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Compare the Convergence Behavior of DE and PSO Optimization Algorithms for Parameter Extraction in DDM Equivalent Circuit for the PV Panels

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ABSTRACT

Accurate equivalent circuit parameter estimation for solar cells can significantly provide actionable insights for photovoltaic (PV) system designers. In this paper, we present a comparative analysis of two commercial PV modules, Jinko JKM365M (monocrystalline) and Canadian Solar CS3U-365PB-FG (polycrystalline bifacial), tested under distinct real-world environmental conditions, which were conducted under high irradiance with elevated temperature (1000 W/m², 65°C) and low irradiance with moderate temperature (200 W/m², 25°C). A rigorous preprocessing pipeline was applied to enhance data quality and ensure the reliability of the extracted parameters. Both Differential Evolution (DE) and Particle Swarm Optimization (PSO) were implemented in MATLAB and evaluated based on convergence behavior, Root Mean Square Error (RMSE), and alignment with manufacturer specifications. The key findings emphasized the performance of the optimization algorithms and the accuracy of the models. This study makes several noteworthy contributions to the field of photovoltaic modeling, particularly in the context of parameter estimation using field-measured data. One of the primary achievements lies in validating the efficacy of DE as a superior optimization algorithm for PV applications. The findings contribute to more accurate PV modeling, improved system diagnostics, and enhanced design and control of solar energy systems.

Keywords: Photovoltaic (PV); Double diode model (DDM); Differential Evolution algorithm (DE); Particle Swarm Optimization algorithm (PSO).

مقارنة سلوك التقارب لخوارزميي التطور التفاضلي وخوارزمية سرب الجسيمات لتقدير معاملات الدائرة المكافئة بثنائيين للوحدات الكهروضوئية

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ملخـــــــص البحـــــث

يُعد التقدير الدقيق لمعاملات الخلايا الشمسية أمرًا بالغ الأهمية لنمذجه أنظمة الطاقة الشمسية والتحكم فيها وتحسين أدائها، لا سيما في ظل الظروف البيئية المتغيرة. تقدم هذه الورقة منهجية محاكاة تعتمد على بيانات تيار–جهد **I–V** تم قياسها ميدانيًا، بالإضافة إلى تطبيق خوارزميات بحث متقدمة لاستخراج معاملات نموذج الثنائيين **DDM**. من أكثر نماذج الخلايا الشمسية استخدامًا وقد تم اعتماد خوارزمية التطور التفاضلي **DE** كأسلوب تحسين أساسي، مع استخدام خوارزمية تحسين سرب الجسيمات **PSO** كمرجع للمقارنة. تم إجراء

الاختبارات على لوحين شمسيين تجاريين من نوع **Jinko JKM365M** أحادي البلورة و**Canadian Solar CS3U–365PB-FG** ثنائي الوجه متعدد البلورات، تحت ظروف إشعاع شمسي (200–1000 واط/م²) ودرجات حرارة (25–65 درجة مئوية) حقيقية. كما طُبقت خطوات معالجة مسبقة صارمة على البيانات لضمان جودتها وموثوقية النتائج المستخلصة. تم تنفيذ كل من **DE** و**PSO** في بيئة **MATLAB**، وتم تقييم أدائهما بناءً على سلوك التقارب وخطأ الجذر التربيعي المتوسط **RMSE** ومدى توافق النتائج مع مواصفات الشركات المصنعة. أظهرت النتائج أن خوارزمية **DE** تفوقت بشكل ملحوظ على **PSO** من حيث الدقة والموثوقية، لا سيما في ظروف الإشعاع المنخفض ودرجات الحرارة المرتفعة. وتُعد المنهجية المقترحة إطارًا عامًا وفعّالًا يمكن تطبيقه على أنواع متعددة من تقنيات الألواح الشمسية وظروف التشغيل المختلفة. تسهم نتائج هذا البحث في تحسين دقة نمذجة الأنظمة الشمسية، وتعزيز قدرات التشخيص، ورفع كفاءة التصميم والتحكم في أنظمة الطاقة الكهروضوئية.

