



## Analytical Approach to the Modelling and Optimal Parameter Estimation of Photovoltaic Modules using the L4P Model and Excel Optimization Framework: An Empirical Study in Potiskum, Nigeria

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### ABSTRACT

Accurate parameter estimation of photovoltaic (PV) modules is a prerequisite for system prediction and optimization. This study proposes an L4P single-diode model parameter estimation method that integrates analytical parameter extraction, least-squares fitting, and the Generalized Reduced Gradient (GRG) nonlinear optimization algorithm implemented in Microsoft Excel, with an empirical validation in the arid region of Potiskum, Nigeria. The method extracts initial parameters from manufacturer datasheets, applies irradiance and temperature corrections, and then uses the GRG algorithm to simultaneously optimize the photocurrent, diode reverse saturation current, series resistance, and ideality factor. Experimental validation was conducted using an AP-PM-330W monocrystalline module and an array tester under irradiance levels of 560–860 W/m<sup>2</sup> and tool for PV system design, performance evaluation, and maximum power point tracking (MPPT).

### ARTICLE INFO

#### Article History

Received: April, 2026

Received in revised form: May, 2026

Accepted: August, 2026

Published online: September, 2026

### KEYWORDS

PV Modelling; L4P model; Parameter Estimation; Excel optimization; GRG Algorithm; Potiskum

### INTRODUCTION

The global PV industry continues to expand at a rapid pace. In 2025, global solar PV additions exceeded 600 GW for the first time, bringing cumulative installed capacity to approximately 2.8 TW, with solar PV accounting for more than three-quarters of new renewable capacity additions worldwide. PV deployment in sub-Saharan Africa has also accelerated, with Nigeria adding 803 MW in 2025—a 141% year-on-year increase—making it the second-largest PV market in Africa. However, approximately 96% of Nigeria's PV capacity is off-grid, reflecting structural deficiencies in the national grid's supply capacity.

Nigeria's solar resource endowment is favorable, with national solar radiation ranging from approximately 3.7 to 7.0 kWh/m<sup>2</sup>/day. Yet high-temperature environments impose significant constraints on PV performance. Paudyal and Imenes (2021) reported that PV efficiency decreases by approximately 0.03–0.05% per degree Celsius increase in temperature. In semi-

arid regions such as Yobe State, the combined effect of high ambient temperature and intense irradiance drives module operating temperatures well above standard test conditions, resulting in noticeable degradation of open-circuit voltage and output power.

Accurate mathematical models are fundamental tools for addressing these challenges. The four-parameter single-diode model (L4P) is widely adopted for its structural simplicity and its ability to effectively characterize the nonlinear I-V and P-V behavior of PV modules. However, parameter extraction presents inherent difficulties: in the SDM equation, the current appears simultaneously on both sides of the equation, forming an implicit transcendental equation, and the parameter space exhibits non-convex characteristics. Analytical methods rely on algebraic simplification and offer low computational cost but limited accuracy under certain operating conditions. Numerical iterative methods offer higher accuracy but are sensitive to initial values. Metaheuristic algorithms possess

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strong search capabilities but carry significant computational burden and produce stochastic results.

Recent research has shown a trend toward hybridization. Saadaoui et al. (2024) combined differential evolution with backtracking search optimization to improve parameter estimation stability under varying operating conditions. Calasan et al. (2024) obtained analytical solutions using the Lambert W function and coupled them with optimization methods, balancing computational efficiency and accuracy. The review by Pedroza-Díaz et al. (2025) indicated that explicit formulation of implicit equations reduces implementation difficulty and is suitable for rapid simulation and real-time estimation scenarios. In the domestic research context, parameter extraction methods based on swarm intelligence and hybrid strategies have also been widely explored in the field of PV modeling.

Against this research backdrop, a question worth examining is whether a parameter estimation pathway exists that maintains sufficient accuracy while avoiding dependence on complex external software for resource-constrained application scenarios. The Solver tool built into Microsoft Excel provides GRG nonlinear optimization capability, and its widespread availability and transparent interface may offer a practical alternative for PV parameter identification. Kemmer and Keller (2010) demonstrated the feasibility of Excel for nonlinear least-squares fitting, but systematic application to the L4P PV model with empirical validation in arid regions remains insufficiently explored.

