Fast Online Parameter Identification for Current Source Operated PV Modules in DC Microgrids

AHMED M. A. OTEAFY, (Senior Member, IEEE), ABDULRAHMAN ABOMAZID, (Member, IEEE), AND ARAM S. MONAWAR, (Member, IEEE)

The authors are the director and affiliate members, respectively, at the Joint Smart Grids & Electric Vehicles R&D Center (JSEC), Alfaisal University, Riyadh 11533, Saudi Arabia (e-mail:aoteafy@alfaisal.edu)

Corresponding author: A. Oteafy (e-mail: aoteafy@alfaisal.edu).

This work was supported by New Energy Transfer Co., and the Office of Research & Innovation grant IRG 21206, Alfaisal University.

ABSTRACT This paper presents a non-iterative online approach to identify the modeling parameters of a photovoltaic (PV) module. It is motivated by the fact that accurate and reliable modeling of distributed energy resources (DERs) in DC Microgrids improves their stability and efficiency under a wide range of operational conditions. In particular, the case where PV modules are used as DERs in their current-source region is considered. The proposed method addresses the limitations associated with parameter identification in these settings. Specifically, the method works under varying temperature and insolation conditions relying only on current and voltage sensors that already exist in the power electronic converters tying the PV DER to the Microgrid. Also, its algorithm is practical and reliable as it does not rely on a priori knowledge or an initial guess, and it is non-iterative, so it does not risk divergence (or require proof of convergence) as other iterative algorithms. Moreover, it is both fast and of a low computational complexity, which enables its implementation on microcontrollers within PV DER systems. The development of this method is detailed in the paper along with its application steps to facilitate its adoption. Furthermore, an experimental setup was used to test the proposed method under different ambient conditions and demonstrated its efficacy with algorithm execution times of under 1 second and high modeling accuracy on a microcontroller.

INDEX TERMS Photovoltaic system modeling, DC microgrids, parameter identification, maximum power point, non-iterative techniques.

NOMENCLATURE

PV Model Variables and Parameters

\begin{align*}
N_s & \quad \text{Number of cells in series forming a string.} \\
N_p & \quad \text{Number of strings in parallel in a module.} \\
V_c, I_c & \quad \text{Cell terminal voltage and current.} \\
V & \quad \text{Module terminal voltage, } V = N_s V_c. \\
I & \quad \text{Module terminal current, } I = N_p I_c. \\
P_m & \quad \text{Module maximum power point (MPP).} \\
V_m, I_m & \quad \text{Module voltage and current at MPP.} \\
I_{ph} & \quad \text{Cell photoelectric current.} \\
I_d & \quad \text{p-n junction diode current.} \\
I_0 & \quad \text{p-n junction diode scaling (saturation) current.} \\
V_T & \quad \text{p-n junction thermal voltage.} \\
S & \quad \text{Module insolation.} \\
T & \quad \text{p-n junction Temperature.}
\end{align*}

\begin{align*}
n & \quad \text{p-n junction ideality factor.} \\
\alpha & \quad \text{scaling factor, } = nV_T. \\
R_s & \quad \text{Cell series resistance.} \\
R_p & \quad \text{Cell parallel (shading) resistance.} \\
G_p & \quad \text{Cell parallel conductance, } = 1/R_p. \\
PV Models \\
SDM & \quad \text{Single diode model.} \\
SSDM & \quad \text{Simplified SDM, eliminates } R_s. \\
ISDM & \quad \text{Ideal SDM, eliminates } R_s \text{ and } R_p. \\
Identification Model \\
y, W & \quad \text{Regressor vector and matrix.} \\
K & \quad \text{Vector of unknown parameters.} \\
N & \quad \text{Total number of sampled data points.} \\
\text{Index of sampled data points.} \\
EI & \quad \text{Identification model error index.}
\end{align*}
A. Oteafy et al.: Fast Online Parameter Identification of PV modules

I. INTRODUCTION

Photovoltaic (PV) systems are becoming the main distributed energy resource (DER) of choice in modern-day deployment of renewables. Whether these PV systems are on rooftops or part of a large-scale power plant, they are competitively bringing down the cost of renewables in the electric power production market. In medium to large-scale PV systems, PV modules are connected in strings with a string inverter converting their DC power to an AC bus supplying power to the main grid. PV DER modules can alternatively be connected within an autonomous Microgrid. Modeling their performance in these Microgrids is essential for their reliable operation.

A. PV SYSTEMS IN DC MICROGRIDS

Relatively recent paradigms consider integrating PV systems within DC microgrids; see the surveys by Olivares et al. [1], Dragicevic et al. [2], and Chen et al. [3]. These Microgrids are electrical networks consisting of DERs, loads, Energy Storage Systems (ESS’s), and supervisory control and data acquisition (SCADA) systems. They allow an entity, e.g., a university campus or a neighborhood, to have autonomous operation that can be either islanded from or connected to the main AC power grid. Optimal operation of these Microgrids requires modeling of their modules to achieve and maintain their autonomous, resilient, and maximum power production capabilities. Therefore, effective models of PV modules that are both accurate and practically identifiable are needed to overcome difficulties in active control, failure detection, Maximum Power Point (MPP) identification and tracking, and overall reliable operation of the DERs within Microgrids. This is particularly important when insolation and temperature conditions change throughout the day. Accurate current vs. voltage I-V and power vs. voltage P-V models are also required to deliver specific power outputs and achieve balanced operation. Moreover, PV systems can be operated in their current-source or voltage-source regions. Either region along with the MPP can be sufficient in providing the full range of operating points (and power outputs) for the DC Microgrid. The current-source region is suitable when the Microgrid is of a low voltage or an isolated high-frequency DC to DC converter is used, while the voltage-source region is especially suited to more efficiently achieve a high step up in DC voltage when a non-isolated boost converter is used.