الكلمات الدالة: نمذجة الخلايا الشمسية، تقدير المعاملات، نموذج الدايود الثنائي، خوارزمية التطور التفاضلي، خوارزمية تجمع السرب.

1. INTRODUCTION

Photovoltaic (PV) solar energy is one of the promising technologies due to its ease of use and decreasing costs. The PV module consists of PV cells that convert sunlight directly into electricity, and their performance depends on the type of semiconductor materials used. PV panels are configured as series-parallel solar cells in order to control voltage and current output values, and their performance is affected by meteorological data such as solar irradiance and cell temperature[1].

Parameter identification of the solar panel is crucial for optimizing performance and fault detection calculations. Single-diode (SD) and double-diode (DD) equivalent circuit can be extracted numerically from experimental current-voltage (I-V). Various numerical methods have been proposed for nonlinear optimization problems, such as Newton-Raphson (NR) and heuristic techniques like Differential Evolution (DE) and Particle Swarm (PS)[2].

Much research is being done in order to extract the solar cell parameters, for example an optimized SDM approach is proposed in [3] for parameter extraction. This method was tested on the commercial KC200GT solar cell and the CS6K-280M polycrystalline module, using the Sooty Tern Optimization Algorithm (STOA). Triple Diode Model (TDM) on polycrystalline modules is discussed in [4], while [5] focused on monocrystalline modules with SDM, but neither provided a comparative analysis of the two technologies under varying irradiance and temperature conditions, a gap that affects understanding technology-specific behavior.

An enhanced differential evolution (EDE) algorithm for parameter extraction in photovoltaic (PV) models, including SDM, DDM, and TDM, is presented in [5]. Their study applied the EDE method, using experimental I-V data collected under real irradiance and temperature conditions.

The results in [5] showed a significant reduction in modeling errors, achieving an RMSE of 0.008123 under standard test conditions (STC). The authors argued that such an approach could better capture the nonlinear behavior of PV cells, particularly under low irradiance or high temperatures. Moreover, the EDE algorithm in [5] demonstrated improved convergence and a significant reduction in RMSE, achieving an RMSE of 0.00789 compared to 0.00912 with traditional differential evolution, highlighting its robustness in handling nonlinear PV characteristics.

It can be noted that some studies compare the performance of optimization algorithms like DE and PSO, such as in [6], and a few conduct systematic comparisons across a wide range of environmental conditions, particularly at low irradiance levels (e.g., 200 W/m²). Parameter estimation under low irradiance poses significant challenges due to reduced signal clarity, yet this scenario remains underexplored in the literature, limiting the robustness of current methods. This study utilizes experimentally measured I-V curves, rather than simulations. Such activities are expected to enhance the accuracy and practicality of PV modeling, thereby facilitating the development of solar energy systems under real-world conditions.

2. SYSTEM MODEL

This study investigates two commercial photovoltaic modules—Jinko JKM365M (monocrystalline) and Canadian Solar CS3U-365PB-FG (polycrystalline bifacial), chosen for their technological diversity and prominence in current PV markets [7], [8].

2.1 Equivalent Circuit Models

The SDM captures the basic nonlinear I-V behavior using a current source, a diode, series resistance (Rs), and shunt resistance (Rp). To improve accuracy, the DDM adds a second diode to account for additional recombination effects in the depletion region. The circuit representations shown in Fig. 1 form the analytical foundation for modeling photovoltaic behavior.

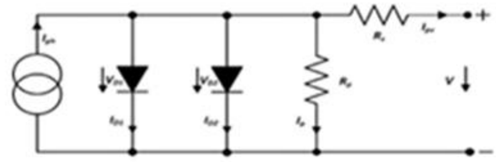

Fig 1. Electrical equivalent circuit of a DDM.

