Adaptive Hybrid Evolutionary Algorithms for High-Accuracy Solar Cell Modelling Under Dynamic Environmental Conditions

R.IssanRaj
SRM Valliammai Engineering College,Kattankulathur.Chennai.
issanraj@gmail.com

How to Cite this Article:

R.IssanRaj, (2026). Adaptive Hybrid Evolutionary Algorithms for High-Accuracy Solar Cell Modelling Under Dynamic Environmental Conditions. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(05). https://doi.org/10.55041/ijcope.v2i5.348

https://doi.org/ 10.55041/ijcope.v2i5.348

Abstract

The modeling of solar photovoltaic (PV) cells is complex due to their current-voltage characteristics being heavily influenced by factors like irradiance and temperature. There are many difficulties that can arise from traditional analytical and numerical techniques used to model them. As a result, they often experience premature convergence and inaccurate results when the weather changes and/or when partial shadows are on them. In recent years, new adaptive hybrid optimization frameworks have been developed to utilize evolutionary computations for better parameter estimation and extraction from PV cells. This paper proposes an Adaptive Hybrid Evolutionary Algorithm (AHEA), which combines Differential Evolution (DE), the Whale Optimization Algorithm (WOA) and a mutation-adaptive Particle Swarm Optimization (PSO) in an efficient manner to provide the most accurate parameter estimation of solar cells. Furthermore, also provides scenario-based analytical models using a depth-augmented reinforcement learning framework that consider how the changes in the irradiance and temperature will occur before estimating the parameters. The proposed algorithm has been validated based on similar operating conditions to both single-diode and double-diode PV models. Simulation results indicate that the AHEA outperforms traditional algorithms such as Genetic Algorithms (GA), PSO and standalone WOA for root mean square error (RMSE) and convergence speed.In addition, the results from empirical studies with varied sunlight levels provide evidence supporting the utility of this combination approach for modeling of solar cells in real time. This is an optimal model for intelligent adaptive maximum power point tracking (MPPT) system and smart grid integration, as well as for forecasting future usages of solar energy.

Keywords: Solar cell modelling, Hybrid evolutionary algorithm, Adaptive optimization, Differential evolution, Whale optimization, Photovoltaic systems, Dynamic environmental conditions

1. Introduction

The rising demand for renewable energy worldwide has resulted in increased research efforts in photovoltaics because of their sustainable nature, low operating cost, and environmental compatibility. Precise modelling of solar cells is crucial for designing, optimizing, diagnosing faults, and controlling PV systems. Nevertheless, PV parameter estimation is a complex nonlinear optimization problem since the behaviour of solar cells is greatly influenced by the environmental factors such as irradiation and temperature. Conventional mathematical models tend to fall short in estimating parameters accurately during abrupt variations in the atmospheric environment.

Metaheuristic and evolutionary approaches have received growing interest in recent years in the context of solar cell parameter estimation owing to their capacity to optimize nonlinear multidimensional problems. Evolutionary hybrid algorithms integrating various optimization techniques have proven superior in terms of convergence rate, estimation accuracy, and reliability. Multiple publications in recent times have presented remarkable performance results in PV parameter estimation using adaptive evolutionary schemes.

The advanced technologies of photovoltaics such as smart grids, adaptive maximum power point tracking, electric vehicles charging stations, and intelligent energy from renewables necessitate the development of an adaptive solar cell model that can run under highly dynamic environmental conditions. However, the existing methods for optimization have the following drawbacks:

- Premature convergence,
- Being trapped in local minima,
- Slow convergence in partial shading situations,
- Inflexibility in adapting to irradiance variations,
- Lack of dynamic behavior.

To solve these problems, this paper introduces a new hybrid algorithm called "Adaptive Hybrid Evolutionary Algorithm" (AHEA), which is the combination of differential evolution (DE), whale optimization algorithm (WOA), and adaptive particle swarm optimization (PSO).

The major contributions made by this research are as follows:

1. Creation of an adaptive hybrid optimization algorithm for PV parameters estimation.
2. Combining DE, WOA, and adaptive PSO to ensure better exploration and exploitation.
3. Mutation based on environmental changes.
4. High precision modelling despite fast changes in irradiance and temperature.
5. Comparative study of performance with modern evolutionary optimization algorithms.