B. PV CIRCUIT MODELS

Researchers have considered several lumped-parameter circuit models of a PV cell in order to obtain its characteristic I-V and P-V curves. Moreover, they, e.g., Kennerud [4] and Masters [5], have detailed the impact of parameter variations within these models on the characteristic curves and the performance of the PV cell. The models directly extend to panels with cells connected in series to form a string providing more voltage as well as strings connected in parallel providing more current. Furthermore, the model can be extended for panels connected to form an array. The simplest model of the PV cell includes an insolation dependent current-source in parallel with a diode representing its p-n junction. This model, known as the Ideal Single-Diode Model (ISDM), captures the nonlinear I-V relationship under varying temperature and insolation conditions. Three parameters are key to this model, namely, a photoelectric current $I_{ph}$, a diode scaling current $I_0$, and an exponential term scaling factor $\alpha$ itself the product of the diode’s ideality factor $n$ and thermal voltage $V_T$. However, the ISDM cannot explain the existence of a parallel resistive path within the cell that is especially important for modeling partially shaded panels, and it does not explain the voltage regulation effects occurring near the open-circuit condition due to the effective series resistance of the path to the terminals of the cell [5]. Therefore, a more accurate model adds a parallel resistance $R_p$ and a series resistance $R_s$ to model these two phenomena, respectively. This results in a five parameter nonlinear Single-Diode Model (SDM). Other higher precision models exist for the PV cell that include a double-diode model [6], [7] or even a triple-diode model [8]. However, the parameter identification for such models is more complex and requires a priori data due to their high degree of nonlinearity. A commonly proposed simplification of the SDM is to eliminate $R_p$. Instead, we propose to eliminate $R_s$ referring to this model as the Simplified SDM, or SSDM.

C. PARAMETER IDENTIFICATION

A parameter identification method is then required to fit the model of a given PV module. In the literature, the majority of these methods rely on data collected over the full range of the I-V curve from the short-circuit current $I_{sc}$ to the open-circuit voltage $V_{oc}$ operating points to fit the SDM. Kennerud [4], for example, used specific points on the I-V curve including the slopes near $I_{sc}$ and $V_{oc}$ in an iterative algorithm to simultaneously solve a set of nonlinear equations for the parameters. He demonstrated the impact of varying each parameter on the performance of the PV cell. Similarly, Haouari-Merbah et al. [6] employed an iterative technique to identify the parameters of the SDM model. They emphasized the importance of avoiding measurement errors in current and slope calculations near the $V_{oc}$ and those in the voltage near the $I_{sc}$. Also, Phang et al. [9] used the same points as [4] including the I-V curve slopes in addition to the junction temperature measurement, but they solve for the parameters directly in a non-iterative manner with some simplifications. Toledo et al. [10] have utilized a linear least-squares method to find the parameters of the SDM in a non-iterative manner as a first step. This generates a large but finite number of parameter sets that are then searched for the set that yields the minimum error between the estimated curve and the
data. Next, the authors use a refinement process to further reduce the modeling error in the identified parameter set. This method is both non-iterative and precise, however, the search step and refinement processes can limit its use in online parameter identification. Moshkar and Ghanbari [11] reduce the model equations by reformulating them in terms of the independent variables, and then solving the resulting set of equations as a convex optimization problem, without a priori information, using an adaptive gradient descent iterative method. Lim et al. [12] use a different linear approach, where the nonlinear SDM is converted into the problem of solving a set of linear differential equations, using the Laplace transform, to obtain the parameters. However, the value of $R_s$ must be iteratively adjusted in an outer loop containing the integrals of the differential equations until the algorithm converges.

Alternatively, using information from the data sheet of the PV panel, the SDM model parameters were identified using iterative algorithms by Sera et al. [13] and by Villalva et al. [14]. In both these cases, the model accounts for variations in temperature and insolation, which facilitates using them in circuit simulation models. If instead both $R_s$ and $R_p$ are ignored, the simpler ISDM can be solved explicitly as shown by [15] but this results in a lower modeling accuracy.

On the other hand, a linear polynomial curve fitting of the SDM model was used by several researchers, see Xiao et al. [16], Andrei et al. [17], Paviet-Salomon et al. [18] and references therein. This approach results in polynomials of orders ranging from four to eight (depending on the type of PV cell and the number of data points extracted from the $I$-$V$ curve), which simplifies solving for specific operating points instead of iteratively solving the nonlinear PV models. A comparison was performed by Ibrahim and Anani [19] between different methods. It showed that some analytical techniques with simplified models can produce comparable results to iterative methods of higher computational cost.

Moreover, a wealth of heuristic and meta-heuristic algorithms have been developed for the parameter identification of PV modules. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), for example, were utilized in [20], [21] to identify the parameters of PV cells. A PSO is employed in [22], which involves a large amount of input data to the algorithm in order to extract the cell parameters. For the double diode model (DDM), Bradaschia et al. [23] use a combination of analytical equations and a pattern search iterative algorithm to estimate them. An improved multiswarm PSO iterative algorithm was developed by Nunes et al. [24] for the DDM that achieves high modeling accuracy, and it takes about a minute for convergence on a 3.6 GHz CPU. In [25], a modified flower pollination algorithm (FPA) is presented to estimate the parameters of SDM and DDM of PV cells and modules. Despite its accuracy, the algorithm requires a high number of iterations before it converges. Using an improved opposition-based tunicate swarm algorithm (OTSA), the work in [26] estimates the parameters of SDM for polycrystalline and monocrystalline PV modules. For PV SDM and DDM modules, a chaotic gradient-based optimization (CGBO) algorithm is proposed in [27] to find their parameters. In [28], a dynamic self-adaptive and mutual-comparison teaching-learning-based optimization (DMTLBO) algorithm is presented for extracting PV parameters. Also, Huang et al. [29] developed a meta-heuristic search algorithm for the SDM and DDM models that is self-adaptive in the iteration steps. The results of their algorithm are precise, however, it takes minutes to conclude on a CPU. Such algorithms have a high computational complexity and are therefore suited for offline parameter identification.

