

A NOVEL TRIANGULATION TOPOLOGY AGGREGATION ALGORITHM OPTIMIZER FOR PHOTOVOLTAIC MODEL PARAMETER EXTRACTION

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ARTICLE INFO

Article History

Received: October 7, 2025
 Reviewed: February 1, 2026
 Accepted: April 7, 2026
 Published: May 29, 2026

Keywords:

Parameters extraction,
 TTAO Optimizer,
 PV module,
 Meta-heuristic,
 Optimization.

ABSTRACT

Accurately determining photovoltaic (PV) model parameters is essential for evaluating and optimizing the performance of solar energy systems. However, existing parameter extraction methods often struggle with achieving an optimal balance between global search (exploration) and local refinement (exploitation), leading to incomplete or suboptimal solutions. In this study, we introduce a novel optimization approach, the Triangulation Topology Aggregation Algorithm Optimizer (TTAO), tailored to address these challenges in PV model parameter extraction. The proposed algorithm leverages mathematical triangulation principles to iteratively explore the solution space through two distinct strategies: global aggregation for enhancing solution diversity across triangular structures and local aggregation for fine-tuning results in promising regions. The effectiveness of TTAO is validated by applying it to a PV single-diode model using real-world data. Performance comparisons with existing optimization techniques highlight the superiority of TTAO in terms of accuracy, convergence speed, and robustness. The results demonstrate that TTAO is a powerful and efficient method for precise PV model parameter extraction, offering improved outcomes over other approaches.



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I. INTRODUCTION

With the increasing global demand for clean and renewable energy sources, photovoltaic (PV) systems have emerged as a cornerstone of sustainable energy generation. In fact, the global PV market increased from 236 GWp in 2022 to at least 350 GWp in 2023, and this presents a growth of almost 48% year to year [1]. Accurate modeling of PV systems is essential to analyze their performance [2], optimize energy production [3], facilitate system design, PV generator monitoring and diagnosis [4-6]. At the heart of PV modeling lies the challenge of extracting the parameters of mathematical models, such as the single-diode and double-diode models, which are widely used to describe the current-voltage (I-V) characteristics of solar cells [7], [8]. These parameters include unknown variables such as the diode ideality factor, series resistance, shunt resistance, and photocurrent, all of which directly influence the accuracy of PV performance prediction [9]. Recently, meta-heuristic algorithms inspired by physical phenomena, mathematical concepts, and various other sources—as discussed in the subsequent paragraphs—have demonstrated significant potential in solving complex optimization problems. In [10], the authors present an optimization approach that extracts SDM parameters by combining the Rao-1 optimization technique with a chaotic generator. In [11], the Adolescent Identity Search Algorithm (AISA) was employed to determine the unknown parameters of several benchmark of PV models. In [12], a 320W-72P polycrystalline solar panel module's characteristics are optimized under real operating conditions applying an Artificial Hummingbird Algorithm (AHA). In [13], researchers developed and applied a method named a Rao-1 algorithm for extracting PV module parameters. Their approach demonstrated superior performance in terms of both accuracy and robustness.

In [14], the authors present an innovative variant of the Rao optimization method, named the Fully Informed Search Algorithm (FISA). They showcase its efficiency in two different cases. The proposed algorithm exhibits superior performance in terms of system

