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Research Article

Development of a MATLAB App designer for determining solar panel parameters using nonlinear optimization algorithm

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Abstract
The developed framework is focused on determining the intrinsic parameter values of a solar photovoltaic (PV) panel, which are unavailable in the data sheet and play a very essential role in determining the panel's performance. Comprehensive mathematical equations are derived for the Single diode model (SDM) based on three distinct operating points from the manufacturer's data sheet for a solar PV panel. To determine the intrinsic parameter values of a solar PV panel, the Newton-Rhapson (NR) -algorithm is employed in MATLAB. To justify the robustness and validate the proposed NR-algorithm prototype, an experimental dataset of two different technologies, i.e., a Radiotechnique Compelec (RTC) France monocrystalline silicon solar cell and a polycrystalline SPR6-120/36 silicon solar panel, was considered and compared with the simulated data. The proposed Newton-Raphson-based framework showed excellent agreement with experimental data. In the case of monocrystalline module, Root Mean Square Error (RMSE) was 0.00086068 and NSE was 0.9999, whereas for polycrystalline panel, RMSE was 0.016907 and Nash–Sutcliffe Efficiency (NSE) was 0.99979. These low RMSE and high NSE values show that the method's prediction accuracy and robustness are strong. This work presents a deterministic NR-based parameter estimation framework for a single-diode PV models, in which explicit nonlinear equations and physically meaningful constraints were used to ensure stable and reliable parameter extraction. A MATLAB App Designer-based implementation of the proposed methodology is also provided, which supports practical deployment and reproducibility. Accurate photovoltaic parameter estimation enables accurate prediction of solar panel energy production, enabling efficient system design and integration into the grid, increasing the share of renewable energy and reducing dependence on fossil fuels, thereby contributing to greenhouse gas emission and climate change mitigation.

Keywords: MATLAB App, NR-optimization algorithm, Parameters estimation, PV modelling, Solar Panel

INTRODUCTION

In the year of global climate change, as fossil fuels are rapidly depleting, renewable energy has emerged as an alternative source for power generation. Use of renewable energy has increased by 42% over the last decade, according to the Renewable Energy Market Update (International Energy Agency, 2023). Solar photovoltaic (SPV) added about 602 GW of new capacity in 2024, accounting for 81% of global renewable energy growth and making it the fastest growing renewable technology. This makes it clear that solar energy will play a fundamental role in the development of clean energy, and that solar PV and storage will be the key means to achieve the renewable energy target by 2030 (Gluzman, 2025).

A numerical estimation technique using MATLAB was introduced by Cheddai *et al.* (2021) to determine the five intrinsic parameters of a solar PV module. Under varying environmental conditions, polycrystalline and monocrystalline modules are tested and provide accurate and satisfactory results. To estimate the five parameters for a single diode model, an iterative method is proposed.

An m-code has been developed for the iterative method. On simulation, minimum error with high accuracy and efficiency is obtained under variable environmental conditions (Stornelli *et al.*, 2019). As referenced in Ali and Kazmi (2020), the fsolve function is utilized to quantify the unknown quantities of a solar PV module. The results achieved are almost accurate, and the RMSE of 3.68 × 10^-3 is lower than the previous approaches for both the cases provided in (Easwarakhanthan *et al.*, 1986). A simple, reliable, and innovative technique has been developed for a single-diode model based on the data sheet's information. The simulated values compare with experimental data and are evaluated as the closest to the actual values (Gnetchejo *et al.*, 2021). An m-code based on the Particle Swarm Optimisation (PSO) algorithm was developed and implemented, matched with other effective algorithms, and the results were found to be very close to the experimental data, providing an effective alternative solution (Nashoor *et al.*, 2022). Recently, bio-inspired swarm optimization techniques, such as the Dandelion Optimisation Algorithm (DOA), have been successfully applied to SDM and DDM parameter extraction, yielding very low errors and strong statistical consistency (Vais *et al.*, 2023). Alluhaidan *et al.* (2025) proposed an improved Sinh cosh optimizer with trigonometric operators for PV parameter estimation in Single diode model (SDM), Double diode model (DDM) and Triple diode model (TDM) models, demonstrating superior RMSE performance and enhanced convergence stability across multiple PV datasets.

Although numerous metaheuristic optimization techniques such as PSO, Adaptive Differential Genetic Evolution (ADGE), Fitness Distance Balance – Stochastic Fractal Search (FDB-SFS), and hybrid bio-inspired algorithms have demonstrated strong global search capability, these approaches inherently rely on stochastic population-based search mechanisms, resulting in increased computational overhead and lack of repeatable convergence behaviour. Liu *et al*. (2023) proposed a Boosting Flower Pollination Algorithm (BFPA) for accurate parameter estimation of single and double-diode models, demonstrating improved convergence stability and lower RMSE than several existing metaheuristic techniques. Advanced swarm-based optimizers such as the Artificial Hummingbird technique (AHT) have also been proposed for SDM and DDM parameter extraction, demonstrating strong global search performance and improved RMSE convergence across different PV modules (El-Sehiemy *et al.,* 2023). However, such metaheuristic approach inherently depends on population-based stochastic search mechanism, which increases computational efforts and reduce deterministic reproducibility. Moreover, performance often depends on parameter tuning and random initialization (Bakır, 2023). In reference (Nautiyal *et al.*, 2024), deterministic solvers such as Levenberg-Marquardt (LM) technique and fsolve-based approach provide faster convergence but suffers from sensitivity to initial conditions and lack explicit formulation transparency when implemented as black-box solvers. A comprehensive review and datasheet-based parameter estimation using the MATLAB 'fsolve' routine has also been reported, highlighting the systematic formulation of nonlinear equations for SDM and DDM models (Kamal R *et al.,* 2023). Therefore, there exists a need for a mathematically explicit, reproducible, and computationally efficient deterministic framework for low-dimensional PV parameter estimation problems. The present work addresses this gap by formulating an analytically derived NR-based nonlinear system with physically constrained initialization to ensure stable and repeatable convergence. Ndegwa *et al.*(2020), proposed a fast analytical method for extracting the five parameters of the single-diode model directly from manufacturer datasheet information, demonstrating high accuracy with reduced computational complexity. At the same time, datasheet-based simple techniques give good results even on reduced data, making it clear that the direction of PV parameter estimation is now moving towards intelligent and optimization-based methodologies (Rawa *et al.*, 2022; Duan *et al.*, 2023; Singla *et al.*, 2023; Rathod and Subramanian, 2024; Charu *et al.*, 2024).

Many researchers have used metaheuristic algorithms, but studies have revealed that the Newton–Raphson (NR) algorithm is a reliable due to its simplicity, stable convergence, and accuracy. Based on this, recent work has developed a MATLAB program to effectively identify PV cell parameters. (Adak *et al.*, 2023).

The motivation for the present work was to present a comprehensive approach for developing a MATLAB App to determine intrinsic parameter values embedded in solar PV modules, and to conduct a comparative assessment of the practicality and structure of implementation of MATLAB App-based software platforms. Ultimately, the MATLAB App aimed to facilitate the practical adoption and use, as well as the reproducibility, of PV parameter extraction methods.

MATERIALS AND METHODS

Basics of solar PV cell/module

The term 'photo' represents the photons or light, and the term 'voltaic' means producing a direct electric current by chemical functioning, ignoring the loss mechanism. A device that converts the solar energy in photons directly into electrical energy is called a photovoltaic (PV) cell. An electrical equivalent circuit prototype model is utilized to explain the behaviour of an ideal SPV cell. This model includes a constant current source (CCS) in parallel with the diode. This CCS represents the photo-generated current $\mathbf{I_{ph}}$ as shown in Fig. 1, and this current $\mathbf{I_{ph}}$ is proportional to the incident solar energy.

