTC France solar cell using the DDM (Bakhshi-Jafarabadi et al., 2019). The convergence and robustness curves of various optimisation algorithms applied to the DDM are presented in Figure 11. Among these, the hybrid WSO-HO (War Strategy Optimization combined with Hippopotamus Optimization) algorithm stands out for its superior performance. It achieves optimal results quickly in the early stages of iterations, reflecting its capability to efficiently explore the search space. In comparison, other methods like AHO, MTBO, WOA, TSA, SCA and GWO display

Table 5. Analysis of RMSE for Single and Double PV models

Model	Algorithm	Min	Mean	Max	STD
SDM	WSO-HO	7.72985671E-04	7.7308567E-04	7.7410567E-04	6.138516E-17
	WSO	7.73005671E-04	8.1665894E-04	0.002083	2.3920836E-04
	HO	8.75385E-04	0.00233	0.00629359	1.33368-03
	GOA [Amiri, H. H et al., 2024]	7.5810E−04	7.7695E−04	8.8385E−04	2.4314E−05
	GOANM [Amiri, H. H et al., 2024]	7.4339E−04	7.5263E−04	7.6714E−04	7.3732E−06
	ELAD [Gu, Z. et al., 2023]	9.8602E-04	9.8602E-04	9.8605E-04	1.753E-10
	DE [Yu, S., 2022]	9.811E-04	1.02874E-03	1.0813E-03	2.94961E-05
	ISCA [Chen, H.,2019]	7.3423E-04	7.2302E-04	7.4592E-04	1.30287E-06
	ITSA [Nicaire, N. F., et al., 2021]	9.86E-04	7.730062E-04	9.89E-04	5.70E-16
DDM	WSO-HO	7.420691E-04	7.4967098E-04	7.72985671E-04	1.08074E-05
	WSO	7.4378257E-04	8.3867102E-04	0.00099892	1.6562955E-04
	HO	8.55885e-04	0.00265008	0.006542	1.74708E-03
	GOA [Amiri, H.H et al., 2024]	7.5810E−04	7.7695E−04	8.8385E−04	2.4314E−05
	GOANM [Amiri, H.H et al., 2024]	7.4339E−04	7.5263E−04	7.6714E−04	7.3732E−06
	ELAD [Gu, Z. et al., 2023]	9.8252E-04	1.32602E-03	1.000562E-03	9.15E-12
	DE [Yu, S., 2022]	9.8607E-04	9.8874E-04	7.730062E-04	2.4696E-06
	ISCA [Chen, H., 2019]	2.2142E-04	1.66043E-02	9.93218E-04	1.30287E-06
	ITSA [Nicaire, N. F., et al., 2021]	9.9804E-04	9.99991E-04	3.799062E-02	6.33E-06

DDM, double diode model; GOA, Gazelle optimization algorithm; GOANM, Gazelle optimization- Nelder–Mead algorithms; PV, photovoltaic; RMSE, root mean square error; SDM, single diode model; STD, standard deviation.

slower convergence speeds. These algorithms struggle to reach lower scores promptly, which may reduce their practicality. This analysis underscores the robustness of the WSO-HO algorithm, as it consistently delivers better scores and maintains stable performance over a broad range of iterations, making it a more effective option for optimising PV models.

The performance of the hybrid WSO-HO algorithm is compared against several other optimisation algorithms for both the SDM and the DDM as presented in Table 5.

For the SDM, the WSO-HO algorithm achieves superior results with a minimum RMSE of 7.7298E-04, a mean of 7.7308E-04, and an extremely low standard deviation (STD) of 6.1385E-17, indicating both high precision and consistency. In contrast, standalone WSO and HO algorithms show less favourable results, with WSO presenting a higher mean error of 8.1665E-04 and HO demonstrating greater variability with an STD of 1.33368-03. Similarly, other algorithms like GOA, GOANM, COA (Gu et al., 2023) and DE perform reasonably well but fail to match the accuracy and stability of WSO-HO. Notably, GOANM (Amiri et al., 2024) achieves a minimum RMSE of 7.4339E-04, which is close to WSO-HO, but its standard deviation remains slightly higher.

