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Enhancing Photovoltaic Solar Model Parameter Optimization: WSO-MTBO Hybrid Approach based on Newton-Raphson Method

Abstract. *In recent years, accurate parameter estimation in photovoltaic (PV) system modeling has become increasingly crucial for optimizing overall system performance. The main contribution is to combine War Strategy Optimization (WSO) and Mountaineering Team-Based Optimization (MTBO) algorithms based on the Newton-Raphson technique, a novel hybrid model, WSO-MTBO, allows to estimate parameters in solar cell models. Finally, simulation results are presented and compared with other algorithms, that illustrate enhanced parameter estimation accuracy.*

Streszczenie. *W ostatnich latach dokładne szacowanie parametrów w modelowaniu systemów fotowoltaicznych (PV) stało się coraz ważniejsze dla optymalizacji ogólnej wydajności systemu. Głównym wkładem jest połączenie algorytmów War Strategy Optimization (WSO) i Mountaineering Team-Based Optimization (MTBO) opartych na technice Newtona-Raphsona, nowy hybrydowy model WSO-MTBO pozwala na szacowanie parametrów w modelach ogniw słonecznych. Na koniec przedstawiono wyniki symulacji i porównano je z innymi algorytmami, które ilustrują zwiększoną dokładność szacowania parametrów.* ***(Ulepszanie optymalizacji parametrów modelu fotowoltaicznego: hybrydowe podejście WSO-MTBO oparte na metodzie Newtona-Raphsona)***

Keywords: Solar PV system, WSO, MTBO, Newton-Raphson method,Parameter Optimization
Słowa kluczowe: System fotowoltaiczny, WSO, MTBO, metoda Newtona-Raphsona, Optymalizacja parametrów

Introduction

Solar power is increasingly recognized as a sustainable source of energy, notable for its accessibility, minimal maintenance needs, and beneficial environmental impact. Nonetheless, the variable nature of solar energy production presents significant challenges in its large-scale incorporation into power generation networks[1]. The deployment of accurate photovoltaic (PV) models plays a pivotal role in enhancing the performance of electrical grids and enabling effective energy management strategies[1, 2]. The most efficient models for depicting solar cells include those based on single and double diode configurations. Techniques for refining these models fall into three primary categories: analytical, deterministic, and metaheuristic approaches. Metaheuristic methods are particularly valued for their ability to identify local optima, offering critical insights in the determination of solar cell parameters[2] .To extract parameters with a high degree of precision, metaheuristic algorithms are employed, especially in response to the inherent non-linearity of photovoltaic models and the growing number of parameters that need to be estimated[4]. A diverse range of optimization techniques has been explored for the extraction and assessment of PV parameters [3].

Due to the non-linear complexity of photovoltaic models and the growing need to estimate a multitude of parameters, metaheuristic algorithms have become indispensable for achieving high precision in parameter extraction. A variety of optimization techniques have been employed to extract and estimate the parameters of PV systems. As cited in [26], the Retroactive Search with Multiple Learning (MLBSA) algorithm has been specifically designed for accurate and reliable estimation of PV parameters. To balance exploration and exploitation, this method combines the Grey Wolf Optimizer (GWO) and the Cuckoo Search Algorithm (CSA) into a technique called GWOCS, as stated in [27]. Another approach that leverages the exploratory and exploitative principles of the Sinus-Cosinus algorithm (SCA) has been utilized to identify optimal parameters. It combines local research with an opposition and sinus-cosinus approach [28]. The parameters of the PV cells were also determined using the well-known high-performance Chaotic Logistic JAYA algorithm (LCJAYA) [29]. In the same domain, photovoltaic parameters have been extrapolated using the Competitive Leader with Dynamic Gaussian Mutation and the Coyote Optimization Algorithm (COA) [31]. The Moth Flame Algorithm and the Orthogonal Nelder-Mead Moth Flame Optimization (NM-SOLMFO) were two of the optimization techniques used to extract the seven unknown parameters of the Double Diode Model (DDM). These techniques were particularly used to enhance the accuracy and consistency of the optimization procedure. Furthermore, the advanced and conventional versions of the Teaching-Learning-Based Optimization algorithm (ITLBO), renowned for its high accuracy and reliability, were used to determine the Photovoltaic (PV) parameters [33]. [34]. Subsequently, methods like the Bound Global Optimization Algorithm and the Interval Branch Method were used to estimate these parameters.