Concept of five undefined parameters: I_{ph}, I_s, R_s, R_p & m

a) Photo-generated current (I_{ph}):

The constant current source (CCS) signifies that the photo-generated current (I_{ph}) is essentially proportional to the incident solar power and temperature. The short-circuit current (I_{sc}), cell operating temperature (T_c), and solar irradiation are all factors that affect the photos generated current and is expressed as (1)

$$I_{Ph} = \{I_{SC} + k_i(T_C - T_{ref})\}\frac{G}{G_n} \tag{1}$$

where, k_i: short-circuit temperature coefficient expressing the change of light flux with temperature, I_{sc}: short-circuit current on reference temperature (T_{ref}), G : solar irradiation in W/m^2, and G_n : solar irradiation level normalized to 1000 W/m^2.

If, T_c=T_{ref} and G=G_n, then the photo-generated current can also be called a short-circuit current I_{ph} =I_{sc}.

b) Diode current (I_d) and reverse saturation current (I_{rs})

In absence of solar irradiance, the SPV cell performs like a diode and the diode current I_d that can flow through the diode expressed in (2):

$$I_d = I_{rs}\left(\exp\left(\frac{q.V_d}{K.T_c\,.m}\right) - 1\right) \tag{2}$$

As per p-n junction theory, the term 'I_{rs}' is called reverse saturation current and is a measure of the recombination in a diode. V_d is the diode voltage in volts. The diode saturation current (I_s) is inversely proportional to the significant quantity and directly proportional to temperature T_c and expressed as (3):

$$I_s = K_a.T_c^x.\exp\left(\frac{-V_{GO}}{m.V_T}\right) \tag{3}$$

Such that, K_a is a constant depending upon the dimension of p-n junction and material properties.V_{G0} is the equivalent band gap energy in electron volt (eV) that ranges from 1.16 to 1.21 for Silicon & x = 1.5 for Silicon.

Equation (4) can also be used to express the diode saturation current I_s.

$$I_s = \frac{I_{sc} + k_i\Delta T}{\exp\left(\frac{V_{oc} + k_i\Delta T}{m.V_t}\right) - 1} \tag{4}$$

Here, V_{oc} is the open circuit voltage of a solar PV panel. K_i: temperature coefficient of short circuit current in A/°C. V_t is volt equivalent of temperature of thermal voltage and is given as:

$$V_t = \frac{K * T_c}{q} = \frac{T_c}{11600} \tag{5}$$

At room temperature, T=300 °K, Vt=26mV,

Here, q: electron's charge and, K: Boltzmann's constant.

c) Ideality factor (m)

The "m" term is called the ideality factor, which depends on the material. Its approximate value for silicon is about 2 (Millman and Halkias, 2010), and it varies across semiconductors; see Table 1 of (Bellia *et al.*, 2014). According to Shockley's diode theory, the value of *'m'* should be 1 in an ideal situation. However, in practice, a value of *'m'* greater than 1 becomes necessary to accommodate imperfections introduced during the manufacturing process. Adjusting the diode factor's value exerts a pronounced impact, especially within the region of the current-voltage curve mentioned as 'knee,' where the maximum power point P_{max} is located.

d) Series resistance (R_s)

Series resistance refers to the intrinsic resistance of the semiconductor layer used in the manufacturing of SPV cells. Depending upon temperature and the nature of the semiconductor layer, the intrinsic resistance of the internal material may vary accordingly. It also signifies the electrical contact between the cell and the wire leads. The effect of series resistance on an SPV cell can be significant. When the output current (I) passes through, there is a voltage drop across the terminal. Due to this voltage drop, the terminal voltage of the PV cells decreases, thereby reducing conversion efficiency and fill factor.

e) Parallel resistance (R_p)

Many factors, such as manufacturing defects, impurities, pollution, and microcracks in the semiconductor material, can cause parallel resistance in PV cells. Parallel resistance refers to an undesirable parallel path or leakage effect that impedes the flow of electric current. If the parallel resistance of the SPV cell is extremely low, the current will flow largely through this low-resistance path, thereby reducing efficiency and potential performance. Excessive electric current flows due to low parallel resistance can cause potential damage to the hotspot and the cell. Therefore, high-quality materials are used in the manufacture of PV cells, thereby increasing the parallel resistance and improving overall performance and efficiency.

Electrical equivalent circuit of an ideal SPV cel

From Fig.1, SPV cell current (I) is obtained as

$$I = I_{Ph} - I_d \tag{6}$$

$$I = I_{Ph} - I_{rs}\left(\exp\left(\frac{V_d\, q}{m\, K\, T_c}\right) - 1\right) \tag{7}$$

Equation (7), represents for an ideal SPV cell.

But in an actual solar PV cell, when considering the IV characteristic of a typical photovoltaic cell, it is observed that a portion of the IV characteristic, the photovoltaic cell behaves like a constant current source (CCS), while another portion behaves like a more or less constant voltage source (CVS), as shown in the Fig. 2.

So, the SPV cell has the unique feature of combining a CVS and a CCS. The dotted horizontal and vertical line represents the constant-current (CC) and constant-voltage (CV) line, respectively. These lines provide insight into the slope of a constant-current portion, implying the existence of parallel resistance (R_p) with high resistance across CCS, shown in Fig. 2. Similarly, the slope of the voltage line portion of the characteristics implies a series resistance (R_s) in series with the terminals. Fig. 3. illustrates an electrical equivalent circuit model of a SPV cell with the inclusion of R_s and R_p

Expression for output current of an actual solar photovoltaic (SPV) cell/ module/ array

From Fig. 3,

$$\text{Voltage at node A} = V + IR_s \tag{8}$$

$$\text{Voltage across diode } (V_d) = V + IR_s \tag{9}$$

$$I_{R_p} = \frac{V + IR_s}{R_p} \tag{10}$$

The SPV cell current can be modified as:

$$I = I_{ph} - I_d - I_{R_p} \tag{11}$$

$$I = I_{ph} - I_{rs}\left(\exp\left(\frac{(V + IR_S)q}{m\, K\, T_c}\right) - 1\right) - \left(\frac{V + IR_S}{R_p}\right) \tag{12}$$

Using equation (5) in equation (12)

$$V_t = \frac{K.\ T_c}{q}$$

Equation (12) modified as,

$$I = I_{ph} - I_{rs}\left(\exp\left(\frac{(V + IR_S)}{m\, V_t}\right) - 1\right) - \left(\frac{V + IR_S}{R_p}\right) \tag{13}$$

Let,

$$V_T = m.V_t \tag{14}$$

V_T is defined as the modified ideality factor (Chouder *et al.*, 2012).

Therefore, equation (13) expressed as:

$$I = I_{ph} - I_{rs}\left(\exp\left(\frac{(V + IR_S)}{V_T}\right) - 1\right) - \left(\frac{V + IR_S}{R_p}\right) \tag{15}$$

If R_s and R_p are neglected, the equation (15) will become, and the output PV solar current for an ideal cell will be given as:

$$I = I_{ph} - I_{rs}\left(\exp\left(\frac{V}{V_T}\right) - 1\right) \tag{16}$$

A single cell can produce a maximum voltage of up to 0.5 V to 0.8 V, which is very low voltage to supply the electrical loads. To meet the requirements of an electrical load, cells are typically arranged in series, parallel, or both arrangements to provide the required voltage and current. These arrangements constitute a module, and the modules are interconnected in a series-parallel configuration to form a solar PV array. Let, N_s and N_p are number of series and parallel connected cells, then the output SPV cell current is modified as:

$$I_{array} = N_p I_{ph} - N_p I_{rs}\left(\exp\left(\frac{\frac{V}{N_s} + I\frac{R_s}{N_p}}{V_T}\right) - 1\right) - \left(\frac{\frac{V}{N_s} + I\frac{R_s}{N_p}}{R_p}\right) \tag{17}$$

Mathematical modelling: Formulation of nonlinear equations

The electrical parameters under STC are provided in the solar module datasheet, including I_{sc}, V_{oc}, V_{mpp}, K_i and temperature coefficient of open voltage (kv) in $V/°C$ in . These parameters are located on the IV and PV characteristic curves, shown in Fig. 4, and are the remarkable points used to derive the first three equations of a PV module.

