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REGULAR ARTICLE

Optimization Technique for Parameter Estimation in Solar Photovoltaic Systems Using Nanomaterials

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Nanomaterial integration in solar photovoltaic systems improves the efficiency of solar photovoltaic systems through better light capture and charge carrier transportation. To estimate parameters for these systems, improved optimization can fine-tune the efficiency of energy conversion and improve system robustness. This study aims to develop an optimization technique for accurate parameter estimation in solar photovoltaic systems using nanomaterials. This approach seeks to enhance the efficiency and performance of solar cells by leveraging advanced optimization algorithms. Intelligent Ant Colony Optimization (IACO) helps to estimate the parameters of solar photovoltaic systems with a more accurate simulation of the behavior of ants and their optimization functions to nanomaterials for energy production. For realizing enhanced accuracy and convergence in solar photovoltaic parameters, the Scalable Cuckoo Search Algorithm (SCSA) is used in the light of cuckoo nesting. The research uses two primary photovoltaic models (Updated One-Diode, and Updated Two-Diode) to assess the effects of nanomaterial integration. The integration of nanomaterials with the hybrid IACO-SCSA optimization led to significant improvements in solar cell efficiency. The study showed that the UODM and UTDM, while optimizing using hybrid IACO-SCSA, outperformed better than other models, such as SSE (Sum of Squared Error), RMSE (Root Mean Squared Error), and MAE (Mean Absolute Error).

Keywords: Intelligent Ant Colony Optimization (IACO), Scalable Cuckoo Search Algorithm (ICSA), Updated One-Diode, Updated Two-Diode.

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1. INTRODUCTION

Solar photovoltaic (PV) systems are a well-known global choice for delivering renewable energy [1]. These systems directly convert sunlight into electrical energy; thus, they are good examples of clean technologies that free society from reliance on non-renewable resources, such as fossil fuels [2]. Another factor that defines the PV performance is the levels of accuracy of the estimated parameters that play a decisive role in the efficiency as well as the amount of power yielded. That makes it easier to design, control and manage the PV systems for the optimum use of solar resources; this is because of the right assessment of parameters. But reaching such a level of accuracy is not very easy because of the nonlinear characteristics exhibited by PV systems and also they depend on other parameters, such as temperature, irradiance and shading conditions [3].

There is also another approach that should be used to enhance the efficiency of the utilized parameter estimation, and it is the method of nanomaterials incorporation in the PV cells. Due to the presence of various characteristics, nanomaterials can increase light trapping, reduce damages, and enhance solar cell perf ormance [4]. For example, such materials as quantum dots, carbon nano tubes and nanowires have enhanced optical and electrical properties, which will be useful for enhancing energy absorption and conversion efficiencies in the PV cells [5]. These materials can be further used to fine-tune all the parameters that are connected with the internal work of the PV system. As demand for energy storage from renewable sources continues to rise, these nanomaterials for solar opportunities advance approaches to enhance the efficiency of PV devices [6]. This is important because it would provide researchers and engineers with more accurate estimates of parameters for

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PV power systems, leading to increase efficiency in the design of these systems and offering more ideal solutions to solar energy challenges. Besides, this approach contributes to the promotion of PV systems as well as the objectives of achieving the sustainable development goals, providing better conditions for the use of renewable resources [7].

2. RELATED WORKS

The impact of the coatings on photovoltaic (PV) panel's performance was evaluated in the research by [8]. Under three distinct conditions, first solar PV was utilized for the self-cleaning procedure after being coated with a hydrophobic SiO_2 nanomaterial. The second photovoltaic panel was hand-cleaned without any kind of coating. Every day, the second photovoltaic panel was hand cleaned without any kind of coating. Throughout the experiment, the final solar panel was left uncoated and unclean; it served as a standard for all measurement procedures.

Applying a temporal three-dimensional model, a quantitative simulation of a PV thermal system utilizing nanofluids and nano-enhanced stage transition materials was conducted in the research [9]. The responsive surface technique was used to create a predictive model that predicted how the system would respond. Both phase change material and working fluid were treated with aluminum oxide nanoparticles to enhance their thermal performance.

To improve the optimization technique based on the salp swarm method (SSA) for recovering parameters from PV models, [10] proposed a modified salp swarm optimizer (MSSA). Parameters from three PV models were extracted to determine how the suggested technique was presented. Experimental results were showed that the suggested MSSA was more accurate and reliable than the original SSA when compared to alternative methods.

