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# Improvement teaching-learning-based optimization algorithm for solar cell parameter extraction in photovoltaic systems

***Introduction.*** *This study investigates parameter extraction methods for solar cell analytical models, which are crucial for accurate photovoltaic (PV) system design and performance.* ***Problem.*** *Traditional single-diode models, while widely used, often lack precision, leading to inefficiencies in parameter extraction essential for reliable PV systems.* ***Goal.*** *The work aims to improve the Teaching-Learning-Based Optimization (TLBO) algorithm to enhance the accuracy of parameter extraction in PV models.* ***Methodology.*** *We adopt an enhanced single-diode model, integrating modifications into the TLBO algorithm, including dynamic teaching factor adjustment, refined partner selection, and targeted local searches with the fmincon function. Comparative analysis with experimental data from four PV systems validates the model's accuracy.* ***Results.*** *The enhanced TLBO algorithm achieves superior convergence and reliability in parameter extraction, as evidenced by 500 independent runs.* ***Originality.*** *Key contributions include methodological improvements such as dynamic adjustment of the teaching factor and a new approach to partner selection, which significantly optimizes the algorithm's performance.* ***Practical value.*** *This research provides a robust framework for solar cell parameter extraction, offering practical benefits for PV system designers and researchers in improving model accuracy and efficiency.* References 35, table 1, figures 15.

*Key words:* **photovoltaic system, teaching-learning-based optimization, Newton-Raphson method, parameter optimization.**

***Вступ.*** *У цьому дослідженні вивчаються методи отримання параметрів для аналітичних моделей сонячних елементів, які мають вирішальне значення для точного проєктування фотоелектричних (PV) систем і їх продуктивності.* ***Проблема.*** *Традиційні моделі з одним діодом, хоч і широко використовуються, часто не достатньо точні, що призводить до неефективності вилучення параметрів, необхідного для надійних PV систем.* ***Мета.*** *Робота спрямована на покращення алгоритму оптимізації на основі навчання (TLBO) для підвищення точності вилучення параметрів у PV моделях.* ***Методологія.*** *Ми приймаємо вдосконалену модель з одним діодом, інтегруючи модифікації до алгоритму TLBO, включаючи динамічне коригування коефіцієнта навчання, уточнений вибір партнера та цільовий локальний пошук з функцією fmincon. Порівняльний аналіз з експериментальними даними із чотирьох PV систем підтверджує точність моделі.* ***Результати.*** *Удосконалений алгоритм TLBO досягає значної збіжності та надійності при вилученні параметрів, про що свідчать 500 незалежних запусків.* ***Оригінальність.*** *Основні вклади включають методологічні удосконалення, такі як динамічне коригування коефіцієнта навчання та новий підхід до вибору партнера, що значно оптимізує продуктивність алгоритму.* ***Практична цінність.*** *Це дослідження забезпечує надійну основу для отримання параметрів сонячних елементів, пропонуючи практичні переваги для розробників та дослідників PV систем у плані підвищення точності та ефективності моделей.* Бібл. 35, табл. 1, рис. 15.

*Ключові слова:* **фотоелектрична система, оптимізація на основі викладання-навчання, метод Ньютона-Рафсона, оптимізація параметрів.**

**1. Introduction.** Optimizing solar cell parameters across varying operating conditions is crucial for generating the voltage current curve of photovoltaic (PV) systems and accurately estimating their power output. The accuracy of these parameters is essential for the effective analysis of PV systems, and the choice of parameter extraction method is fundamental to addressing this challenge. Over the years, a range of techniques have been utilized for extracting parameters from solar cells, which can be broadly classified into three types. The first one is analytical methods, which are appreciated for their simplicity and computational speed but may suffer from precision issues because of specific presumptions. Notably, reference [1] gives a detailed analysis of the extraction of solar PV system parameters through the application of optimization techniques based on one- and two-diode models. The second one includes deterministic methods, which necessitate differentiability and convexity and can be sensitive to initial conditions. Examples of such methods include intrinsic proprieties of solar cells [2], the Newton approach [3], the Newton-Raphson method [4], and the nonlinear algorithm method [5]. The third, metaheuristic methods have emerged as viable options for parameter extraction in PV models, aiming to overcome the limitations of previous approaches. These techniques don't require strict conditions and are simple to use.

Current research on metaheuristic algorithms have demonstrated their value in improving accuracy in a number of engineering domains, including microarray data-based cancer classification [6], picture segmentation [7], and identification of faces [8]. Current researches on PV model parameters have been estimated using a variety of metaheuristic techniques. Obviously, these include techniques such as the improved algorithm, namely Genetic Algorithm based on Non-Uniform Mutation (GAMNU) [9], Particle Swarm Optimization (PSO) and Newton–Raphson method [10], nonlinear least squares fitting algorithm [11], and the supply-demand-based optimization algorithm [12]. Other approaches, like chaotic optimization approach [13], adaptive differential evolution [14], symbiotic organic search [15], and Improved Shuffled Complex Evolution algorithm (ISCE) [16] have also been employed. Moreover, an Enhanced Hybrid JAYA and Rao-1 algorithm, called (EHRJAYA) [17], as well as the integration novel hybrid Algorithm based on Rat Swarm optimization with Pattern Search (hARS-PS) [18], have shown significant effectiveness. Similarly, the Improved Gaining-Sharing Knowledge (IGSK) algorithm [19] has also demonstrated success. Other techniques, including chaos game optimization algorithm for estimating the unknown parameters of the three-diode PV model [20], Self-adaptive Ensemble-based Differential Evolution (SEDE) algorithm [21], bio-inspired algorithm called sooty tern optimization algorithm [22], and hybridized interior search algorithm [23] have been successfully implemented. Further methods include an enhanced Spherical Evolution algorithm (SE) based on a novel Dynamic Sine-Cosine mechanism (DSCSE) [24], combined analytical and numerical approaches [25], and newer algorithms like the gorilla troops optimization [26]. The robust approach based on Stochastic Fractal Search (SFS) optimization algorithm is introduced to estimate accurate and reliable values of solar PV parameters for its precise modeling [27] and Supply-Demand Optimization (SDO) algorithm [28] are also part of this diverse toolkit.

