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Enhanced Parameter Estimation Approach for Modeling of Three-Diode Solar Photovoltaic System

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Abstract. Parameter estimation of the photovoltaic (PV) models is required to be accurate to attain high efficacy and reliability of solar energy systems. This paper introduces a more advanced model construction and optimization method of PV parameter estimation with three-diode model using Teaching-Learning-Based Optimization (TLBO) optimization algorithm. The three-diode model (TDM) has the benefit of being able to model both complex recombination and leakage processes in the solar cell with better accuracy under different irradiance and temperature conditions than single or two-diode models. TLBO was inspired by the teaching-learning process of classroom and was proposed to estimate the model parameters. The process is designed to reduce the root mean square error RMSE between the measured and simulated I-V data of current voltage. The proposed TLBO-based algorithm is implemented on the RTC France solar cell data and is found to be superior in convergence and accuracy over the algorithms used as benchmarking algorithms. The results confirm that TLBO is an efficient and reliable tool in the PV system modeling and optimization and can be applied to find a balance between global exploration and local exploitation without any algorithm-specific control parameters.

1 Introduction

As the world continues to struggle to discover sustainable and renewable sources of energy, solar energy is a viable and non-depletable alternative to fossil fuels. It forms one of the pillars in the transition of energy sustainability across the world due to its plenary nature, being universal and environmentally friendly. Photovoltaic (PV) technology is the technology that directly converts sunlight to electricity through semiconductor-based solar cells, as it offers an emission-free source of energy generation and is scalable. The trend of infiltrating PV systems into power grids worldwide has increased the need to have proper modelling and effective methods of estimating parameters, which is necessary to make predictions and optimize PV systems and control their performance.
Its capability to recreate the nonlinear current-voltage characteristics at different environmental conditions, especially the sun irradiance and cell temperature, controls the PV system. Equivalent circuit models can be used to mathematically describe the relationship between the internal semiconductor properties and the external operating conditions and the behavior of a solar cell [1]. The level of accuracy of a PV model is directly related to the

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extent to which it captures the physical processes that take place in the cell, like carrier recombination, carrier diffusion, and series or shunt losses. Due to this, several models with diode-based equivalent circuits have been formulated to enhance the fidelity of experimental and simulated data values.

The modeling of solar PV cells has now gone beyond the simplicity and idealized circuits to more complex multi-diode models. The one-diode model simplifies the problem and can perform well in most standard operating cases. Yet, when high-efficiency cells are being modeled or when low irradiance operation is being studied, recombination effects cannot be neglected, which makes the parameter extraction an analytical and basic numerical method, as the number of variables involved is small. The two-diode model is more accurate, as it considers diffusion currents as well as recombination currents. The three-diode and four-diode models have also been demonstrated to be more predictive than the analytical models, especially at low temperatures and in the presence of radiation. The three-diode model is the most precise in curve-fitting over an extremely wide range of operational conditions and has been shown to have strong value in research, diagnostics, and simulation [2]. These complex models typically need metaheuristic algorithms to estimate the numerous unknowns in them. In short, It has been well understood that although simple models are easy and fast, complex models with strong metaheuristic optimization can achieve unrivalled accuracy and stability in solar PV modeling, supporting the expansion and integration of solar energy applications into a wide range of applications [3]. PV models result in the numerical procedures of the Newton-Raphson and the Levenberg-Marquardt (LM) algorithms, used iteratively to solve nonlinear equations to achieve a minimization between observed and simulated I-V curves. The development of the PV modeling methods reflects the evolution of the estimation methods. The initial efforts were on the one-diode model, where analytical methods were used to provide simplicity and rapid results. The model parameters are directly determined through analysis of the experiment's critical points. Those methods are easy and fast to calculate, based on some idealistic assumptions that frequently ignore the temperature changes and non-ideal diode behavior. They are therefore not as accurate when they are used on complex or multi-diode models.

The metaheuristic algorithms have, over the recent years, surpassed other PV parameter estimation techniques as the preferred one because of their ability to withstand nonlinearity [4]. Based on these natural or physical processes, these population-based algorithms include Particle Swarm Optimization (PSO), which is a search algorithm that evaluates multiple swarm solutions to identify the best one. This refers to a search algorithm whereby the swarm solutions are assessed against each other to determine the optimal solution. Grey Wolf Optimizer (GWO) [5], Artificial Bee Colony (ABC) [6], and Combined machine learning or local refinement algorithms.