To indicate the thermal efficiency of pyramid solar distillers (PSD) [11], a mathematical modeling technique was developed that used responding surface methodology (RSM) to be employed in solar distillers under various environmental factors and nanoparticle kinds and concentrations. The three most important climatic process characteristics taken into consideration were wind speed, ambient temperature, and sun intensity.

To precisely identify the five characteristics of the individual diode models of solar cells, [12-13] presented a non-iterative method. By making the calculating process simpler, the approach solved the issues of accuracy and complexity. To acquire the appropriate five characteristics from the *I-V* curve, it was necessary to dynamically alter key components of the equation.

3. METHODOLOGY

This research uses four primary solar photovoltaic models (One-Diode, Updated One-Diode, Two-Diode, and Updated Two-Diode) to assess the effects of nanomaterial integration. Intelligent Ant Colony Optimization (IACO) helps to estimate the parameters of solar photovoltaic system with a more accurate simulation of the behavior of ants and their optimization functions to nanomaterials for energy production. For realizing enhanced accuracy and convergence in solar photovoltaic parameters, the Scalable Cuckoo Search Algorithm (SCSA) is used in light of cuckoo nesting.

3.1 Nanomaterials

Titanium Dioxide (TiO_2) nanoparticles, Copper Indium Gallium Selenide (CIGS) nanoparticles, Silicon nanowires, Copper Oxide (CuO_2) nanoparticles, and Molybdenum Disulfide (MoS_2) nanosheets are incorporated to increase light trapping, charge mobility and photovoltaic conversion efficiency of the solar systems. These nanomaterials are useful in optimization strategies by improving the parameter estimation methods and reducing energy dissipation resulting in enhanced performance and efficiency of the solar cells.

3.1.1 One-Diode Model (ODM)

The ODM seems to fit well *I-V* characteristics of photovoltaic (PV) cells incorporating nanomaterials, as illustrated in Figure 1. However, this photon absorption efficiency can be greatly improved when nanomaterials are integrated into the semiconductor. Nanomaterials enhance the light capture and carrier density-recombination rate because they have a high surface area to volume ratio and it can easily tune their electronic features to develop the general efficiency of the solar cell. Due to nanostructuring, the absorption efficiency in solar cells is high, resulting in greater power generation. The given information on the potential difference across the circuit and current flow shows that the electric field present at the *P-N* junction is efficient in the process of separating the generated carriers and further, these carriers are collected through electrodes, thus giving rise to a photovoltaic current. At this point, if a photovoltaic current is not present, the cell will function as an ordinary diode. The diode current drift follows the Shockley diode equation, as shown in Equation (1).

$$I = I_{ph} - I_d\left(f^{\frac{V+IR_{se}}{NV_T}} - 1\right) - \frac{V+IR_{se}}{R_{sh}} \tag{1}$$

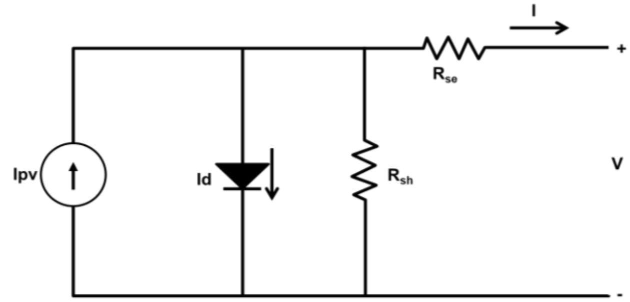

Fig. 1 – ODM Circuit

3.1.2 Updated One-Diode Model (UODM)

To incorporate the additional resistance due to grain boundaries in the quasi-neutral regions, a modification of the one-diode model is made to develop the UODM as shown in Fig. 2. The separation of charge is enhanced with the help of nanomaterials in these applications, thus minimizing recombination losses and improving conductivity. This serves to increase a photovoltaic current, as shown in equation (2).

$$I = I_{ph} - I_c\left(f^{\frac{V+IR_{se}-I_dR_s}{NV_T}} - 1\right) - \frac{V+IR_{se}}{R_{sh}} \tag{2}$$

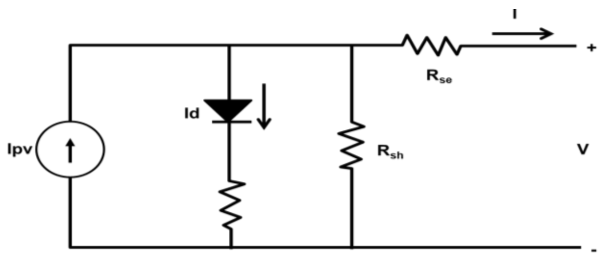

Fig. 2 – UODM Circuit

3.1.3 Two-Diode Model (TDM)

The improvement achieved by TDM is even higher as the second diode is placed in parallel with the current source, as described in Figure 3. This addition refers to recombination effects that are important in PV cells with nanostructures, since boundary and interface factors largely influence the mobility and recombination of the carrier. The additional diode contributes to the recombination current, improving accuracy, particularly while illuminating lights of lower intensity or amount. TDM is improved through the use of nanomaterials, since recombination inside the cell is minimized. For example, quantum dots can generate more than one exciton (electron-hole pair) per photon, increasing photocurrent and minimizing energy losses, as shown in equation (3).