Recent studies have explored advanced optimization techniques to improve solar PV systems, including opposition-based on PSO algorithm for Maximum Power Point Tracking (MPPT) [30]. Moreover, a plant-propagation-inspired method for partial shading conditions [31], and a beta-based MPPT controller for efficient power tracking [32]. Other studies have focused on improving power quality with modular inverter structures [33]. Furthermore, authors [34] proposed work enhances system performance by using hysteresis modulation with a Z-source inverter and improves power quality through the inclusion of a shunt active harmonic filter, and designing optimal energy grids with dynamic programming and PSO [35]. These studies offer valuable insights into optimizing solar PV systems and can complement the enhancement of Teaching-Learning-Based Optimization (TLBO) algorithms for solar cell parameter extraction.

In this paper our motivation and contributions, it is as follows, we introduce an enhanced version of the TLBO metaheuristic method. This enhancement includes various modifications aimed at improving the TLBO's performance. The key advancements in this work center around several innovative modifications to the standard TLBO algorithm, significantly enhancing its performance. One of the primary improvements is the dynamic adjustment of the Teaching Factor (TF), which evolves with each generation, allowing the algorithm to better adapt and converge efficiently over time. Additionally, we introduce a new partner selection strategy, designed to improve solution diversity and ensure a more thorough exploration of the search space. An optional mutation step is also incorporated to reduce the likelihood of premature convergence by introducing variability at critical stages of the search. Finally, we embed a local search mechanism using the *fmincon* function, which refines solutions and drives the algorithm toward more precise global optima. These enhancements collectively represent a substantial contribution to the efficiency, accuracy, and robustness of the TLBO algorithm in solving complex optimization problems. Furthermore, we propose an improvement to the SDM by expressing the conventional diode model as two composite functions. To extract the unknown parameters from the modified model, particularly we employ the TLBO method. To validate our novel approach, we compare the results obtained using our proposed model with other recent results and well-established works in the literature that employ the classical model and new metaheuristic algorithms.

**2. Methods analysis.** This section analyzes the mathematical framework of the electrical model for both the SDM and the PV model of a PV system, depicted in Fig. 1, 2, respectively. We also propose a new variant, the Modified Single-Diode Model (MSDM).

The mathematical SDM gives an analytical current output $I_{an}$, which is expressed as:

$$I_{an} = I_{ph} - I_D - I_{Rsh}, \tag{1}$$

where $I_{an}$ is the SDM output analytical current; $I_{ph}$ is the photogenerated current; $I_D$ is the diode current; $I_{Rsh}$ is the shunt resistor current.

Equations (2), (3) define the diode current $I_D$ and the shunt resistor current $I_{Rsh}$:

$$I_D = I_{sd}\left[\exp\left(\frac{V_{Lex} + R_s I_{ex}}{nV_t}\right) - 1\right]; \tag{2}$$

$$I_{Rsh} = \frac{V_{Lex} + R_s I_{ex}}{R_{sh}}; \tag{3}$$

$$V_t = kT/q, \tag{4}$$

where $V_{Lex}$ is the output voltage; $I_{sd}$ is the saturation current; $I_{ex}$ is the experimental current data; $R_s$ is the series resistance; $R_{sh}$ is the shunt resistance; $n$ is the diode ideality factor; $V_t$ is the thermal voltage of the diode; $k$ is the Boltzmann constant; $q$ is the electron charge; $T$ is the cell temperature.

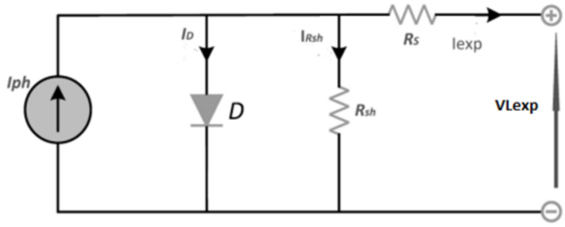


Fig. 1. Equivalent circuit of SDM model

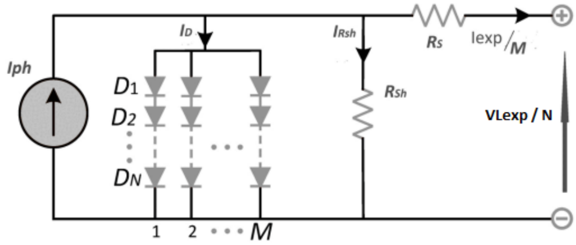


Fig. 2. Equivalent circuit of PV model

According to (1), (2) the 5 unknown parameters to be determined in the SDM are: $I_{ph}$, $I_{sd}$, $n$, $R_s$ and $R_{sh}$. The goal of our contribution is to ensure that the analytical current $I_{an}$ closely matches the experimental current $I_{ex}$.