The literature has employed a variety of metaheuristic optimization techniques to determine parameters for photovoltaic (PV) systems. These include the standard Genetic Algorithm (GA) and its improved variants [40], [42], as well as the Differential Evolution technique and its most recent iterations [43][45]. Moreover, algorithms like the Salp Swarm-Inspired Technique [41], the Enhanced Ant Lion Algorithm [38], and the Artificial Bee Swarm [46] have been used. Biogeography Based Optimization [44], a sophisticated version of the Cuckoo Search Algorithm, Bird Mating Optimization Strategies [45], and the Hybrid Bee Pollinator Flower Pollination Approach have also been applied in this field. This field of study has also benefited from the development of the Artificial Immune System and the Bacterial Foraging Algorithm [43]. Regarding Single Diode Models (SDM), several techniques have been investigated. These include the Improved Electromagnetic-Like Algorithm [42], the Grasshopper Optimization Algorithm [41], the Enhanced Whale Optimization Algorithm [35], the Shark Smell Optimizer, and the Harris Hawks Optimizer with a Boosted Mutation Feature [40].

Motivation and the main contributions.

The paper presents a pioneering hybrid methodology that integrates two meta-heuristic optimization algorithms: "War Strategy Optimization" (WSO) and "Mountaineering Team-Based Optimization" (MTBO), as well as Newton Raphson's method. This fusion leverages the distinctive strengths of each algorithm, thereby improving the overall efficiency of the optimization process. WSO, inspired by military tactics, takes a strategic approach to navigating the search space, with a focus on identifying and applying optimal solutions [46, 47]. The MTBO, similar to a group of mountain climbers exploring various terrains, facilitates broad exploration of the solution space. This is particularly beneficial for identifying

local optima and discovering new promising areas. In this hybrid approach, the algorithms are used sequentially. Initially, WSO is used to identify promising areas. Subsequently, MTBO is deployed for further exploration of these identified areas. This synergistic integration allows the WSO to guide the MTBO toward potentially optimal areas, while the MTBO refines the solutions identified by the WSO. The interaction between these algorithms is regulated by a migration interval, maintaining a harmonious balance between exploration and exploitation. This integrated approach significantly increases the likelihood of discovering the most effective solution and alleviates the limitations inherent in each individual method. It demonstrates exceptional efficiency in complex scenarios, such as in our study focused on extracting photovoltaic system parameters, where accuracy and efficiency are paramount. Furthermore, the results of our proposed model are juxtaposed with other recent and established works in the literature that use classical models. and new metaheuristic algorithms.
The organization of the article is structured as follows:
In Section 2, we have exploring Solar Cell single Diode Models and double diode models with a succinct overview with parameter extraction methods. Moreover, It explains on the objective function employed in parameter extraction. Section 3 an presents an overview of the War Strategy Optimization Algorithm (WSO) and the Mountaineering Team-Based Optimization (MTBO) methods before delving into the detailed description of the proposed hybrid method, WSO-MTBO. We elaborate the main contributions by WSO-MTB hybridization Algorithms based on the Newton-Raphson method in section 4. Section 5, this section presents simulation and comparative results analysis. Fanally,a conclusion is given with future scope in section 6.

PV Cell Modeling

Comprehensive reviews of the literature place a strong emphasis on comprehending the physical behavior of photovoltaic cells in order to develop efficient designs for photovoltaic systems. As proposed in the Single Diode Model (SDM), Double Diode Model (DDM), and Triple Diode Model (TDM) are suggested for more accurate representation due to their simplicity and ability to strike a balance between precision and simplicity [8].

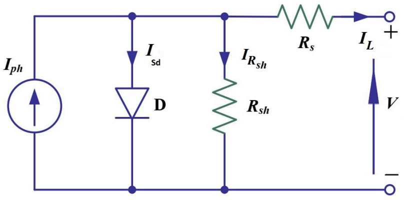

Fig. 1. Equivalent circuit of SDM

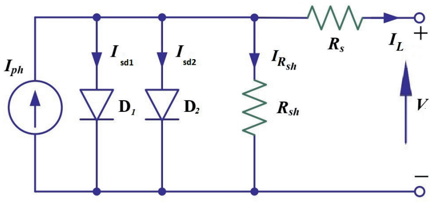

Fig. 2. Equivalent circuit of DDM

Single diode model: Comparable circuit models outline a cell, module, or array's whole IV curve as a continuous function under particular operating conditions. A widely used equivalent circuit model is the Single Diode Model, which is based on physical principles (e.g., Gray, 2011) and is represented by the circuit for a single solar cell shown below [7]. Besides the known parameters, there are five unknown parameters [26] that need to be determined:

$$I_L = \mathrm{I}_{ph} - \mathrm{I}_s d - \mathrm{I}_{Rsh} \tag{1}$$

Where I_{ph} is the photocurrent, I_L is the output current of the PV cell, $I_s d$ is the diode current and $I_R sh$ is the shunt resistance current [1]. The current expressions are as follows:

$$\mathrm{I}_L = \mathrm{I}_{ph} - \mathrm{I}_{sd}\left(e^{\frac{\mathrm{q}(V_L + I_L R_S)}{\mathrm{nKT}}} - 1\right) - \frac{V_L\mathrm{T} + I_L R_S}{R_{sh}} \tag{2}$$