stability, faster convergence, and higher accuracy. In [15], the authors proposed a hybrid approach to self-tune the optimized PV module parameters and avoid premature convergence. By integrating a gradient-based optimizer with a symmetric chaotic sequence generator, they achieved more accurate estimation of PV parameters for solar cells and modules. To address the challenges of high complexity and estimation difficulties, the Success-History Adaptation Differential Evolution algorithm with Linear Population Size Reduction (L-SHADE) is employed [16]. Specifically, the bi-parameter coordinated updating L-SHADE, enhanced with a parameter decomposition method (CSPL-SHADED), is utilized for improved performance. Author in [17] categorizes metaheuristic algorithms used for SDM parameters estimation into several groups, Physically-inspired algorithms [18], [19], Mathematically-inspired algorithms [20-22], Nature-inspired algorithms [23], Bio-inspired algorithms [24], [25], Swarm-inspired algorithms [26-29], Chaotic-oriented algorithms [30-32], Teaching-learning-inspired algorithms [33-35], Hybrid variant algorithms [36], [37]. However, these techniques often face limitations including susceptibility to local optima, sensitivity to initial guesses, and an imbalance between global exploration and local exploitation during the optimization process, especially when applied to high-dimensional and complex optimization problems.

Physical phenomena, social behavior, mathematical concepts, and various other algorithm types have been widely adopted for PV parameter extraction. As a result, obtaining accurate and reliable parameters remains a significant challenge, particularly when dealing with noisy or incomplete data. According to the No Free Lunch (NFL) theorem [38], no single optimization algorithm can consistently outperform others across all problem types, emphasizing the need for specialized approaches. Despite advancements, many recently proposed MAs have not undergone systematic evaluation for PV Single Diode model parameter identification. To address these gaps, this paper introduces a Triangulation Topology Aggregation Algorithm (TTAO) for PV model parameter extraction [39]. TTAO is a mathematics-inspired meta-heuristic algorithm that combines the principles of triangular topology with stochastic optimization strategies. The algorithm employs two primary mechanisms: global aggregation, which facilitates exploration by exchanging information across triangular topological structures, and local aggregation, which enhances exploitation by refining solutions in promising regions. This dual approach ensures a more effective balance between global search and local convergence, leading to improved parameter estimation accuracy and robustness of one diode model. Providing insights into the effectiveness of TTAO in balancing exploration and exploitation, ensuring reliable convergence to optimal solutions. The main contributions of this paper are as follows:

- Proposing a novel optimization algorithm, TTAO, for solving PV model parameter extraction of an SDM with enhanced accuracy and efficiency.
- Demonstrating the application of TTAO to single-diode PV model, using real-world dataset.
- Comparing the performance of TTAO with state-of-the-art optimization techniques through extensive experiments and statistical analysis.

The rest of this paper is organized as follows: Section 2 describes the proposed TTAO methodology, And the SDM model in detail. Section 3 presents the experimental setup and results, including comparisons with seven alternative algorithms. Section 4 discusses the findings and implications, and Section 5 concludes the paper with future research directions.

II. PHOTOVOLTAIC MODELS AND TTAO ALGORITHM

II.1 STANDARD SINGLE DIODE MODEL (SDM)

The Single Diode Model (SDM) is the most widely used equivalent circuit model (ECM) and the simplest to implement. A photovoltaic (PV) module consisting of N_s cells connected in series and/or N_p cells arranged in parallel can be mathematically represented by equations (1) and (2) accordingly:

$$I_{pv} = I_L - I_s \left[\exp \left(\frac{q(V_{pv} + I_{pv}R_s)}{nkT} \right) - 1 \right] - \frac{V_{pv} + I_{pv}R_s}{R_p} \quad (1)$$

$$I_{pv} = N_p I_L - N_p I_s \left[\exp \left(\frac{q(V_{pv} + (N_s/N_p)I_{pv}R_s)}{nN_s kT} \right) - 1 \right] - \frac{V_{pv} + (N_s/N_p)I_{pv}R_s}{(N_s/N_p)R_p} \quad (2)$$

Where I_{pv} represents the output current, I_s is the reverse saturation current, and I_L denotes the photo-generated current. The electron's charge is given by $q = 1.60217646 \times 10^{-19}$ C, while the output voltage is represented by V_{pv} . k is Boltzmann's constant (1.380653×10^{-23} J/K), and T denotes the cell temperature. Additionally, R_p and R_s correspond to the parallel and series resistances, respectively, while n represents the diode ideality factor. It is essential to highlight that the previous models include five parameters— R_p , R_s , n , I_L , and I_s —that have not been specified and need to be determined. The corresponding one-diode circuit is illustrated in Figure 1.