Obviously, the experimental current data of a solar mathematical PV module is given as:

$$I_{ex} = I_{ph}N_p - I_{sd}N_p\left[\exp\left(\frac{q(V_{Lex} + \frac{N_s R_s I_{ex}}{N_p})}{nN_s kT}\right) - 1\right] - \frac{V_{Lex} + \frac{N_s R_s I_{ex}}{N_p}}{R_{sh}\frac{N_s}{N_p}}, \tag{5}$$

where $N_p$, $N_s$ are the number of cells in parallel and series, and as the solar cells are largely connected in series, for this reason we assume that $N_p = 1$. The resultant output current of the PV module will be presented as:

$$I_{ex} = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_{Lex} + N_s R_s I_{ex})}{nN_s kT}\right) - 1\right] - \frac{V_{Lex} + N_s R_s I_{ex}}{R_{sh}N_s}. \tag{6}$$

**2.1. Modified Single-Diode Model (MSDM).** The previously derived equations including (1), (2) form the basis for the MSDM. By applying these equations, the following expression is obtained:

$$I_{out} = I_{ph} - I_{sd}\left[\exp\left(\frac{V_{Lex} + R_s I_{ex}}{nV_t}\right) - 1\right] - \frac{V_{Lex} + R_s I_{ex}}{R_{sh}}. \tag{7}$$

The output current is represented by the term $I_{out}$, which was first introduced in (7) and is further described in (8). Typically, the analytical current $I_{an}$ is calculated from the experimental values of $V_{Lex}$ and $I_{ex}$. The proposed modification involves calculating $I_{an}$ using $I_{out}$, which is determined by (7). This modification enhances the convergence of the TLBO estimation algorithm and minimizes the Root Means Square Error (RMSE):

$$I_{an} = I_{ph} - I_{sd}\left[\exp\left(\frac{V_{Lex} + R_s I_{out}}{nV_t}\right) - 1\right] - \frac{V_{Lex} + R_s I_{out}}{R_{sh}}. \quad (8)$$

Finally, (8) defines the MSDM. According to (7), (8) the parameters that must be determined for the MSDM include $I_{ph}$, $I_{sd}$, $n$, $R_s$ and $R_{sh}$. Note that, an objective function is using based on experimental values, by comparing the analytical current values with the experimental values that minimizes the RMSE. The goal is to minimize the objective function $F$ with respect to the parameter set. In theory, $F$ should be zero when the parameters are precisely determined [3]:

$$F = \min_{X \in [lb, ub]} \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(f(V_{Lex}(i), I_{ex}(i), X)\right)^2}. \quad (9)$$

The $f()$ expressions is:

$$f(V_{Lex}, I_{ex}, X) = I_{ex} - I_{an}; \quad (10)$$

$$f(V_{Lex}, I_{ex}, X) = I_{ex} - (I_{ph} - I_{sd}\left[\exp\left(\frac{V_{Lex} + R_s I_{out}}{nV_t}\right) - 1\right] - \frac{V_{Lex} + R_s I_{out}}{R_{sh}}), \quad (11)$$

where $\boldsymbol{X} = [I_{ph}, I_{sd}, R_s, R_{sh}, n]$ is the vector of unknown parameters; $N$ is the number of data points; $[lb, ub]$ are the lower and upper bounds on parameter vector $\boldsymbol{X}$.

**2.2. Teaching-learning-based optimization (TLBO).** The TLBO algorithm, developed authors in [29], draws inspiration from the educational process, modeling the interactions and influence between teachers and students within a classroom to optimize solutions. The operation of TLBO is based on two phases, the «Teaching Phase» and the «Learning Phase». The operation of the two phases is explained below.

**Initialization phase**. The TLBO algorithm begins with the initialization of a population of solutions (learners). Each learner represents a potential solution to the optimization problem, the population size is denoted by $N_{pop}$, and the problem dimension is denoted by $D$, learners are initialized randomly within the predefined lower ($lb$) and upper ($ub$) bounds of the problem [28].

**Teaching phase.** During the teaching phase, the algorithm attempts to improve the quality of solutions based on the knowledge of the best solution (Teacher). The best solution in the population is considered the Teacher, the mean (*Mean*) of the population in each dimension is calculated, each learner's solution is updated as:

$$NewSol_i = pop_i + \mathrm{rand}(1, D)[Teacher - TF_{static} Mean], \quad (12)$$

where $TF_{static}$ is the static teaching factor, typically set to 1 or 2; rand(1, $D$) is a vector of random numbers in [0, 1]:

$$TF_{static} = \mathrm{rand}\,([1,2], 1, 1). \quad (13)$$

Solutions are bounded within the $[lb, ub]$ limits.

**Learning phase.** It allows learners to learn from each other. Each learner $i$ is updated by interacting with another randomly chosen learner $j$. If learner $j$ has a better performance, learner $i$ attempts to learn:

$$NewSol_i = pop_i + \mathrm{rand}(1, D)(pop_i - pop_j)\mathrm{sign}[\mathrm{obj}(j) - \mathrm{obj}(i)], \quad (14)$$

where obj($i$), obj($j$) are the objective values of the solutions of learners $i$ and $j$, respectively; solutions are bounded within the the $[lb, ub]$ limits.