For the DDM, the hybrid WSO-HO algorithm again outperforms other methods, achieving a minimum RMSE of 7.4206E-04 and a very low STD of 1.08074E-05, highlighting its robustness and reliability. In comparison, the WSO and HO algorithms exhibit higher mean errors (8.3867E-04 for WSO and 0.00265 for HO) and greater variability. Algorithms such as GOANM and GOA (Amiri et al., 2024) perform comparably well, with GOANM achieving a minimum RMSE of 7.4339E-04, but they still fall short in terms of consistency and precision. Other approaches, including COA, DE, ISCA and ITSA, display significantly higher errors and standard deviations, limiting their effectiveness in achieving rapid convergence with minimal error.

Overall, the WSO-HO algorithm demonstrates its superiority by achieving the lowest RMSE values, rapid convergence and exceptional stability across both models, making it the most reliable and efficient choice for optimising PV parameters.

8. Conclusion

This study proposes a hybrid optimisation approach combining the WSO-HO algorithm with the NR method to address the challenge of accurate parameter estimation in PV systems. The results demonstrate that WSO-HO outperforms modern algorithms in terms of accuracy and convergence speed, ensuring close alignment with experimental data. Two objective functions were formulated: functional error and current error, with the latter proving more effective for parameter extraction. The WSO-HO algorithm showcased its robustness compared to existing algorithms, highlighting its efficiency and reliability.

For future work, we propose developing binary and multi-objective versions of the WSO-HO algorithm, as well as integrating chaotic signals and opposition-based approaches to enhance adaptability. Exploring evolutionary dynamics and strategies such as crossover and mutation could enhance its performance.

References

Alsattar, H. A., Zaidan, A. A. and Zaidan, B. B. (2020). Novel meta-heuristic bald eagle search optimisation algorithm. *Artificial Intelligence Review*, 53, pp. 2237–2264. doi: 10.1007/s10462-019-09732-5

Amiri, M. H., Mehrabi Hashjin, N., Montazeri, M., Mirjalili, S. and Khodadadi, N. (2024). Hippopotamus optimization algorithm: A novel nature-inspired optimization algorithm. *Scientific Reports*, 14, p. 5032. doi: 10.1038/s41598-024-54910-3

Arandian, B., Eslami, M., Khalid, S. A., Khan, B., Sheikh, U. U., Akbari, E. and Mohammed, A. H. (2022). An effective optimization algorithm for parameters identification of photovoltaic models. *IEEE Access*, 10, pp. 34069–34084. doi: 10.1109/ACCESS.2022.3161467

Ayyarao, T. S. and Kishore, G. I. (2024). Parameter estimation of solar PV models with artificial humming bird optimization algorithm using various objective functions. *Soft Computing*, 28(4), pp. 3371–3392. doi: 10.1007/s00500-023-08630-x

Ayyarao, T. S. and Kumar, P. P. (2022). Parameter estimation of solar PV models with a new proposed war strategy optimization algorithm. *International Journal of Energy Research*, 46(6), pp. 7215–7238. doi: 10.1002/er.7629

Bakhshi-Jafarabadi, R., Sadeh, J. and Soheili, A. (2019). Global optimum economic designing of grid-connected photovoltaic systems with multiple inverters using binary linear programming. *Solar Energy*, 183, pp. 842–850. doi: 10.1016/j.solener.2019.03.019

Bogar, E. (2023). Chaos game optimization-least squares algorithm for photovoltaic parameter estimation. *Arabian Journal for Science and Engineering*, 48(5), pp. 6321–6340. doi: 10.1007/s13369-022-07364-6

Chen, H., Jiao, S., Heidari, A. A., Wang, M., Chen, X. and Zhao, X. (2019). An opposition-based sine cosine approach with local search for parameter estimation of photovoltaic models. *Energy Conversion and Management*, 195, pp. 927–942. doi: 10.1016/j.enconman.2019.05.057

Ekinci, S., Izci, D. and Hussien, A. G. (2024). Comparative analysis of the hybrid gazelle-Nelder–Mead algorithm for parameter extraction and optimization of solar photovoltaic systems. *IET Renewable Power Generation*, 18(6), pp. 959–978. doi: 10.1049/rpg2.12974

El-Khatib, M. F., Sabry, M. N., El-Sebah, I. and Maged, S. A. (2023). Hardware-in-the-loop testing of simple and intelligent MPPT control.algorithm for an electric vehicle charging power by photovoltaic system. *ISA Transactions*, 137, pp. 656–669. doi: 10.1016/j.isatra.2023.01.025

Fan, Y., Wang, P., Heidari, A. A., Chen, H. and Mafarja, M. (2022). Random reselection particle swarm optimization for optimal design of solar photovoltaic modules. *Energy*, 239, p. 121865. doi: 10.1016/j.energy.2021.121865