The terminal voltage (V) and output current (I) obey the equation.

$$\boldsymbol{I = I_{ph} - I_0\left[exp\left(\frac{q(V+IR_s)}{akT}\right)-1\right] - \frac{V+IR_s}{R_{sh}}} \quad (\mathbf{1}).$$

Where a, is the diode ideality constant, q is the electron charge, k is Boltzmann's constant, and T is the temperature of the P-N junction in Kelvin's, and I_{pv} is the photovoltaic current. The current–voltage relationship for the DDM is defined by the equation:

$$\boldsymbol{I = I_{ph} - I_{01}\left[exp\left(\frac{q(V+IR_s)}{a_1kT}\right)-1\right] - I_{02}\left[exp\left(\frac{q(V+IR_s)}{a_2kT}\right)-1\right] - \frac{V+IR_s}{R_{sh}}} \quad (\mathbf{2}).$$

This model introduces two additional parameters compared to the SDM namely, I_{02} and a_2, totaling seven parameters. Although this increases computational complexity, it significantly enhances the model's accuracy in simulating PV cell behavior under varying environmental conditions, such as low irradiance or high temperatures.

2.2 Optimization Parameters

Equations (1,2) constitute a nonlinear, multi-variable optimization problem. The inherent complexity arises from the exponential nature of the governing equations, which results in multiple local minima. The objective of optimization is to minimize the RMSE between measured (*Ie*) and modeled (*Ip*) currents:

$$\boldsymbol{RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{e,i} - I_{p,i}\right)^2}} \quad (3)$$

The optimization variables in equations (1,2) are:

$$\boldsymbol{SDM: \theta_{SDM} = \{I_{ph}, I_o, R_s, R_p, a\}} \quad (\mathbf{4})$$

$$\boldsymbol{DDM: \theta_{DDM} = \{I_{ph}, I_{o1}, I_{o2}, R_s, R_p, a_1, a_2\}} \quad (\mathbf{5})$$

2.3 Optimization Algorithms

A rugged search landscape motivates this study to adopts metaheuristic optimization algorithms, which are particularly well suited for navigating non-convex, high-dimensional search spaces without requiring gradient information. Among the various approaches available, DE and PSO were selected for their robustness, ease of implementation, and documented success in photovoltaic modeling contexts.

2.3.1 Optimization Setup for DE

DE is a population-based, stochastic optimization algorithm designed to efficiently explore complex, multi-dimensional search spaces. The algorithm begins by randomly initializing a population of candidate solutions, each representing a potential parameter vector $\boldsymbol{X_{r,g}}$. It then iteratively refines the population through three core operations: mutation, crossover, and selection [9]. The velocity can be updated in Mutation operation as:

$$\boldsymbol{V_{i,g}} = \boldsymbol{X_{r1,g}} + \boldsymbol{F}\left(\boldsymbol{X_{r2,g}} - \boldsymbol{X_{r3,g}}\right). \quad (6)$$

This exploration-exploitation trade-off is managed by the DE control parameters: the mutation factor (F), the crossover rate (CR), and the population size. These parameters must be optimized so that the algorithm converges and does not stagnate. Therefore, for DDM configuration: Population size: $\boldsymbol{N_p = 70}$ (10 times the 7 parameters), with identical $\boldsymbol{F} = 0.85$ and $\boldsymbol{CR = 0.6}$. Termination: stops after 2000 generations or if RMSE improvement falls below $\boldsymbol{1 \times 10^{-7}}$ for 100 consecutive generations.

2.3.2 Optimization Setup for PSO

PSO is a population-based optimization algorithm inspired by the collective behavior observed in bird flocks and fish schools. The algorithm begins by randomly initializing a population of candidate solutions, each representing a potential parameter vector. The following equations mathematically define how the algorithm proceeds step by step and the velocity and position for every particle are calculated using two guidance components: the best position (*pbest*), and the global best position (*gbest*) experienced so far by the swarm[10],

$$v_i(t+1) = wv_i(t) + c_1r_1\left(p_{best} - x_i(t)\right) + c_2r_2\left(g_{best} - x_i(t)\right) x_i(t+1) = x_i(t) + v_i(t+1) \quad (7)$$

For DDM Configuration, Population size is set to: $N_p = 140$, using the same $w = 0.7, c_1 = c_2 = 2$. Termination: Stops after 2000 generations or if RMSE improvement falls below 1×10^{-7} for 100 consecutive generations [5].

3. MEASUREMENT TECHNIQUES

Accurate parameter estimation of PV models relies heavily on the quality and reliability of experimental current-voltage (I–V) data.