To determine the unidentified parameter values of a single diode model SPV module, further analysis of these remarkable data points is carried out as:

1. Open-Circuit Point (OCP) at point 'a':

here, $V = V_{oc}$ and $I = 0$ putting these values in equation (16) expressed as (18)

$$I_{Ph} = I_{rs}\exp\left(\frac{V_{oc}}{V_T}\right) - I_{rs} + \frac{V_{oc}}{R_p} \tag{18}$$

2. Short-Circuit Point (SCP) at point 'b':

here, $V = 0$ and $I = I_{sc}$, putting these values in equation (15) expressed as (19)

$$I_{sc} = I_{Ph} - I_{rs}\exp\left(\frac{I_{sc}R_s}{V_T}\right) + I_{rs} - \frac{I_{sc}R_s}{R_p} \tag{19}$$

3. Maximum Power Point (MPP) at point 'c':

here, $V = V_{mpp}$ and $I = I_{mpp}$, putting these values in equation (15) expressed in (20)

$$I_{mpp} = I_{Ph} - I_{rs}\exp\left(\frac{V_{mpp} + I_{mpp}R_s}{V_T}\right) + I_{rs} - \left(\frac{V_{mpp} + I_{mpp}R_s}{R_p}\right) \tag{20}$$

Equations (15), (18), (19) and (20) are utilized to obtain equations (21), (22) and (23), which are the three crucial equations.

$$V_T = \frac{V_{mpp} + I_{mpp}R_s - V_{oc}}{\ln\left(\frac{I_{sc}R_p + I_{sc}R_s - I_{mpp}R_p - V_{mpp} - I_{mpp}R_s}{I_{sc}R_p + I_{sc}R_s - V_{oc}}\right)} \tag{21}$$

However, the actual expression does not contain the V_{oc} term and also does not have a repeated $I_{mpp}R_s$ term in the denominator for the expression of V_T as claimed by (Shongwe and Hanif, 2016).

$$R_s = \frac{V_{oc} - V_{mpp} + V_T \ln\left[\frac{I_{mpp}V_TR_s + I_{mpp}V_TR_p - V_{mpp}V_T}{V_{mpp}\left(I_{sc}R_p + I_{sc}R_s - V_{oc}\right) - I_{mpp}(R_sI_{sc}R_p + R_sI_{sc}R_s - R_sV_{oc})}\right]}{I_{mpp}} \tag{22}$$

$$R_p = \frac{V_TR_s + \left(R_pI_{sc}R_s + R_sI_{sc}R_s - V_{oc}R_s\right)\exp\left(\frac{I_{sc}R_s - V_{oc}}{V_T}\right) + R_pV_T}{\left(I_{sc}R_p + I_{sc}R_s - V_{oc}\right)\exp\left(\frac{I_{sc}R_s - V_{oc}}{V_T}\right) + V_T} \tag{23}$$

Here, $V=V_{mpp}$ and $I=I_{mpp}$ are the voltage and current at maximum power point of a IV characteristic.

Parameter estimation algorithm using NR-algorithm technique

Newton-Raphson (NR) algorithm is a most popular iterative technique for finding solution of the transcendental or nonlinear equation in the form $F(X)=0$, where $F(X)$ is a differentiable and continuous function.

Algorithm overview

Steps involved to extract the unknown three parameters are:

Formation of transcendental or non-linear equation with three variables:

$$F_1(V_T, R_s, R_p) = 0$$
$$F_2(V_T, R_s, R_p) = 0 \tag{24}$$
$$F_3(V_T, R_s, R_p) = 0$$

Setting $K=1$ and $K_{max}=100$, which are the initial and maximum number of iterations.

Selecting the initial guess for

$$V_T = 0.1, R_s = 0 \text{ and } R_p = 1000.$$

Calculate $F(X(K))$ using equation (25).

Calculate the Jacobian matrix.

$$J = \begin{bmatrix} \frac{\partial F_1}{\partial V_T} & \frac{\partial F_1}{\partial R_s} & \frac{\partial F_1}{\partial R_p} \\ \frac{\partial F_2}{\partial V_T} & \frac{\partial F_2}{\partial R_s} & \frac{\partial F_2}{\partial R_p} \\ \frac{\partial F_3}{\partial V_T} & \frac{\partial F_3}{\partial R_s} & \frac{\partial F_3}{\partial R_p} \end{bmatrix} \tag{25}$$

Using the Jacobian matrix and the current values of $V_T(K)$, $R_S(K)$ and $R_P(K)$ calculating the next iteration values $V_T(K+1)$, $R_S(K+1)$ and $R_P(K+1)$, using the NR-iteration formula:

$$X(K+1) = X(K) - [J]^{-1}F(X(K))$$
$$X(K+1) = X(K) - Y(K) \tag{26}$$

Check the convergence criterion:

$$\mathit{If}\ |Y(K)| < \varepsilon\ (\text{tolerance}) \tag{27}$$

break the loop;

otherwise, go to step 4.

Return the solution:

$$V_T = V_T(K+1)$$
$$R_s = R_s(K+1) \tag{28}$$
$$R_p = R_p(K+1)$$

To illustrate the implementation procedure of the Newton-Raphson (NR) algorithm, the corresponding flowchart is shown in Fig. 5. However, the NR-algorithm technique has stable convergence and is suitable for both single-variable and multi-variable equations. The convergence of the NR-algorithm for nonlinear systems is not guaranteed; it highly depends on the initial guess, and otherwise it may lead to an erroneous solution estimate.

In this work, the extracted parameters of a photovoltaic (PV) panel are presented as deterministic single values obtained using the Newton–Raphson (NR) algorithm. Although measurement noise is naturally present in the validation data, this study did not explicitly include uncertainty quantification in the form of confidence intervals or standard errors. The purpose of the presented comparison is not to draw statistical conclusions but to demonstrate numerical consistency and determined accuracy. Probabilistic uncertainty analysis has been identified as a promising direction for future research.

Mathematical formulation: Explicit formulation of NR-based nonlinear equation system

1. Let the unknown parameter vector to be estimated using the NR-algorithm be defined as:

$$x = [V_T, R_s, R_p]^T \tag{29}$$

2. the nonlinear system solved using the NR-algorithm is expressed as:

$$F(x) = \begin{bmatrix} F_1(V_T, R_s, R_p) \\ F_2(V_T, R_s, R_p) \\ F_3(V_T, R_s, R_p) \end{bmatrix} = 0 \tag{30}$$

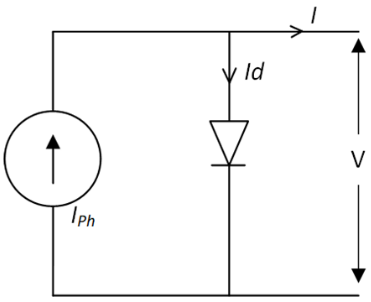

Fig. 1. *Ideal solar photovoltaic (PV) cell*

where F1, F2 and F3 correspond to the nonlinear equations derived from open-circuit, short-circuit and maximum power point condition, respectively. The explicit algebraic expressions of F1, F2 and F3 are obtained from equations (21) – (23) respectively and are therefore not repeated for.

3. Jacobian Matrix Definition: The Jacobian Matrix J(x) employed in the NR iteration is defined as:

$$J(x) = \begin{bmatrix} \frac{\partial F_1}{\partial V_T} & \frac{\partial F_1}{\partial R_s} & \frac{\partial F_1}{\partial R_p} \\ \frac{\partial F_2}{\partial V_T} & \frac{\partial F_2}{\partial R_s} & \frac{\partial F_2}{\partial R_p} \\ \frac{\partial F_3}{\partial V_T} & \frac{\partial F_3}{\partial R_s} & \frac{\partial F_3}{\partial R_p} \end{bmatrix} \quad (31)$$

The Jacobian matrix is evaluated at each iteration using the updated values of V_T,R_S and R_P .