The objectives of this study are to develop and validate an Excel-based L4P analytical-optimization parameter estimation framework, using Potiskum, Nigeria, as the empirical scenario; to examine the prediction accuracy and convergence robustness of this framework under single-module and series configurations; and to discuss the findings in comparison with recent parameter extraction methods reported in the literature.

## LITERATURE REVIEW

### The Methodological Spectrum of PV Parameter Extraction

PV parameter extraction methods can be grouped into three major categories: analytical methods, numerical optimization methods, and metaheuristic search methods. Analytical methods rely on key-point information from manufacturer datasheets (short-circuit current, open-circuit voltage, maximum power point) to solve parameters through algebraic equations. The five-parameter analytical extraction model developed by De Soto et al. (2006) was integrated into NREL's System Advisor Model (SAM) and has become one of the industry benchmarks.

The adaptive analytical extraction method proposed by Feng et al. (2024) achieved low RMSE values across single-diode, double-diode, and triple-diode models, validating the feasible balance between efficiency and accuracy that analytical methods can achieve. However, analytical methods face inherent difficulties when parameters are highly coupled or when the transcendental nature of the equations is significant. Wang et al. (2024) pointed out that significant coupling exists among the reverse saturation current, series resistance, and ideality factor, making independent analytical solutions difficult to guarantee global optimality.

Numerical optimization methods estimate parameters by iteratively minimizing an objective function (typically the sum of squared residuals between measured and model currents). Nautiyal et al. (2024) applied the Levenberg-Marquardt method to a five-parameter model and effectively estimated the maximum power point from module characteristics. The advantage of numerical methods lies in their theoretical maturity and analyzable convergence behavior, but initial-value sensitivity is their primary limitation. Souaidi et al. (2026) improved the convergence stability of the single-diode model by combining analytical equations with Regula-Falsi iteration, demonstrating that coupling analytical and numerical approaches is an effective strategy for mitigating initial-value dependence.



Metaheuristic algorithms have become a research hotspot in recent years due to their gradient-free nature and global search capability. Particle swarm optimization, genetic algorithms, differential evolution, and their variants have been widely applied in PV parameter extraction. The hybrid differential evolution/backtracking search algorithm of Saadaoui et al. (2024) demonstrated improved estimation accuracy under varying operating conditions. However, the inherent stochasticity of metaheuristic methods causes results to fluctuate across runs, and convergence speed often decreases near the global optimum. A comparative study presented at an IEEE conference in Troyes (2025) found that under standard test conditions, metaheuristic methods achieved the lowest RMSE ( $2.7 \times 10^{-2}$ ), but this advantage came at the cost of significantly increased computational cost and implementation complexity.

#### The Position of the Four-Parameter Model

Within the continuum of single-diode, double-diode, and triple-diode models, the four-parameter L4P model reduces the number of parameters to be estimated from five to four photocurrent  $I_{ph}$ , reverse saturation current  $I_0$ , series resistance  $R_s$ , and ideality factor  $\alpha$ , by neglecting the shunt resistance term (assuming  $R_{sh} \rightarrow \infty$ ). This simplification is acceptable for most crystalline silicon modules because modern manufacturing processes typically yield sufficiently large shunt resistances whose effects are negligible within the normal operating voltage range.

The appeal of the L4P model lies in improved parameter identifiability. In the five-parameter model, partial redundancy exists among  $R_s$ ,  $I_0$  and  $\alpha$ , which can lead to multiple nearly equivalent residual minima in the optimization landscape. Reducing one degree of freedom helps mitigate this issue. Orioli et al. (2013) demonstrated that simplified models can effectively characterize PV behavior when manufacturers provide only basic datasheet information. The selection of L4P in this study is based on this methodological consideration.