Metaheuristic methods have their objective functions optimized, which reduces the disparity between experimentally and simulation-based current values within the I V curve. It is their strength that they are flexible to high-dimensional spaces to search, and therefore essential to complex systems, such as the triple-diode and quad-diode circuits. Recent studies also include the combination of machine learning and metaheuristics, and such methods as reinforcement learning (RL) or linear regression (LR) can give adaptive adjustments to parameters and higher convergence rates. These hybridized systems are based on blending the search power of metaheuristics and the foresight of learning systems, and result in the most efficient and accurate parameter estimation systems [7]. Although the original number of parameters is augmented, the metaheuristic-based hybrid solutions have rendered the retrieval of correct parameter sets computationally feasible. These models are not just used to increase the predictive reliability but also to achieve some purpose in diagnostics, fault detection, and optimization of the PV systems in real-time [8].

The TLBO algorithm is a powerful metaheuristic with reference to teaching learning process that takes place in a classroom setting [9]. TLBO, suggested by Rao et al., works in two primary steps, i.e., the teacher step, during which learners gain knowledge based on the most successful one (teacher), and the learner step, during which learners develop their knowledge because of interaction with peers. TLBO is simple, robust, and computationally efficient, unlike other evolutionary algorithms. Due to its high global search and low parameter tuning, TLBO has found wide usage in the solution of complex nonlinear optimization problems, such as the solar photovoltaic (PV) parameter estimation.

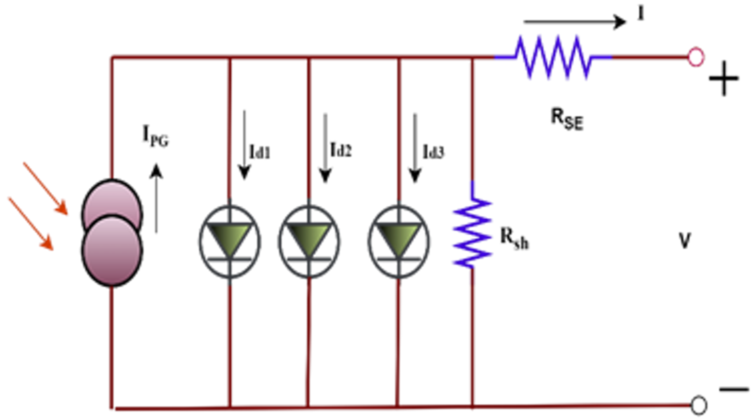


Fig 1: Circuit Diagram of Three-Diode Model Solar Cell.

2 Problem formulation - Three Diode Model

A solar photovoltaic (PV) cell, modeled as a fine circuit equivalent, is a circuit that involves three exponential diode terms, representing various phenomena of recombination and leakage present in the junction and bulk regions of the PV cell as presented in Figure 1. The model is more detailed and physically representative in describing the behavior of the PV cell, especially in extreme conditions of irradiance and temperature.

Fig. 1. Circuit Diagram of Three-Diode Model Solar Cell [3].

$$I = I_{PG} - I_{d1} - I_{d2} - I_{d3} - I_{sh} \tag{1}$$

$$I = I_{PG} - I_{d1} - I_{d2} - I_{d3} - \left(\frac{V+IR_{se}}{R_{sh}}\right) \tag{2}$$

$$Where \quad I_{d1} = I_{s1}\left[exp\left(\frac{v+IR_{se}}{a_1 V_T N_{se}}\right) - 1\right]$$

$$I_{d2} = I_{s2}\left[exp\left(\frac{v+IR_{se}}{a_2 V_T N_{se}}\right) - 1\right]$$

$$I_{d3} = I_{s3}\left[exp\left(\frac{v+IR_{se}}{a_3 V_T N_{se}}\right) - 1\right]$$

$$I = I_{PG} - I_{s1}\left[exp\left(\frac{v+IR_{se}}{a_1 V_T N_{se}}\right) - 1\right] - I_{s2}\left[exp\left(\frac{v+IR_{se}}{a_2 V_T N_{se}}\right) - 1\right] - I_{s3}\left[exp\left(\frac{v+IR_{se}}{a_3 V_T N_{se}}\right) - 1\right] - \left(\frac{V+IR_{se}}{R_{sh}}\right) \tag{3}$$

Where I_{d1}, I_{d2},and I_{d3}, are the diode currents and I_{s1}, I_{s2}, I_{s3},are the saturation currents.