$$I = I_{ph} - I_d\left(f^{\frac{V+IR_{se}}{NV_T}} - 1\right) - I_{d1}\left(f^{\frac{V+IR_{se}}{NV_T}} - 1\right) - \frac{V+IR_{se}}{R_{sh}} \tag{3}$$

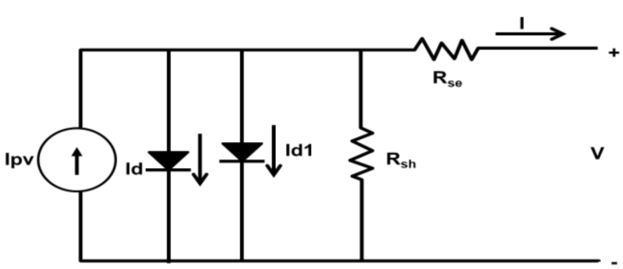

Fig. 3 – TDM Circuit

3.1.4 Updated Two-Diode Model (UTDM)

To consider the specific resistance in nanomaterial-based PV cells, the UTDM extends the TDM by including additional resistance, as illustrated in Fig. 4. Some nanostructures have different resistances at grain boundaries compared to the crystallite boundaries, hence affecting the carrier transport across the boundaries. Carbon nanotubes and nanowires improve the UTDM by increasing the electron transporting capacity between the particles. This addition of resistance is consistent with the characteristic electron transport in the nanostructured PV cells. The UTDM equation (4) is defined below.

$$I = I_{ph} - I_d\left(f^{\frac{V+IR_{se}-I_dR_s}{NV_T}} - 1\right) - I_{d1}\left(f^{\frac{V+IR_{se}-I_dR_s}{NV_T}} - 1\right)\frac{V+IR_{se}}{R_{sh}} \tag{4}$$

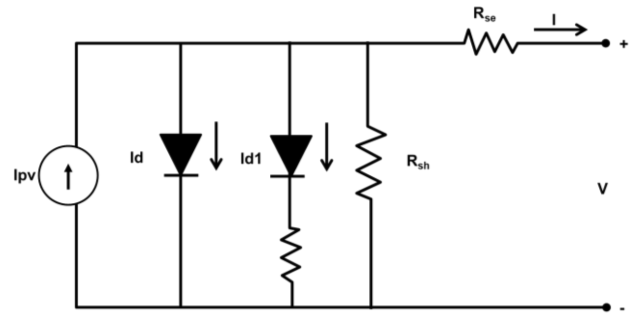

Fig. 4 – UTDM Circuit

3.2 Intelligent Ant Colony Optimization (IACO)

The advanced algorithmic technique developed for the enhancement and optimization of solar photovoltaic (PV) systems and incorporated with nanomaterials is known as Intelligent Ant Colony Optimization (IACO). Real-world problems are solved through the use of simulated ants where by IACO makes adjustments to different parameters like orientation and efficiency of the PV material to get the maximum yields on solar energy. With this nanomaterial, IACO seeks to optimize photovoltaic performances and durability when exposed to climatic conditions, thereby providing a dependable solar energy system solution.

In the conventional ACO algorithm, every ant is assigned to a city at random. Ants use a probabilistic decision-making method to choose the next city to visit while constructing an optimal solution. Equation (5) calculates the probability of ant l going to the following city i that is next to city j at time s while ant l remains in city j and creates the partial solution.

$$o_{ji}^{l}(s) = \begin{cases} \frac{\tau_{ji}^{\alpha}(s)\eta_{ji}^{\beta}(s)}{\sum_{l\in allowed_l}\tau_{jl}^{\alpha}(s)\eta_{jl}^{\beta}(s)} & if\ i \in allowed_l \\ 0 & otherwise \end{cases} \tag{5}$$