Therefore, depending on the application at hand, the PV system requires a specific model coupled with an effective parameter identification method. The aforementioned techniques are more than adequate to address applications such as offline characterization (e.g., for certification) or the development of simulation models, however, they are not practical for online identification. More recently, online parameter identification was addressed by Lappalainen et al. [30] for the SDM model using the data sheet information as an initial guess, with an iterative technique that modifies the parameter values to best fit the measured $I$-$V$ curves.

The aforementioned literature on parameter identification methods can be summarized as shown in Table 1.

| PV Models | Parameter Identification Methods |
|-----------|----------------------------------|
| ISDM      | Non-iterative explicit solution [15]. |
| SDM       | Iterative [4], [6], [11]–[14]; iterative for online operation [30]; non-iterative requiring more information & simplifications [9]; non-iterative but suited for offline operation [10]; iterative heuristic methods using GA [20] and PSO [21], and iterative meta-heuristic methods using enhanced FPA [25], improved OTSA [26], CGBO [27], and DMTLBO [28]. |
| Polynomial | Polynomials with orders that vary depending on cell type, region of interest, convergence, desired accuracy, and other factors [16]–[18]. |
| DDM       | Heuristic methods including iterative pattern search [23], improved multiswarm PSO iterative algorithm [24]; and iterative meta-heuristic methods using enhanced FPA [25], CGBO [27], DMTLBO [28], and improved learning search algorithm [29]. |

**TABLE 1. Summary of parameter identification methods**

In this work, an online parameter identification method is developed and demonstrated that is capable of:

1. Accurately identifying the MPP.
2. Identifying any specific output power operating point.
3. Operating under varying insolation and temperature.
4. Online parameter identification, i.e., conducted while the PV system is supplying power to a DC Microgrid.
5. Using a limited data range, without pre-identification of $I_{sc}$, $V_{oc}$, the MPP, or any other operating point.
6. Fast operation with minimal memory complexity when implemented on a microcontroller.
7. Reliable determination of SSDM model parameters.
As such, to the best knowledge of the authors, it is the only online identification method that is non-iterative and accurately models the PV module in the current-source region of operation. Reliability of iterative techniques requires proof of convergence, otherwise they can risk diverging during online operation. The remainder of the paper is organized as follows: The proposed PV cell and module models are given in Section II. In Section III, the equations underlying the proposed parameter identification method are developed. This is followed by an experimental validation of the proposed method and an outline of its practical implementation in Section IV. Conclusions are drawn in Section V with suggestions for future work.

II. PROPOSED PV MODELING

The modeling of any DER, and indeed any electrical device, starts with obtaining its $I$-$V$ characteristic curve at its terminals. As a DER the power output capability at different voltage levels is also important, and is represented by its $P$-$V$ characteristic curve. For a PV module, the $I$-$V$ and $P$-$V$ curves depicted in Figures 1 and 2, respectively, represent a typical PV module and can be obtained offline by varying a connected resistive load between the short-circuit and open-circuit operating points, registering $I_{sc}$ and $V_{oc}$, respectively.

Moreover, when a PV DER is connected to a Microgrid through a power electronic converter, several operating modes are possible. It can regulate its duty ratio to attain the MPP, noting that $V_m$ and $I_m$ are the voltage and current at the MPP, and $P_m$ is the MPP. Alternatively, it can target an operating point with a specific lower power output (to balance the Microgrid) either in the current-source region or in the voltage-source region. The type of converter used depends on the voltage level at the main bus of the Microgrid. So, for example, if a higher level DC voltage is required at the main bus, a boost converter is used, and in practice, if the current-source region is selected, the exact short-circuit condition and its neighboring region is not reachable due to the voltage drop across the power transistor used by the boost converter. This fact can limit the amount of data collected by an online parameter identification method. Also, operating online in one region (e.g., the current-source) may limit the amount of data collected in the other (e.g., voltage-source). So online parameter identification techniques must account for limitations in data collection.

A. PV CELL MODEL

As previously mentioned, the simplest model to consider for a PV cell is the ISDM in Figure 3a, which consists of a current-source generated by insolation and is connected in parallel to a p-n junction diode model of the cell. Accounting for the linear drop in the output current in the current-source region requires $R_p$, and similarly, the voltage regulation effect in the voltage-source region requires $R_s$. Including both these resistances in the circuit model results in the SDM shown in Figure 3b. In this work, we focus on the operation of the PV system as a DER tied to a DC Microgrid in the current-source region, including the MPP. Therefore, we propose using a simplified SDM (SSDM).
eliminating $R_s$ as shown in Figure 3c, and keeping $R_p$, which is the basis for developing a practical real-time online approach in this work. However, for other applications where voltage-source operation is desired, either the SDM or a simplified SDM that only ignores $R_p$ should be used.

The resulting PV cell model is given by the I-V relationship:

$$I_c = I_{ph} - I_d - I_p = I_{ph} - I_0[e^{V_c/V_T} - 1] - \frac{V_c}{R_p}, \quad (1)$$

where $I_c$ is the cell output current, $I_{ph}$ is the photoelectric current that is proportional to the insolation, $I_d$ is the p-n junction diode recombination current, $I_p$ is the current in the parallel path through the cell, $I_0$ is the scaling current, $V_c$ is the cell terminal (output) voltage, $n$ is the ideality factor of the p-n junction, and $V_T$ is the thermal voltage.