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

Where q represents the charge of an electron, n is the ideality factor of a diode, V_L is the output voltage of a photovoltaic cell, $I_s d$ is the reverse saturation current of a diode, k is the Boltzmann constant, R_s is the series resistance, $R_s h$ is the shunt resistance, and T denotes temperature.[11]

The following equations can be employed to calculate the output current of a PV cell. In equation (1), substitute equations (2) and (3):

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

Five unknown parameters [26] must be determined in addition to the know ones :$\mathrm{I}_{ph}, \mathrm{I}_{sd}, R_s, R_{sh}, \mathrm{n}.$

The double diode model: As illustrated in Figure 2, the equivalent circuit for the double diode model can be used to determine the load current.

$$I_L = \mathrm{I}_{ph} - \mathrm{I}_{d1} - \mathrm{I}_{d2} - \mathrm{I}_{sh} \tag{5}$$

Using the same method as in the model of a single diode, the final output current of a PV cell is represented as:

$$\begin{aligned} \mathrm{I}_L = \mathrm{I}_{ph} - \mathrm{I}_{sd1}\left(e^{\frac{\mathrm{q}(V_L + I_L R_S)}{\mathrm{n1KT}}} - 1\right) \\ -\mathrm{I}_{sd2}\left(e^{\frac{\mathrm{q}(V_L + I_L R_S)}{\mathrm{n2KT}}} - 1\right) - \frac{V_L\mathrm{T} I_L R_S}{R_{sh}} \end{aligned} \tag{6}$$

Where,I_{sd1} , I_{sd2} are the diode reverse saturation currents and n1 ,n2 are the diode ideality factors.The DDM has seven unknown parameters $\mathrm{I}_{ph}, \mathrm{I}_{sd1}, \mathrm{I}_{sd1}, R_S, R_{sh}, \mathrm{n1}, \mathrm{n2}$ in addition to the wellknown ones that need to be estimated.

WSO and MTBO overview

In this section, we will provide an overview of the War Strategy Optimization Algorithm (WSO) and the Mountaineering Team-Based Optimization (MTBO) methods before delving into the detailed description of the proposed hybrid method, WSO-MTBO.
Mountaineering Team-Based Optimization: leader guiding a group of climbers towards the summit, which symbolizes the optimal solution to an optimization problem [1]. In this analogy, each climber, or "mountaineer," follows the lead of the leader, who represents the current best solution, while overcoming obstacles like avalanches along the way.

This approach emphasizes teamwork and strategic problem-solving techniques [24].

- First phase (Coordinated Mountaineering): During the first phase, the best member of the algorithm's population takes on the role of the leader, directing the group towards the best overall solution in the current iteration, much like the most experienced member leading an alpine team. The position of each member is updated according to the following process:

(7)
$$X_i^{new} = X_i + rand(X_{leader} - X_i) + rand(X_{ii} - X_i)$$

where X_{ii} is the position of the member directly in front.

- Second Phase (Avalanche Crisis): The second phase of the MTBO optimization approach deals with natural disasters, specifically avalanches. The position of each member is updated based on the worst-case scenario (XWorst)[15] or its equivalent (XAvalanche):

$$X_i^{new} = X_i \times rand(X_{Avalanche} - X_i) \quad (8)$$

- Third Phase (Coordinated and Group Effort against Disasters): The third phase of the MTBO algorithm is inspired by the coordinated efforts of a group to rescue their trapped members. The position of each member aligns with the group's average position (Xmean or XTeam),[15] reflecting their cooperative behavior:

$$X_i^{new} = X_i + rand(X_{team} - X_i) \quad (9)$$

War Strategy Optimization Algorithm: The WSO algorithm is inspired by historical military strategies, where the king and commanding officer dynamically adjust their tactics in response to various battle scenarios. The soldiers, akin to algorithmic elements, adjust their positions based on cues from their leaders [19].