#### Research Gaps

The existing literature has shortcomings in the following respects. First, most high-accuracy methods rely on MATLAB, Python, or specialized optimization software, which imposes certain requirements on equipment conditions and user technical proficiency. Second, although the fusion of analytical and numerical methods has proven effective, research implementing this fusion on the Excel platform is relatively scarce, despite Excel's accessibility in engineering education and field practice being far higher than that of specialized computational platforms. Third, empirical modeling studies targeting PV systems in Nigeria's arid regions are relatively lacking. The climatic characteristics of the Potiskum area high irradiance, high temperature, and significant seasonal fluctuations provide representative test conditions for model validation.

#### METHODOLOGY

##### Model Selection and Theoretical Basis

The single-diode equivalent circuit of a PV cell consists of a photocurrent source, a parallel diode, a series resistance  $R_s$ , and a shunt resistance  $R_{sh}$ . In the L4P model,  $R_{sh}$  is neglected, and the current output equation is:

$$I = I_{ph} - I_0 \left[ \exp \left( \frac{V + IR_s}{nV_t} \right) - 1 \right] \quad (1)$$

where  $\alpha = nN_s V_t$  is the modified ideality factor and  $V_t = k_B T / q$  is the thermal voltage.

Where  $k_B$  is the Boltzmann constant ( $1.38065 \times 10^{-23}$  J/K),  $T$  is the cell temperature in Kelvin (K), and  $q$  is the electron charge ( $1.60218 \times 10^{-19}$  C). The implicit nature of Equation (1) means that the output current  $I$  appears simultaneously on both sides of the equation, necessitating iterative solution.

A PV cell can be understood as a parallel combination of a "light-controlled current pump" and a "one-way valve" (diode). The photocurrent  $I_{ph}$  represents the total pumped current, while the diode allows a portion of the current to "leak" back under forward bias. The series resistance  $R_s$  acts like friction loss in a pipe,



causing the effective output voltage to be lower than the ideal value. The simplification of the L4P model lies in assuming that the "pipe sidewalls" (shunt resistance) are sufficiently sealed and that leakage can be neglected.

### Parameter Extraction Procedure

Parameter extraction is divided into three stages:

**Stage One:** STC analytical initial estimation. Using the manufacturer data sheet values of  $I_{sc,STC}$ ,  $V_{oc,STC}$ ,  $I_{mp,STC}$ ,  $V_{mp,STC}$ , and temperature coefficients, initial values for the four parameters are obtained through standard analytical relationships.  $I_{ph,STC} \approx I_{sc,STC}$ . The initial ideality factor is taken in the range of 1.2–1.5 (typical for crystalline silicon). The initial  $R_s$  value is approximated from the maximum power point condition.  $I_0$  is back-calculated from the open-circuit condition where  $I = 0$ .

**Stage Two:** Environmental correction. The STC parameters are corrected according to measured irradiance  $G$  and temperature  $T$ :

$$I_{ph} = [I_{ph,STC} + K_I(T - T_{STC})] \frac{G}{G_{STC}} \quad (2)$$

$$a(T) = \frac{\alpha_{STC}}{T \cdot T_{STC}} \quad (3)$$

$$I_0 = I_{0,STC} \left( \frac{T}{T_{STC}} \right)^3 \exp \left[ \frac{qE_g}{nk} \left( \frac{1}{T_{STC}} - \frac{1}{T} \right) \right] \quad (4)$$

(Where  $E_g$  is the material's bandgap energy, roughly 1.12 eV for silicon). The temperature dependence of  $R_s$  is weak and is approximately held at the STC value.

**Stage Three:** GRG optimization refinement. Using the analytical estimates as initial values, an objective function (sum of squared residuals) is constructed in Excel, and the Solver's GRG nonlinear engine is invoked to simultaneously optimize the four parameters. The objective function is:

$$SSE = \sum_{k=1}^N [I_{meas,k} - I_{model,k}(p)]^2 \quad (5)$$

Where  $p = [I_{ph}, I_0, R_s, a]^T$ . For each voltage sampling point, the model current

$I_{model,k}$  is obtained by internally iterating Equation (1).