Given that $R_s$ is ignored in this model, the terminal voltage $V_c$ is equal to the voltage appearing across the p-n junction. Also, under short-circuit conditions $I_{sc} = I_{ph}$.

Defining a scaling factor $\alpha = nV_T$, accounts for variations in $n$ for different types of PV cells (different p-n junction electron-hole recombination processes) and in $V_T$ that varies with temperature as $V_T = kT_c/q$, where $k$ is Boltzmann’s constant $(1.3806 \times 10^{-23} \text{ J/K})$, $T_c$ is the p-n junction temperature, and $q$ is the electron charge $(1.6021 \times 10^{-19} \text{ C})$.

Accordingly, the PV cell model is given by

$$I_c = I_{ph} - I_0[e^{\frac{V_c}{\alpha V_T}} - 1] - \frac{V_c}{R_p}, \quad (2)$$

Finally, during the operation of the PV cell, $I_{ph} \gg I_0$, therefore, the model simplifies to

$$I_c = I_{ph} - I_0 e^{\frac{V_c}{\alpha V_T}} - \frac{V_c}{R_p}, \quad (3)$$

with four model parameters to be identified at any given temperature and insolation level, namely, $I_{ph}$, $I_0$, $\alpha$ and $R_p$.

### B. PV MODULE MODEL

The proposed SSDM can be extended to a module with $N_s$ cells connected in series forming a string, and $N_p$ strings in parallel forming a module. Its circuit is depicted in Figure 4. Then, the terminal voltage and current are related to the cell voltage and current by $V = N_s V_c$ and $I = N_p I_c$, respectively.

The I-V characteristics for the PV module are therefore

$$I = N_p I_c = N_p I_{ph} - N_p I_0 e^{\frac{V_c}{\alpha V_T}} - \frac{N_p V_c}{R_p}. \quad (4)$$

Substituting for $V_c = V/N_s$ we have

$$I = N_p I_{ph} - N_p I_0 e^{\frac{V}{\alpha V_T}} - \frac{N_p V}{N_s R_p}. \quad (5)$$

Then, in application, the PV module model in (5) may be used or, alternatively, a scaled model that has the same form as (3) but represents the average performance of the cells in the module, that is,

$$I_c = I_{ph} - I_0 e^{\frac{V_c}{\alpha V_T}} - \frac{V_c}{R_p}. \quad (6)$$

To use this scaled model, the measured $V$ and $I$ are simply divided by $N_s$ and $N_p$ to obtain the scaled voltage $V_c$ and current $I_c$, respectively. Note that this scaled model is not the actual performance of any individual cell due to mismatches, e.g., in the fabrication of the cells.

### III. PARAMETER IDENTIFICATION MODEL DERIVATIONS

Using the scaled PV module model (6), two sets of identification model equations can be derived to obtain the unknown parameters in a non-iterative process using data collected over a limited range of the I-V curve. The known parameters are the number of cells in series $N_s$ and the number of strings in parallel $N_p$. The measurable variables are $I$ and $V$ of the PV module, from which the scaled variables $V_c = V/N_s$ and $I_c = I/N_p$ are directly computed. These variables are measured in a range starting near the short-circuit condition up to any point beyond the MPP, i.e., towards the open-circuit condition. The $N$ recorded data points are arranged with an index of $n = 1, 2, ..., N$. The unknown parameters to be found are the parallel resistance per cell $R_p$, the photoelectric current $I_{ph}$, the scaling factor $\alpha$, and the scaling current of the p-n junction model $I_0$. Note that any variations in junction temperature and insolation are captured by identifying these parameters, so only current and voltage sensors are required for data collection.

#### A. IDENTIFICATION OF $I_{ph}$ AND $R_p$

The first identification model is used to find $I_{ph}$ and $R_p$. Near the short-circuit operating point $V_c \approx 0$, and (6) simplifies to

$$I_c \approx I_{ph} - G_p V_c, \quad (7)$$

where, the parallel conductance $G_p = 1/R_p$. This can be written in regressor form as

$$y = W K, \quad (8)$$

where,

$$y \triangleq I_c, \quad W \triangleq \begin{bmatrix} 1 & -V_c \end{bmatrix}, \quad K \triangleq \begin{bmatrix} \kappa_1 & \kappa_2 \end{bmatrix}^T \triangleq [I_{ph} \ G_p]^T.$$
That is, $y$ and $W$ are known from the measured variables, and $K$ contains the unknown parameters. To solve this regressor, $N_{sc}$ data points that are sampled near the short-circuit operating point are used. These samples are indexed as $n=1, 2, \ldots, N_{sc}$. To find the vector $K$, we define the mean squared error as

$$E^2(K) = \sum_{n=1}^{N_{sc}} (y(n) - W(n)K)^2.$$  \hspace{1cm} (9)

Multiplying out we get

$$E^2(K) = R_y - R_{Wy}^T K - K^T R_W y + K^T R_W K,$$  \hspace{1cm} (10)

where,

$$R_y = \sum_{n=1}^{N_{sc}} y^2(n),$$

$$R_W = \sum_{n=1}^{N_{sc}} W^T(n) W(n),$$

$$R_{Wy} = \sum_{n=1}^{N_{sc}} W^T(n) y(n).$$  \hspace{1cm} (11)

If the data collected sufficiently excites the model then $R_W$ will be invertible, and we can minimize the error by

$$\frac{\partial E^2(K)}{\partial K} = -2R_{Wy} + 2R_W K = 0,$$  \hspace{1cm} (12)

or

$$K = R_W^{-1} R_{Wy}.$$  \hspace{1cm} (13)

Note that $V_c(n)$ is nonnegative over the range of $n = 1, \ldots, N_{sc}$, with one zero value at the short-circuit operating point and positive values otherwise. Therefore, the matrix $W^T(n)W(n)$ is full rank and so is $R_W$. Consequently, $R_W$ is invertible and (13) will yield $\kappa_1 = I_{ph}$ and $\kappa_2 = G_p$ where $R_p = 1/G_p$, which minimize the squared error in (10). Notwithstanding the fact that $R_W$ is full rank, it is important to use Gaussian elimination or LU decomposition to obtain $R_W^{-1}$ in real-time implementation, as opposed to calculating it through the adjugate matrix. This minimizes numerical errors and is common practice in linear algebra libraries such as the BasicLinearAlgebra library [31] used on the Arm Cortex M3 microcontroller in this work.