- Random Attack In this phase, the troops, representing algorithmic elements, are randomly distributed to attack the opposing army. The strongest individual, akin to the army chief, leads the various units.
- Attack Strategy: The primary objective of this strategy is to attack the opposition. The King, representing the best solution, leads the troops. The troops dynamically change their position based on the positions of the King and the Commander, akin to adjusting algorithm parameters[19].
- Signaling by Drums: The King, or the best solution, gives orders to change the strategy based on the situation. The soldiers, or algorithmic elements, adopt a new strategy and adjust their positions based on these signals.
- Defense Strategy: The primary objective of this strategy is to protect the King, or maintain the best solution. The commander takes the lead and forms a protective chain around the King using the troops. The troops explore a large area of the battlefield, or search space, and dynamically change their strategy to confuse the opposition.

Mathematical Modeling of the War Strategy: The WSO algorithm models a war strategy where the roles of the King and Commander are crucial. Soldiers, representing algorithmic elements, start with the same weight and rank. As the war progresses, their weights and ranks are updated based on their performance [28]. The soldier with the greatest attack strength is known as the King. The position of each soldier is updated as follows [20]:

(10)
$$X_i(t+1) = X_i(t) + 2 \cdot \rho \cdot (C - K) + \text{rand} \cdot (W_i \cdot K - X_i(t))$$

If the attack strength in the new position (F_n) is less than in the previous position F_p, the soldier reverts to the previous position:

(11)
$$X_i(t+1) = (X_i(t+1)) \cdot (F_n \geq F_p) + (X_i(t)) \cdot (F_n < F_p)$$

If the soldier successfully updates his position, his rank (R_i) will be upgraded:

$$R_i = (R_i + 1) \cdot (F_n \geq F_p) + (R_i) \cdot (F_n < F_p) \quad (12)$$

Based on the rank, the new weight is calculated as:

$$W_i = W_i \cdot \left(1 - \frac{R_i}{\text{Max\_iter}}\right) \cdot \phi \quad (13)$$

The update of the position in the second strategy is based on the positions of the King, the army head, and a random soldier:

(14)
$$X_i(t+1) = X_i(t) + 2 \cdot \rho \cdot (K - X_{\text{rand}}(t)) + \text{rand} \cdot W_i \cdot (C - X_i(t))$$

WSO-MTBO Hybridation Algorithms

WSO-MTBO represents an advanced optimization technique that amalgamates the finest attributes of two distinct approaches—War Strategy Optimization (WSO) and Mountaineering Team-Based Optimization (MTBO). This method aims to forge a more dependable and efficient optimization strategy [46].

- Search Engine Optimization at its Best (WSO) The optimization algorithm known as WSO has drawn inspiration from wolf hunting strategies. It utilizes a collective hunting model where several wolves (representing research agents) collaborate to find the target (best solution). In WSO, the most proficient wolf, referred to as the "KING," guides the other wolves towards the most promising location within the research domain. As they scour the area together, the other wolves adjust their positions based on the direction of the king and other pack members.

$$\text{Positions}_{\text{new}}(i,:) = \text{Positions}(i,:) + \text{D}_{\text{V}}(i,:) \quad (15)$$

where D_V represents the position variation based on the position of the King and other wolves.

- Optimization Based on the Alpine Team (MTBO) MTBO draws inspiration from alpine teams' tactics. In order to achieve the peak, this algorithm prioritizes teamwork and member adaptation: Each team member (research agent) picks up knowledge from the others and adjusts to the surroundings. The group dynamic is used to effectively explore the research space, emphasizing cooperation and information sharing to identify the best solution.

$$\begin{aligned} \text{new\_sol.Position} &= \text{pop(i).Position} \\ &+ \text{rand} \times (\text{pop(ii).Position} - \text{pop(i).Position}) \\ &+ \text{rand} \times (\text{Leader.Position} - \text{pop(ii).Position}) \end{aligned} \quad (16)$$

WSO-MTBO Hybridation: In the advanced optimization technique WSO-MTBO, Wolf Search Optimization (WSO) and Mountaineering Team-Based Optimization

(MTBO) techniques are combined to create a strategy that is both reliable and effective [46]. During the WSO phase, each wolf evaluates its physical state, and the strongest one ascends to the role of King, leading the research efforts towards feasible solutions. The MTBO then leverages these positions for a more comprehensive cooperative exploration, aiming to discover optimal solutions that might have been overlooked by the WSO. The objective of this hybridization is to merge the understanding of the global search space with efficient local exploration. By integrating the capabilities of WSO with the methodology of MTBO, the hybridization seeks to enhance global research on optimal solutions.

- Combination of Various Approaches: The hybrid process combines the collective hunting model of WSO with the cooperation and adaptation techniques of MTBO. This synergy enhances the methodological approach of MTBO and leverages the speed of WSO, allowing for a more comprehensive exploration of the research space.
- Solution Migration: A crucial component that enhances solution diversity and avoids local optima traps is the periodic migration of solutions between WSO and MTBO populations. We establish regular intervals to share a subset of solutions between the algorithms, facilitating the combination of tactics and research knowledge. During migration, an exchange of solutions occurs between the WSO and MTBO populations.