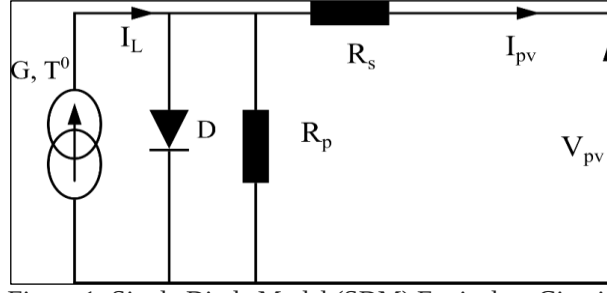


Figure 1: Single Diode Model (SDM) Equivalent Circuit.
Source: Authors, (2026).

II.2 COST FUNCTION

Optimization algorithms typically require an objective function to guide the minimization or maximization process during each update step. In this research, the objective function is the difference between computed (calculated) and observed (measured) data. The total difference is measured using the Root Mean Square Error (RMSE), acting as the cost function.

$$RMSE(x) = \sqrt{\frac{1}{M} \sum_{i=1}^N (I_{meas} - I_{simu})^2} \quad (3)$$

Where M is the number of data points. I_{meas} and I_{simu} are the measured and the simulated current, respectively.

II.3 TRIANGULATION TOPOLOGY AGGREGATION OPTIMIZER (TTAO):

The Triangulation Topology Aggregation Optimizer (TTAO) is a meta-heuristic algorithm inspired by the mathematical properties of triangular similarity [39]. It is designed to solve continuous optimization problems by iteratively constructing and updating triangular topological units, which balance exploration (global search) and exploitation (local search). The algorithm operates through two key strategies: generic aggregation and local aggregation. The optimization process consists of a sequence of well-defined steps.

II.3.1 Parameters Initialization:

The population is initialized with N individuals, divided into $[N/3]$ triangular topological units. Each unit consists of three vertices, and the remaining individuals are randomly generated. The position of each individual is initialized as:

$$\overrightarrow{AB_{i,1}} = r_0 \cdot (\overrightarrow{UB} - \overrightarrow{LB}) - \overrightarrow{LB} \quad (4)$$

Where r_0 is a random number in $[0,1]$. $\overrightarrow{LB}$ and $\overrightarrow{UB}$ are the lower and upper bounds of the variables.

II.3.2 Formation of Triangular Topological Units:

Each triangular unit is formed by generating two additional vertices using trigonometric transformations:

$$\overrightarrow{X_{i,2}} = \overrightarrow{X_{i,1}} + l * \overrightarrow{f(\theta)} \quad (5)$$

$$\overrightarrow{X_{i,3}} = \overrightarrow{X_{i,1}} + l * \overrightarrow{f\left(\theta + \frac{\pi}{3}\right)} \quad (6)$$

Where $l = 9 * e^{-t/T}$ is the size of the triangular unit, which decreases over iterations, and $\overrightarrow{f(\theta)}$ is a direction vector calculated using cosine functions. An internal point within the unit is generated as:

$$\overrightarrow{X_{i,4}} = r_1 \times \overrightarrow{X_{i,1}} + r_2 \times \overrightarrow{X_{i,2}} + r_3 \times \overrightarrow{X_{i,3}} \quad (7)$$

Where $r_1 + r_2 + r_3 = 1$.

II.3.3 Generic Aggregation (Exploration):

This strategy promotes exploration by exchanging information between different triangular units. A new solution is generated by combining the best individuals from two units:

$$\overrightarrow{X_{i,new1}^{t+1}} = r_4 \times \overrightarrow{X_{i,best}^t} + (1-r_4) \times \overrightarrow{X_{rand,best}^t} \quad (8)$$

Where r_4 is a random number in $[0,1]$. $\overrightarrow{X_{i,best}^t}$ and $\overrightarrow{X_{rand,best}^t}$ are the best individuals from unit i and a randomly selected unit at the t^{th} generation.