**B. IDENTIFICATION OF $\alpha$ AND $I_0$**

This step is used to identify the scaling factor $\alpha$ of the exponential term and the scaling current $I_0$. Differentiating $I_c$ with respect to $V_c$, i.e., for any two neighboring points on the $I$-$V$ curve

$$\frac{\partial I_c}{\partial V_c} = -\frac{1}{\alpha} I_0 e^{\frac{V_c}{R_p}} - \frac{1}{R_p},$$  \hspace{1cm} (14)

or

$$\frac{\alpha}{\alpha} \frac{\partial I_c}{\partial V_c} + \frac{1}{\alpha} \frac{1}{R_p} = -I_0 e^{\frac{V_c}{R_p}}.$$  \hspace{1cm} (15)

Substituting back in (6) and rearranging gives

$$I_{ph} - I_c - \frac{V_c}{R_p} = \alpha \left( -\frac{\partial I_c}{\partial V_c} - \frac{1}{R_p} \right).$$  \hspace{1cm} (16)

Note that in normal operation, the left hand side of (16) is always positive, and the derivative $\partial I_c/\partial V_c$ is always negative. Next, rearranging (6)

$$I_{ph} - I_c - \frac{V_c}{R_p} = I_0 e^{\frac{V_c}{R_p}}.$$  \hspace{1cm} (17)

Now, taking the natural logarithm of both sides, which are always nonnegative, and rearranging we obtain

$$V_c = \alpha \ln \left( I_{ph} - I_c - \frac{V_c}{R_p} \right) - \alpha \ln (I_0).$$  \hspace{1cm} (18)

Combining (16) and (18) in regressor form we get

$$y_2 = W_2 K_2,$$  \hspace{1cm} (19)

where,

$$y_2 \triangleq \begin{bmatrix} I_{ph} - I_c - \frac{V_c}{R_p} & V_c \end{bmatrix}^T,$$

$$W_2 \triangleq \begin{bmatrix} -\frac{\partial I_c}{\partial V_c} - \frac{1}{R_p} & 1 \end{bmatrix},$$

$$K_2 \triangleq \begin{bmatrix} \kappa_3 & \kappa_4 \end{bmatrix}^T = \alpha \left( \ln (I_0) \right)^T.$$

As with the previous regressor, $y_2$ and $W_2$ are known from the measured variables, and $K_2$ is the unknown parameter. In this case, however, the data points $n = N_{sc}, N_{sc} + 1, \ldots, N$ are used to avoid singularity in the matrix $W_2$ near the short-circuit condition, as $\partial I_c/\partial V_c \approx -1/R_p$, resulting in a zero row. Therefore, with this selected data range, singularity can be avoided in the matrix $W_2$ and consequently in $R_{Wy}$. The squared error is calculated as

$$E^2(K_2) = R_{y2} - 2R_{Wy2}^T K_2 + K_2^T R_{Wy2} K_2,$$  \hspace{1cm} (20)

where,

$$R_{y2} = \sum_{n=N_{sc}}^{N} y_2^T(n)y_2(n),$$

$$R_{Wy2} = \sum_{n=N_{sc}}^{N} W_2^T(n)W_2(n),$$

$$R_{Wy2} = \sum_{n=N_{sc}}^{N} W_2^T(n)y_2(n).$$  \hspace{1cm} (21)

Then, $K_2$ can be found as

$$K_2 = R_{Wy2}^{-1} R_{Wy2},$$  \hspace{1cm} (22)

minimizing the squared error in (20), with the remaining SSDM PV model parameters $\alpha = \kappa_3$ and $I_0 = \exp (\kappa_4/\kappa_3)$. 

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IV. IMPLEMENTATION AND RESULTS
The proposed PV parameter identification approach is demonstrated experimentally in this section. First, validation metrics are defined, and then, the implementation procedure is outlined to clarify and facilitate its practical application. Next, the experimental setup is described, and the results are detailed to discuss the effectiveness of the proposed method using a microcontroller to perform the measurements and calculations.

A. VALIDATION METRICS
The accuracy of the parameter identification method is validated using three different metrics: an Error Index for each identification model equation, the relative errors at the MPP operating points, and a normalized relative error over the current-source and voltage-source ranges.

The error index relates to the squared error in (10) and (20). It determines whether the identified parameters provide a good fit for the data, see [32]–[34], and is defined as follows

\[
EI = \sqrt{\frac{E^2(K^*)}{E^2(0)}} \leq 1.
\]

(23)

where the squared error is evaluated with the estimated parameter vector \( K^* \) and compared to the squared error if we arbitrarily select zeros as the estimated parameters. The result should be less than one; otherwise the estimated value is as good as any arbitrary set of parameters. Two error indices with subscripts 1 and 2, are used for identification model equations (13) and (22), respectively.

The MPP is a key operating point, and a relative error can be calculated as

\[
RE = \left| \frac{x_{exp} - x_{est}}{x_{exp}} \right| \times 100\%,
\]

(24)

where, \( x_{exp} \) represents the \( V_m, I_m, \) and \( P_m \) obtained from the measured data, and \( x_{est} \) represents their estimated counterparts from the SSDM after the proposed parameter identification is conducted.