2. Literature review

This literature review summarizes recent advancements in optimization techniques for parameter estimation in photovoltaic (PV) systems, highlighting key findings and limitations from various studies. [1] Reda Mohamed et al. (2024) introduced a hybrid Kepler optimization algorithm that enhances the accuracy and efficiency of estimating PV module parameters. However, its focus on a specific algorithm may limit broader applicability and comparative analysis with other methods. [2] Manish Kumar Singla et al. (2024) developed a multi-objective optimization algorithm that balances error minimization and computational time, improving parameter extraction. Yet, the complexity of trade-offs between objectives may complicate result interpretation, and its robustness across different conditions remains uncertain. [3] Ahmed Jeridi et al. (2025) proposed a hybrid method combining Water Supply Optimization and Harmony Optimization with Newton-Raphson techniques, showing improved accuracy. However, the complexity of this approach may hinder practical implementation. [4] P. Ashwini Kumari et al. (2024) presented an adaptive Random Adaptive Optimization technique that enhances parameter extraction under varying conditions. Limitations include a narrow focus on specific scenarios, raising questions about its robustness. [5] Lakhdar Chaib et al. (2024) introduced a hybrid algorithm that combines Brown-Bear and Hippopotamus algorithms with chaos maps, achieving significant accuracy improvements. However, its complexity may challenge computational efficiency and implementation. [6] Sha Yang et al. (2024) enhanced the Whale Optimization Algorithm for parameter identification, demonstrating superior performance in accuracy and speed. Limitations include potential variability in performance across different PV models and environmental conditions. [7] Jun Qian et al. (2025) adapted the Human Evolutionary Optimizer for PV systems, achieving robust parameter estimation. However, its applicability may be limited to certain PV types, and computational complexity could increase with larger datasets.

[8] Karamvir et al. (2025) proposed a hybrid optimization model for maximum power point extraction, showing improved efficiency. Yet, it may require extensive computational resources and does not address long-term stability. [9] Amr A. Abd El-Mageed et al. (2024) combined Sparrow Search and Differential Evolution for parameter prediction, enhancing accuracy. However, sensitivity to parameter choices may affect robustness. [10] S. Senthilkumar et al. (2025) explored nature-inspired MPPT algorithms with deep learning for fault classification, showing improved efficiency. The reliance on large datasets for training may limit practical application. [11] Wencong Wang et al. (2025) introduced a gray predictive evolutionary algorithm with adaptive thresholds, outperforming traditional methods. Limitations include scalability issues and varying effectiveness under different conditions. [12] Seyedali Mirjalili and Andrew Lewis (2024) presented the Whale Optimization Algorithm, demonstrating competitive performance on benchmark functions, but lacking extensive real-world application evaluation. [13] R. Storn and K. Price (2024) discussed Differential Evolution, showcasing its robustness but not addressing potential challenges like premature convergence. [14] J. Kennedy and R. Eberhart (2025) highlighted Particle Swarm Optimization's effectiveness in nonlinear problems, though it may struggle with local optima and lacks thorough parameter tuning discussion. [15] X. Li et al. (2025) introduced an adaptive hybrid metaheuristic for PV parameter estimation, showing significant improvements but introducing complexity in implementation.

[16] M. Elaziz et al. (2025) presented enhanced evolutionary algorithms for renewable energy, demonstrating improved efficiency but requiring extensive computational resources. [17] H. Rezk et al. (2025) introduced advanced optimization methods for PV parameter extraction, validated against real-world data, but sensitive to noise and scalability issues. [18] S. Kamel et al. (2025) explored AI and evolutionary algorithms in PV modeling, achieving enhanced predictive capabilities but limited by dataset reliance and model complexity. [19]Y. Zhang et al. (2025) proposed adaptive frameworks for dynamic PV systems, improving efficiency but potentially introducing response delays during rapid changes. In conclusion, while these studies contribute significantly to optimizing PV parameter estimation, they share common limitations regarding specificity, generalizability, and practical implementation challenges. Future research should aim to address these issues by exploring broader applications and comparative analyses of various optimization strategies