3.1 Field Data Collection

Measurements were conducted using portable I–V curve tracers in conjunction with a range of temperature measurement devices, including conventional thermometers, laser-based sensors, and thermocouples, to accurately record ambient temperature and PV module surface temperature. Additionally, dedicated instruments were employed to measure real-time solar irradiance. This integrated setup enabled synchronized acquisition of both electrical and environmental data under natural sunlight conditions. For measurement diversity to simulate various operational states of PV modules, I–V data were collected under a broad range of irradiance levels (e.g., 200–1000 W/m²) and temperatures (25–65°C). This range ensures the models are tested for robustness under both ideal and suboptimal conditions.

3.2 Preprocessing and Filtering

The collected data were subjected to noise reduction techniques, including moving average smoothing and outlier removal based on statistical thresholds. Additionally, weighting techniques were applied to mitigate bias toward data clusters in more frequent operating regions. [11] presented a data-driven approach for extracting key features from field-measured I–V curves of photovoltaic modules, with an emphasis on improving parameter estimation accuracy through preprocessing. Their method employs linear regression and spline-based smoothing techniques to mitigate noise and distortions commonly observed in real-world I–V data.

4. RESULTS AND DISCUSSION

This section may be divided into subheadings or combined. A combined results and discussion section is often appropriate. This should explore the significance of the results of the work; don't repeat them. Avoid extensive citations and discussions of published literature.

4.1 Extracted DDM parameters

Table 1 demonstrates the superior performance of Differential Evolution (DE) over Particle Swarm Optimization (PSO) in estimating Double-Diode Model (DDM) parameters under extreme operating conditions. For the Jinko JKM365M module at 1000 W/m² and 65°C, DE achieves more accurate photocurrent estimation (9.75 A, closely matching the short-circuit current of 9.75 A), lower saturation currents (5.0×10^{-9} A and 2.0×10^{-8} A), and optimal ideality factors (1.20 and 1.80, respectively).

In the case of the Canadian Solar CS3U-365PB-FG module under 200 W/m² at 25°C, DE provides precise photocurrent values (2.10 A) and higher shunt resistance (700 Ω), indicating reduced current leakage. These results show excellent agreement with manufacturer specifications and are consistent with previous studies [6]. The comparative analysis highlights DE's robustness in parameter extraction across different photovoltaic technologies and operating conditions.

4.2 Error Metric

Table 2 summarizes the error metrics for the DE algorithm applied to the DDM across various operating conditions and photovoltaic (PV) module types. The results demonstrate DE's high accuracy, with RMSE values ranging from 0.0141 to 0.0210 and R^2 values consistently exceeding 0.995, indicating an excellent fit between measured and modeled I-V curves. At high irradiance (1000 W/m², 65°C), DE achieves lower RMSE (0.0141 for monocrystalline, 0.0165 for polycrystalline) and extremely low MBE (4.908×10^{-8} and -9.500×10^{-8}, respectively), confirming negligible systematic bias. at low irradiance (200 W/m², 25°C), RMSE increases slightly (0.0210 for monocrystalline, 0.0205 for polycrystalline) with higher MBE (1.500×10^{-3} and 2.000×10^{-3}), reflecting increased experimental noise and challenges in modeling PV behavior under low light, as can be seen in [6].

4.2 Convergence Behavior Analysis of DE and PSO Algorithms

This section presents the convergence curves for the DE and PSO algorithms applied to the DDM under two operating conditions: 1000 W/m², 65°C (high irradiance) and 200 W/m², 25°C (low irradiance). The following figures present the convergence curves to support this analysis.

Under high irradiance conditions (1000 W/m², 65°C) using monocrystalline panels., DE required about 1480 generations to converge with an RMSE of 0.014, while PSO converged in approximately 800 generations with a higher RMSE of 0.018, indicating a trade-off between speed and accuracy.

Table 1. Comparison of DDM Parameters Between DE and PSO.