**Iterative process phase.** The teaching and learning phases are repeated for a predefined number of generations or until a convergence criterion is met, the best solution at the end of the iterations is considered the optimal solution. The standard TLBO algorithm is an effective method for solving optimization problems by mimicking the teaching and learning process in a classroom setting. Its simplicity and lack of hyper-parameters make it a robust choice for various applications.

**2.3. Modified TLBO using dynamic teaching factor.** In this work we will examine the modifications made to the standard TLBO algorithm that can improve the estimation of PV model parameters.

**Dynamic teaching factor**. One of the main features of our improvement is the dynamic adjustment of the TF based on the current generation number. This adaptation enables TLBO to more effectively adjust to the changing landscape of optimization over successive generations, hence optimizing the search for optimal solutions. The following equation characterizes this factor:

$$TF_{dynamic} = TF_{current} + \left(1 - \frac{\text{current generation}}{\text{maximun number of generation}}\right), \quad (15)$$

where $TF_{current}$ is the teaching factor for the current generation; $TF_{dynamic}$ is the actual student position of the dynamic teaching factor.

**Different partner selection procedure.** An alternative partner selection approach was introduced by the algorithm's improved version. This change aims to diversify potential partners, which may help prevent the algorithm from stagnating in local optimal:

$$NewSol_i = pop_i + \mathrm{rand}(1, D) \cdot [Teacher - TF_{dynamic} \cdot Mean]. \quad (16)$$

**2.4. Improved TLBO using dynamic factor with mutation rate.** In the first case, this method is based on mutation facultative step. However, this mutation makes it possible to introduce diversity into the individual population, which may be essential for exploring new areas of the research domain. The facultative mutation gives the algorithm additional flexibility to adapt to different kinds of problems.

Note that each student makes mutation with probability $P_m$. Using a function rand, we apply the mutation rate as follows:

When $P_m$ > rand

$$SolMut_i = NewSol_i + Mut_{rate}[ub - lb]rand; \quad (17)$$

When $P_m$ < rand

$$SolMut_i = NewSol_i, \quad (18)$$

where $SolMut_i$ is the solution mutation; $Mut_{rate}$ is the mutation rate, which is the factor determining the mutation magnitude.

In a second case, we aim to optimize the TLBO algorithm obliviously, we combined the previews modification using local search based on MATLAB function denoted *fmincon*. The updated version includes a local search step that uses the *fmincon* function. This step enables the candidate solutions to be refined using more sophisticated local search techniques. This could have a major impact on raising the caliber of solutions produced by the evolutionary algorithm.

The following representation of the local search step equation is as follows:

$$Optimized_{solution} = \\ = \mathrm{fmincon}\left(F, Current_{solution}, \mathrm{Constraints}\right), \qquad (19)$$

where $F$ is the objective function given by (9); $Current_{solution}$ is the solution mutation given by (17); Constraints [*lb*, *ub*] for each parameter. However, the solution that has been optimized with the help of the *fmincon* function is denoted by the term «Optimized Solution» in this equation. The function *fmincon* takes into account the function to minimize, the initial solution, and all requirements that must be met. It conducts local research to find an improved solution within the constraints of the available data. This step allows the quality of the solutions generated by the evolutionary algorithm to be improved by affining them through local optimization (Fig. 3).

```
: function: Improved TLBO
: initialTF = 5 % Initial value of TF
: for each generation gen = 1 to T do
:    Calculate TF = initialTF / (1 + gen)
:    Find [best_obj, best_idx] = min(obj) (minimum objective value and its index)
:    best_student = pop(best_idx, :) (select best solution)
:     for each population member i = 1: NPop do
:             Calculate teach_factor = rand * (best_student - mean(pop))
:             Generate NewSol = pop(i, :) + rand(1, D) .* teach_factor
:             Bound the solution: NewSol = max(min(ub, NewSol), lb)
:             Evaluate NewSolObj = FITNESSFCN(NewSol)
:             if (NewSolObj < obj(i)) then
:                     Update population: pop(i, :) = NewSol
:                     Update objective value: obj(i) = NewSolObj
:             end if
:    end for
:    for each population member i = 1:NPop do
:              Select partner_idx = randi([1, NPop])
:             While partner_idx == I do
:                     Re-select partner_idx = randi([1, NPop])
:             end while
:              if (obj(i) < obj(partner_idx)) then
:                     Generate NewSol = pop(i, :) + rand(1, D) .* (pop(i, :) - pop(partner_idx, :))
:             else:
:                      Generate NewSol = pop(i, :) + rand(1, D) .* (pop(partner_idx, :) - pop(i, :))
:             end if
:             Bound the solution: NewSol = max(min(ub, NewSol), lb)
:             Evaluate NewSolObj = FITNESSFCN(NewSol)
:              if (NewSolObj < obj(i)) then
:                     Update population: pop(i, :) = NewSol
:                     Update objective value: obj(i) = NewSolObj
:             end if
:    end for
:    for each population member i = 1: NPop do
:             if (rand() < 0.05) then % Adjust mutation probability as needed
:                     Generate mutation_factor = rand(1, D) .* (ub - lb) (random mutation)
:                     Generate NewSol = pop(i, :) + mutation_factor
:                     Bound the solution: NewSol = max(min(ub, NewSol), lb)
:                     Evaluate NewSolObj = FITNESSFCN(NewSol)
:                     if (NewSolObj < obj(i)) then
:                             Update population: pop(i, :) = NewSol
:                             Update objective value: obj(i) = NewSolObj
:                     end if
:             end if
:    end for
:    Store best objective value for each generation: [BestFVALIter(gen), ~] = min(obj)
: end for
: At the end of all generations:
: Find the best solution: [~, ind] = min(obj)
: X = pop(ind, :) (best individual)
: FVAL = obj(ind) (best objective value)
: Set optimization options: options = optimset('Display', 'off')
: Refine solution using fmincon : [X, FVAL] = fmincon (FITNESSFCN, X, lb, ub, options)
: Store final best objective value: [BestFVALIter(end), ~] = min(FITNESSFCN(X))
: end function
```