4. Partial derivatives: Each element of the Jacobian matrix is obtained by analytically differentiating the corresponding nonlinear function Fi with respect to the unknown parameters V_T,R_S and R_P . The derivatives are summarised as follows:

$\frac{\partial F_i}{\partial V_T}, \frac{\partial F_i}{\partial R_s}, \frac{\partial F_i}{\partial R_p}$, for i=1,2,3

The explicit forms of these derivatives are directly obtained from the single diode model current equation (Eq. (16)) under the respective operating condition (open-circuit, short-circuit, and maximum power point), applying standard analytical differentiation rules.

5. Implementation: In every NR iteration, analytical expressions are evaluated using updated parameter values (V_T,R_S,R_P). From these values the Jacobian matrix is created and the correction vector is calculated:

$$\Delta x = -J^{-1}(x)F(x)$$

The parameter vector is updated step-by-step until the defined convergence criterion is satisfied. This clear and explicit mathematical formulation ensures full mathematical reproducibility of the proposed NR-based parameter estimation method, and helps any researcher to implement it independently without relying on proprietary software or source code.

In this work, the NR-algorithm was tested using multiple initial guesses selected within physically meaningful parameter ranges. Consistent convergence was observed when the initial values were chosen within these bounds; however, convergence outside these ranges is not guaranteed, as expected for gradient-based methods. Therefore, as shown in Table 1, the NR-algorithm was initialized with physically meaningful parameter bounds commonly reported in the PV modelling literature to ensure stable and reliable convergence. As with any Newton-based technique, the convergence of the proposed method is sensitive to the choice of initial condition; therefore, the MATLAB App restricts initial guesses to physically realistic bounds to ensure stable, reliable convergence for the general user.

In this work, a range of physically meaningful initial guesses was tested for all three variables, selected based on datasheet information and commonly reported bounds in PV modelling literature. Consistent convergence was observed when the initial values were chosen within these bounds; however, convergence outside these ranges is not guaranteed, as expected for gradient-based methods. Therefore, the NR-

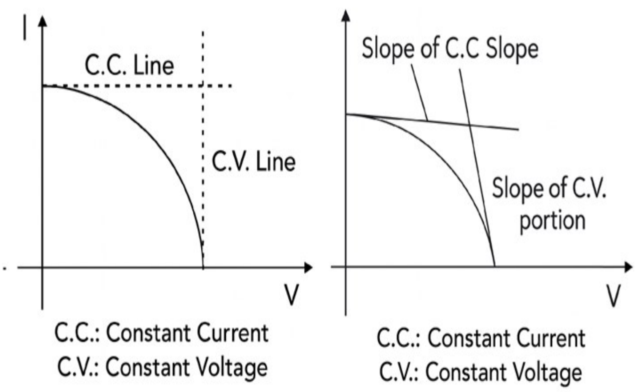

Fig. 2. *Constant current and constant voltage behaviour of a* photovoltaic *(V) solar module*

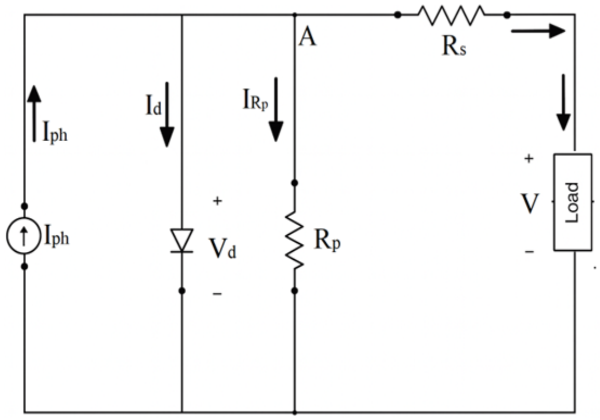

Fig. 3. *Electrical equivalent circuit of a SPV cell*

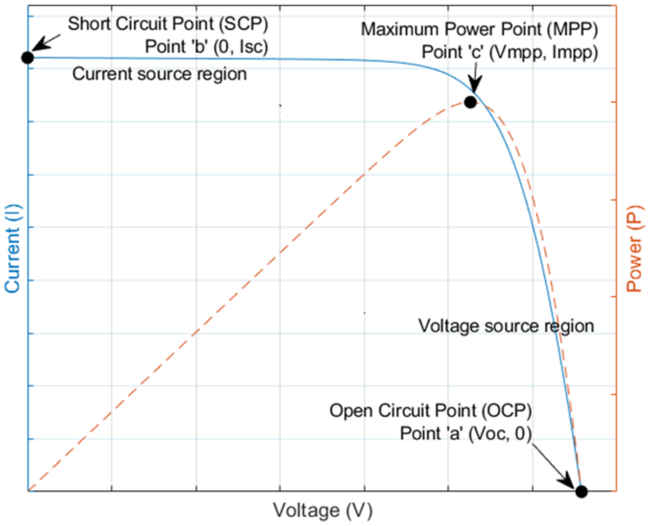

Fig. 4. *Characteristic of* photovoltaic *(PV) solar module with remarkable data points*

algorithm was initialized using physically meaningful parameter bounds commonly reported in PV modelling literature to ensure stable and reliable convergence.

As with any Newton-based technique, the convergence of the proposed method is sensitive to the choice of initial condition, therefore, the MATLAB App restricts initial guesses to physically realistic bounds to ensure stable and reliable convergence for the general user.

RESULTS AND DISCUSSION

Test cases

To assess the correctness and effectiveness of the intended NR-algorithm, the iterative method is implemented across two different PV solar panel topologies under varying environmental conditions. Standard Test Condition (STC) was assumed at irradiance $G=1000\ W/m^2$, cell temperature $T=25°C$ and air mass . $AM=1.5$ in addition to STC, irradiance levels were varied from $200\ W/m^2$ to $1000\ W/m^2$ at constant temperature to evaluate radiation sensitivity, while cell temperature was varied from $25°C$ to $100°C$ at fixed irradiance $G=1000\ W/m^2$ to assess thermal influence on electrical characteristic. Furthermore, for robustness analysis, 3% synthetic Gaussian measurement noise was added to the current data to emulate practical environmental and sensor uncertainties.

The experimental data sets from two different technologies have been utilized to verify the robustness, precision and closeness of the suggested NR-algorithm. Many researchers have used this experimentally collected data as a standard to confirm the outcomes of their suggested models for parameter extraction in solar PV modules (Easwarakhanthan *et al.*, (1986) Jadli *et al.,* (2018); Ali, M. S. *et al.,* (2020); Tong, N. T. *et al.,*

