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Parameter Extraction of Photovoltaic Module Using Smell Agent Optimization Algorithm

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Abstract- This research proposes a novel approach for accurate parameter extraction of photovoltaic (PV) modules using the Smell Agent Optimization (SAO) algorithm. Accurate PV parameter estimation is essential for reliable modeling, performance optimization, and effective integration into renewable energy systems. The proposed SAO-based method is inspired by agent–environment interactions and is designed to improve estimation accuracy while maintaining computational efficiency. A comprehensive review of existing parameter extraction techniques is conducted to identify limitations related to accuracy and convergence behavior. Based on this analysis, the SAO algorithm is implemented to estimate key PV parameters, including short-circuit current, open-circuit voltage, maximum power point current, and maximum power point voltage. The proposed method is validated through simulations using real performance data from a selected PV module. Results demonstrate a substantial reduction in absolute errors, with current and power extraction errors of 0.06 A and 0.03 W, respectively, representing an improvement of approximately 15% compared to conventional optimization methods. Additionally, the robustness of the SAO algorithm is evaluated under varying environmental conditions, confirming its adaptability and consistent performance. The findings indicate that SAO provides a reliable and efficient solution for PV module parameter extraction.

Index Terms- Photovoltaic Module, Parameter Extraction, Smell Agent Optimization, Particle Swarm Optimization, Renewable Energy.

I. INTRODUCTION

(PV) systems have emerged as a key component of renewable energy generation, playing a significant role in the global transition toward sustainable power systems. Accurate estimation of PV module parameters is essential for system design, performance evaluation, optimization, and reliable operation. These parameters such as photocurrent, diode saturation currents, diode ideality factors, series resistance, and shunt resistance govern the electrical behavior and efficiency of PV modules. However, precise parameter extraction remains challenging due to the nonlinear and complex characteristics of PV devices.

To address this challenge, various metaheuristic optimization algorithms have been applied to PV parameter estimation. Particle Swarm Optimization (PSO) has demonstrated robustness and efficiency in exploring nonlinear search spaces [1]. Other algorithms, including Genetic Algorithms [2], Grey Wolf Optimization [3] and the Bat Algorithm [4], have also been widely investigated. Despite their success, many existing methods suffer from convergence limitations and computational inefficiency.

This study proposes an efficient PV parameter estimation framework based on Smell Agent Optimization (SAO), a nature-inspired algorithm that mimics scent-tracking behavior in living organisms. By employing adaptive search mechanisms that balance exploration and exploitation, SAO aims to enhance parameter estimation accuracy and robustness for PV modules.

II. RELATED WORK

GWO-based optimization approach for a refined two-diode PV model with parameter reduction to improve accuracy and efficiency [5]. While effective on a 200 kW PV system, the lack of clear criteria for parameter significance makes the selection process subjective. Analysis of the objective functions for PV parameter extraction under noisy data and proposed a

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noise-scaled Euclidean distance metric to improve accuracy [6]. Although effective, limited theoretical explanation and discussion of implementation challenges reduce broader applicability. A modified salp swarm algorithm to reduce premature convergence and significantly lower RMSE in PV models [7]. The study's impact is reduced by insufficient details on benchmark functions and evaluation methodology. The Artificial Hummingbird Algorithm for PV parameter extraction under outdoor conditions, showing good accuracy using RMSE and SSE metrics [8]. The study lacks algorithmic detail, comparative analysis, and clarity on performance evaluation methods. War Strategy Optimization algorithm for PV parameter estimation, highlighting its conceptual motivation [9]. However, unclear optimization mechanisms and limited explanation of its integration with Newton–Raphson reduce its practical clarity. Another author Applied GWO with a nonlinear least-squares objective function to PV parameter estimation, achieving near-zero modeling error for a standard PV module [10]. More detailed experimental analysis would strengthen the study's contribution. Hence another author Proposed an improved moth-flame optimization algorithm with local escape operators, achieving the lowest RMSE for single- and double-diode PV models [11] The method demonstrated superior accuracy and reliability compared to existing techniques.