Fig. 3. Improved TLBO algorithm

**3. Simulation results and discussion.** In this study, we delve into the analysis of parameters derived from the TLBO algorithm. The study compares the traditional SDM for PV systems with an enhanced model using the TLBO algorithm. The data set for this analysis comprises a variety of PV devices, including the RTC solar cell from France, the Photowatt-PWP201, STM 6-40/36, and STP6-120/36 PV panels. The performance evaluation is carried out using the RMSE as a benchmark to compare the results from the traditional model and the enhanced model that employs the TLBO algorithm.

Additionally, an assessment of the suggested model and the TLBO algorithm in comparison to a number of accepted techniques, which presented in [17], [19], [23], [24] and SDO [28] are some of these.

To obtain more comprehensive information on solar cell parameter extraction and to illustrate the validity of the new method we carried out several simulation results. Obviously, we execute 30 separate runs to determine the robustness of our suggested model. The TLBO algorithm uses 30 runs, and each run has 500 iterations. The lower limit values (*lb*) of the 5 characteristic parameters $I_{ph}$(A), $I_{sd}$(μA), $n$, $R_s$(Ω) and $R_{sh}$(Ω) are the same (0, 0, 1, 0, 0) for the 4 PV devices. The upper limit values (*ub*) of the 5 parameters are respectively (1, 1, 2, 0.5, 100) for the RTC France cell, (2, 5, 2, 1, 2000) for the PWP201, (5, 3, 2, 1, 2000) for STM 6-40/36 and (10, 3, 2, 1, 2000) for STP6-120/36.

**3.1. Comparison between the classic SDM and the MSDM.** In this study, the simulation results considered for 4 PV devices are analyzed and the modified model is compared with the traditional SDM. However, to find the unknown parameters of the PV systems, the TLBO method is employed. Obviously, for this comparative analysis we perform 30 independent runs presented in Fig. 4–7. The optimal run is selected based on 2 evaluation criteria. The first criterion is the real-time absolute error, denoted as $|I_{ex} - I_{an}|$, where the experimentally measured current is $I_{ex}$, and the analytically computed current is $I_{an}$. RMSE's decimal logarithm serves as the basis for the second criterion. The absolute errors for the suggested and classical models $|I_{ex} - I_{an}|$ between the calculated and experimental current values are shown in Fig. 4–7. Obviously, Fig. 4 shows the absolute error for the STM6-40/36 panel, the performance of both models is comparable, though the proposed model exhibits a slight advantage. The absolute inaccuracy for the STP6-120/36 module is shown in Fig. 5, where the proposed model's error ranges from 0 to 0.05, while the inaccuracy of the conventional model varies from 0 to 0.15, highlighting the enhanced functionality of the suggested model. Figure 6 shows the absolute error for the RTC France solar cell, where the proposed model exhibits better convergence towards zero, indicating improved accuracy over the classical model. Additionally, Fig. 7 illustrates the absolute error for the Photowatt-PWP201 module, where the proposed model also achieves more stable and precise results. A thorough comparison of absolute errors between different PV systems is shown in Fig. 4–7, which also emphasizes how much better the suggested model is at precision and convergence than the conventional model.

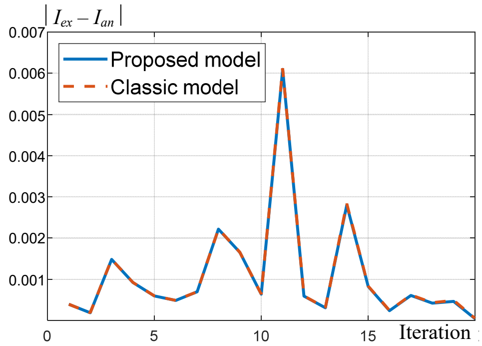


Fig. 4. The absolute error of classical and proposed model for the solar panel STM 6-40/36

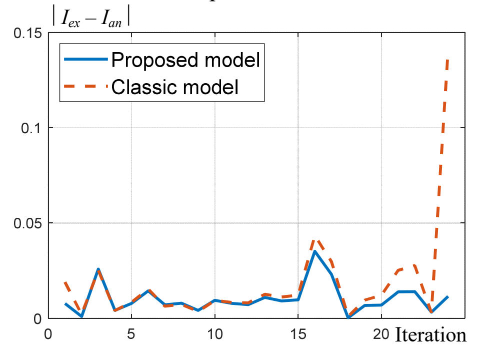


Fig. 5. The absolute error of classical and proposed model for the solar panel STP6-120/36