If parameter estimation is likened to "tuning an instrument," the analytical stage provides the "approximate pitch," and the GRG optimization is the "fine tuning." The analytical initial values place the optimizer in a reasonable region near the optimal solution, avoiding convergence to local optima or physically unrealistic parameter values that can result from starting at random initial values.

### Experimental Setup

The experiment employed a Sunshine Solar AP-PM-330W monocrystalline silicon module (72 cells in series, nominal power 330 W) and an array tester for outdoor I-V and P-V characteristic measurements. Measurements were conducted under actual meteorological conditions in the Potiskum area (11.71°N, 11.08°E, elevation 427 m). The operating conditions covered by the tests were: irradiance 560–860 W/m<sup>2</sup>, ambient temperature 26–37°C. For series configuration validation, two and four modules were connected in series and the measurements were repeated. Data quality was ensured through the following measures: measurements were taken during periods of stable irradiance; irradiance, ambient temperature, and I-V curves were recorded for each valid data set; and the same tester and calibrated sensors were used throughout to ensure consistency.

## RESULTS AND DISCUSSION

### Single-Module Model Validation

Figures 1 and 2 present comparisons of I-V and P-V curves for the AP-PM-330W under typical operating conditions. The model predictions show good agreement with measured data in all three key regions: short-circuit current, open-circuit voltage, and maximum power point.

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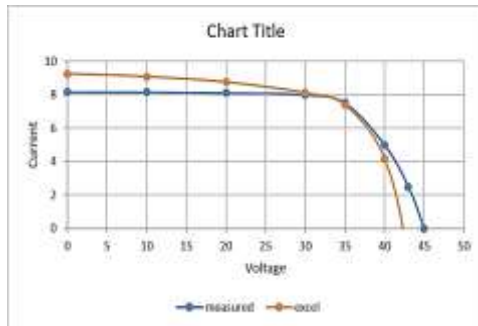


Fig. 1. PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet model.

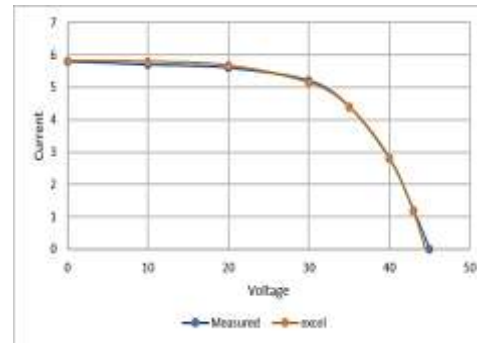


Fig. 4. PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet model.

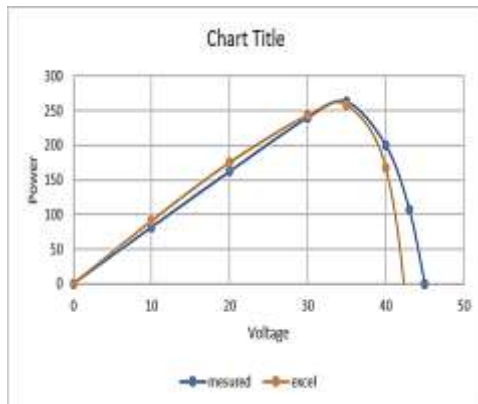


Fig. 2. PV module AP-PM-330W P-V curves for measurements and the L4P Excel worksheet at 860W/m<sup>2</sup> and 37°C.

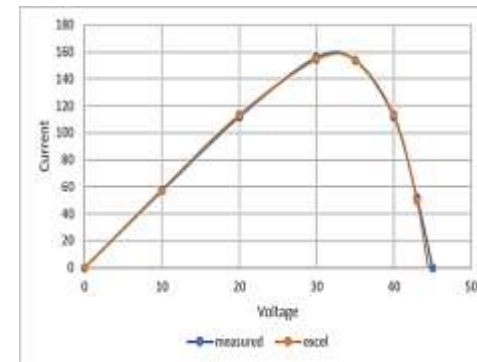


Fig. 5. PV module AP-PM-330W P-V curves for the experimental measurements and the L4P Excel worksheet at 690W/m<sup>2</sup> and 36°C.