3 Methodology

3.1 Objective Function

To apply the proposed algorithm to a four-diode model, the objective function is defined, which measures the root mean square error between the measured current and simulated current.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(I_{measured} - I_{Simulated})^2} \qquad (4)$$

3.1 Teaching Learning Based Optimization

The TLBO is a metaheuristic algorithm informed by the teaching learning process in a classroom [10].
It has two core stages:
a. Teacher Phase b. Learner Phase

Step 1: Initialization
initialize population of N learners (students). Initializing each variable randomly.

$$X_{i,j}=X_{jmin}+ rand(0,1) \times (X_{jmax}-X_{jmin}) \qquad (5)$$

Using objective function fitness of each learner is evaluated.

Step 2: Teacher Phase
During this stage, the most qualified learner will be the teacher that attempts to boost overall performance of the group.

$$X_{i,jnew}=X_{i,j} + r \times (X_{teacher,j}-T_f \times M_j) \qquad (6)$$

The random number r is in [0,1]. Parameters are then clipped back into bounds after updating. The old learner is substituted with the new one if it attains a lesser RMSE.

Step 3: Learner Phase:
Learners interact with each other to enhance their knowledge.
For any two learners X_i and X_j:

$$\begin{aligned} &If\ f(X_i) < f(X_j): X_i^{new} = X_i + r \times (X_i - X_j) \\ &Else: X_i^{new} = X_i + r \times (X_j - X_i) \end{aligned} \qquad (7)$$

Step 4: Termination
Repeat both phases until the maximum number of iterations is reached. The final solution gives the estimated constraints.

4 Results and Discussion

The present approach is employed for the RTC France Solar Cell at 33°C, 1000 W/m2 for the three-diode model. The algorithm was executed on the Windows operating system (64-bit), with 8.00GB RAM. The limits of unknown constraints are listed in Table 1. The results obtained by the proposed algorithm have been compared with other popular algorithms, as shown in Table 2.

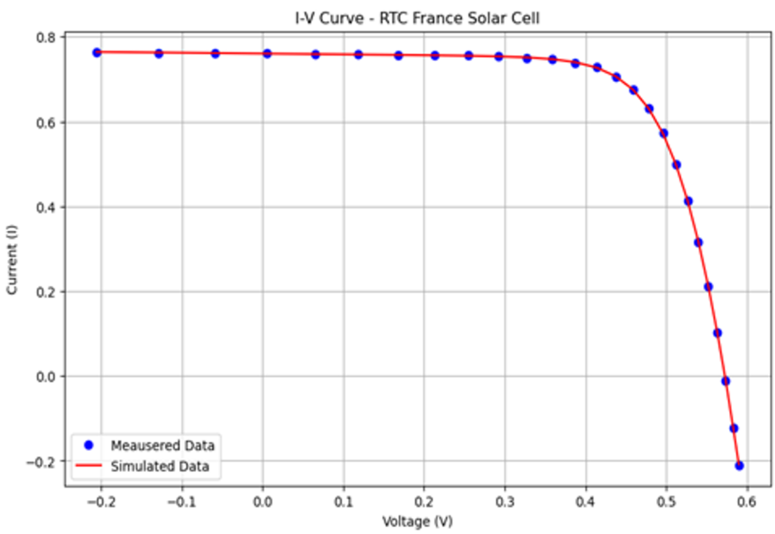
Table 1. Limits of RTC France Solar Cell

Constraint	I_{PG} (A)	I_{S1} (A)	I_{S2} (A)	I_{S3} (A)	R_{Se}(Ω)	R_{Sh}(Ω)	a	a_1	a_2	a_3
Lower Limit	0	0	0	0	0	0	1	1	1	1
Upper limit	1	1E-06	1E-06	1E-06	0.5	100	2	2	2	2

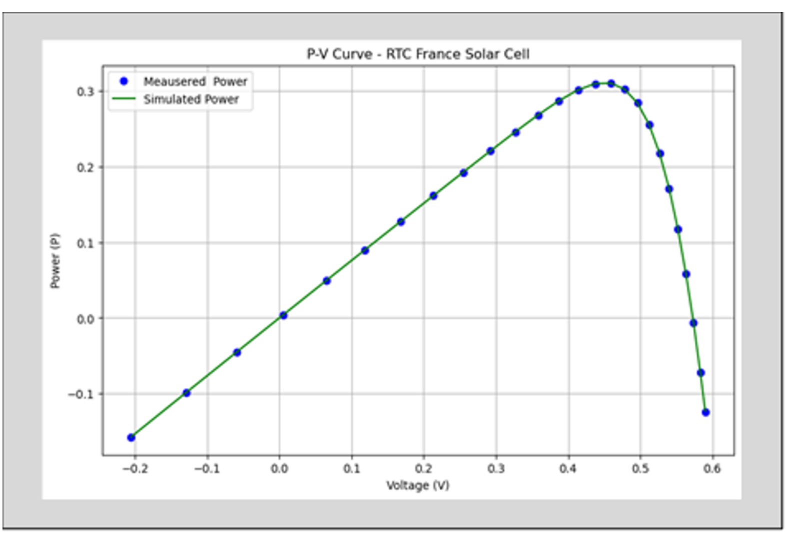
Table 2. Comparative Analysis of the Obtained Results