Additionally, the normalized relative error (NRE) between the collected \( I-V \) data and the estimated model curve can be directly calculated [33], [35], and is defined as follows

\[
\bar{e}_x = \frac{1}{N_2 - N_1} \sum_{n=N_1}^{N_2} \left| \frac{x_{act}(nT) - x_{est}(nT)}{x_{act}(nT)} \right|,
\]

(25)

where, \( x \) is the state variable of interest, \( x_{est} \) is its estimated counterpart, and \( N_1 \) and \( N_2 \) are the start and end data points. Specifically, two NRE values calculated, namely, \( \bar{e}_I \) and \( \bar{e}_V \) corresponding to the current-source and voltage-source regions, respectively. For \( \bar{e}_I \), data collection starts near the short-circuit condition at \( N_1 = 1 \) up to \( N_2 = N_{MPP} \), while for \( \bar{e}_V \), the voltage-source region starts at \( N_1 = N_{MPP} \) up to \( N_2 = N \). That is, the MPP is included in both NRE calculations.

B. PARAMETER IDENTIFICATION STEPS
The online implementation of the parameter identification method is summarized as follows:

1. Collect \( I[n] \) and \( V[n] \) for data points \( n = 1 \) to \( N \). E.g., vary the duty ratio \( D \) of the boost converter over its online operational range \( D \in [D_{min}, D_{max}] \) in increments \( D_{inc} = (D_{max} - D_{min})/N \).
2. Apply a low pass filter on the data, to remove the impact of the boost converter PWM and measurement noise.
3. Determine the range of filtered data \( n = 1 \) to \( n = N_{sc} \), near the short-circuit operating point, e.g., all data points from \( I[1] \) down to 90% of \( I[1] \), i.e., \( I[N_{sc}] \approx 0.90I[1] \).
4. Use this data to calculate \( R_y \), \( R_{Wy} \) and \( R_W \) in (10). Then, find the parameters \( I_{ph} \) and \( R_p \) using (13), and compute \( EI_1 \) to check that it is less than 1, see (23).
5. Use the range of of filtered data \( n = N_{sc} \) to \( N \) for the second identification model by first calculating the partial derivative \( \partial I_c/\partial V_c \) using the center difference approach at every \( n \).
6. Then, use them along with the estimated \( I_{ph} \) and \( R_p \) to calculate \( R_{y2} \), \( R_{Wy2} \) and \( R_{W2} \) in (20) to find the parameters \( \alpha \) and \( I_0 \) using (22) and compute \( EI_2 \).

The parameter identification algorithm can be implemented online in a DC Microgrid for any PV DER module as often as is necessary to keep track of changing temperature and insolation conditions. Moreover, changes in the parameters beyond a certain range, e.g., in \( R_p \), can be used to detect the end-of-life or degradation in the PV module.

C. EXPERIMENT: DC MICROGRID CONNECTED PV MODULE
The experimental setup represents a PV DER connected to the regulated bus of a DC Microgrid through a power supply.
increases with temperature) as follows:

\[ I \propto \frac{S}{STC} \]

The collected and filtered data, both \( I \) and \( V \) versus time, for the three cases are shown in Figure 7.

The results of the parameter identification steps are listed in Table 3. It can be seen from the results in the table that the relative errors are very low. Specifically, in all cases at the MPP they are less than 1.23% for \( V_m \), 0.97% for \( I_m \), and 1.61% for \( P_m \). Moreover, the maximum error indices for the first and second identification models given in (13) and (22) were \( EI_1 = 0.0053 \) and \( EI_2 = 0.2169 \), respectively, showing that the parameters resulted in a very good fit to the data used in the estimation. In addition, the NRE in the current-source region \( \bar{e}_I \) is less than 0.4% for all three cases, demonstrating a negligible discrepancy between the estimated model and the collected (and filtered) data in this region. On the other hand, the \( \bar{e}_V \) reaches up to 1.43% (case 3) in the voltage-source region as a result of ignoring \( R_s \) in the SSDM.

Furthermore, the estimated \( I-V \) and \( P-V \) model curves for all three cases are plotted alongside the collected and filtered experimental data in Figures 8a and 8b, respectively. It can be seen that these curves are closely matched particularly in the current-source region, around the MPP, and well into the voltage-source region. This result is not obtainable in the current-source region if \( R_s \) is ignored. However, the impact of ignoring \( R_s \) in the SSDM equations is that there is a discernable discrepancy between the \( I-V \) curves of the measurements and estimated model in the voltage-source range near the \( V_{oc} \), particularly in case 3. Therefore, the algorithm consistently yields a closely matched model for the collected experimental data under each one of these varied conditions.

A noteworthy remark is that the majority of data points obtained were in the current-source region in this DC Microgrid setup. In all three cases, \( N_{sc} \) is more than 800 data points, i.e., the number of points from \( I_{sc} \) down to 0.91\( I_{sc} \), see Table 3. This is despite evenly varying the duty ratio of the boost converter (in fixed increments) between 0 and second order discrete-time low pass Butterworth filter was applied to the collected data series, once forward and then reverse to eliminate any phase shift, see for example the \texttt{filtfilt} function in the MATLAB software environment.

![Equivalent circuit diagram of the experimental setup.](image)

**TABLE 2.** Electrical characteristics of the USST50-36M PV module

| Parameter                        | Value          |
|----------------------------------|----------------|
| Maximum power at STC (\( P_{m,STC} \)) | 50 W           |
| Optimum Operating Voltage (\( V_{m,STC} \)) | 18.1 V         |
| Optimum Operating Current (\( I_{m,STC} \)) | 2.76 A         |
| Open-Circuit Voltage (\( V_{oc,STC} \)) | 22.1 V         |
| Short-Circuit Current (\( I_{sc,STC} \)) | 2.93 A         |

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99% over \(N = 1000\) points. Therefore, the current-source region can provide a wider practical range of operating points for the control of the PV DER’s power output under these settings compared to the voltage-source region.