II.3.4 Local Aggregation (Exploitation):

This strategy focuses on exploitation by refining the search within each triangular unit. The position of the best individual in each unit is perturbed based on the difference between the best and suboptimal individuals:

$$\overrightarrow{X_{i,new2}^{t+1}} = \overrightarrow{X_{i,best}^{t+1}} + \alpha \times (\overrightarrow{X_{i,best}^{t+1}} - \overrightarrow{X_{i,sbest}^{t+1}}) \quad (9)$$

Where α is a decreasing parameter that controls the scope of the local search. After each iteration, the performance of each individual is evaluated, and the best candidates are stored. The triangular units are updated for the next iteration, ensuring a dynamic balance between exploration and exploitation.

III. RESULTS AND DISCUSSIONS:

This section presents the findings related to the parameter estimation for various PV modules using the proposed TTAO algorithm. Specifically, the TTAO algorithm is applied to the following cases involving PV modules of different technologies, with the ranges of all unknown parameters provided in Table 1.

Table 1: Parameters boundaries for the used modules.

Parameters	Poly-solar 320W-72P		CLS-220P	
	Min	Max	Min	Max
R_s [Ω]	0	0.1	0	0.1
I_L [A]	0	10	0	10
R_p [Ω]	0	50000	0	50000
n	1	2	1	2
I_s [A]	0	1	0	100

Source: Authors, (2026).

The effectiveness of TTAO is assessed by comparing its performances with those of seven alternative algorithms: Rao-1 [40], HHO [41], IGWO [42], RUN [43], GTO [44], CPA [45], and the CDO method [46]. The performance of the TTAO algorithm is compared with the performance of the selected algorithms, in terms of the RMSE, standard deviation (Std), and convergence.

III.1 CASE STUDY-1: CLS-220P TECHNOLOGY:

The outcomes of the study of the photovoltaic (PV) electrical system consisting of three CLS-220P polycrystalline modules represent important findings for this first case study. With respect to the estimated parameters, RMSE, and standard deviation obtained using various techniques, including the proposed TTAO algorithm, are summarized in Table II. As shown, the TTAO algorithm achieved the lowest RMSE, whereas the RUN algorithm yielded a slightly higher RMSE, positioning it just after the TTAO algorithm in terms of performance. Also, Tab. II shows the superior stability and accuracy of the TTAO algorithm compared to other methods. The parameters estimated in Table II are also used to generate the I-V characteristic (Figure 2) alongside the experimental data points for the first case study.

Table 2: Optimized parameter estimates for the CLS-220P array at the optimal RMSE value.

Parameters	R _s	R _{sh}	I _{ph}	n	I ₀	Std	RMSE
TTAO	9,727E-03	49887,13	7,2630	1,2219	1,660E-07	9,3306E-03	2,300304E-02
CDO	5,063E-03	29523,00	7,3431	1,8894	8,842E-05	2,4278E-02	1,193997E-01
HHO	9,277E-03	49686,26	7,2745	1,3158	5,835E-07	1,7546E-02	3,787143E-02
RUN	9,556E-03	49998,91	7,2627	1,2403	2,163E-07	2,2580E-02	2,395876E-02
GTO	8,445E-03	35591,81	7,2376	1,4111	1,770E-06	6,0216E-01	5,933905E-02
IGWO	9,612E-03	7135,06	7,2660	1,2398	2,149E-07	8,6410E-03	2,476164E-02
CPA	8,078E-03	30708,81	7,2846	1,4773	3,536E-06	3,8729E-01	5,737346E-02
Rao1	9,512E-03	32098,25	7,2540	1,2542	2,639E-07	9,0721E-03	3,419976E-02

Source: Authors, (2026).