(17)
$$\text{popWSO}(\text{indicesWSO}, :) \leftrightarrow \text{popMTBO}(\text{indicesMTBO}, :)$$

- Enhancement of Performances: In order to find good solutions, hybridization aims to take advantage of MTBO's extensive and cooperative research space exploration and combine it with WSO's efficacy. Combining these two approaches reduces the likelihood of premature convergence while accelerating the convergence toward the ideal solution.

The Newton-Raphson Method:
The Newton-Raphson method is used in conjunction with the HYBRID WSO-MTBO optimization algorithm in this approach. To calculate the currentfor the SDM and DDM model, the nonlinear equation is solved as follows:

$$\begin{aligned} f(x) =& I_{\text{ph}} - I_{\text{sd}}\left(e^{\frac{q(V_L+I_LR_S)}{nKT}} - 1\right) \\ & - \frac{V_LT + I_LR_S}{R_{\text{sh}}} - x \end{aligned} \tag{18}$$

$$\begin{aligned} g(x) =& I_{\text{ph}} - I_{\text{sd1}}\left(e^{\frac{q(V_L+I_LR_S)}{n1KT}} - 1\right) \\ & - I_{\text{sd2}}\left(e^{\frac{q(V_L+I_LR_S)}{n2KT}} - 1\right) - \frac{V_LT + I_LR_S}{R_{\text{sh}}} - x \end{aligned} \tag{19}$$

Simulation Results and Statistical Analysis

In this section, we evaluate the performance of the hybrid WSO-MTBO algorithm in extracting parameters for three different diode models: the Single Diode Model (SDM),and Double Diode Model (DDM). The data used for this evaluation is derived from an experimental setup involving a commercial silicon solar cell (R.T.C. France), [2] with a diameter of $57mm$, operating under a solar radiation of $(1000W/m^2)$ and for given temperature (33^0C). The configurations of the parameters of the WSO-MTBO algorithm, applied to SDM,and DDM, are presented respectively in Table 1. Each

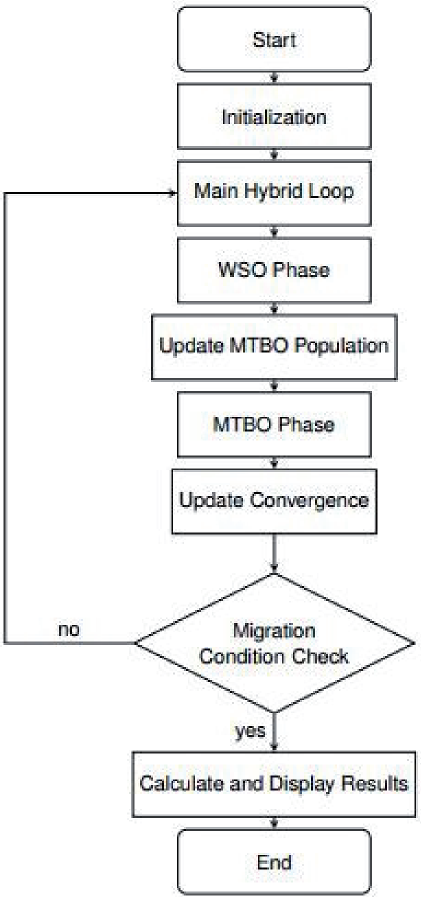

Fig. 3. Flowchart Hybrid WSO-MTBO Algorithm

model requires the extraction of a different number of parameters: five for SDM,and seven for DDM . Before starting the optimization process, it is essential to establish the boundaries of each parameter, thus defining the search space of the algorithm [14]. These boundaries, which have been adopted in numerous studies, [2, 6], [10]. To ensure the stability and reliability of the analysis, the WSO-MTBO algorithm was simulated using Matlab for 30 iterations, [1, 7, 46]. Optimization algorithms are used to extract parameters from various photovoltaic cell models. These techniques require an objective function to evaluate potential solutions. Optimization problems are defined in bounded spaces, with these limits specified in Table 1.