In all cases, the model was successfully identified online in under 1 second. In fact, it took only 0.11 seconds to perform the filtering and identification calculations on the Arm Cortex M3 microcontroller. This demonstrates the reliability and low computational complexity of implementing this algorithm online; which in turn facilitates frequently reapplying it in a PV DER system as conditions change.

### TABLE 3. Detailed validation results of the experiment

| Case          | Case 2 | Case 3 |
|---------------|--------|--------|
| \(S \text{ (kW/m}^2\) | 0.57   | 0.45   | 0.61   |
| Cell Temp. \(T_c\) (\(^{\circ}\)C) | 23     | 30     | 36     |
| \(I_{ph}\) (A)   | Estimated 1.6676 | 1.3298 | 1.7819 |
| \(R_c\) (\(\Omega\)) | Estimated 3.5511 | 4.088  | 3.0858 |
| \(\alpha\) (V) | Estimated 0.011709 | 0.014418 | 0.014442 |
| \(I_0\) (A)     | Estimated \(5.465 \times 10^{-23}\) | \(6.849 \times 10^{-18}\) | \(2.206 \times 10^{-17}\) |
| \(P_m\) (W)    | Actual 30.019 | 22.085 | 29.285 |
|                | Estimated 29.796 | 21.924 | 28.815 |
|                | Error (%) 0.74  | 0.73   | 1.61   |
| \(V_m\) (V)    | Actual 20.35 | 18.73 | 18.39 |
|                | Estimated 20.10 | 18.68 | 18.27 |
|                | Error (%) 1.23 | 0.26  | 0.64   |
| \(I_m\) (A)    | Actual 1.4751 | 1.1792 | 1.5927 |
|                | Estimated 1.4824 | 1.1737 | 1.5772 |
|                | Error (%) 0.50 | 0.47  | 0.97   |
| \(EI_1\)       | 0.0050 | 0.0053 | 0.0035 |
| \(EI_2\)       | 0.1989 | 0.1502 | 0.2169 |
| \(\bar{e}_f\) (%) | 0.35 | 0.39 | 0.26 |
| \(\bar{e}_V\) (%) | 0.74 | 0.83 | 1.43 |
| Data Points \(N_{sc}\) | 892 | 823 | 806 |
| Total Data Points \(N\) | 1000 |
| Data Collec. Time (s) | 0.62 |
| Param. Ident. Time (s) | 0.11 |
| Total Exec. Time (s) | 0.73 |

### FIGURE 7. Experimental \(V\) and \(I\) vs. time for all three cases, (a) case 1, (b) case 2, and (c) case 3.

### FIGURE 8. Experimental data vs. estimated model for all three cases, (a) \(I-V\) curves, and (b) \(P-V\) curves.
throughout the day.

V. CONCLUSION

A non-iterative parameter identification method was developed in this work for PV modules and implemented on the restricted online operation scenario where they are connected to regulated DC Microgrids. The practical restrictions in the time allowed for data collection and parameter identification, and the low complexity (in time and memory) required for it to be implemented online on the microcontroller of a PV DER system were addressed. Validation steps were undertaken in an experimental setup, where an accurate estimate of the I-V and P-V characteristic curves was achieved. Specifically, relative errors that are less than 1.6% were recorded in calculating $P_m$, and a total execution time of 0.73 seconds on an Arm Cortex M3 microcontroller was consistently achieved under different temperature and insolation conditions. Future work can focus on adopting the proposed method in DER controllers to accurately and quickly target specific power output levels in DC Microgrids. This would enhance DC Microgrids, encouraging their adoption as a reliable and efficient paradigm in smart grids. In addition, more work could focus on the development of a similar non-iterative method for the full SDM, i.e., with $R_s$, or higher order models.

REFERENCES

[1] D. E. Olivas, A. Mehrizi-Sani, A. H. Eiemadi, C. A. Cañizares, R. Iravani, M. Kazerani, A. H. Hajimiragha, O. Gomis-Bellmunt, M. Saedifard, R. Palma-Behnke, et al. Trends in microgrid control. IEEE Transactions on smart grid, 5(4):1905–1919, 2014.

[2] T. Dragičevič, X. Lu, J. C. Vasquez, and J. M. Guerrero. Dc microgrids-part i: A review of control strategies and stabilization techniques. IEEE Transactions on power electronics, 31(7):4876–4891, 2016.

[3] D. Chen and L. Xu. Ac and dc microgrid with distributed energy resources. In Technologies and Applications for Smart Charging of Electric and Plug-in Hybrid Vehicles, pages 39–64. Springer, 2017.

[4] K. L. Kennerud. Analysis of performance degradation in cdc solar cells. IEEE Transactions on Aerospace and Electronic Systems, AES-5(6):912–917, 1969.

[5] G. M. Masters. Renewable and efficient electric power systems. John Wiley & Sons, 2013.

[6] M. Haouari-Merbah, M. Belhamel, I. Tobias, and J. M. Ruiz. Extraction and analysis of solar cell parameters from the illuminated current–voltage curve. Solar Energy Materials and Solar Cells, 87(1-4):225–233, 2005.

[7] T. Dragišević, X. Lu, J. C. Vasquez, and J. M. Guerrero. Dc microgrids-part i: A review of control strategies and stabilization techniques. IEEE Transactions on power electronics, 31(7):4876–4891, 2016.