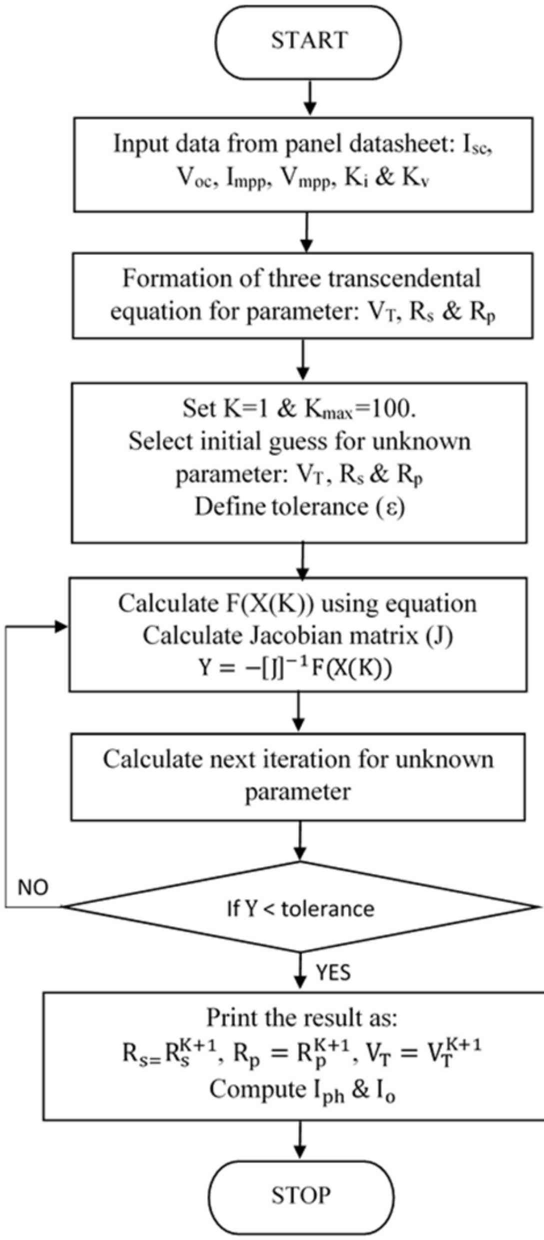

Fig. 5. *Flow chart of the Newton–Raphson (NR) algorithm technique*

(2016); V. Stornelli *et al.*, (2019)).

A comprehensive computation of the model performance, a long with various aspects such as error amounts, their distribution, and their correlation with calculated data, bias, and the ratio of variance, is presented in Tables 3 and 5. An m-code has been developed to execute the NR-algorithm to determine the intrinsic parameter values of Solar PV modules.

Validation of proposed parameter determination by Newton–Raphson (NR) algorithm on monocrystalline SPV cell

The experimentally collected data on voltages and currents of a commercial RadioTechnique Compelec

Table 1. Convergence behaviour of Newton–Raphson (NR) for different initial guesses

Parameter	Initial guess range tested	Convergence observed
V_T	0.02 – 0.06	Yes
R_s	0.001 – 1.0	Yes
R_p	10 – 2000	Yes

Table 2. Comparison index of experimental values and evaluated values (Easwarakhanthan *et al.*, 1986)

Experimental data		Computed data	Proposed NR-Algorithm
V_{exp} (Volts)	I_{exp} (Amps)	I_{eval} (Amps)	I_{comp}(Amps)
-0.2057	0.7640	0.7641	0.7644
-0.1291	0.7620	0.7627	0.7629
-0.0588	0.7605	0.7614	0.7615
0.0057	0.7605	0.7602	0.7602
0.0646	0.7600	0.7591	0.7600
0.1185	0.7590	0.7580	0.7580
0.1678	0.7570	0.7571	0.7570
0.2132	0.7570	0.7561	0.7559
0.2545	0.7555	0.7551	0.7548
0.2924	0.7540	0.7537	0.7534
0.3269	0.7505	0.7514	0.7511
0.3585	0.7465	0.7473	0.7471
0.3873	0.7385	0.7401	0.7400
0.4137	0.7280	0.7274	0.7274
0.4373	0.7065	0.7070	0.7070
0.459	0.6755	0.6754	0.6754
0.4784	0.6320	0.6308	0.6310
0.496	0.5730	0.5722	0.5720
0.5119	0.4990	0.4994	0.4992
0.5265	0.4130	0.4134	0.4130
0.5398	0.3165	0.3472	0.3167
0.5521	0.2120	0.2125	0.2116
0.5633	0.1035	0.1026	0.1025
0.5736	-0.010	-0.0097	-0.0090
0.5833	-0.123	-0.1241	-0.1235
0.5900	-0.210	-0.2093	-0.2078

(RTC) France monocrystalline silicon solar cell reported by Easwarakhanthan *et al*. (1986) have been utilized and are given in Appendix 1. The measurements were originally reported in the cited work, and the present study utilized these published datasets solely for validation.

Table 2 summarises the measured voltages and currents, and the right column includes the calculated currents. An error analysis matrix has been performed and as presented in Table 3. The developed NR-based parameter extraction algorithm shows good agreement with the experimental data, with comparatively lower RMSE and Mean absolute percentage error (MAPE) values, and demonstrates performance comparable to the reference data across the evaluated metrics. The NSE value of 0.9999 indicates that the model effectively captures data variability.

Fig. 6, shows that the curve obtained from the simulat-

Table 3. Error analysis matrix for monocrystalline silicon solar cell (Easwarakhanthan *et al.*, 1986)

S. No.	Parameters	Computed data	Proposed NR-Algorithm
1	MAPE	0.64957%	0.55866%
2	RMSE	0.0060658	0.00086068
3	NRMSE	0.62277%	0.088365%
4	PBIAS	0.0080726%	-0.00010728%
5	NSE	0.9996	0.9999

ed data by Easwarakhanthan *et al*. (1986) deviates from the curve, i.e., from V=0.5265 V to V=0.5521 V, whereas the experimental curve and the curve obtained from the proposed NR-Algorithm method match very closely. Therefore, developed an NR-algorithm that displays good agreement with experimental data and provides consistent, reliable predictive performance across the assessed measures.

Validation of proposed parameter determination by NR-algorithm on Polycrystalline SPV Panel

In this work, the experimental dataset for voltages and currents of a polycrystalline STP6-120/36 solar panel, reported by Tong and Pora (2016), was used. The electrical specifications of the solar panel are given in Appendix 1. These specifications have been chosen to validate the proposed NR-Algorithm method.

Table 4 presents the experimentally measured voltage and current data, while Table 5 presents the comparision error analysis matrix. A comparison of the statistical performance indices indicates that the proposed NR-algorithm shows good agreement with the reference data. The proposed NR-algorithm exhibits comparable or lower values of MAPE, RMSE, Normalized Root Mean Square Error (NRMSE), Percent Bias (PBIAS) and NSE, indicating reduced prediction error and minimal bias. In addition, the higher NSE value obtained using the proposed NR-algorithm indicates effective model efficiency and agreement with the experimental measurements.

Fig. 7, shows the comparison of the experimental and simulated current-voltage curves. The experimental and computational data curves indicated in the right two columns of Table 5 closely resemble the experimental data. While there is divergence between the experimental curve and the curve drawn using the right two columns in Table 4, i.e., from V = 15.71 V to V = 16.34 V. These differences may be due to variation in global irradiance or cell temperature. The difference is small and can be ignored.

Close numerical agreement between the results obtained from the proposed NR-algorithm and the mathematically calculated data reported in prior studies is expected, as all methods have been validated against the same benchmark data set. The purpose of this comparison is not to show numerical deviation, but to confirm the correctness and consistency of the proposed formulation. In contrast to previous methods, the presented method uses an explicitly derived, deterministic NR-based formulation that employs physically restricted initial values. This ensures stable and repeated convergence without relying on stochastic search or

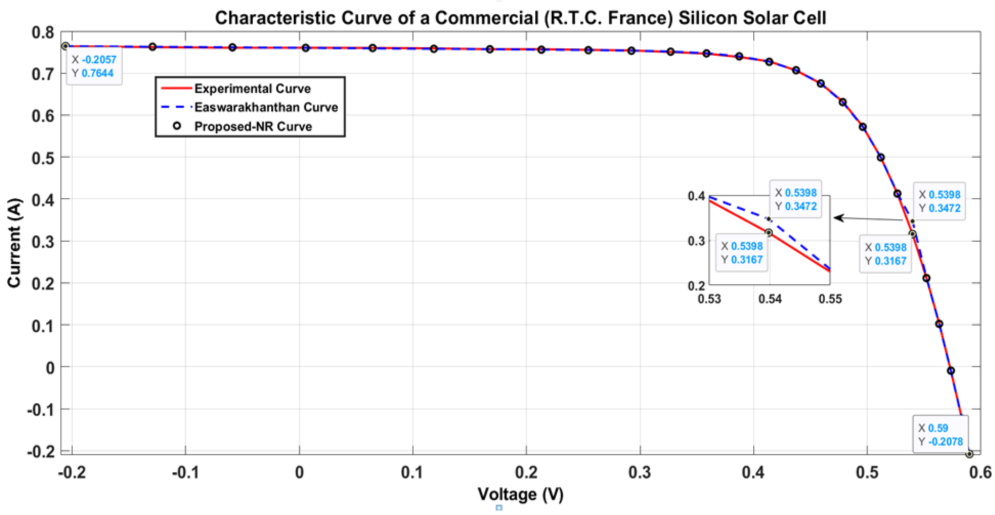

Fig. 6. *Experimental (-), reference (Easwarakhanthan et al., 1986) (--) and NR-Algorithm (**o**) current-voltage curve for commercial radiotechnique compelec france silicon solar PV cell.*