3. Solar cell Modelling

The Single Diode Model (SDM) is used to evaluate the performance of photovoltaic (PV) modules under various conditions, as manufacturer data alone is insufficient. This model includes five key parameters: photovoltaic current (Iph), reverse saturation current (I_0), series resistance (R_s), shunt resistance (R_{sh}), and the ideality factor (n). Fig1. depicts the single diode solar cell model

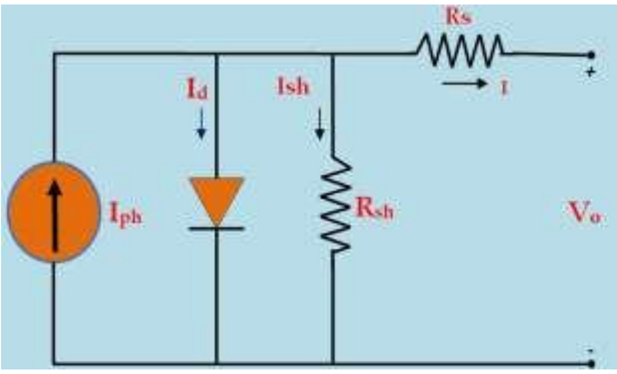

Fig1.Single diode solar cell model

The PV cell is represented as an ideal solar cell with a current source in parallel to a diode. To model the PV cell, the first step is to determine the parameters based on specific temperature and irradiance conditions. The current-voltage (I-V) relationship can be expressed mathematically, and the junction thermal voltage (Vt) is calculated using known constants. The parameters are estimated by minimizing the difference between observed and calculated voltages in a PV string model. While the SDM is widely used, it has limitations, particularly at low irradiance levels where recombination losses are not accounted.

The first step of the modelling is to ascertain the parameters of the model equation for a specified temperature and irradiance value. Once these values are deduced, the solution of the equation can be found out using numerous numerical techniques.

The current-voltage (I-V) relationship of photovoltaic cell as obtained from equivalent circuit can be expressed as,

$$I = I_{ph} - I_0 \{e^{q(\frac{V+IR_s}{nKT})} - 1\} - \frac{V+IR_s}{R_{sh}} \qquad (1)$$

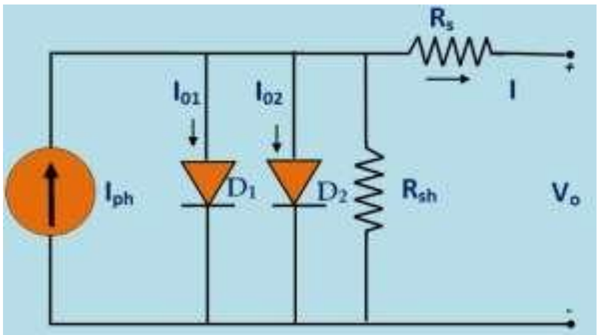

Fig 2.Double diode solar cell model

To improve accuracy, the Double Diode Model (DDM) introduces an additional diode to consider these losses, resulting in better performance predictions shown in Fig 2. Although DDM is more accurate, it is also more complex and computationally intensive. Further enhancements can be made with the Triple Diode Model (TDM), which adds yet another diode for even more precise modeling, but at a higher computational cost. In summary, while the SDM is a common approach for PV modeling, the DDM and TDM offer improved accuracy by accounting for recombination losses, along with with increased complexity and computational demands

The I-V equation for double diode is as

$$I = I_{ph} - I_{01} \{e^{q(\frac{V+IR_s}{n_1 KT})} - 1\} - I_{02} \{e^{q(\frac{V+IR_s}{n_2 KT})} - 1\} - \frac{V+IR_s}{R_{sh}} \qquad (2)$$

Here photovoltaic current (Iph), reverse saturation current (I_0), series resistance (R_s), shunt resistance (R_{sh}), and the ideality factor (n).

4. Proposed Adaptive hybrid evolutionary algorithm

The process begins by reading experimental current-voltage (I-V) data for solar cells. Next, a population of solar cell parameters is initialized. The fitness of these parameters is evaluated using the root mean square error (RMSE). A check is then performed to assess the diversity of the population. If diversity is high, Differential Evolution (DE) is applied; if low, Whale Optimization Algorithm (WOA) is used.