Where $\eta_{ji} = \frac{1}{c_{ji}}$ is the heuristic value of traveling from city j to city i, $allowed_l$ is the set of cities visited by ant l, and $\tau_{ji}(s)$ is the volume of pheromone trail on $arc(j,i)$ at time s. These parameters α and β regulate the comparative weight of the pheromone trail and heuristic values. The standard ant colony optimization approach has many drawbacks, including a slow speed of convergence and a tendency to consolidate on a local optimal solution. To improve the global search capability, prevent being stuck in a localized optimal solution, and accelerate convergence, it suggests a distance heuristic element in addition to the standard ACO method. Using the lowest sum of the distances between the present node and the next node, as well as the next node and the destination node, improve η_{ji} and the impact of the destination node on the following node, as shown in Equation (6).

$$m_{ji} = \frac{1}{\min[dis(j,i)+dis(i,n)]} \tag{6}$$

Where the distance between node j and the following node i is $dis(j,i)$, and the distance between node i and the destination node n is $dis(i,n)$ in equation (7).

$$o_{ji}^{l}(s) = \begin{cases} \dfrac{[\tau_{ji}(s)^{\alpha}]\cdot\left\{\frac{1}{\min[dis(j,i)+dis(i,n)]}\right\}^{\beta}}{\sum_i[\tau_{jl}(s)]^{\alpha}\cdot\left\{\frac{1}{\min[dis(j,i)+dis(i,n)]}\right\}} \\ 0 \quad otherwise \end{cases} \tag{7}$$

Over time, a path's pheromone trail decreases. Equations (8) and (9) are used to modify the trail strength after time n.

$$\tau_{ji}(s+t) = \rho\tau_{ji}(s) + \Delta\tau_{ji} \tag{8}$$

$$\Delta\tau_{ji} = \sum_{l=1}^{m}\Delta\tau_{ji}^{l} \tag{9}$$

Where the value of ρ, a coefficient that indicates the trail's evaporation between time s and $s+t$, ranges from 0 to 1. Ant l lays trail substance (similar to a genuine ant's pheromone) on edge (j,i) between time s and $s+t$, with $\Delta\tau_{ji}^{l}$ being the amount per unit of length, and m being the overall number of ants. Equation (10) illustrates the use of the ant-cycle network data updating model.

$$\Delta\tau_{ji}^{l} = \begin{cases} \frac{R}{K_l} \quad are\ (j,i) belongs\ to\ best\ tour \\ 0 \quad otherwise \end{cases} \tag{10}$$

Here, R is one of the constants related to the total pheromone and serves the same purpose as in conventional pheromone updating techniques. The lth ant's passage length is denoted by K_l. After a predetermined number of iterations, this method will stop until an ideal path is determined.

4. RESULT AND DISCUSSION

Python 3.12 operated on Windows 11 with an 11th-generation Core i7 processor and 32 GB of RAM. It made multitasking and development duties demanding performance evaluations much easier due to this modern laptop design. The study compared the three methods, such as SCSA, IACO, and Hybrid ICSA-SACO with the Updated One-Diode Model (UODM) and Updated Two-Diode Model (UODM) of solar PV using nanomaterial, in this they compared the proposed model's execution time and statistical results using SSE, MAE, and RMSE.

4.1 Execution Time for UODM

It compares the performance of three algorithms in Table 1: Combined results of IACO, SCSA, and Hybrid IACO-SCSA in terms of different parameters. For the IACO model, SCSA model, and Hybrid IACO-SCSA model, the maximum power point voltage (I_{pv}) is found to be 9.25 V, 9.30 V, and 9.275 V respectively. The Alpha1 values of efficiency parameters are 1.45 for IACO, 1.43 for SCSA, and 1.44 for the proposed hybrid method. R_{se} & R_{sh} both give better results with SCSA than with the others 0.0180 & 260 respectively. The current (I_{01}) values have not changed and the series resistance (R_s) indicates that SCSA offers the lowest value. Hybrid IACO-SCSA demonstrates the best results and takes the shortest time of 1.1 seconds for execution.

Table 1 – UODM parameters

Para-meters	IACO	SCSA	Hybrid IACO-SCSA
I_{pv}	9.2500	9.3000	9.2750
Alpha1	1.4500	1.4300	1.4400
R_{se}	0.1000	0.0180	0.0590
R_{sh}	255.000	260.000	257.500
I_{01}	3.60×10^{-7}	3.50×10^{-7}	3.55×10^{-7}
R_s	0.1000	0.0160	0.0580
Execution time	1.2500	1.2000	1.1000

4.2 Execution Time for Updated Two-Diode Model (UTDM)

It compares the performance of three algorithms: Comparative analysis of IACO, SCSA, and Hybrid IACO-SCSA based on several indexes. The I_{pv} values of IACO, SCSA, and hybrid model are 9.125 V, 9.215 V, and 9.170 V respectively. There are efficiency parameters denoted by Alpha1 and Alpha2; based on these values, it can be realized that IACO possesses improved Alpha1 & Alpha2 values. IACO has the lowest R_{se} for series resistance error at 0.016 while the highest R_{sh} at 268.5. For the current values, it is more stable in the hybrid model than in SCSA in terms of I_{01} and I_{02}. Finally, according to the results obtained in Table 2, the Hybrid IACO- SCSA requires less time for execution in specific seconds and this is computed to be 1.17.

