PARAMETER EXTRACTION OF SOLAR PHOTOVOLTAIC MODELS USING WAR STRATEGY OPTIMIZATION (WSO) ALGORITHM.

Abstract

In many spheres of human endeavor, renewable energy is gaining ground as a possible replacement for fossil fuels. Researchers have been inspired by solar energy's endless supply, accessibility, environmental friendliness, and ease of installation and maintenance in worldwide power networks. More specifically, solar radiation is converted to electrical energy in large part by photovoltaic (PV) cells. Recently, the trend topic driving researchers' attention has been solar photovoltaic (PV) systems. The construction of a practical model that can replicate the current vs. voltage characteristics of a genuine solar cell and the precise calculation of the PV cell's parameter values provide challenges to the optimal design of PV cells, which is an essential undertaking. The goal of this research is to estimate the parameters of three PV models—the single, double, and triple diode PV modules using an optimization method based on the War Strategy. The addition of the War strategy optimization (WSO) algorithm guarantees the diversity of options and improves the capabilities of exploration and exploitation. The Sharp ND-R250A5 module is subjected to an optimization method under varying temperature and irradiance circumstances in order to further confirm its efficacy. The results of the simulation show that the WSO method can extract PV model parameters with good accuracy and high performance when comparing the three PV module.

Keywords: Solar PV Module,ND R250A5,Optimization Algorithm.

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I. INTRODUCTION

The global surge in photovoltaic (PV) energy in recent years can be likened to a strategic conquest, propelled by its compelling attributes— abundance, noiseless operation, pollution-free, and widespread distribution [1–4]. This surge is further fueled by the tactical advantage gained from the plummeting prices of PV cells/modules, enhancing its competitiveness in the energy landscape. Similar to a dynamic battlefield, a PV system is made up of several PV cells or modules that work together to generate a nonlinear dynamic system. The key to its effective operation and control lies in the art of emulating the nonlinear dynamic characteristics, a mission critical to the success of the overall campaign. The challenge of simulating PV cells and modules and guaranteeing their correctness sets the battlefield—a challenge of paramount importance. The implementation of similar circuits based on the strategic Single Diode Model (SDM), Double Diode Model (DDM), and Tripple Diode Model (TDM) is the solution to the first question [5-7]. After these circuits are carefully chosen, the second challenge becomes how to modify them to simulate various PV models under various operating circumstances. Determining precise values is a strategic need since these analogous circuits, like seasoned commanders, are extremely nonlinear and house multiple unknown model factors and aligning with the overarching goal of the mission. Researchers, resembling generals in this energy warfare, have strategically introduced diverse approaches to address this formidable challenge. The analytical technique [8–14], a quick and practical tactic, consists of obtaining simpler formulations based on certain points in order to compute parameter values directly. The numerical approach iteratively moves over the solution space by using well-known techniques including the least squares method [20,21], the Gauss-Seidel method [19], and the Newton-Raphson method [18]. Yet, the unreliability stemming from heavy dependence on initial starting points exposes it to traps in a nonconvex solution space, leading to inaccurate parameters [22–24].In the arms race of optimization methodologies, the metaheuristic approach emerges as a formidable force, unrestricted by conditions on search domains or objective functions [25].]. This approach, akin to unconventional warfare, has witnessed a surge in applications in recent years. Prominent examples include search for symbiotic organisms [29], flexible particle swarm optimization [30], simulated annealing [28], genetic algorithms [26], and particle swarm optimization [27]. All of these techniques use different strategies to effectively extract parameters.