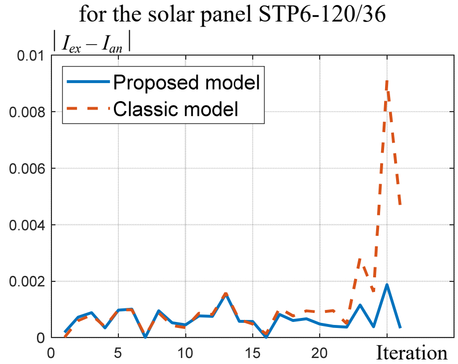


Fig. 6. The absolute error of classical and proposed model for the solar cell RTC France

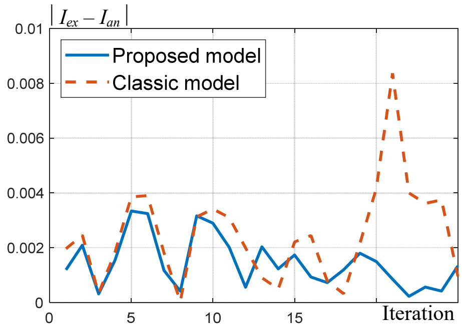


Fig. 7. The absolute error of classical and proposed model for the solar panel Photowatt-PWP201

Figures 8–11 show the evolution of the decimal log of the RMSE for the 4 PV devices. In comparison to the classical model, the suggested model exhibits better convergence over the course of the simulation, as presented in Fig. 8–11. In the initial iterations, the classical model demonstrates better convergence, as indicated by the RMSE evolution for the STM6-40/36 panel shown in Fig. 8. Still, the suggested model performs better at convergence starting with iteration 300. A detailed examination of the convergence behavior for both models during the simulation results are shown in Fig. 8–11, which show that the suggested model outperforms the traditional model in terms of convergence and accuracy, especially in the later phases.

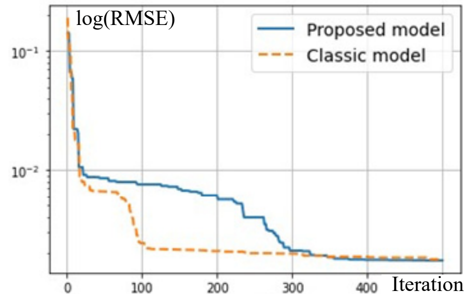


Fig. 8. The decimal log of the best RMSE for the solar panel STM6-40/36

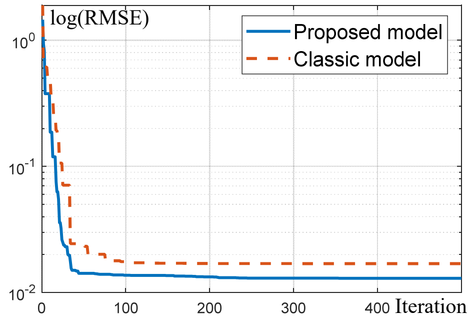


Fig. 9. The decimal log of the best RMSE for the solar panel STP6-120/36

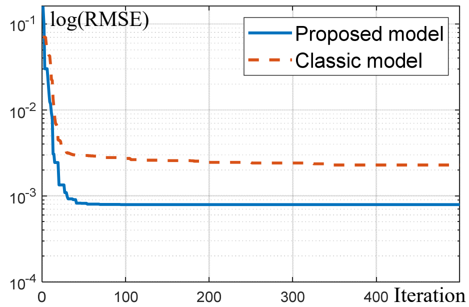


Fig. 10. The decimal log of the best RMSE for the solar cell RTC France

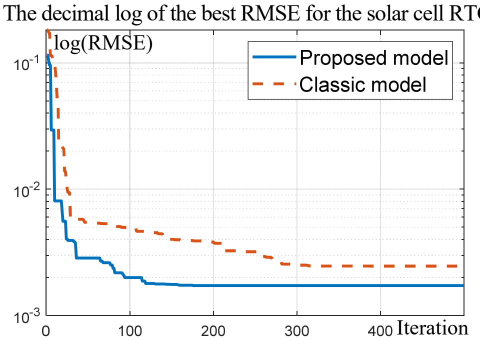


Fig. 11. The decimal log of the best RMSE for the solar panel Photowatt-PWP201

**3.2. Statistical analysis and comparison of parameter estimation algorithms.** To evaluate the robustness of the proposed model, we conduct several iterations corresponding to the tables of values from the available measurements. This section compares the robustness of the classical model against the modified model. The robustness curves for the suggested model, which is based on the TLBO method, and the classical model, over 30 different runs, are shown in Fig. 12–15. In terms of forecasting the behavior of the 4 PV devices, the analysis of Fig. 12–15 makes it abundantly evident that the suggested model routinely outperforms the traditional models. The evaluation relies on RMSE, a metric that reflects model accuracy, with lower RMSE values signifying better performance. For each of the four PV devices, the suggested model continuously outperforms the conventional models in terms of RMSE values throughout the course of 30 independent runs. This implies that the predicted values of the proposed model are consistently closer to the actual values of the PV devices than those of the classical models.