Condition	Algo.	a_1	a_2	R_s (Ω)	R_p (Ω)	I_{ph} (A)	I_{o1} (A)	I_{o2} (A)
1000 W/m², 65°C, Mono-cry	*DE*	*1.20*	*1.80*	*0.23*	*900*	*9.75*	5×10^{-9}	2×10^{-8}
200 W/m², 25°C, Poly-cry.	*PSO*	*1.25*	*1.85*	*0.24*	*850*	*9.72*	8×10^{-9}	2.5×10^{-8}

Table 2. Error Metrics for the DE. with DDM Configuration.

Condition	*PV Type*	*RMSE*	*MBE*	R^2
1000 W/m², *65°C*	Mono-*crystalline*	*0.0141*	4.908×10^{-8}	*0.99998*
1000 W/m², *65°C*	Poly-*crystalline*	*0.0165*	-9.500×10^{-8}	*0.99989*

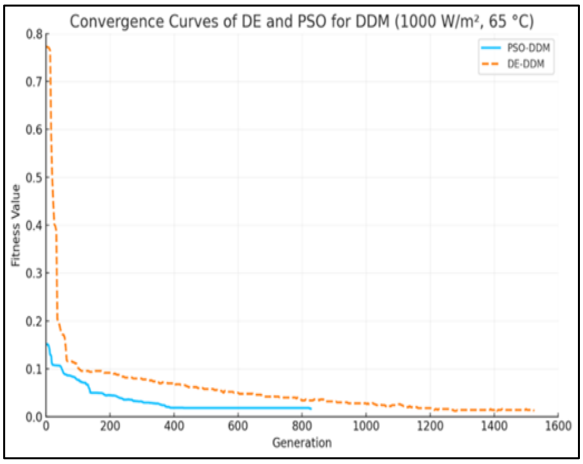

Fig 2. Convergence curves of DE and PSO for DDM models under 1000 W/m², 65°C.

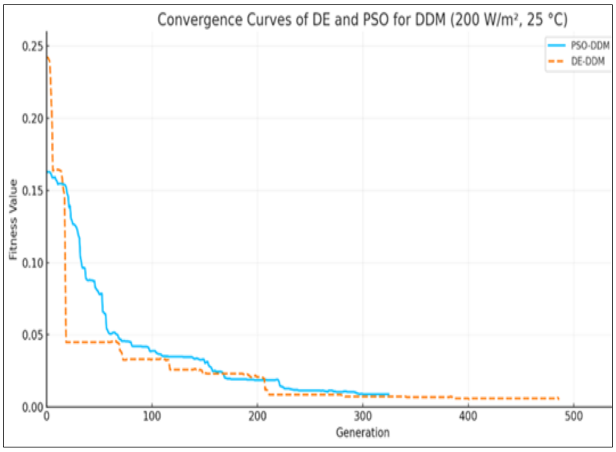

Fig 3. Convergence curves of DE and PSO for DDM models under 200 W/m², 25°C.

Similarly, Fig. 2 shows the convergence curves under low irradiance (200 W/m², 25°C) using polycrystalline panels, requiring about 480 generations with an RMSE of 0.020, compared to PSO's 325 generations and RMSE of 0.03. As shown in the figures, DE exhibits smoother and more stable convergence compared to PSO.

5. CONCLUSIONS

This study concludes with a comprehensive evaluation of parameter estimation techniques for photovoltaic (PV) modules, drawing on field-measured current-voltage (I-V) data to model two distinct PV technologies under varying environmental conditions. The study employed Differential Evolution (DE) as the primary optimization algorithm, with Particle Swarm Optimization (PSO) serving as a benchmark, to extract parameters for Double-Diode Model (DDM). The DDM, despite its superior accuracy, brings with it a computational burden; therefore, finding a middle ground between precision and processing speed continues to be a critical area needing further exploration.

Even though this study offers an elaborate assessment of PV parameter estimation techniques, the following limitations apply: Environment Coverage, Quality of Data, Algorithmic Constraints, and Assumptions of the Model. These limitations are offset by extensive data preprocessing, datasheet benchmarking of PV module manufacturers, and prudent evaluation of algorithmic performance.

Generally speaking, the findings affirm the superiority of DE over PSO in terms of accuracy and convergence efficiency, with the DDM emerging**.**

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