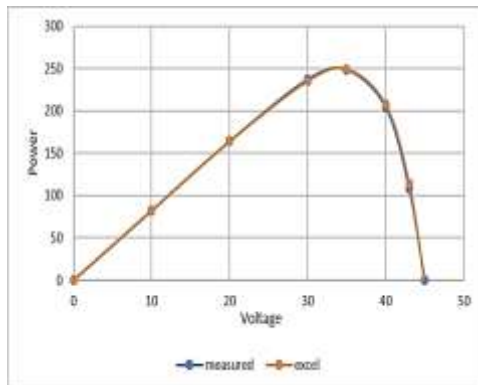


Fig. 3. PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet model.

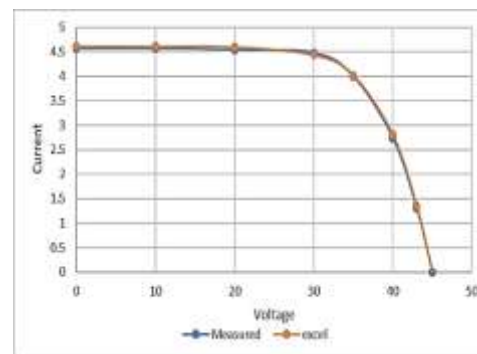


Fig. 6. PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet model.

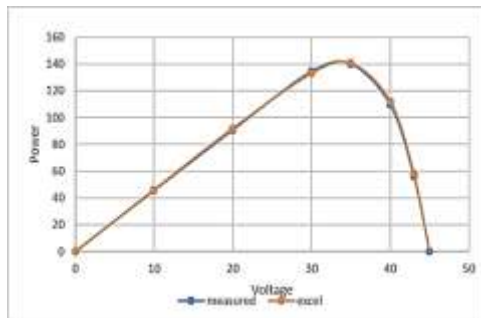


Fig.7 PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet at 560 W/m<sup>2</sup> and 26°C. measurements and the L4P Excel worksheet at 560 W/m<sup>2</sup> and 26°C

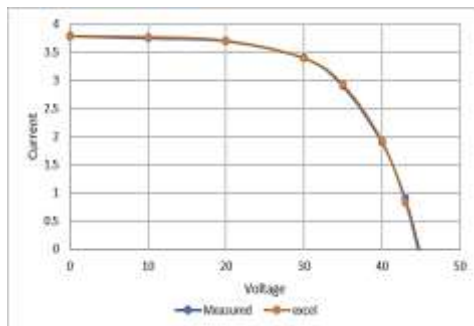


Fig.8 PV module AP-PM-330W P-V curves for the experimental measurements and the L4P Excel worksheet at 560 W/m<sup>2</sup> and 26°C

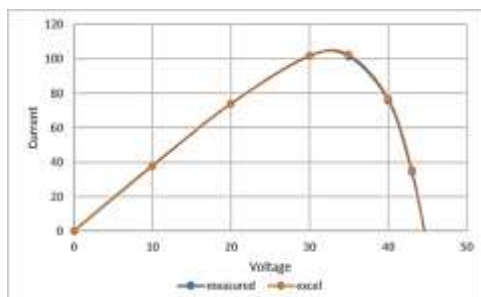


Fig.9 PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet at 450 W/m<sup>2</sup> and 34°C measurements and the L4P Excel worksheet at 450 W/m<sup>2</sup> and 34°C

drops sharply, reflecting the enhanced diode shunt effect. The L4P model accurately captures the position and steepness of this "bend," indicating that its parameter estimates capture the core electrical characteristics of the module.

Under irradiance of 860 W/m<sup>2</sup> and temperature of 37°C, the model's maximum power prediction deviation is less than 3%. This accuracy is comparable to the performance reported by De Soto et al. (2006) for similar datasheet-parameter models under similar operating conditions. Notably, as irradiance decreases from 860 to 560 W/m<sup>2</sup>, model accuracy remains stable, indicating that the environmental correction equations effectively handle the linear scaling effect of irradiance variation on  $I_{ph}$ .