Table 4. Comparison of values derived from experiments and those calculated from the polycrystalline solar PV panel model (Bencherif and Nabil.Brahmi, 2018)

Experimental Measured data		Computed data	Proposed NR-Algorithm
V_{exp} (Volts)	I_{exp} (Amps)	I_{comp} (Amps)	I_{eval} (Amps)
17.65	3.83	3.836	3.837
17.41	4.29	4.28	4.2533
17.25	4.56	4.5541	4.5293
17.10	4.79	4.794	4.7725
16.90	5.07	5.093	5.0735
16.76	5.27	5.287	5.2688
16.34	5.75	5.794	5.7811
16.08	6.00	6.055	6.0463
15.71	6.36	6.3691	6.3619
15.39	6.58	6.5881	6.5831
14.93	6.83	6.8334	6.83
14.58	6.97	6.9748	6.972
14.17	7.10	7.1014	7.0987
13.59	7.23	7.2265	7.2233
13.16	7.29	7.2898	7.286
12.74	7.34	7.3345	7.3301
12.36	7.37	7.3643	7.3594
11.81	7.38	7.3947	7.3893
11.17	7.41	7.4174	7.4116
10.32	7.42	7.4352	7.4291
9.74	7.44	7.4426	7.4366
9.06	7.45	7.4487	7.4428

extensive parameter tuning. Therefore, the main advantage of the proposed method lies not in producing different numerical results for the same physical system, but in its formulation transparency, robustness and simplicity of implementation.

Statistical analysis indicates that the proposed NR-algorithm provides consistent and reliable parameter estimation for the given datasets, with performance comparable to other reported models across multiple performance indices (MAPE, RMSE, NRMSE, PBIAS, and NSE). In this, the values of error indices RMSE is very low, while the values of efficiency indices such as NSE is high, supporting the validity and reliability of the obtained results. The calculated PBIAS value indicates competitive accuracy. Therefore, the implementation of NR-algorithm provides consistent and reliable estimation. Many of the statistical indices presented in Tables 3 and 5 are mathematically related and therefore provide information similar to each other. These metrics are included primarily for completeness and comparison with previously published literature. Among these, RMSE and MAPE are the most representative indicators of model performance.

Design and development of MATLAB App designer for estimation of intrinsic parameters of SPV panel

MATLAB App Designer is an interactive tool that provides users the ability to design professional apps for a system without using specialized design software. Users can design a graphical user interface (GUI) by coding their own program in the integrator editor and dragging and dropping components as required to create any system. It provides a comprehensive environment for app development, design, and coding.

In this, the MATLAB App is designed to determine the intrinsic parameters for any solar PV panel. The user has to input the data from the manufacturer's datasheet in the 'Input Parameters' column and press the 'execute' button. As a result, the 'Output Parameter' column will display the estimated intrinsic parameters at STC.

Table 5. Comparison error analysis for proposed model of polycrystalline solar PV panel (Bencherif and Nabil.Brahmi, 2018)

S.No.	Parameters	Computed data	Proposed NR-Algorithm
1	MAPE	0.19205%	0.20192%
2	RMSE	0.017498	0.016907
3	NRMSE	0.48338%	0.46704%
4	PBIAS	0.0059726%	-0.00046844%
5	NSE	0.99978	0.99979

The accuracy metric is defined as the complement of the percentage error, where the percentage error is calculated as

$$\text{percentage error} = \left|\frac{P_{max\_e} - P_{max\_m}}{P_{max\_e}}\right| * 100\%$$

where,

$P_{max\_e} = V_{mpp} * I_{mpp}$: Maximum power defined in datasheet provided by manufacturer.

P_{max_m}: Calculated maximum power using NR-algorithm method.

Mathematically, the accuracy is defined as:

$$\text{Accuarcy} = 100 - \text{pecentage error}$$

Application of MATLAB App designer on PV Kyocera KC200GT solar PV panel

The robustness and effectiveness of a MATLAB App Designer have been tested by using the technical specifications of the polycrystalline Kyocera KC200GT solar panel (see Appendix 1), which is the most common choice of the researchers. The electrical characteristics used for validation are obtained from the manufacturer's datasheet as reported in the cited reference, and no experimental measurements were performed in this study.

Fig. 8, illustrates that the current-voltage curve (ICV) and the power-voltage curve (PVC) achieved from the MATLAB app match exactly at the P_{max} as specified in the manufacturer's data sheet. It should be noted that the feedback obtained from the proposed NR-algorithm method fully matches the actual characteristics of the Kyocera KC200GT PV solar panel.

Fig. 9, presents the IVC and PVC of the Kyocera KC200GT solar PV panel at fixed cell temperature T=25° under varying irradiance conditions. On the other hand, Fig. 10, illustrates the IVC and PVC of the same solar PV module under different cell temperatures while maintaining a constant irradiance (G) of 1000 W/m^2.

Table 6 illustrates the comparison of the parameters evaluated by different researchers for the KC200GT solar panel using different methods. Parameters like I_o, I_{ph}, R_s, R_p and m are calculated, along with their respective RMSE errors.

Recent studies have extensively investigated both metaheuristic and deterministic approaches for photovoltaic parameter estimation. For example, the Artificial Hummingbird Technique (AHT) demonstrated competitive accuracy for single and double-diode models, with strong convergence (El-Sehiemy *et al*., 2023). Similarly, a Levenberg–Marquardt (LM) based numerical framework was proposed to reduce the complexity of nonlinear models and improve convergence efficiency for SDM parameter extraction (Nautiyal *et al*., 2024). More recently, an improved Sinh–Cosh Optimisation (I-SCHO) algorithm was reported to enhance stability and reduce estimation error across multiple PV models (Alluhaidan *et al*., 2025). In addition, systematic datasheet-based iterative estimation strategies have been reviewed and refined to improve parameter consistency under STC conditions (Kamal *et al*., 2023). As shown in Table 6, the proposed NR-based deterministic formulation achieves an RMSE of 0.11 for the KC200GT module at STC, which is comparable to or lower than that of several reported optimization-based techniques. Unlike population-based metaheuristic algorithms that rely on stochastic search mechanisms and repeated fitness evaluations, the proposed approach ensures a mathematically explicit formulation with reduced computational overhead and repeatable convergence behaviour under physically constrained initialization. This demonstrates that the deterministic NR framework provides competitive accuracy while maintaining structural transparency and reproducibility. It should be noted that the present study does not claim explicit computational time superiority over metaheuristic approaches. While population-based techniques may involve higher computational overhead due to repeated fitness evaluations, detailed timing-based benchmarking under identical hardware conditions is considered as future work. Furthermore, the current formulation is limited to the single-diode model (SDM), and extending it toward a DDM-based deterministic implementation is identified as a potential research direction.