II. LITERATURE REVIEW

This literature review aims to provide a comparative analysis of a diverse array of war strategy algorithms in terms of their effectiveness in addressing optimization problems. Genetic Algorithms: Whitley [1] lays the foundation for genetic algorithms, a nature-inspired optimization technique replicating natural selection processes. Populations, genetic operators, and selection processes are all used in these algorithms. Differential Evolution: A simple yet effective heuristic for global optimization, differential evolution is introduced by Storn and Price [2]. It is predicated on keeping a population of potential solutions and progressively refining them by recombination and mutation.WSO method: The War Strategy Optimization (WSO) method is a novel metaheuristic designed for global optimization, as proposed by Ayyarao et al. [3]. It has been particularly created to tackle optimization difficulties and has proven successful in resolving intricate engineering design issues. Evolutionary Optimization Algorithms: Simon [4] explores the theoretical underpinnings and applications of evolutionary optimization algorithms. To find the best answers, these algorithms mimic the processes of natural development. Kennedy and Eberhart [5] provide particle swarm optimization, a model that mimics the social behavior of birds. A population of particles is kept moving across the search space by the algorithm, which modifies their placements in response to both individual and group experiences. Ant Colony Optimization: Based on ant foraging behavior, Dorigo, Birattari, and Stutzle [6] introduce ant colony optimization. Pheromone communication is used by this algorithm to direct decentralized search for the best answers.Bacterial Foraging Optimization: Modeling the foraging behavior of bacteria, Das et al. [6] offer an algorithm for bacterial foraging optimization. To obtain the best answers, the algorithm makes use of reproduction, swarming, and chemotaxis mechanisms. Grey Wolf Optimizer: Inspired by the social structure and hunting habits of grey wolves, Mirjalili et al. [7] present the Grey Wolf Optimizer. Alpha, beta, delta, and omega wolves are utilized by this algorithm to facilitate effective search space exploration.Whale Optimization Algorithm: Based on humpback whale hunting behavior, Mirjalili and Lewis [8] describe the Whale Optimization Algorithm. The algorithm efficiently explores and exploits the search space by utilizing encircling, spiraling, and tail-slapping actions. Moth Flame Optimization Algorithm: Drawing inspiration from moths' navigational habits, Mirjalili [9] presents the Moth-Flame Optimization Algorithm. The program uses the principle of moth attraction to flames as a guide to find the best possible solutions. [10] present the Salp Swarm algorithm. Grasshopper Optimization Algorithm: Based on the swarming behavior of grasshoppers, Saremi, Mirjalili, and Lewis [11] offer the Grasshopper Optimization Algorithm. For effective exploration and exploitation, the algorithm integrates several grasshopper species and movement tactics. Artificial Bee Colony Algorithm: Based on an imitation of honeybee foraging behavior, Karaboga and Basturk [12] evaluate the effectiveness of the Artificial Bee Colony (ABC) algorithm. To explore and utilize the search space, it makes use of scout bees, hired bees, and observer bees. Algorithm Inspired by Bats: Yang [13] presents a metaheuristic algorithm that draws inspiration from bat echolocation. To get the.

Yang [14] introduces the Firefly Algorithm, which simulates the flashing characteristic of fireflies. This optimization method uses the allure of firefly flashes to direct the pursuit of the best answers. The Cuckoo Search Algorithm was proposed by Yang and Deb [15] and is based on the brood parasitism of some species of cuckoo. Levy flights and random walk processes are used by the method to efficiently explore and utilize the search space. The Spherical Search Algorithm is a metaheuristic that was created for bound-constrained global optimization problems. It was first introduced by Kumar et al. [16]. The method efficiently finds the best answers by using spherical exploration. Cuevas et al. [17] present the Social-Spider Algorithm, a swarm optimization technique that draws inspiration from social spider behavior. The Social-Spider Algorithm solves optimization issues by combining cooperative techniques and web-building. The Marine Predators Algorithm was developed by Faramarzi et al. [18] and is based on the hunting techniques of marine predators. The cooperative and strategic hunting methods found in nature are modeled by this algorithm. Crow Search Algorithm: Askarzadeh [19] introduces the Crow Search Algorithm, which draws inspiration from crows' foraging habits. To identify the best answers, the program uses the crow's exploration and exploitation methods. Krill Herd Algorithm: Inspired by the collective behavior of krill, Gandomi and Alavi [20] propose the Krill Herd Algorithm. In order to maximize results, this program imitates reproductive processes and swarm dynamics. Chimp Optimization Algorithm: Inspired by chimpanzees' feeding habits, Khishe and Mosavi [21] present the Chimp Optimization Algorithm. This program mimics the social structure of chimpanzee societies by using a multi-agent method. Squirrel Search Algorithm: Inspired by squirrels' hunting habits, Jain, Singh, and Rani [22] present the Squirrel Search Algorithm. This optimization method makes use of processes for exploration and exploitation found in squirrels' natural habitat. Yang [23] introduces the Flower Pollination Algorithm, which is based on how flowers pollinate themselves. This method makes use of flower pollination techniques to improve the search space's exploration and exploitation. Manta Ray Foraging Optimization: Inspired by the foraging habits of manta rays, Zhao, Zhang, and Wang [24] present the Manta Ray Foraging Optimization Algorithm. This optimization method imitates manta ray movement and feeding habits. Sailfish Optimizer: Drawing inspiration from sailfish hunting behavior, Shadravan, Naji, and Bardsiri [25] propose the Sailfish Optimizer. To optimize solutions, this algorithm combines exploration and exploitation tactics.