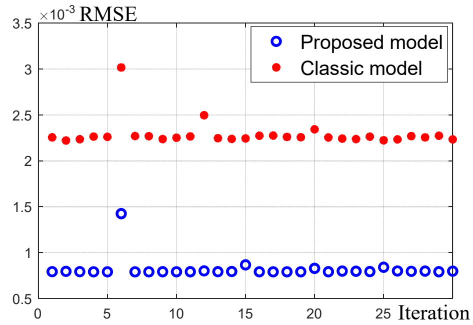


Fig. 12. The different RMSEs for the 30 iterations for the solar cell RTC France

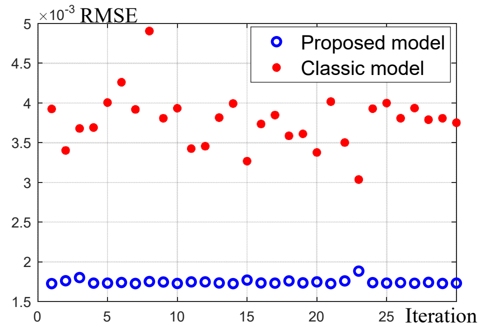


Fig. 13. The different RMSEs for the 30 iterations for the solar panel Photowatt-PWP201

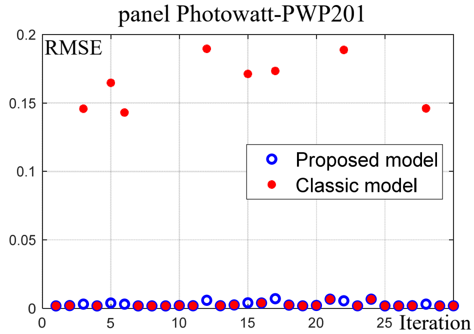


Fig. 14. The different RMSEs for the 30 iterations for the solar panel STM 6-40/36

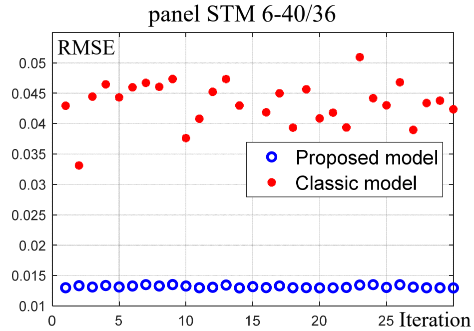


Fig. 15. The different RMSEs for the 30 iterations for the solar panel STP6-120/36

Table 1 presents a performance comparison between the proposed method and other recent works in the literature. This table shows the estimated parameters and

RMSE values for the proposed model and other classic models. The proposed model's RMSE is better than that of classic models across all studied PV systems. This indicates that the proposed model demonstrates higher precision or predictive performance compared to the classic model used in the other works for the analyzed PV systems.