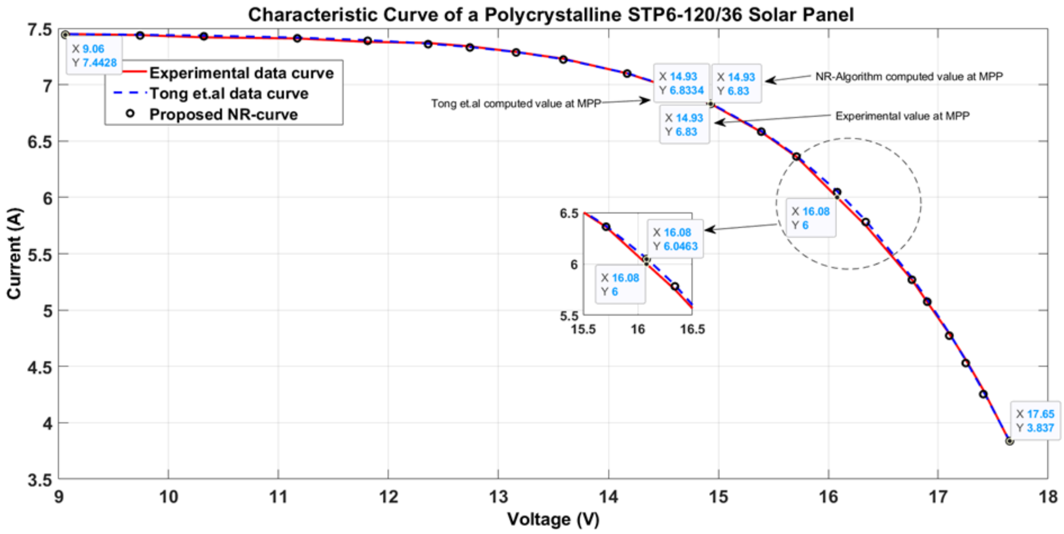

Fig. 7. *Experimental (-), reference (Tong and Pora, 2016) (--) and NR-Algorithm (**o**) current-voltage curve for polycrystalline STP6-120/36 solar panel*

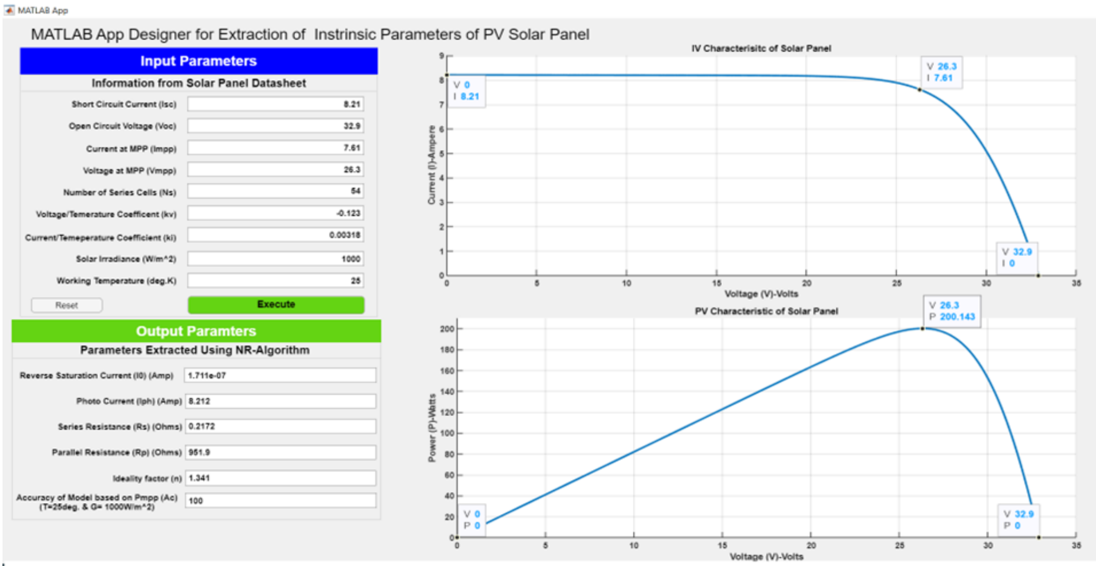

Fig. 8. *IV and PV characteristic curve at STC*

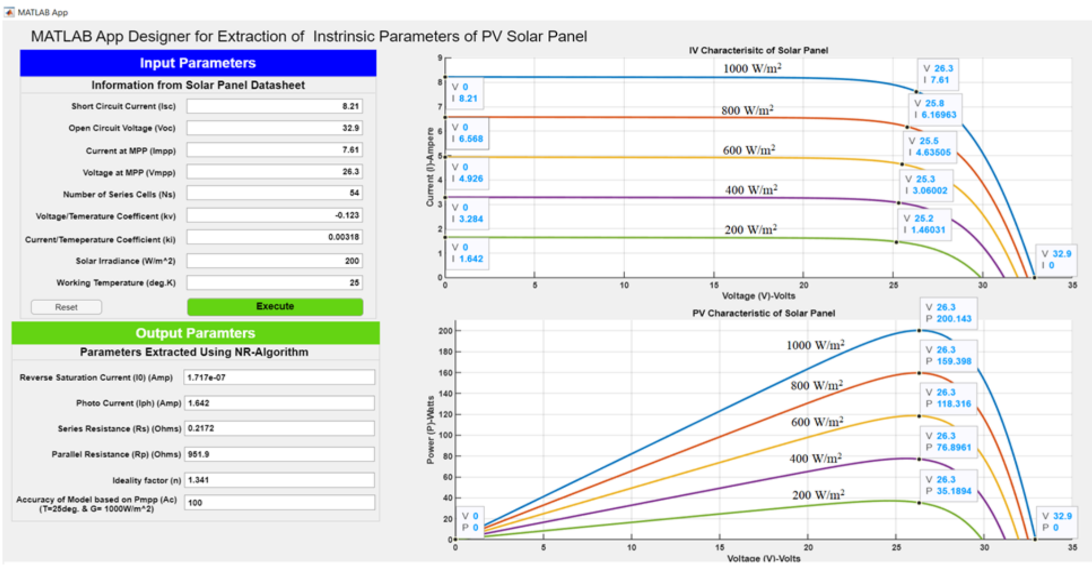

Fig. 9. *IV and PV curve for various radiations at fixed cell temperature 25ºC*

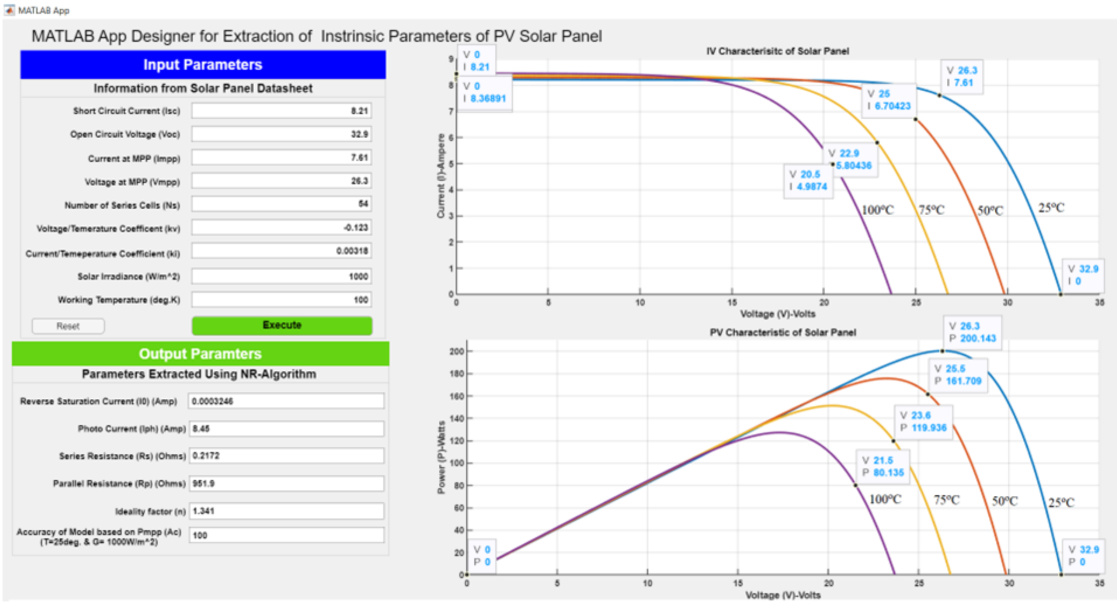

Fig. 10. *IV and PV curve at various temperature at fixed irradiance G=1000 W/m^2*