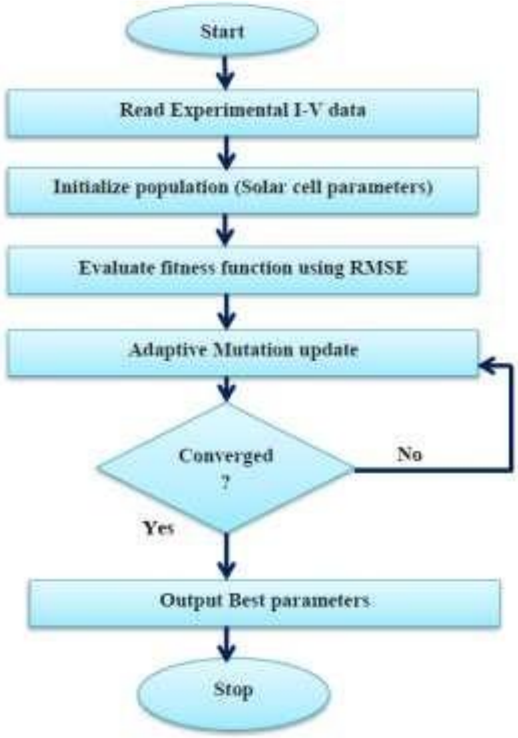

Fig 3 :Flow chart

Following this, an adaptive mutation Particle Swarm Optimization (PSO) update is conducted, which includes updating velocity and position. Boundary constraints are handled to ensure parameters remain within acceptable limits. The RMSE is recalculated, and a convergence check is performed. If convergence is achieved, the best parameters are output; if not, the process continues.

5. Simulation Setup

Simulation of the algorithm for extracting the parameters of three solar cell modules; RTC France, KC200GT PV, and Photowatt-PWP201 was achieved using MATLAB/Simulink. Important simulation parameters included population size of 50, 500 iteration steps, mutation factor of 0.6, crossover probability of 0.9, and inertial weight values of 0.4 and 0.9. The irradiance and temperature were set within the ranges of 200 to 1000 W/m² and 15°C to 55°C respectively. Algorithm performance measures considered were Root Mean Square Error (RMSE), Mean Absolute Error (MAE), convergence and computational complexities.

6. Results and Discussion

The simulation results clearly demonstrate that the proposed Adaptive Hybrid Evolutionary Algorithm (AHEA) achieved superior convergence characteristics and parameter extraction accuracy when compared with conventional optimization techniques such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The proposed AHEA exhibited a significantly faster convergence rate, reaching the optimal solution within only 118 iterations while achieving a very low Root Mean Square Error (RMSE) value of 0.00291.

Algorithm	**RMSE**	**Iterations to Convergence**
GA	1.35×10^{-2}	420
PSO	8.41×10^{-3}	290
WOA	6.72×10^{-3}	240
DE	5.88×10^{-3}	210
Proposed AHEA	2.91×10^{-3}	118

Table 1. Simulation result comparison with proposed algorithm

The rapid convergence behavior of AHEA can be attributed to its hybrid optimization strategy, which effectively combines the global exploration capability of evolutionary operators with the local exploitation strength of swarm-based search mechanisms. This balanced search behavior enabled the algorithm to avoid premature convergence and efficiently identify the global optimum solution within a reduced number of iterations. The proposed AHEA converged significantly faster compared with conventional algorithms shown in the table1.