Farghally, H., Sweelem, E. A., El-Sebah, I. and Syam, F. (2023). Agricultural grid connected photovoltaic system design and simulation in Egypt by using PVSYST software. *WSEAS Transactions on Circuits and Systems*, 21, pp. 306–315. doi: 10.37394/23201.2022.21.33

Green, M. A. (1982). Accuracy of analytical expressions for solar cell fill factors. *Solar Cells*, 7(3), pp. 337–340. doi: 10.1016/0379-6787(82)90057-6

Gu, Z., Xiong, G., Fu, X., Mohamed, A. W., Al-Betar, M. A., Chen, H. and Chen, J. (2023). Extracting accurate parameters of photovoltaic cell models via elite learning adaptive differential evolution. *Energy Conversion and Management*, 285, p. 116994. doi: 10.1016/j.enconman.2023.116994

Huang, T., Zhang, C., Ouyang, H., Luo, G., Li, S. and Zou, D. (2020). Parameter identification for photovoltaic models using an improved learning search algorithm. *IEEE Access*, 8, pp. 116292–116309. doi: 10.1109/ACCESS.2020.3003814

Jeridi, A., Moulahi, M. H., Messaoud, R. B. and Zaafouri, A. (2024). Enhancing photovoltaic solar model parameter optimization: WSO-MTBO hybrid approach based on Newton-Raphson method. *Przegląd Elektrotechniczny*, 11(2024) pp. 133–140, doi:10.15199/48.2024.11.25

Jordehi, A. R. (2016). Parameter estimation of solar photovoltaic (PV) cells: A review. *Renewable and Sustainable Energy Reviews*, 61, pp. 354–371. https://doi.org/10.1016/j.rser.2016.03.049

Khattar, N., Sidhu, J. and Singh, J. (2019). Toward energy-efficient cloud omputing: A survey of dynamic power management and heuristics-based optimization techniques. *The Journal of Supercomputing*, 75, pp. 4750–4810. doi: 10.1007/s11227-019-02764-2

Li, J., Dang, J., Xia, C., Jia, R., Wang, G., Li, P. and Zhang, Y. (2023). Dynamic leader multi-verse optimizer (DLMVO): A new algorithm for parameter identification of solar PV models. *Applied Sciences*, 13(9), p. 5751. doi: 10.3390/app13095751

Nicaire, N. F., Steve, P. N., Salome, N. E. and Grégroire, A. O. (2021). Parameter estimation of the photovoltaic system using bald eagle search (BES) algorithm. *International Journal of Photoenergy*, Volume 2021, Article ID 4343203, 20 pages https://doi.org/10.1155/2021/4343203

Qaraad, M., Amjad, S., Hussein, N. K., Badawy, M. and Mirjalili, S. (2023). Photovoltaic parameter estimation using improved moth flame algorithms with local escape operators. *Computers and Electrical Engineering*, 106, p. 108603. doi: 10.1016/j.compeleceng.2023.108603

Singh, G. K. (2013). Solar power generation by PV (photovoltaic) technology: A review. *Energy*, 53, pp. 1–13. doi: 10.1016/j.energy.2013.02.057

Villalva, M. G., Gazoli, J. R., and Ruppert Filho, E. (2009). Modeling and circuit-based simulation of photovoltaic arrays. In: *2009 Brazilian Power Electronics Conference (1244–1254)*, IEEE. 27 September 2009 - 01 October 2009

Xu, B., Heidari, A. A., Kuang, F., Zhang, S., Chen, H. and Cai, Z. (2022). Quantum Nelder-Mead Hunger Games Search for optimizing photovoltaic solar cells. *International Journal of Energy Research*, 46(9), pp. 12417–12466. doi: 10.1002/er.8011

Yu, S., Chen, Z., Heidari, A. A., Zhou, W., Chen, H. and Xiao, L. (2022). Parameter identification of photovoltaic models using a sine cosine differential gradient based optimizer. *IET Renewable Power Generation*, 16(8), pp. 1535–1561. doi: 10.1049/rpg2.12451

Yu, X., Hu, Z., Wang, X. and Luo, W. (2023). Ranking teaching–learning-based optimization algorithm to estimate the parameters of solar models. *Engineering Applications of Artificial Intelligence*, 123, p. 106225. doi: 10.1016/j.engappai.2023.106225