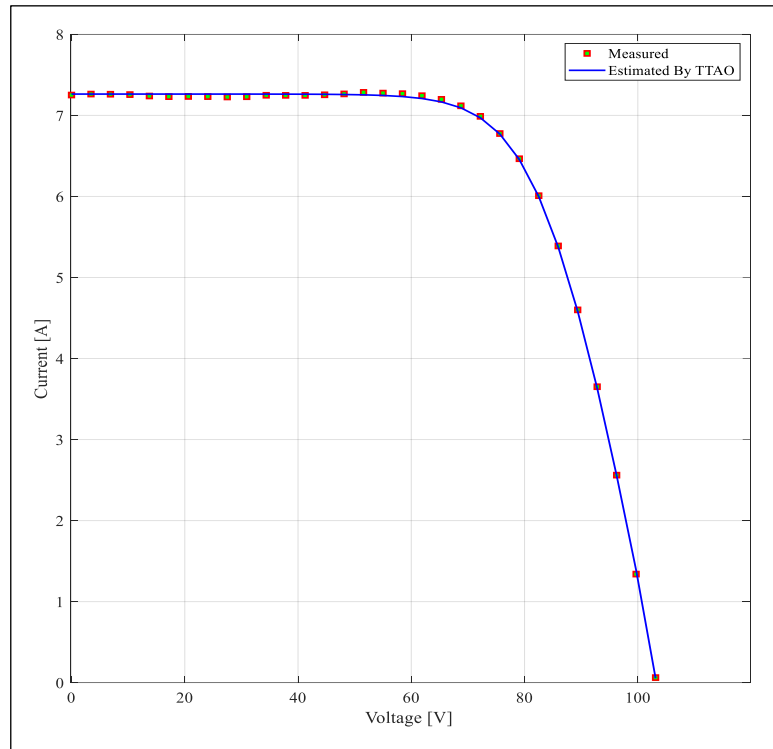


Figure 2: Experimental and computed data for CLS-220P technology.
Source: Authors, (2026).

Furthermore, Figure 3 illustrates the convergence curves of various algorithms, providing additional confirmation of the computational efficiency and precision achieved by the TTAO method.

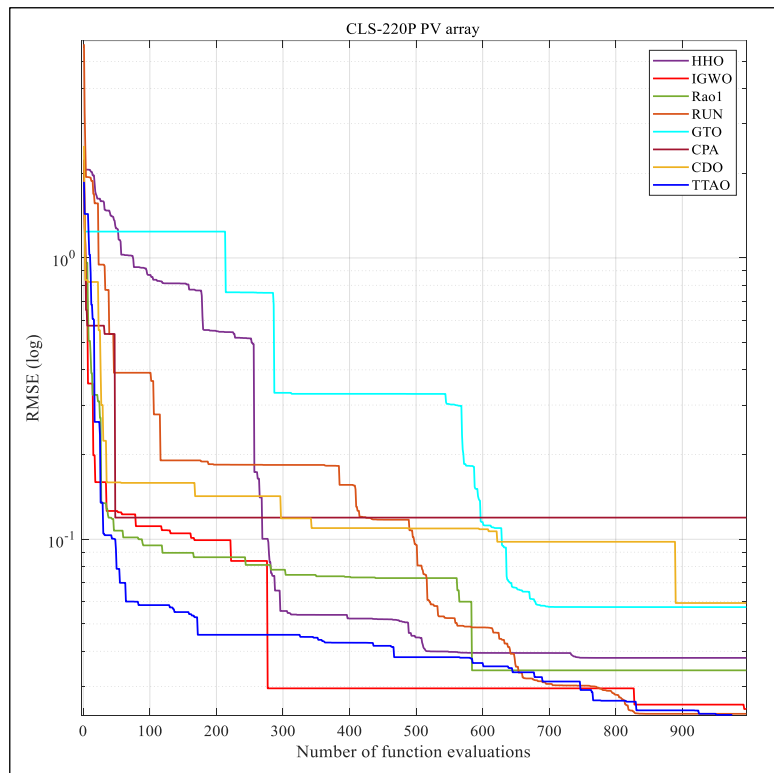


Figure 3: Trend of the graphs representing convergence for the different algorithms for CLS-220P technology.
Source: Authors, (2026).