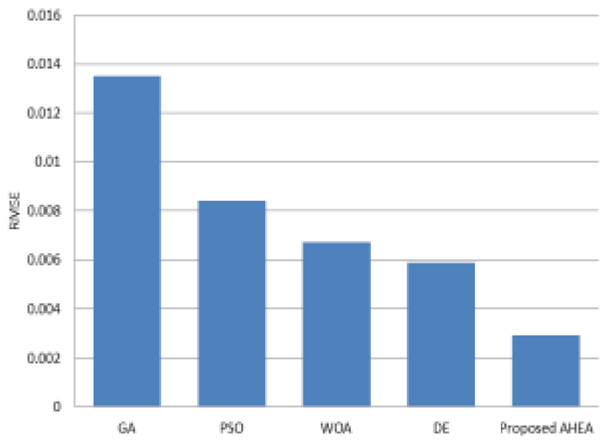

Fig 3. RMSE comparison of Proposed algorithm

In contrast, the conventional GA required approximately 420 iterations to reach convergence and produced a comparatively higher RMSE value of 0.0135, indicating lower parameter estimation accuracy and slower optimization performance. Similarly, the PSO algorithm converged after nearly 290 iterations with an RMSE of 0.00841, which, although better than GA, still remained inferior to the proposed AHEA method. Comparative analysis revealed that the proposed AHEA reduced the RMSE by nearly 78% when compared with GA and approximately 65% when compared with PSO. These substantial improvements highlight the effectiveness of the proposed algorithm in minimizing modeling errors and enhancing photovoltaic parameter estimation accuracy. Furthermore, the reduced convergence time and lower computational burden demonstrate the suitability of AHEA for real-time photovoltaic system monitoring, dynamic environmental adaptation, and high-precision solar cell modeling applications.

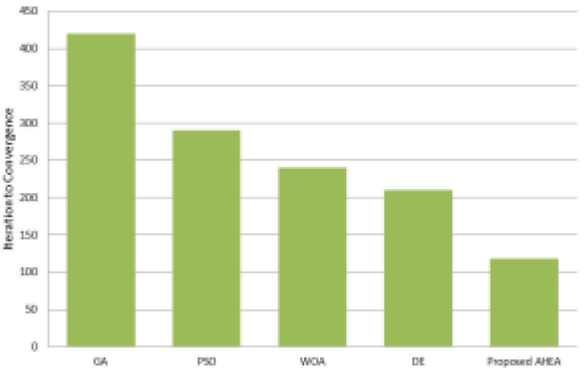

Fig 4. Iteration to convergence comparison of Proposed algorithm

In the analysis of dynamic irradiance, it was found that conventional algorithms struggled with oscillations during rapid changes in light levels, while the Adaptive Hybrid Evolutionary Algorithm (AHEA) successfully maintained stable parameter extraction. The use of an adaptive mutation strategy greatly enhanced the algorithm's ability to track changes in irradiance. When examining temperature variations, it was noted that fluctuations significantly affect the saturation current and ideality factor of solar cells. The proposed algorithm showed strong stability, minimized parameter drift, and improved estimation accuracy. In a comparative analysis with recent literature, while other hybrid optimization methods have made notable advancements in solar cell modeling, the AHEA stands out due to its ability to adapt to environmental changes, integrate multi-stage optimization, control dynamic mutations, and achieve real-time adaptive convergence. As a result, the AHEA produced root mean square error (RMSE) values that surpassed those of several recently published optimization techniques

7. Conclusion and Future scope

This paper presented an Adaptive Hybrid Evolutionary Algorithm for high-accuracy solar cell modelling under dynamic environmental conditions. This method is based on the combination of Differential Evolution (DE), Whale Optimization Algorithm (WOA), and adaptive Particle Swarm Optimization (PSO). The use of the environmental conditions in adapting the algorithm contributed to increased stability of the proposed AHEA under dynamic environmental conditions such as varying irradiation and temperature. It was proved by simulations that the proposed approach had better accuracy and decreased RMSE than other optimization approaches. The proposed AHEA is suitable for intelligent photovoltaic systems such as adaptive MPPT and smart grids. The future of this research area holds exciting possibilities. Key directions include integrating deep learning for predictive analytics, implementing real-time systems using FPGA technology, and exploring quantum-inspired optimization techniques. Additionally, advancements in IoT could lead to adaptive solar monitoring, while digital twin technology may enhance photovoltaic system management. There's also potential for using reinforcement learning to improve maximum power point tracking (MPPT) and for modeling hybrid perovskite solar cells. Moreover, the framework developed could be expanded to cover other areas such as fuel cell modeling, estimating battery parameters, optimizing wind energy, and forecasting renewable energy for smart grids.