III. BLOCK DIAGRAM

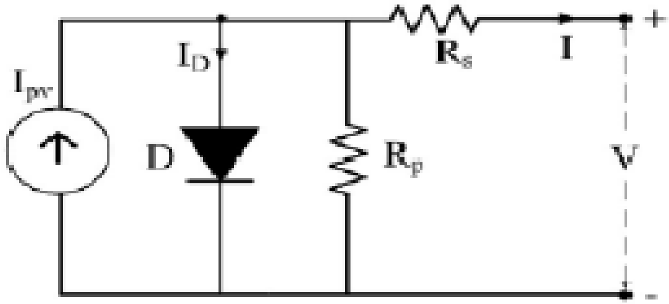

Figure 1: single diode model

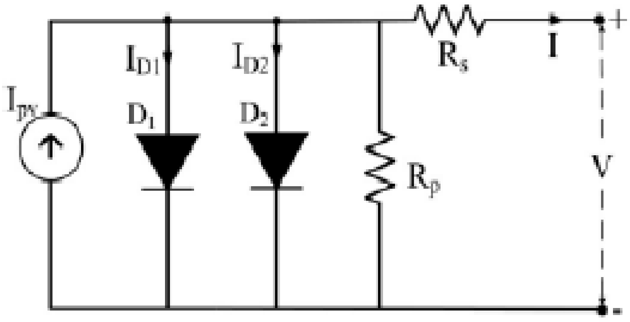

Figure 2:. triple diode model

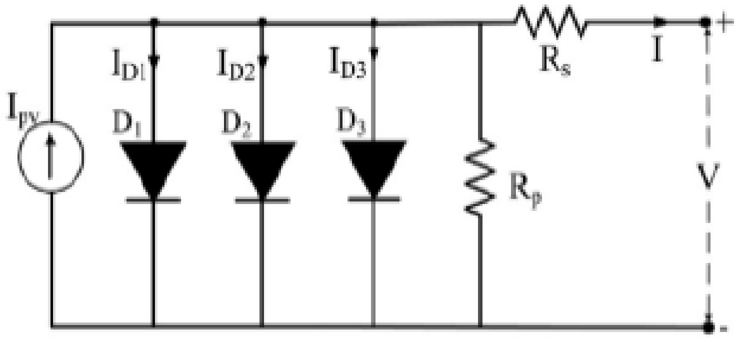

Figure 3: double diode model

IV. NUMERICAL STATISTICS

Single Diode Model

The diagram depicts the electrical equivalent circuit of SDM. The current source, Ipv, is connected in anti-parallel with diode D. Additionally, contact and leakage losses are indicated by series resistance Rs and shunt resistance Rp, respectively [43]. Kirchhoff's current law may be used to determine the current generated by the PV model (KCL).

$$I = I_{pv} - I_D - \frac{(V + IR_s)}{R_p} \qquad I_D = I_{01}\left(exp\left(\frac{(V + IR_s)}{a_1 V_t} - 1\right)\right)$$

Double Diode Model

The DDM model is the second most often utilized model, as it can illustrate how photovoltaic systems behave in many environmental scenarios. Even if the number of parameters may rise, DDM is widely utilized because of its precision.

$$I = I_{pv} - I_{o1}\left[exp\left(\frac{q(V + IR_s)}{a_1 kT}\right) - 1\right] - I_{o2}\left[exp\left(\frac{q(V + IR_s)}{a_2 kT}\right) - 1\right] - \frac{(V + IR_s)}{R_p}$$

where Io1 and Io2 stand for the values of the diffusion and saturation currents, and a1 and a2 represent the ideality factors of D1 and D2, respectively. Ipv is the current generated by the PV cell. In addition, the following parameters will be evaluated in order to simulate DDM: Rs, Rp, Ipv, I01, I02, a1 and a2.