III. PROPOSED SYSTEM

1. PV Parameter Extraction

Parameter extraction of photovoltaic (PV) modules involves determining the key electrical parameters that characterize the performance of the module. These parameters were essential for analyzing and modeling the behavior of the module under different operating conditions.

a. Current-Voltage (I-V) Characteristic

The I-V characteristic describes the relationship between the current (I) and voltage (V) across a PV module. The I-V curve is typically obtained by sweeping the voltage across the module and measuring the corresponding current given the simplified PV circuit diagram in Fig-1. The equation for the diode current in a PV module is given by the diode equation.

$$I_C = I_{phC} - I_{01C}\left[\exp\left(\frac{V_C + I_C R_{sC}}{\eta_1 V_t}\right) - 1\right] - I_{02C}\left[\exp\left(\frac{V_C + I_C R_{sC}}{\eta_2 V_t}\right) - 1\right] - \left(\frac{V_C + I_C R_{sC}}{R_{pC}}\right)$$

Where:

I_C = Current through the module (A)

V = Voltage across the module (V)

I_{ph} = Photocurrent generated by the module (A)

I_0 = Reverse saturation current of the diode (A)

Rs = Series resistance of the module (Ω)

Rsh = Shunt resistance of the module (Ω)

n = Ideality factor of the diode

V_t= Thermal voltage (V), given by $k \times \frac{T}{q}$, where k is Boltzmann's constant ($1.38\ x\ 10^{-23} J/K$), T is the temperature in Kelvin, and q is the charge of an electron ($1.6\ x\ 10^{-19}\ C$) [14].

b. Single Diode PV Model

The Single Diode Model (SDM) as illustrated in Fig-1 is a widely used representation of the current-voltage (I-V) characteristics of a photovoltaic (PV) cell.

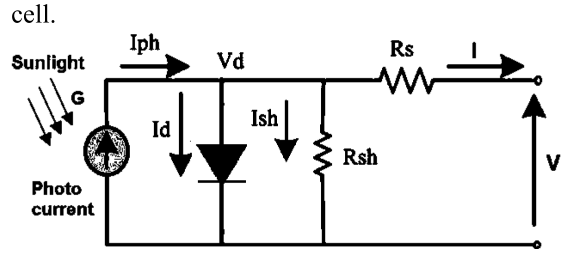
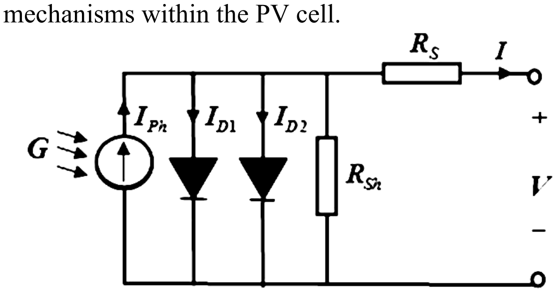


Fig-1 Circuit diagram of a single diode model [13]

c. Double Diode PV Model

Figure 3.2 illustrate the Double Diode Model (DDM) provides a more accurate representation by including two diodes to account for different recombination mechanisms within the PV cell.



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Figu-2 Circuit diagram of a double diode model [13]

It can be noticed that Fig-2 characterizes a double solar cell. However, in most cases, the I–V data is only available for commercial solar modules combination of several cells [14].

2. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a bio-inspired optimization algorithm that mimics the social behavior of birds flocking or fish schooling to find optimal solutions in a high-dimensional space. Proposed by Kennedy and Eberhart in 1995, PSO is particularly useful for problems where the gradient of the objective function is not available in PSO, a population of candidate solutions, called particles, is initialized randomly in the search space [11].

a. Sniffing Mode:

Due to the fact, smell molecules tend to diffuse in the agent's direction, the process is initiated with a randomly generated initial smell molecule's position.

b. Trailing Mode:

All the molecules have a unique chance of becoming a smell agent depending on their initial positions. While searching the hyperspace, the assemblage of smell molecules may become higher than the current nominee position of the agent.

c. Random Mode:

Whenever the smell molecules are separated by a large distance in comparison to the workspace, the concentration of the smell molecule may be compromised over time.