Table 1. The boundaries of extracted photovoltaic parameters

Parameter	Upper bound	Lower bound
$I_{ph}(A)$	0	1
$I_{sd1}, I_{sd2}, I_{sd3}(\mu A)$	0	1
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
n_1, n_2, n_3	1	1.5

Simulation Results for single-diode model
The goal of this task is to predict the five unidentified parameters, namely $[I_{ph}, I_{sd}, R_S, R_{sh}, n]$, for a photovoltaic (PV) cell modeled using a single diode model based on empirical measurements. Table 1 provides the lower and upper limit values for these parameters. The comparison of results for the Single Diode Model (SDM) is presented in Table 2. This table includes the best Root Mean Square Error (RMSE) and the extracted parameters for each algorithm. Based on the output data in Table 2, the RMSE value of 7.7298E-04 is achieved by WSO-MTBO, and for WSO and MTBO indi-

```
Algorithm 1: Hybrid WSO-MTBO Algorithm
Result: Best solution found by the hybrid WSO-MTBO
        algorithm
Initialization: Initialize the populations popWSO and
  popMTBO
for each iteration do
  WSO Phase:
    King, King_fit ← WSO(popWSO)
  Update MTBO Population:
    Update popMTBO with the best solution found
     by WSO (King),
    // The best solution of WSO is shared
       with MTBO

  MTBO Phase:
    Start MTBO optimization using the updated
     population popMTBO
    // MTBO may start with better initial
       solutions

    Best_MTBO ← MTBO(popMTBO)
  Update Convergence:
    Update convergence curve with King_fit
  if Migration Condition is met then
    Migrate Solutions:
      Migrate solutions between popWSO and
       popMTBO
      // Introduces more diversity into the
         populations

  end
  Calculate and Display Results
end
```

Fig. 4. Hybrid WSO-MTBO Algorithm

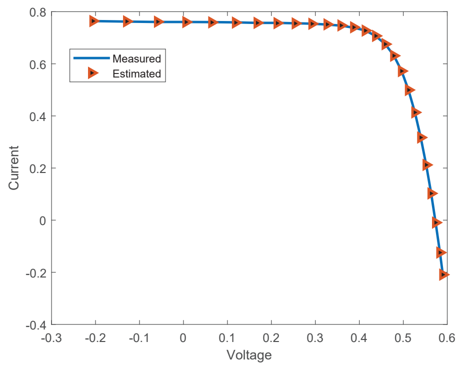

Fig. 6. curves V-I with the measured and estimated data for SDM

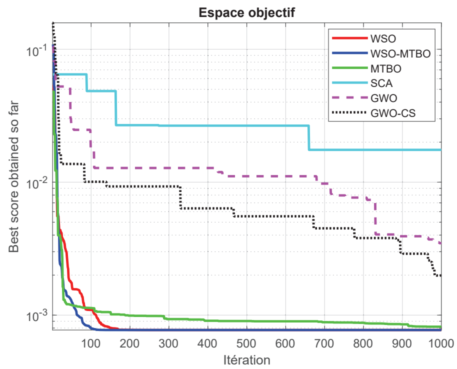

Fig. 7. the Convergence curves for SDM

vidually, the RMSE values are 7.73006E-04 and 7.73023E-04, respectively. The best RMSE value was achieved by the MLBSA algorithm with 9.8600E-04, followed by GWOCS with 9.8607E-04, GWO with 7.5011E-04, ISCA with 9.8602E-04, and ITLBO with 9.8602E-04. For LCJAYA and JAYA, the RMSE values are 0.0047268 and 0.0025565, respectively, and for COA, the RMSE value is 7.7301E-04. The P-V and I-V curves of the SDM were based on the estimated data from WSO-MTBO with the best RMSE, as explained in Figure 4 and 5. In this figure, the proposed WSO-MTBO has been validated by comparing the simulation result. From this figure, it was observed that the simulation data output from the proposed WSO-MTBO for SDM aligns well with the measured data[4]. Thus, the performance of the SDM based on the WSO-MTBO algorithm was more effective.