III.2 CASE STUDY-2: POLY-SOLAR 320W-72P:

In the second case study, a comprehensive analysis is carried out on the results obtained with the Poly-solar 320W-72P PV technology. Figure 4 presents a visual illustration of the PV cell/module curve, comparing the simulated curve using estimated parameters by TTAO algorithm with experimental data points for the same module.

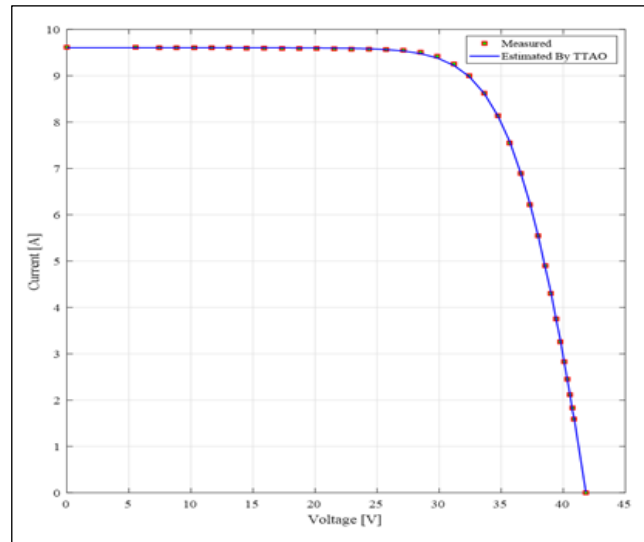


Figure 4: Experimental and modeled curves for the Poly-solar 320W-72P module.
Source: Authors, (2026).

Clearly, the simulated I-V curve using optimized parameters, exhibit an outstanding quality of perfection in mimicking the real PV characteristic. Table III offers the measured PV cell/module parameters, and their corresponding metrics, incorporating both the TTAO method and its alternatives. Remarkably, the lowest RMSE observed ($2,300304E-02$) with a Std of $9,3306E-03$ was attained by the TTAO method. This result validates the remarkable accuracy and stability of the proposed algorithm.

Table 3: Measured parameters of the Poly-Solar 320W-72P technology at the optimal RMSE value.

Parameters	R_s	I_s [A]	R_p	n	I_L [A]	Std	RMSE
TTAO	4,559E-03	1,855E-07	49802,45	1,1857	9,6051	1,5718E-03	2,572551E-02
CDO	4,169E-03	1,000E-06	20641,76	1,3097	9,6192	5,2561E-02	6,073749E-02
HHO	4,565E-03	1,818E-07	17634,65	1,1844	9,6049	2,5865E-02	2,573048E-02
RUN	4,559E-03	1,799E-07	100,68	1,1837	9,6075	7,5334E-03	2,585020E-02
GTO	4,354E-03	2,746E-07	20937,45	1,2121	9,5874	1,5266E-01	3,353632E-02
IGWO	4,550E-03	1,931E-07	38975,06	1,1884	9,6059	9,8399E-04	2,574621E-02
CPA	5,015E-03	2,858E-08	4,68	1,0736	9,6496	3,6535E-01	3,838314E-02
Rao1	4,537E-03	1,941E-07	50000,00	1,1887	9,6047	1,0470E-03	2,581613E-02

Source: Authors, (2026).