Triple Diode Model

The significance of including a third diode in order to enable the DDM to accurately depict the leakage current in the multi-crystalline silicon solar cells' grain boundaries. Afterward, Khanna et al. used the TDM to offer a precise model for commercial solar cells manufactured on a large scale, and Allam et al. used TDM to simulate the multi-crystalline silicon solar cells and modules, taking into consideration the impacts of grain boundaries, carrier recombination, and leakage current.

$$I = I_{pv} - I_{o1}\left[exp\left(\frac{q(V + IR_s)}{a_1 kT}\right) - 1\right] - I_{02}\left[exp\left(\frac{q(V + IR_s)}{a_2 kT}\right) - 1\right] - I_{03}\left[exp\left(\frac{q(V + IR_s)}{a_3 kT}\right) - 1\right] - \frac{(V + IR_s)}{R_p}$$

where Io1, Io2, and Io3 stand for the values of the diffusion, saturation, and reverse saturation currents, and Ipv is the current generated by the PV cell. The ideality factors of D1, D2, and D3 are, correspondingly, a1, a2, and a3. Additionally, the following parameters need to be calculated in order to simulate TDM effectively: Rs, Rp, Ipv, Io1, Io2, Io3, a1, a2, and a3.

V. BLOCK DIAGRAM DISCRIPTION

The single-diode model, the double-diode model, and the modified double-diode model are the three primary diode models used in the extraction of solar parameters. The ideality factor, series resistance, shunt resistance, and photocurrent are only a few of the crucial metrics that may be extracted from solar cell activity using these models. The single-diode model takes into account the forward bias, reverse bias, and saturation current of a single diode in order to simulate the behavior of a solar cell. This model facilitates parameter extraction by offering a straightforward yet accurate depiction of the properties of the solar cell. In order to more fully account for recombination effects, the double-diode model adds another diode to improve the accuracy of the single-diode model. This model provides a more sophisticated understanding of the behavior of the solar cell, especially in situations when the temperature and light levels change. Lastly, the modified double-diode model further refines the representation by incorporating additional parameters to better capture real-world conditions, such as light-induced degradation and series resistance variations. By accounting for these complexities, this model enables more precise parameter extraction, leading to improved performance analysis and optimization strategies for solar cells. In summary, the block diagram depicting these three diode models showcases their progressive refinement in capturing the intricate behavior of solar cells, ultimately facilitating the accurate extraction of critical parameters essential for optimizing solar energy harvesting systems.

VI. METHODOLOGY

Designing a war strategy optimization algorithm inspired by diode-based models necessitates a nuanced approach tailored to the intricacies of military planning and execution. The single, double, and triple diode models act as metaphors to direct the structure and actions of the algorithm. In this context, the unidirectional flow characteristics of a single diode can be mirrored in the strategy’s progression over time, emphasizing the importance of a forward-moving and adaptive approach. The introduction of a double diode model introduces bidirectional aspects, symbolizing the need for strategies to adapt to changing environments and unforeseen challenges. Triple diode models add a layer of complexity, representing strategies that can dynamically adjust and learn from multiple sources, enhancing adaptability further. The algorithmic framework must encapsulate these diode-inspired characteristics into the optimization process. The encoding of war strategies into individuals in the algorithm is crucial, where chromosomes represent the strategic components. The objective function evaluates these strategies, considering factors such as resource allocation, adaptability to dynamic scenarios, and overall mission success. Initialization of the algorithm involves setting up a population of strategies using the diode-based encoding, with randomness injected to simulate the unpredictable nature of war. Evolutionary operators, including crossovers and mutations, draw inspiration from diode behaviors. Crossovers emulate the exchange of information between parent strategies, akin to the interaction in diode junctions. Adaptability mechanisms within the algorithm dynamically adjust parameters to mirror diode responses to changing environments. Population dynamics model the progression of strategies, considering unidirectional, bidirectional, and multidirectional flows influenced by single, double, and triple diode models, respectively. The optimization process's end is defined by conditions for termination, such as convergence or achieving a certain number of iterations. Validation involves assessing the algorithm's performance against historical war scenarios or simulated environments. Key metrics, including convergence speed, solution quality, and adaptability, gauge the algorithm's effectiveness.