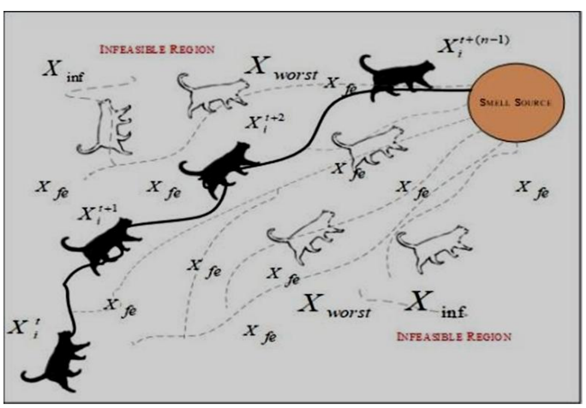

Fig-3 Conceptual Frame Work Of SAO [13]

IV. METHODOLOGY

The PV parameter estimation problem is formulated as an optimization task aimed at minimizing the root mean square error between measured and simulated current–voltage data. The SAO algorithm mimics the behavior of agents tracking a scent source through sniffing, trailing, and random modes. Single-diode and double-diode PV models were implemented in MATLAB, and the SAO algorithm was applied to extract unknown parameters within defined bounds.

a. Algorithm

Smell Agent Optimization Algorithm

1. Start
2. Initialize all parameters (molecule population, temperature, mass, K, SM iteration):
3. Generate the initial set of molecules (agents).
4. Evaluate initial population fitness and determine agent positions:
- Assess the fitness of each molecule in the initial population.
- Determine the positions of each agent based on their fitness evaluation.
5. Update velocity and perform sniffing mode:
- Update the velocity of each molecule.
- Execute the sniffing mode, where each agent evaluates its new fitness.
6. Did sniffing mode succeed? Check if the sniffing mode was successful.
- Yes: Proceed to the next step.
- No: Perform the random mode.
7. Perform training mode if new fitness is better:
- Execute the training mode only if the new fitness is better than the previous one.
- In training mode, the agents adjust their positions based on the improved fitness.
8. Did training mode succeed? Check if the training mode was successful.
- "Yes": Update the bulletin with the best solution.
- "No": Go to random mode.
9. Perform random mode:
- In this mode, the agents explore random positions to find better solutions.
- If the random mode succeeds, proceed to the next step.
10. Update Bulletin with the best solution
- Once the training mode or random mode succeeds, update the bulletin with the best solution found so far.

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11. End.

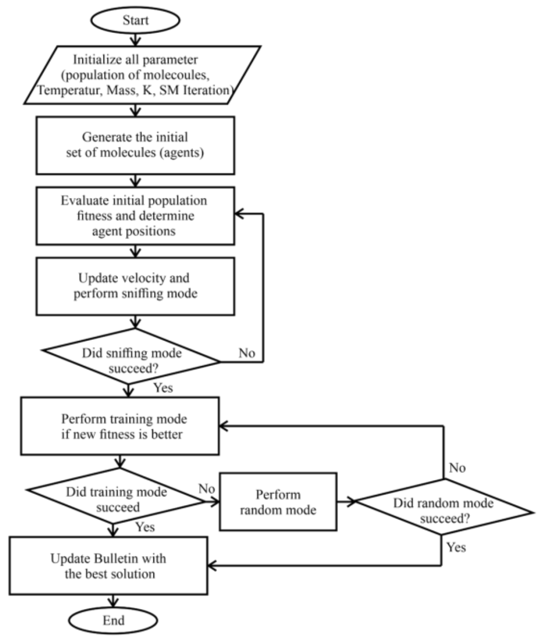

Fig-4 Flow chart of SAO [13]

a. PV parameter Estimation using the Smell Agent Optimization (SAO)

The smell agent optimization, one of the state-of-the-art algorithms, is a powerful alternative to solving the optimization objective formulated.