Additionally, Figure 5 presents the convergence graphs of the TTAO alongside those of CDO, HHO, RUN, GTO, IGWO, CPA, and Rao-1. A closer analysis of these graphs demonstrates that the proposed algorithm attains the optimal RMSE more efficiently, requiring fewer iterations and exhibiting a faster convergence rate.

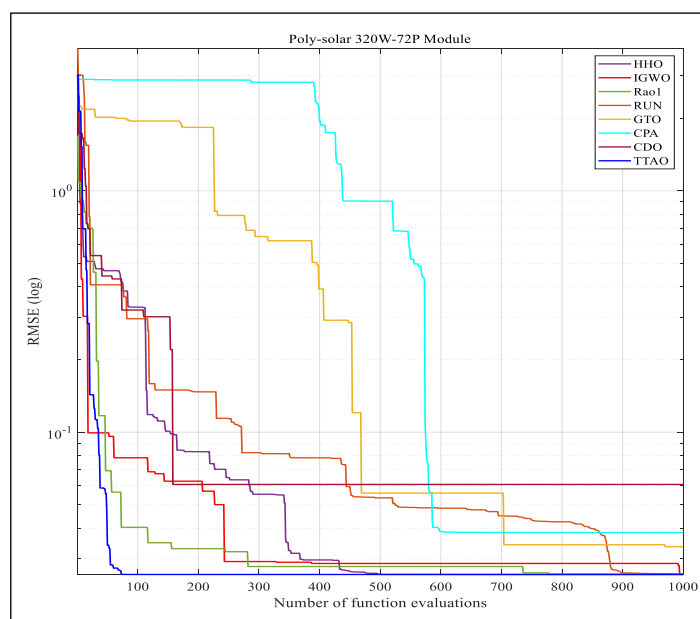


Figure 5: Trend of the graphs representing convergence for the different algorithms for Poly-solar320W-72P technology.
Source: Authors, (2026).

IV. CONCLUSIONS

The present research paper Evaluates the effectiveness of the newly introduced TTAO method for estimating the unidentified parameters in PV cell SDM model. The approach is formulated upon a mathematical property of triangular similarity, known for its Trade-off between exploration (broad search) and exploitation (focused search). This manuscript is organized into four main sections: starting by introducing the stat of the art for PV cell/module parameters estimation, passing through the description of the TTAO method, and its validation through real benchmarks involving two PV module technologies: the Poly-solar 320W-72P technology, and a polycrystalline PV system constructed with more than one CLS-220P module. The findings confirm the precision of parameter extracted implementing the TTAO method. The adopted algorithm managed to minimize the Performance metric (RMSE) until 2,572551E-02 when the Poly-solar 320W-72P technology is used and it attains 2,300304E-02 as for CLS-220P PV technology. Likewise, the experiments unmistakably show the enhanced performance of the TTAO approach compared to seven alternative parameter extraction methods excelling in both precision and stability. In addition, with the significant alignment of computed I–V curve utilizing observed data points. Which conveys that the TTAO technique is an efficient framework for the one diode PV cell model parameters estimation and optimization. As well as in various fields such as PV systems control, monitoring and diagnosis. In the forthcoming research phase, we may use the estimated parameters to implement the model of a real PV photovoltaic arrays and then building a Real-time photovoltaic emulator for monitoring and fault diagnosis.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Abdesslam Belaout, Badis Lekouaghet and Mohammed Haddad.

Methodology: Abdesslam Belaout and Badis Lekouaghet.

Investigation: Abdesslam Belaout, Badis Lekouaghet and Mohammed Haddad.

Discussion of results: Abdesslam Belaout and Badis Lekouaghet.

Writing – Original Draft: Abdesslam Belaoutand.

Writing – Review and Editing: Abdesslam Belaout, Badis Lekouaghet and Mohammed Haddad.

Resources: Badis Lekouaghet and Mohammed Haddad.

Supervision: Badis Lekouaghet.

Approval of the final text: Abdesslam Belaout and Badis Lekouaghet.

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