VII. RESULT ANALYSIS

Table 1: upper and lower boundaries of SDM

Parameters	LB	UB
Rs	0	0.5
Rsh	0	1000
Ipv	0	2
Io	0	2
A	1	2

Table 2: upper and lower boundaries of DDM

Parameters	LB	UB
Rs	0	0.5
Rsh	0	1000
Ipv	0	2
Io1	0	2
Io2	0	2
A1	1	2
A2	1	2

Table 3: upper and lower boundaries of TDM

Parameters	LB	UB
Rs	*0*	*2*
Rsh	0	5000
Ipv	0	9
Io1	0	2
Io2	0	2
Io3	0	2
A1	1	2
A2	1	3
A3	1	5

Table 4: Simulation results

Models	Rs	Rsh	Ipv	Io1	Io2	Io3	A1	A2	A3	RMSE
SDM	3.71e-2	5.06e+1	7.61e-1	2.65e-7	-	-	1.45	-	-	8.05e-4
DDM	3.75e-2	5.68e+1	7.61e-1	1.89e-7	7.84e-7	- -	1.43	1.80		7.65e-4
TDM	3.79e-2	5.69e+1	7.61e-7	1.35e-7	1.58e-7	6.43e-7	1.41	1.94	1.86	7.56e-4

VIII. GRAPHICAL ANALYSIS

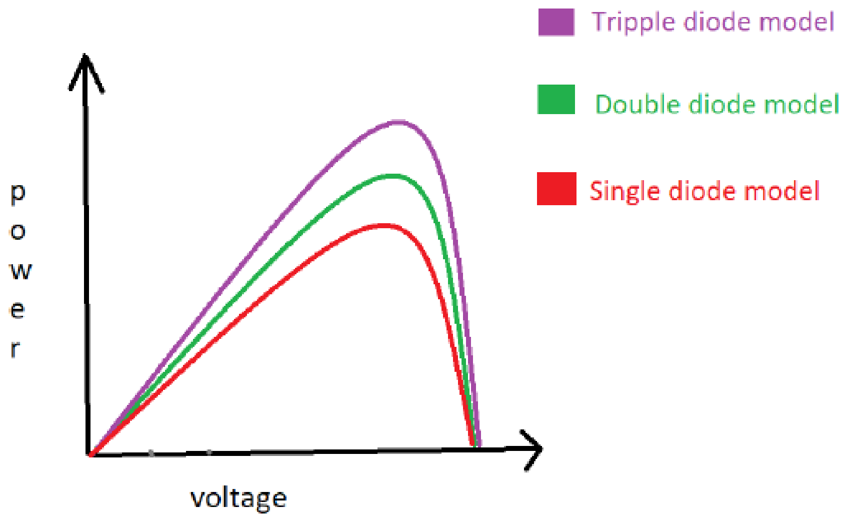

Figure 4

IX. CONCLUSION

In conclusion, the utilization of the War Strategy Optimization (WSO) algorithm for the purpose of extracting parameters from three different photo voltaic (PV) modules has shown great potential and efficacy in the field of solar energy research. Important insights have been gained from comparing the three PV modules—the Single Diode Model (SDM), Double Diode Model (DDM), and Triple Diode Model (TDM)—under various irradiance and temperature operating circumstances. The implementation of the WSO algorithm, which combines self-adaptive methods, opposition-based learning, and genetic algorithms, has shown to be effective in managing the complex and nonlinear PV models. The diverse nature of the three PV modules, each with its unique characteristics, poses a formidable challenge inaccurately estimating their parameters. However, WSO has show cased its adaptability and competitiveness in efficiently exploring and exploiting the solution space, allowing for precise parameter extraction. The comparative analysis revealed that WSO algorithm exhibits high performance and accuracy across the SDM, DDM, and TDM for the Sharp ND- R250A5 module. This suggests that WSO can effectively handle various complexities inherent in different PV models, highlighting its versatility and reliability. The algorithm's ability to tackle real-world challenges, such as variations in ir radiance and temperature, reinforces its robustness in practical applications. However, it is essential to acknowledge that despite the demonstrated success of WSO, challenges such as weak convergence have been identified. This calls for further refinement and enhancement of the algorithm to ensure its continued effectiveness in addressing complex optimization problems.

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