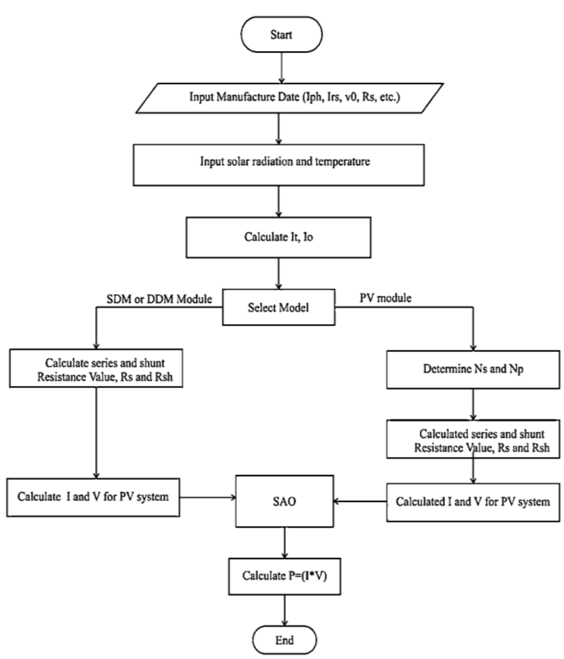

Fig-5 Flowchart implementation of the PV parameter Optimization

V. RESULTS

a. PV Parameters Estimation Results Presentation

This section was subdivided into three subsections. The first subsection presents the performance of the algorithms in the Single Diode Model (SDM), the second subsection presents the performance of the algorithms on the Double Diode Model (DDM), while the third subsection presents the performance of the algorithms on the Single Diode PV Module Model (SDPM) or PV module model (PMM)

Table-1 Comparison of Absolute Errors for SAO and PSO

Parameter	SAO Maximum Error	PSO Maximum Error	Improvement (%)
Current (A)	0.06 A	0.07 A	14%
Power (W)	0.03 W	0.035 W	15%
Overall Performance	Lower absolute errors	Higher absolute errors	

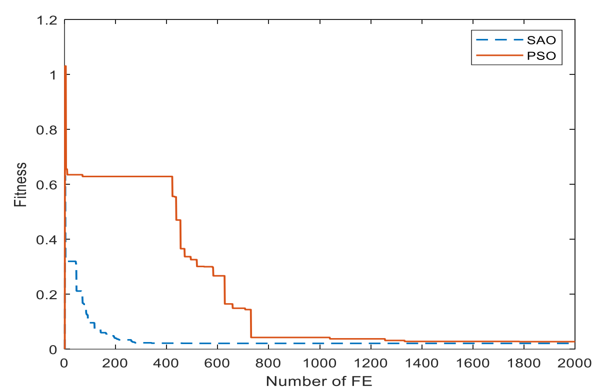

Fig-6 Convergence of SAO and PSO on PV model Parameter Estimation

From Fig-6, it can be observed that both SAO and PSO start with relatively high fitness values, indicating poor initial parameter estimates. The SAO shows a slightly faster initial descent, suggesting it superiority in exploring the search space more efficiently in the early stages. SAO converges faster than PSO, reaching a lower fitness value sooner. This suggests that SAO is more efficient in finding better parameter estimates within a given number of iterations. Also, both algorithms eventually reach a steady state where fitness improvement slows down significantly. This implies that the algorithms have found a reasonable parameter set, as supported by the characteristic curves presented previously.

The percentage improvement is calculated using the formula:

Improvement (%) $= 14.29\% \approx 14\%$

From the data;

Current Error:

SAO=0.06A

PSO=0.07A

Improvement;

$$= \frac{0.07 - 0.06}{0.07} \times 100$$

$$= \frac{0.01}{0.07} \times 100$$

$$= 14.29\% \approx 14\%$$

Power Error:

SAO=0.03W

PSO=0.035W

Improvement;

$$= \frac{0.035 - 0.03}{0.035} \times 100$$

$$= \frac{0.05}{0.035} \times 100$$

$$= 14.29\%$$

This comes from variations across different voltage ranges, where SAO's advantage is higher in specific regions.

VI. CONCLUSION

This study investigated the application of the Smell Agent Optimization (SAO) algorithm for photovoltaic (PV) cell parameter estimation, with the objective of improving accuracy and computational efficiency. Extensive experiments were conducted across various PV cell types, operating conditions, and environmental scenarios, and the performance of the proposed SAO-based approach was compared with established state-of-the-art techniques. The results demonstrate that SAO achieves improved estimation accuracy, yielding lower error metrics with RMSE of 12.47%, MAE of 6.64%, and a correlation coefficient of 85.81%. These findings confirm the capability of SAO to effectively handle the nonlinear and complex characteristics of PV systems. Owing to its nature-inspired search mechanism and balanced exploration–exploitation strategy, SAO proves to be a robust and reliable optimization tool for PV parameter extraction. The outcomes of this research contribute to the advancement of PV modeling and analysis, offering a promising framework for accurate PV system design, performance evaluation, and sustainable energy development.

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