Table. 2 – UTDM parameters

Para-meters	IACO	SCSA	Hybrid IACO-SCSA
I_{pv}	9.1250	9.2150	9.1700
Alpha1	1.9500	1.6800	1.8150
Alpha2	1.5500	1.0200	1.2850
R_{se}	0.0160	0.0350	0.0250
R_{sh}	268.500	158.000	213.250
I_{01}	2.70×10^{-7}	6.10×10^{-7}	4.40×10^{-7}
I_{02}	3.30×10^{-7}	2.10×10^{-7}	3.20×10^{-7}
R_s	0.0150	0.0220	0.0185
Execution time	1.2200	1.2000	1.1700

5. CONCLUSION

The efficiency and performance of solar cells incorporated with nanomaterials in solar photovoltaic systems are enhanced by employing several optimization algorithms, such as the newly developed hybrid Intelligent Ant Colony Optimization-Scalable Cuckoo Search Algorithm (IACO-SCSA). Nanomaterial incorporation enhances the charge transports and light capturing, and minimizes energy dissipation while increasing the efficiency of the optimizing method offering enhances parameter estimations, and enhancing the convergence of the system. When comparing the two main solar PV models using nanomaterials, such as UODM the one-diode model using the hybrid method provides the least SSE value of ($Mean = 4.80 \times 10^{-3}, S.D = 2.10 \times 10^{-3}$), RMSE ($Mean = 1.58 \times 10^{-2}, S.D = 1.05 \times 10^{-2}$), and MAE ($Mean = 3.20 \times 10^{-3}, S.D = 2.20 \times 10^{-3}$) and UTDM the two-diode model using the hybrid method offered the least SSE value of ($Mean = 5.30 \times 10^{-3}, S.D = 2.35 \times 10^{-3}$), RMSE ($Mean = 1.66 \times 10^{-2}, S.D = 1.13 \times 10^{-2}$), and MAE ($Mean = 3.50 \times 10^{-3}, S.D = 2.45 \times 10^{-3}$). Thus, the results of this work may indicate further opportunities for introducing nanomaterials into the development of solar PV technology to enhance efficient renewable energy. Future studies can expand on enhancing nanomaterials and optimizing algorithms to take the efficiency of solar photovoltaic systems to the next level.

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Метод оптимізації для оцінки параметрів сонячних фотоелектричних систем з використанням наноматеріалів

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Інтеграція наноматеріалів у сонячні фотоелектричні системи підвищує ефективність сонячних фотоелектричних систем завдяки кращому захопленню світла та транспортуванню носіїв заряду. Для оцінки параметрів таких систем покращена оптимізація може точно налаштувати ефективність перетворення енергії та підвищити стійкість системи. Метою роботи є розробка методу оптимізації для точної оцінки параметрів у сонячних фотоелектричних системах з використанням наноматеріалів. Цей підхід спрямований на підвищення ефективності та продуктивності сонячних елементів шляхом використання передових алгоритмів оптимізації. Інтелектуальна оптимізація колонії мурах (IACO) допомагає оцінити параметри сонячних фотоелектричних систем за допомогою точнішого моделювання поведінки мурах та їхніх функцій оптимізації для наноматеріалів для виробництва енергії. Для реалізації підвищеної точності та конвергенції параметрів сонячних фотоелектричних систем використовується масштабований алгоритм пошуку зозулі (SCSA) з урахуванням гніздування зозулі. У дослідженні використовуються дві основні фотоелектричні моделі (оновлена однодіодна та оновлена дводіодна) для оцінки впливу інтеграції наноматеріалів. Інтеграція наноматеріалів з гібридною оптимізацією IACO-SCSA призвела до значного покращення ефективності сонячних елементів. UODM та UTDM, оптимізовані за допомогою гібридної IACO-SCSA, показали кращі результати, ніж інші моделі, такі як SSE (сума квадратичних помилок), RMSE (середньоквадратична помилка) та MAE (середня абсолютна помилка).

Ключові слова: Інтелектуальна оптимізація (IACO), Масштабований алгоритм (ICSA), Оновлені однодіодна і дводіодна моделі.