### Scalability Validation Under Series Configuration

Figures 10 through 15 present validation results for 2-series and 4-series configurations. Validation under series configurations has important practical significance: it examines the parameter transferability of the model under voltage-multiplication scenarios, that is, whether the L4P parameters of a single module, after voltage extension, can accurately predict the behavior of multiple modules in series.

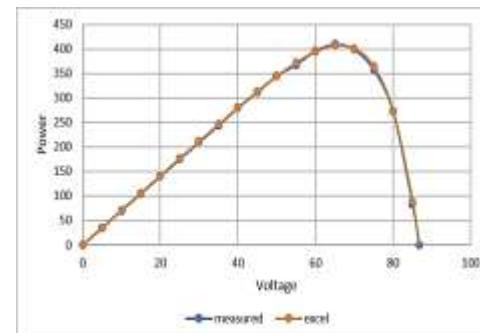


Fig. 10: Two series PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet at 860W/m<sup>2</sup> and 37°C

The I-V curve is approximately horizontal in the low-voltage region, indicating that photocurrent dominates; after the knee point, it

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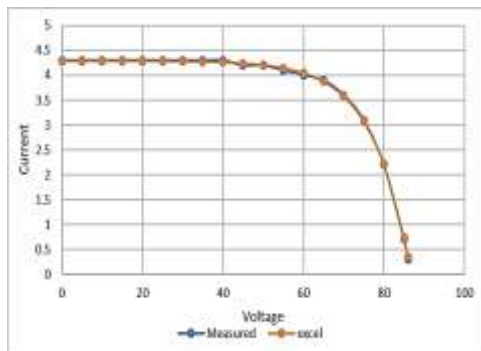


Fig. 11 Two series PV module AP-PM-330W P-V curves for experimental measurements and the L4P Excel worksheet at 860W/m<sup>2</sup> and 37 °C

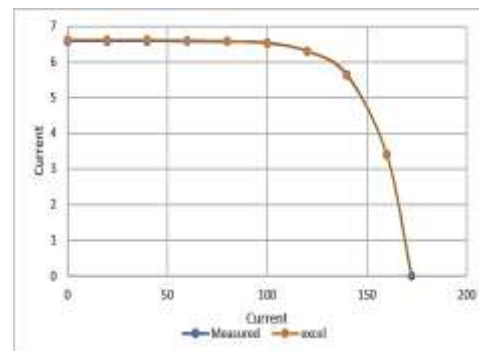


Fig. 14 Four series PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet at 690W/m<sup>2</sup> and 36 °C

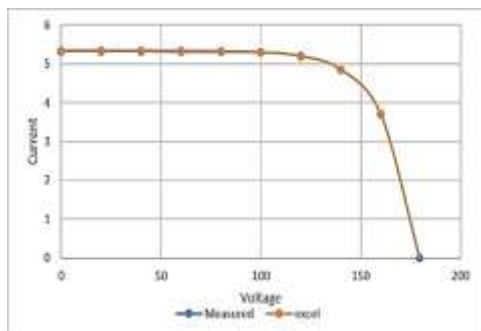


Fig. 12 Four series PV module AP-PM-330W I-V curves for the experimental measurements and the L4P Excel worksheet at 560W/m<sup>2</sup> and 26 °C

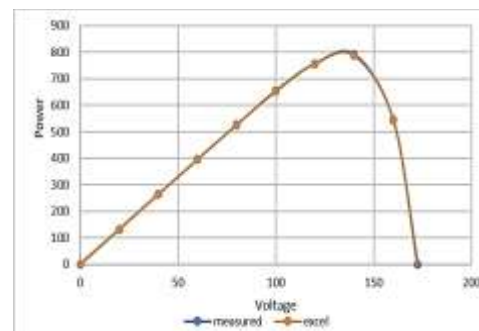


Fig. 15 Four series PV module AP-PM-330W P-V curves for the experimental measurements and the L4P Excel worksheet at 690W/m<sup>2</sup> and 36 °C