Table 6. Comparison of parameters for Kyocera KC200GT solar panel at STC (Stornelli *et al.*, 2019)

Methods	m	I□ [Amp]	I_{pv} (Amp)	R_s [mΩ]	R_p [Ω]	RMSE
Villalva	1.3	85.2e-9	8.193	138.7	466	0.23
Mahmoud	1.412	367e-9	8.193	131.4	∞	0.21
Nayak	1.241	35.8e-9	8.193	198.4	599.9	0.15
Silva	1	0.3e-9	8.193	271	171.2	0.19
Accarino	1.079	2e-9	8.193	236.3	204	0.11
Stornelli	1.12	5.14e-9	8.22	265.6	144.9	0.12
Proposed NR-algorithm	1.341	171.1e-09	8.212	217.2	951.93	0.11

Table 7 presents a mathematical consistency validation at the maximum power point (MPP) under standard test conditions (STC) for the proposed NR-algorithm. Since the MPP parameters are explicitly used in the formulation of the nonlinear equations, the exact reproduction of P_{max} reflects the algebraic consistency of the model and its numerical implementation rather than independent predictive validation. Therefore, the actual performance assessment of the proposed method was carried out using full IV curve–based error metrics rather than relying solely on MPP accuracy. The actual assessment of parameter extraction accuracy is therefore carried out using a full IV curve-based error metric, such as RMSE and MAPE, which are not imposed as input constraints.

Stress testing of the proposed NR-algorithm under noisy measurement conditions

To evaluate the robustness of the proposed Newton–Raphson (NR) based parameter extraction method under non-ideal and realistic operating conditions, a stress test using synthetically noise-corrupted current–voltage (I–V) data was performed. As the voltage and current values are derived from the electrical specification data of the Kyocera KC200GT solar PV module, synthetic Gaussian noise was intentionally added to the current data to replicate practical measurement uncertainties encountered in real-world PV applications.

Gaussian noise with a zero mean and a magnitude of 3% relative to the rated current was added to the current profile, while the voltage data remained unchanged. The same NR-based formulation, initial conditions, and convergence criteria were retained without any modification, ensuring that the analysis reflects the inherent robustness of the deterministic algorithm rather than any algorithmic tuning.

Fig. 11 compares the clean I–V characteristics obtained using the proposed NR-algorithm with the corresponding noisy I–V response. It can be observed that measurement noise introduces small random fluctuations in the current, particularly in the constant-current region. However, the overall shape of the I–V curve, including the knee region and open-circuit behaviour, remains well preserved. The NR-algorithm continues to exhibit

Table 7. Comparison of accuracy based on maximum power (MPP) at STC (Jadli *et al*., 2018)

Extraction technique	Actual maximum point Pe_max (W)	Maximum Power calculated Pmax (W)	Accuracy (%)
Villalva's technique [a]	200.143	199.883	99.87
Accarino technique [b]	200.143	199.973	99.91
Lambert-W function [c]	200.143	199.882	99.87
Iterative method [d]	200.143	199.866	99.86
Silva's method [e]	200.143	206.464	96.84
Stornelli iterative method [f]	200.143	203.147	98.50
Jadli's method [h]	200.143	200.096	99.98
Proposed NR-algorithm	200.143	200.143	100.00

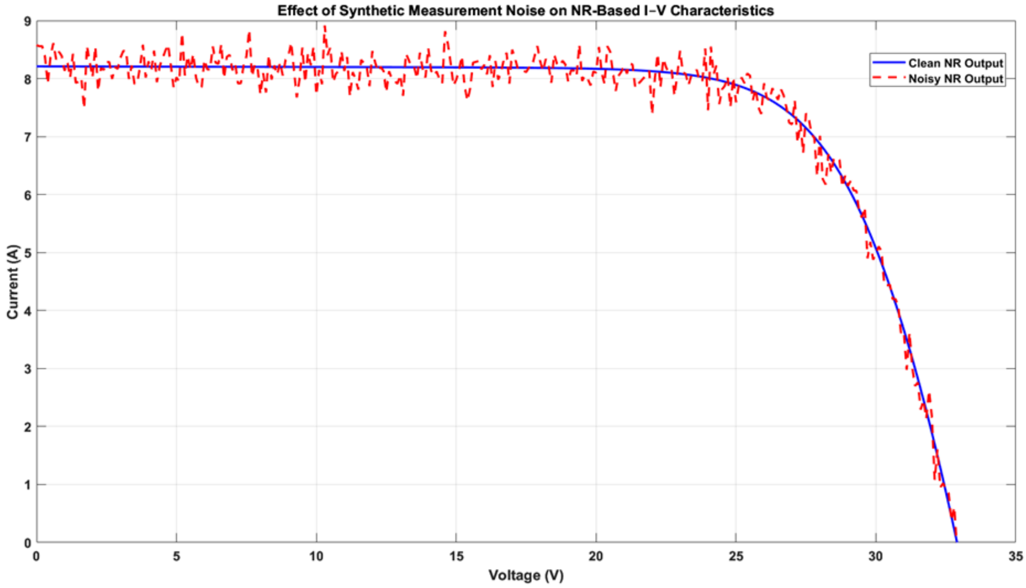

Fig 11. *Comparison of the clean and noise-corrupted I-V characteristic obtained using the proposed NR-based parameter extraction method under 3% synthetic Gaussian measurement noise*

Appendix 1. Electrical specification datasheet

Quantities	R.T.C. france (Values)	STP6-120/136 (Values)	Kyocera KC200GT (Values)	Units
V_{oc}	0.5728	19.21	32.9	V
I_{sc}	0.7603	7.48	8.21	A
I_{mpp}	0.6894	6.83	7.61	A
V_{mpp}	0.4507	14.93	26.3	V
N_s	1	36	54	

stable convergence, and the deviation in the extracted electrical characteristics remains marginal.

These results demonstrate that the proposed NR-based parameter-extraction framework maintains numerical stability and reliable performance under moderate measurement noise. Therefore, the method is suitable not only for ideal benchmark datasets but also for practical photovoltaic applications under non-ideal, noisy measurement conditions.

In this study, the extracted parameters are presented as single point estimates obtained via deterministic optimization on benchmark experimental datasets. This approach is sufficient to demonstrate the accuracy and consistency of the proposed NR-based formulation. However, detailed uncertainty quantification of estimated parameters, such as confidence intervals or standard deviations, is not explicitly included in the work. This aspect is particularly relevant in the presence of measurement noise and data variability. Therefore, repeated noisy data realizations or uncertainty analysis through Monte Carlo–based techniques will be considered in future work, so that the statistical significance and robustness of the extracted parameters can be better assessed.

Conclusion

This study presented a deterministic Newton–Raphson (NR) based framework for extracting intrinsic parameters of the single-diode photovoltaic model using datasheet-derived operating points. The proposed method demonstrated strong agreement with experimental datasets across different PV technologies, achieving RMSE values as low as 0.11 under STC conditions and an NSE approaching unity, confirming stable, reproducible convergence. The primary novelty lies in the explicit nonlinear formulation with physically constrained initialization, ensuring deterministic and transparent parameter estimation without reliance on stochastic optimization. From an environmental perspective, accurate PV parameter estimation enhances system modelling accuracy, improves energy yield prediction, and supports efficient integration of renewable energy systems, contributing to sustainable energy deployment. However, the present work is limited to the single-diode model under standard operating conditions. Future work may extend the framework to partial-shading scenarios, integrat the Double diode model (DDM), and benchmark computational time against advanced optimization techniques.

Conflict of interest

The authors declare that they have no conflict of interest.

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