Parameter	I_{PG} (A)	I_{s1} (A)	I_{s2} (A)	I_{s3} (A)	R_{se} (Ω)	R_{sh} (Ω)	a_1	a_2	a_3	RMSE

ABC[11]	0.7607	2.00E-07	5.0E-07	4.57E-07	0.03668	55.445	1.4543	1.9949	1.8329	9.85E-04
HPO [12]	0.7608	2.35E-07	2.30E-07	4.44E-07	0.0364	53.7185	1.3355	1.4810	2.00	9.83E-04
MRFO [13]	0.7607	4.76E-08	3.60E-07	5.9E-08	0.0339	211.426	1.3232	1.9937	1.7593	9.86E-04
SMA[14]	0.7608	3.82E-08	5.01E-07	2.98E-08	0.0823	66.3402	1.4734	1.7985	1.8493	9.80E-04
Proposed Method	0.7607	3.20E-07	4.67E-07	5.28E-07	0.03437	58.765	1.2648	1.5287	1.2846	9.13E-04



(a)



(b)

Fig. 2. (a) I-V and (b) P-V curves for measured and simulated values of RTC France Solar Cell

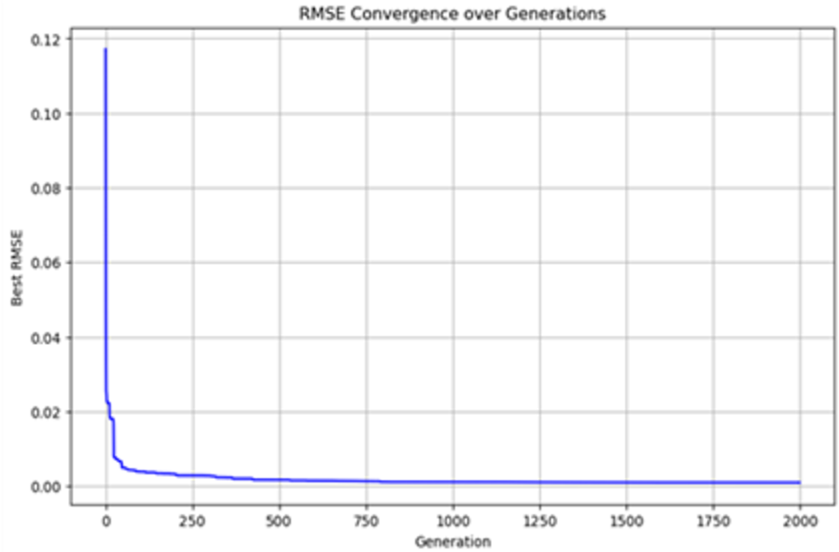


Fig. 3. Convergence curve for RTC France Solar Cell

The TLBO approach is employed to estimate the constraints of the three-diode model, to calculate and the simulated current and voltage values. The results are evaluated with the measured value as shown in Figure 2. The coincidence of these values can be identified by plotting the convergence curve, which shows the minimum objective function value, as represented in Figure 3.