Table 1

Comparing the proposed model with traditional algorithms

| Algorithm | $I_{ph}$, A | $I_{sd}$, A | $n$ | $R_s$, Ω | $R_{sh}$, Ω | RMSE |
|---|---|---|---|---|---|---|
| **Solar cell RTC France** | | | | | | |
| Algorithm | $I_{ph}$, A | $I_{sd}$, A | $n$ | $R_s$, Ω | $R_{sh}$, Ω | RMSE |
| **Improved - TLBO** | 0,76079 | $3,11945 \cdot 10^{-7}$ | 1,47737 | 0,03621 | 52,35576 | $\mathbf{7,89611 \cdot 10^{-4}}$ |
| GAMNU [9] | 0,76077 | $3,25595 \cdot 10^{-7}$ | 1,4821 | 0,03634 | 53,89686 | $9,8618 \cdot 10^{-4}$ |
| ISCE [16] | 0,76078 | $3,23021 \cdot 10^{-7}$ | 1,48118 | 0,03638 | 53,71853 | $9,86022 \cdot 10^{-4}$ |
| EHRJAYA [17] | 0,76078 | $3,23021 \cdot 10^{-7}$ | 1,48118 | 0.03638 | 53,71853 | $9,86022 \cdot 10^{-4}$ |
| hARS-PS [18] | 0,7608 | $3,23 \cdot 10^{-7}$ | 1,481 | 0,0364 | 53,714 | $9,84 \cdot 10^{-4}$ |
| IGSK [19] | 0,76078 | $3,23 \cdot 10^{-7}$ | 1,48118 | 0,03638 | 53,71853 | $9,86022 \cdot 10^{-4}$ |
| SEDE [21] | 0,76078 | $3,23021 \cdot 10^{-7}$ | 1,48118 | 0,03638 | 53,71852 | $9,86022 \cdot 10^{-4}$ |
| DSCSE [24] | 0,76078 | $3,23021 \cdot 10^{-7}$ | 1,48118 | 0,03638 | 53,7185 | $9,86022 \cdot 10^{-4}$ |
| SFS[27] | 0,7609 | $3,167 \cdot 10^{-7}$ | 1,47918 | 0,03648 | 53,2805 | $7,931 \cdot 10^{-4}$ |
| **Solar panel Photowatt-PWP201** | | | | | | |
| Algorithm | $I_{ph}$, A | $I_{sd}$, A | $n$ | $R_s$, Ω | $R_{sh}$, Ω | RMSE |
| **Improved - TLBO** | 1,03235 | $1,79802 \cdot 10^{-6}$ | 1,34714 | 0,03571 | 19,65356 | $\mathbf{1,72569 \cdot 10^{-3}}$ |
| GAMNU [9] | 1,03077 | $3,01623 \cdot 10^{-6}$ | 48,09755 | 1,21912 | 906,27545 | $2,38242 \cdot 10^{-3}$ |
| ISCE [16] | 1,03051 | $3,48226 \cdot 10^{-6}$ | 48,64284 | 1,20127 | 981,98228 | $2,42508 \cdot 10^{-3}$ |
| EHRJAYA [17] | 1,03051 | $3,48226 \cdot 10^{-6}$ | 48,64283 | 1,20127 | 981,98222 | $2,42507 \cdot 10^{-3}$ |
| hARS-PS [18] | 1,0305 | $3,4822 \cdot 10^{-6}$ | 48,6428 | 1,20120 | 981,9823 | $2,42 \cdot 10^{-3}$ |
| IGSK [19] | 1,03051 | $3,4823 \cdot 10^{-6}$ | 48,64283 | 1,20127 | 981,9823 | $2,42507 \cdot 10^{-3}$ |
| SEDE [21] | 1,03051 | $3,48226 \cdot 10^{-6}$ | 48,64284 | 1,20127 | 981,98223 | $2,42507 \cdot 10^{-3}$ |
| DSCSE [24] | 1,03051 | $3,48226 \cdot 10^{-6}$ | 48,6428 | 1,20127 | 981,982 | $2,42507 \cdot 10^{-3}$ |
| SDO[28] | 1,03051 | $3,48 \cdot 10^{-6}$ | 1,35119 | 0,03337 | 27,27729 | $2,425 \cdot 10^{-3}$ |
| **Solar panel STM6-40/36** | | | | | | |
| Algorithm | $I_{ph}$, A | $I_{sd}$, A | $n$ | $R_s$, Ω | $R_{sh}$, Ω | RMSE |
| **Improved - TLBO** | 3,47128 | $1,19181 \cdot 10^{-6}$ | 1,19871 | 0,0157 | 27,38766 | $\mathbf{1,58288 \cdot 10^{-3}}$ |
| ISCE [16] | 1,6639 | $1,73866 \cdot 10^{-6}$ | 1,5203 | 0.00427 | 15,92829 | $1,72981 \cdot 10^{-3}$ |
| EHRJAYA [17] | 1,6639 | $1,73866 \cdot 10^{-6}$ | 1,5203 | 0.00427 | 15,92829 | $1,72981 \cdot 10^{-3}$ |
| hARS-PS [18] | 1,0305 | $3,4822 \cdot 10^{-6}$ | 48,6428 | 1,2012 | 981,9823 | $2,42 \cdot 10^{-3}$ |
| IGSK [19] | 1,6639 | $1,7387 \cdot 10^{-6}$ | 1,5203 | 0,00427 | 15,92829 | $1,72981 \cdot 10^{-3}$ |
| SDO[28] | 1,66391 | $1,74 \cdot 10^{-6}$ | 1,5203 | 0,00427 | 15,92829 | $1,73 \cdot 10^{-3}$ |
| **Solar panel STP6-120/36** | | | | | | |
| Algorithm | $I_{ph}$, A | $I_{sd}$, A | $n$ | $R_s$, Ω | $R_{sh}$, Ω | RMSE |
| **Improved - TLBO** | 7,47482 | $1,46407 \cdot 10^{-6}$ | 1,23924 | 0,005 | 14,70737 | $\mathbf{1,29713 \cdot 10^{-2}}$ |
| GAMNU [9] | 7,469 | $2,739 \cdot 10^{-6}$ | 45,84837 | 0,16269 | 1468,618 | $1,6735 \cdot 10^{-2}$ |
| ISCE [16] | 7,47253 | $2,335 \cdot 10^{-6}$ | 1,2601 | 0,00459 | 22,21991 | $1,66006 \cdot 10^{-2}$ |
| EHRJAYA [17] | 7,47253 | $2,335 \cdot 10^{-6}$ | 1,2601 | 0,00446 | 222,19907 | $1,66 \cdot 10^{-2}$ |
| IGSK [19] | 7,47253 | $2,335 \cdot 10^{-6}$ | 1,2601 | 0,00459 | 22,21989 | $1,66 \cdot 10^{-2}$ |
| SFS[27] | 7,4757 | $3,01 \cdot 10^{-6}$ | 1,2816 | 0,16 | 827,5815 | $1,59 \cdot 10^{-2}$ |
| SDO[28] | 7,47253 | $2,33 \cdot 10^{-6}$ | 1,2601 | 0,0046 | 22,21991 | $1,6601 \cdot 10^{-2}$ |

**4. Conclusions.** This research underscores the significance of precise solar cell modeling to ensure that PV systems are designed effectively. It highlights that in order to improve modeling precision, precise parameter estimate is essential for simple models. In this work, we suggest improving the single-diode model analytically to improve its performance. This improvement incorporates the optimization of unknown parameters and performance evaluation of the model through the application of the TLBO algorithm. When compared to other well-known studies in the field, our findings show that the suggested model outperforms the traditional approach in terms of accuracy and dependability. The application of the TLBO algorithm enables the proposed model to yield more precise and robust results, demonstrating higher rates of convergence. Looking ahead, our future research will explore the use of other metaheuristic algorithms for parameter extraction from single, double and triple diode models. This investigation could offer additional insights and further refine the modeling process. The MPPT issue, which is crucial for maximizing solar power output, will also be covered in our research. To further develop the field of solar cell modeling and PV system design, our future research plan includes investigating alternate metaheuristic algorithms and tackling the MPPT problem.

**Conflict of interest.** The authors declare that they have no conflicts of interest.

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