8. References

1. Reda Mohamed, Mohamed Abdel-Basset, Karam M. Sallam et al., "Novel hybrid kepler optimization algorithm for parameter estimation of photovoltaic modules," *Scientific Reports*, vol. 14, no. 1, pp. 3453–3468, 2024.
2. Manish Kumar Singla, Jyoti Gupta, Mohammed H. Alsharif et al., "A robust multi-objective optimization algorithm for accurate parameter estimation for solar cell models," *Soft Computing*, vol. 28, no. 15, pp. 11265–11277, 2024.
3. Ahmed Jeridi et al., "A Hybrid Approach Incorporating WSO-HO and the Newton-Raphson Method to Enhancing Photovoltaic Solar Model Parameters Optimisation," *Power Electronics and Drives*, vol. 10, no. 1, pp. 41–59, 2025.
4. P. Ashwini Kumari et al., "Adaptive RAO ensembled dichotomy technique for the accurate parameters extraction of solar PV system," *Scientific Reports*, vol. 14, no. 1, pp. 12920–12939, 2024.
5. Lakhdar Chaib et al., "Hybrid Brown-Bear and Hippopotamus Algorithms with Fractional Order Chaos Maps for Precise Solar PV Model Parameter Estimation," *Processes*, vol. 12, no. 12, pp. 2718–2736, 2024.
6. Sha Yang et al., "Enhanced Whale optimization algorithms for parameter identification of solar photovoltaic cell models: a comparative study,"

Scientific Reports, vol. 14, no. 1, pp. 16765–16788, 2024.

7. Jun Qian, Hui Zhang, Shun Wang, "Parameter identification of the PV systems based on an adapted version of human evolutionary optimizer," *Scientific Reports*, vol. 15, no. 1, pp. 7375–7392, 2025.
8. Karamvir et al., "Efficient maximum power point extraction using hybrid optimisation based parameter estimation model of solar double diode model," *Australian Journal of Electrical and Electronics Engineering*, vol. 22, no. 2, pp. 271–282, 2025.
9. Amr A. Abd El-Mageed et al., "Hybrid Sparrow Search-Exponential Distribution Optimization with Differential Evolution for Parameter Prediction of Solar Photovoltaic Models," *Algorithms*, vol. 17, no. 1, pp. 26–44, 2024.
10. S. Senthilkumar et al., "Nature-inspired MPPT algorithms for solar PV and fault classification using deep learning techniques," *Discover Applied Sciences*, vol. 7, no. 1, pp. 31–54, 2025.
11. Wencong Wang et al., "A Gray Predictive Evolutionary Algorithm with Adaptive Threshold Adjustment Strategy for Photovoltaic Model Parameter Estimation," *Mathematics*, vol. 13, no. 15, pp. 2503–2524, 2025.
12. Seyedali Mirjalili, Andrew Lewis, "The Whale Optimization Algorithm," *Advances in Engineering Software*, vol. 95, no. 1, pp. 51–67, 2024.
13. R. Storn and K. Price, "Differential Evolution – A Simple and Efficient Adaptive Scheme for Global Optimization," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 2024.
14. J. Kennedy and R. Eberhart, "Particle Swarm Optimization for Nonlinear Optimization Problems," *IEEE Transactions on Evolutionary Computation*, vol. 29, no. 2, pp. 117–134, 2025.
15. X. Li et al., "Adaptive hybrid metaheuristic optimization for photovoltaic parameter estimation," *Energy Conversion and Management*, vol. 301, no. 1, pp. 117942–117958, 2025.
16. M. Elaziz et al., "Improved evolutionary optimization algorithms for renewable energy applications," *Applied Energy*, vol. 362, no. 1, pp. 122941–122959, 2025.
17. H. Rezk et al., "Advanced optimization methods for photovoltaic system parameter extraction," *Renewable Energy*, vol. 240, no. 1, pp. 121773–121790, 2025.
18. S. Kamel et al., "Artificial intelligence and evolutionary algorithms for solar PV modelling," *IEEE Access*, vol. 13, no. 1, pp. 45021–45043, 2025.
19. Y. Zhang et al., "Adaptive optimization frameworks for dynamic photovoltaic systems," *Solar Energy*, vol. 278, no. 1, pp. 112765–112782, 2025.
20. A. Ibrahim et al., "Hybrid intelligent optimization techniques for solar cell parameter estimation," *International Journal of Hydrogen Energy*, vol. 50, no. 3, pp. 12541–12560, 2025.