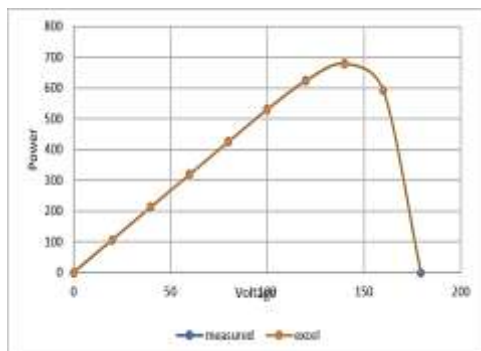


Fig. 13 Four series PV module AP-PM-330W P-V curves for the experimental measurements and the L4P Excel worksheet at 560W/m<sup>2</sup> and 26°C

When modules are connected in series, the current must pass through all modules, so the current limit is determined by the worst-performing module. The model assumes identical parameters for all modules (same batch, same orientation, no partial shading). Under this assumption, series connection affects only the voltage dimension while current characteristics remain unchanged. The close agreement between measurements and predictions confirms the reasonableness of this assumption under the current experimental conditions.

For the 4-series configuration (Figures 12–15), the model-maintained prediction accuracy under combinations of 560 W/m<sup>2</sup> and 690 W/m<sup>2</sup> with 26°C and 36°C. The additive effect on open-circuit voltage was correctly captured, and errors in the position and magnitude of the maximum

power point were within acceptable limits. This result supports the scalability claim of the methodology.

### Convergence Characteristics and Parameter Robustness

Figure 16 shows the RMS residual convergence curves for the four parameters during optimization. Each parameter's convergence curve exhibits a clear U-shape or V-shape, indicating the existence of a unique residual minimum region and stable convergence of the GRG algorithm to that region.

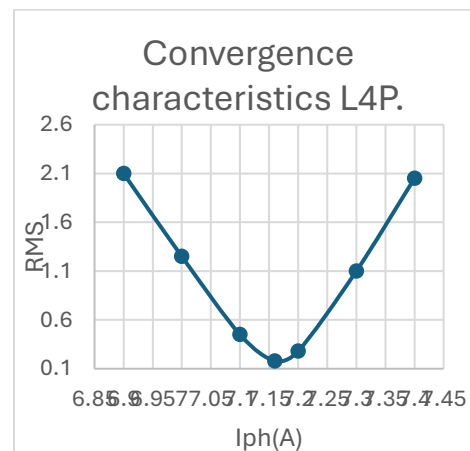
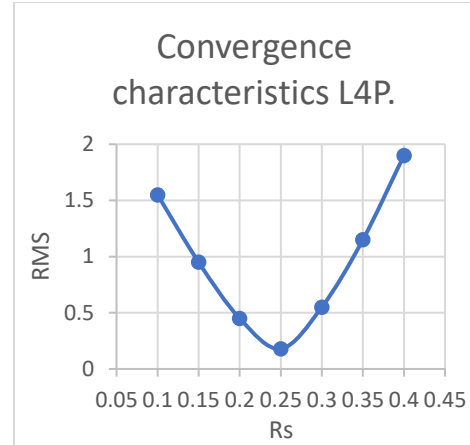
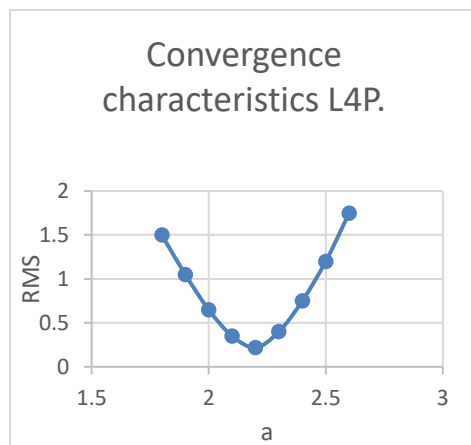
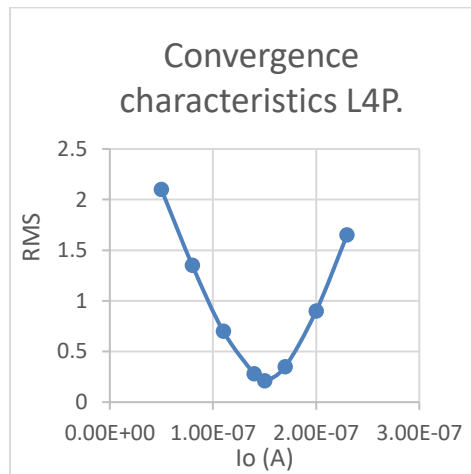