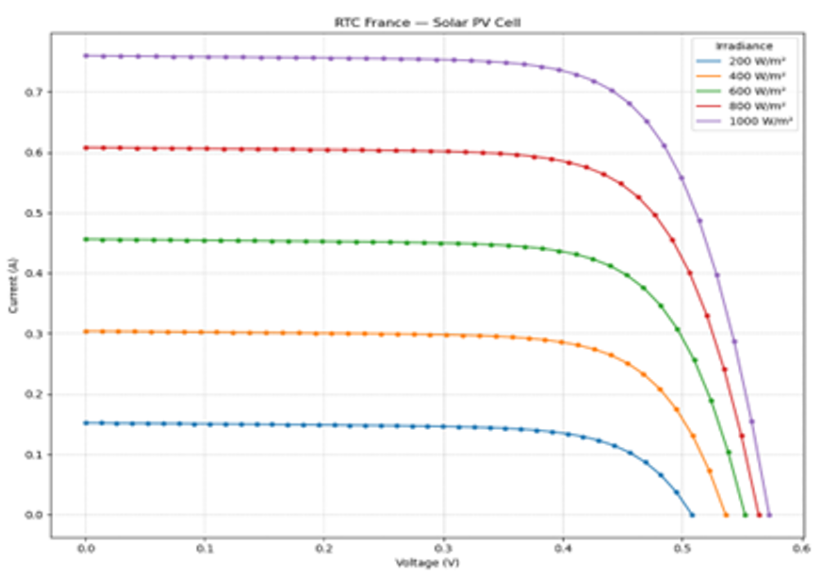


Fig. 4. I-V characteristics at various irradiances for the RTC France Solar cell.

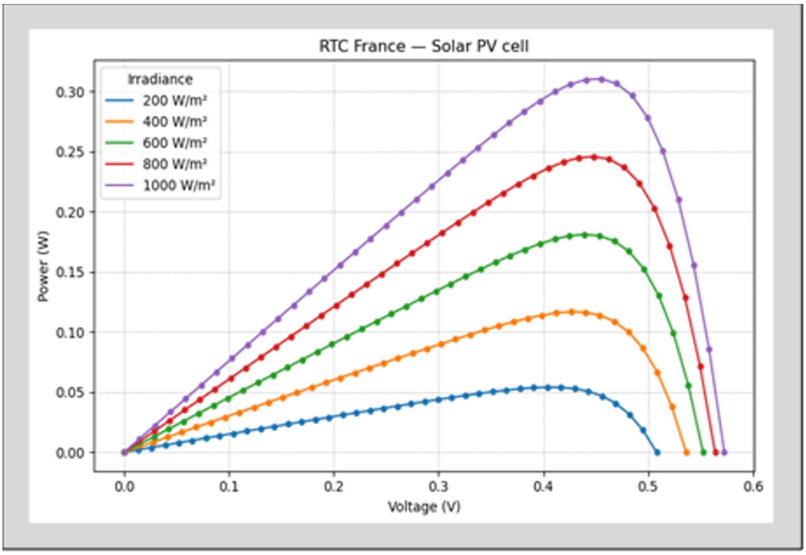


Fig. 5. P-V characteristics at various irradiances for the RTC France Solar cell.

The proposed TLBO-based approach demonstrates high accuracy and robustness in estimating the parameters of the three-diode photovoltaic model, effectively reproducing experimental I–V characteristics under varying conditions. In real-world applications, this method offers computational efficiency due to its parameter-free nature, making it suitable for integration into commercial PV system design and performance monitoring frameworks without the burden of extensive algorithm tuning. Its low computational cost and simplicity facilitate ease of deployment in embedded or cloud-based PV control systems. Moreover, the algorithm shows strong stability and reliability across diverse irradiance and temperature conditions, reflecting its potential for broader environmental adaptability. However, while the method achieves superior convergence and precision for the tested dataset, its generalizability to large-scale or partially shaded PV arrays may require further validation. The algorithm is designed to effectively determine the current-voltage (I-V) and power-voltage (P-V) characteristics under varying levels of solar irradiance. This capability is illustrated in Figures 4 and 5, which showcase the results. Notably, these results closely align with experimental data, reinforcing the reliability of the algorithm. This evidence indicates that the algorithm can be utilized across a wide range of dynamic environmental conditions, extending its applicability beyond just standard test conditions.

4 Conclusion

The article proves to be effective in demonstrating how TLBO algorithm may be utilized in the estimation of the parameters of the Three-diode photovoltaic model, with a high reproducibility of the experimental I-V characteristics. TLBO algorithm has been found to possess high convergence strength, reduced computation power, and steady without any control parameter such as crossover or mutation rate. The outcomes of the comparative analysis of TLBO results with other optimization algorithms prove the quality of the algorithm with high levels of accuracy and stability in minimizing the RMSE of PV cells. The three-diode model contributes to the modeling capability of a system, with recombination and leakage, which contributes to the modeling fidelity across a wide range of operation conditions. The proposed TLBO-based model can be an efficient, parameter-free, and accurate model to estimate PV parameters that can be potentially used in performance-based diagnostics and real-time control of solar photovoltaic systems. Future directions of the research are to hybridize TLBO with learning based or adaptive algorithms to increase convergence behavior and predictive accuracy in future generations.

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