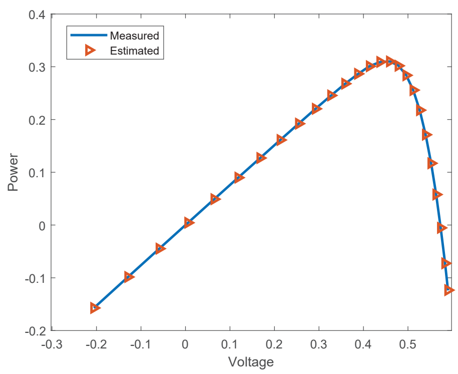

Fig. 5. curves P-V with the measured and estimated data for SDM

Simulation Results for double-diode model

It was a comparative study of results based on the DDM presented in Table 4. It includes the parameters extracted from each algorithm at the best RMSE. The results are in Table 5. The best RMSE value (9.8237E-4) was obtained by the ISCA algorithm and had the second-best RMSE (9.8249E-4). ITLBO with MLBSA achieved the third-best RMSE (7.419808E-4), calculated from the WSO-MTBO algorithm, followed by WSO, MTBO, GWOCS, MFO, CSA, GWO, JAYA, and LCJAYA, respectively.Regarding the DDM, the accuracy of the parameters was evaluated based on RMSE. The P-V and I-V curves for the DDM were based on the WSO-MTBO estimated data at the best RMSE, as explained in Figure 7 and 10. In this context, the proposed WSO-MTBO indeed outperformed other algorithms.From this figure, it is observed that the simulated output data of the proposed WSO-MTBO for the double diode model aligns with the measured data. Therefore, the performance of the DDM based on the WSO-MTBO algorithm was more effective. Therefore, when these results are applied to improve the control law for extracting the maximum power point (MPPT) through PV parameter estimation [47].

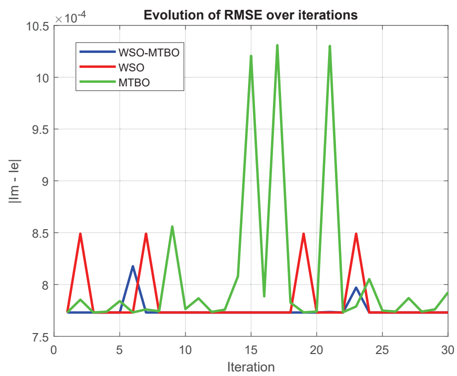

Fig. 8. The robustness curves the for SDM

Table 2. The parameters estimated for single diode model at the best root mean square error (RMSE).

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	n	$R_s(\Omega)$	$R_{sh}(\Omega)$	RMSE
WSO-MTBO	0.76077553	0.32302	1.481183596	0.036377092	53.71852549	**7.729856E-04**
WSO	0.76078796	0.31068457	1.47726968	0.03654694	52.88978844	7.7300629E-04
MTBO	0.76097273	0.29519669	1.472172	0.036767497	50.71687117	7.7302354E-04
MLBSA [26]	0.7608	0.323	1.4812	0.0364	53.7185	9.8600E-04
GWOCS [27]	0.760773	0.32192	1.4808	0.03639	53.632	9.8607E-04
GWO [27]	0.769969	0.91215	1.596658	0.02928	18.103	7.5011E-03
ISCA [28]	0.76077562	0.323017	1.4811822	0.036377148	53.71821748	9.8602E-04
LCJAYA [29]	0.7608	0.323	1.4819	0.0364	53.7185	4.726841E-03
JAYA [29]	0.7608	0.3281	1.4828	0.0364	54.9298	2.556575E-03
COA [31]	0.760788	0.31069	1.47727	0.03655	52.8898	7.7301E-04
ITLBO [33]	0.7608	0.323	1.4812	0.0364	53.7185	9.8602E-04

Table 3. Analysis of root mean square error for single photovoltaic models.

Algorithm	**Min**	**Mean**	**SD**
WSO-MTBO	7.729856E-04	7.730062E-04	1.663587E-12
WSO	7.730062E-04	7.730062E-04	1.663597E-12
MTBO	7.730235E-04	8.047029E-04	6.97887E-5
MLBSA[26]	9.8602E-04	9.8602E-04	9.15E-12
GWOC[27]	9.8607E-04	9.8874E-04	2.4696E-06
GWO[27]	7.5011E-03	2.5617E-02	1.6071E-02
ISCA[28]	7.3423E-04	7.23043E-04	1.30287E-06
LCJAYA[29]	9.86E-04	9.86E-04	5.70E-16
JAYA[29]	9.8946E-04	1.1617E-03	1.8796E-04
ITLBO[33]	9.8602E-04	9.8602E-04	2.19E-17

Table 4. The parameters estimated of a double diode model at the best RMSE.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	n_1	R_s (Ω)	R_{sh} (Ω)	I_{sd2} (μA)	n_2
WSO-MTBO	0.76080586	0.078436	1.37169	0.03769	56.14046	0.999907	1.80802581
WSO	0.7607824	0.97068205	1.99996571	0.03707875	55.2912	0.19113	1.43649
MTBO	0.7607367	0.00267075	1.65271834	0.03605	55.2946	0.346183177	1.4883
MLBSA	0.7608	0.2273	1.4515	0.0367	55.4612	0.7384	2
GWOCS	0.76076	0.53772	2	0.03666	54.7331	0.24855	1.4588
GWO	0.761668	0.40302	1.646	0.03265	72.52775	0.45338	1.5527
ISCA	0.760781079	0.7493463	2	0.036740	55.4845	0.22597	1.4510169
JAYA	0.7607	0.006763	1.8436	0.0364	52.6575	0.31507	1.4788
COA	0.76081	0.08656	1.37278	0.03803	52.3562	0.21597	2