Fig. 16 Convergence characteristics L4P

Figure 16 (a)(b)(c) and (d), illustrates the convergence characteristics of the estimated L4P parameters for the AP-PM-330W monocrystalline photovoltaic module series. The sharper the "valley bottom" of the convergence curve, the better the parameter identifiability. The convergence curves for  $R_s$  and  $a$  are relatively flat, indicating lower sensitivity of residuals to parameter perturbations, this reflects the "identifiability trade-off" caused by parameter coupling certain combinations of  $R_s$  and  $a$  can produce similar I-V curves, so their individual estimates may carry some uncertainty, but the combined effect is constrained at the model prediction level.



Compared with metaheuristic methods in the literature, GRG achieves comparable accuracy while significantly reducing computational burden. The Levenberg-Marquardt method of Nautiyal et al. (2024) achieved similar convergence stability in a five-parameter model but required approximation of the Jacobian matrix; the analytical initial-value strategy of this study provides GRG with more favorable starting conditions than random initialization.

### Comparison with Recent Literature

A comparative study published at an IEEE conference in Troyes (2025) reported that metaheuristic methods achieved the lowest RMSE of  $2.7 \times 10^{-2}$  (after normalization) in SDM parameter estimation. The GRG framework of this study achieved normalized RMSE values of the same order of magnitude within the experimental operating range, but with far lower computational resource requirements than swarm intelligence algorithms. This comparison indicates that classical gradient optimization remains competitive when initial value quality is assured. The hybrid differential evolution/backtracking search method of Saadaoui et al. (2024) is noteworthy for its adaptability under varying operating conditions, but its algorithmic complexity involves population management and mutation strategy parameter tuning. The "analytical initial value + GRG" strategy of this study achieves comparable engineering accuracy with a lower implementation threshold.

One limitation that must be acknowledged is that the GRG method itself does not guarantee global search. Under extreme weather conditions (such as unusual combinations of high irradiance and low temperature), the analytical initial values may deviate significantly from the optimal region, and GRG risks convergence to local optima. This risk is partially mitigated through multi-start testing but cannot be completely eliminated methodologically. For applications requiring strict global optimality guarantees, metaheuristic or hybrid strategies remain the more robust choice.

### CONCLUSION

This study proposed and validated an Excel-based L4P PV model parameter estimation framework, using the arid region of Potiskum, Nigeria, as the empirical scenario. The main findings are as follows:

1. The coupling strategy of analytical initial estimation and GRG optimization achieved high-accuracy prediction of I-V and P-V curves under irradiance of 560–860 W/m<sup>2</sup> and temperatures of 26–37°C, validating the effectiveness of the environmental correction equations.
2. Series configuration validation demonstrated that L4P parameters have good transferability under voltage-extension scenarios, supporting the feasibility of applying the method at the PV array scale.
3. Convergence analysis confirmed the stability of GRG optimization under reasonable initial value conditions, while revealing the inherent identifiability limitations caused by coupling between  $R_s$  and  $a$ .
4. Comparison with recent metaheuristic methods showed that this framework maintains engineering-acceptable accuracy while significantly reducing computational burden and implementation complexity, making it suitable for scenarios with limited equipment conditions or requiring a transparent parameter identification process.

Future work directions include extending the framework to the five-parameter model to evaluate the effect of shunt resistance under low-irradiance conditions; introducing multi-start strategies to enhance the global convergence guarantee of GRG; and conducting long-term validation across multiple seasons to examine the model's adaptability under a broader range of meteorological conditions.



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