Table 5. Analysis of Root Mean Square Error for DDM Photovoltaic Models

Algorithm	**Min**	**Mean**	**SD**
WSO-MTBO	**7.419808E-04**	7.518064E-04	1.12127E-05
WSO	7.42004E-04	8.22471E-04	2.63418E-04
MTBO	7.60147E-04	9.308604E-04	1.82916E-04
GBO	9.825779E-04	1.00054E-03	7.231E-05
MFO	1.00752E-03	3.34906E-02	5.74432E-03
CSA	1.12349E-03	2.07298E-03	2.366E-04
GWOC[27]	9.8334E-04	1.0017E-03	9.5937E-06
GWO[27]	2.2124E-03	3.7996E-02	1.9113E-02
ISCA[28]	9.8342E-04	9.86863E-04	1.65397E-06
LCJAYA[29]	9.83E-04	9.86E-04	1.31E-06
JAYA[29]	1.31E-06	1.4793E-03	1.9356E-04
ITLBO[33]	9.8248E-04	9.8812E-04	1.54E-06
MLBSA[26]	9.8249E-04	9.8249E-04	1.35E-06

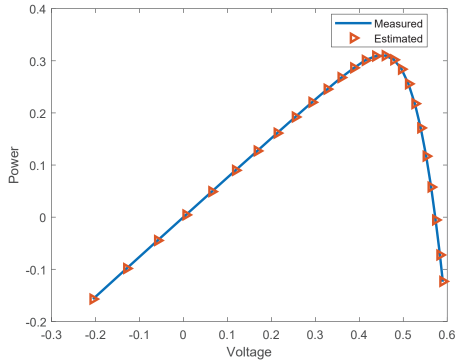

Fig. 9. curves P-V with the measured and estimated data for DDM

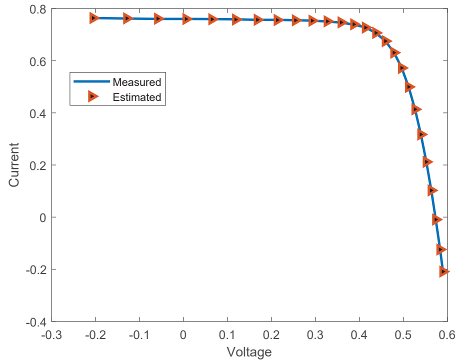

Fig. 10. curves V-I with the measured and estimated data for DDM

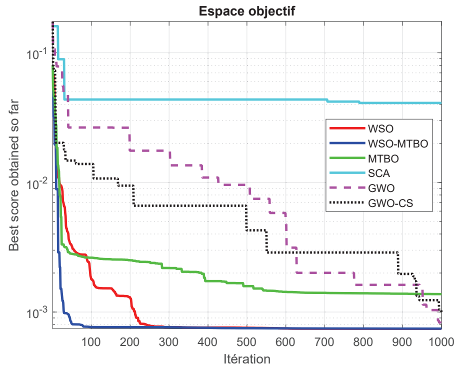

Fig. 11. the Convergence curves for DDM

Conclusion

The unknown parameters for PV Cell models are extracted using the WSO-MTBO hybridization algorithms based on the Newton-Raphson method. Moreover, from the outcome of our investigation, it is possible to conclude that the WSO-MTBO hybridization algorithms based on the Newton-Raphson method affirm a significant leap forward in optimizing the parameters of the photovoltaic system. Based on the RTC France solar cell data, this study underscores the hybridization algorithms' efficiency. This approach is used to extract the parameters across diverse solar cell models. However, this approach stands out for its thorough comparison of the WSO-MTBO algorithms compared to the recent algorithms proposed in the literature, which showcases its robustness and reliability in parameter optimization.Based on the promising findings presented in this paper, work on the remaining issues is continuing and will be presented in future papers. We can introduce these parameter optimizations to improve the control law for extracting the maximum power point (MPPT) through PV parameter estimation.

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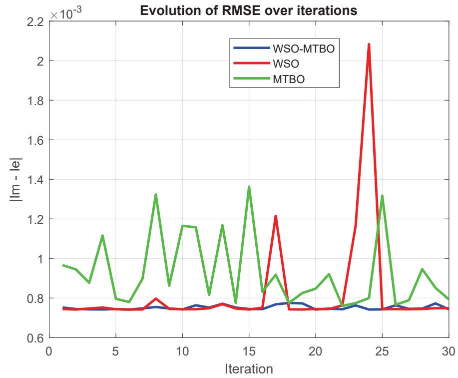

Fig. 12. The robustness curves the for DDM

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