[8] D. Chen and L. Xu. Ac and dc microgrid with distributed energy resources. In Technologies and Applications for Smart Charging of Electric and Plug-in Hybrid Vehicles, pages 39–64. Springer, 2017.

[9] K. Nishioka, N. Nakatani, Y. Uraoka, and T. Fukuji. Analysis of multicrystalline silicon solar cells by modified 3-diode equivalent circuit model taking leakage current through periphery into consideration. Solar Energy Materials and Solar Cells, 91(13):1222–1227, 2007.

[10] J. C. H. Phang, D. S. H. Chan, and J. R. Phillips. Accurate analytical method for the extraction of solar cell model parameters. Electronics Letters, 20(10):406–408, 1984.

[11] F. J. Toledo, J. M. Blanes, and V. Galiano. Two-step linear least-squares method for photovoltaic single-diode model parameters extraction. IEEE Transactions on Industrial Electronics, 65(8):6301–6308, 2018.

[12] N. Moshkhar and T. Ghanbari. Adaptive estimation approach for parameter identification of photovoltaic modules. IEEE Journal of Photovoltaics, 4(4):624–623, 2014.

[13] D. H. H Lim, Z. Ye, J. Ye, D. Yang, and H. Du. A linear identification of diode models from single i-v characteristics of pv panels. IEEE Transactions on Industrial Electronics, 62(7):4181–4193, 2015.

[14] D. Sera, R. Teodorescu, and P. Rodriguez. Pv panel model based on datasheet values. In IEEE International Symposium on Industrial Electronics ISIE 2007, pages 2392–2396. IEEE, 2007.

[15] M. Villalva, J. Garcia, and E. Ruppert Filho. Comprehensive approach to modeling and simulation of photovoltaic arrays. IEEE Transactions on power electronics, 24(5):1198–1208, 2009.

[16] E. Saloux, A. Teysedou, and M. Sorin. Explicit model of photovoltaic panels to determine voltages and currents at the maximum power point. Solar energy, 85(5):713–722, 2011.

[17] W. Xiao, M. Lind, W. Dunford, and A. Capel. Real-time identification of operational operating points in a photovoltaic power systems. IEEE Transactions on Industrial Electronics, 53(4):1017–1026, 2006.

[18] H. Andrei, T. Ivanovic, G. Predusca, E. Diaconu, and P. C. Andrei. Curve fitting method for modeling and analysis of photovoltaic cells characteristics. In Automation Quality and Testing Robotics (AQTR), 2012 IEEE International Conference on, pages 307–312. IEEE, 2012.

[19] B. Paviet-Salomon, J. Levrat, V. Fakhfouri, Y. Pelet, N. Rebeaud, M. Despeisse, and C. Ballif. Accurate determination of photovoltaic cell and module peak power from their current–voltage characteristics. IEEE Journal of Photovoltaics, 6(6):1564–1575, 2016.

[20] H. Ibrahim and N. Anani. Evaluation of analytical methods for parameter extraction of pv modules. Energy Procedia, 134:69–78, 2017.

[21] M. Zagrouba, A. Sellami, M. Bouaïcha, and M. Ksouri. Identification of pv solar cells and modules parameters using the genetic algorithms: Application to maximum power extraction. Solar energy, 84(5):860–866, 2010.

[22] M. Azab. Identification of one-diode model parameters of pv devices from nameplate information using particle swarm and least square methods. In Smart Grid and Renewable Energy (SGRE), 2015 First Workshop on, pages 1–6. IEEE, 2015.

[23] H. Qin and W. J. Kimball. Parameter determination of photovoltaic cells from field testing data using particle swarm optimization. In Power and Energy Conference at Illinois (PECI), 2011 IEEE, pages 1–4. IEEE, 2011.

[24] F. Bradaschia, M. C. Cavalcanti, A. J. do Nascimento, E. A. da Silva, and G. M. de Souza Azevedo. Parameter identification for pv modules based on an environment-dependent double-diode model. IEEE Journal of Photovoltaics, 9(5):1388–1397, 2019.

[25] H. G. G. Nunes, P. N. C. Silva, J. A. N. Pombo, S. J. P. S. Mariano, and M. R. A. Calado. Multiswarm spiral leader particle swarm optimisation algorithm for pv parameter identification. Energy Conversion and Management, 225:113388, 2020.

[26] M. Khursheed, M. A. Alghamdi, M. F. Nadeem Khan, A. K. Khan, I. Khan, A. Ahmad, A. T. Kiani, and M. A. Khan. Pn model parameter estimation using modified fpa with dynamic switch probability and step size function. IEEE Access, 9:42027–42044, 2021.

[27] A. Sharma, A. Sharma, A. Dasgupta, V. Jately, M. Ram, S. Rajput, M. Averbukh, and B. Azzopardi. Opposition-based tune algorithm for parameter optimization of solar cells. IEEE Access, 9:125590–125602, 2021.

[28] M. Premkumar, P. Jangir, C. Ramakrishnan, G. Naliniripriya, H. H. Alhelou, and B. S. Kumar. Identification of solar photovoltaic model parameters using an improved gradient-based optimization algorithm with chaotic drifts. IEEE Access, 9:62347–62379, 2021.

[29] L. Li, G. Xiong, X. Yuan, J. Zhang, and J. Chen. Parameter extraction of photovoltaic models using a dynamic self-adaptive and mutual- comparison learning-based optimization. IEEE Access, 9:52425–52441, 2021.

[30] T. Huang, C. Zhang, H. Ouyang, G. Luo, S. Li, and D. Zou. Parameter identification for photovoltaic models using an improved learning search algorithm. IEEE Access, 8:116292–116309, 2020.

[31] K. Lappalainen, P. Manganiello, M. Piliougine, G. Spagnuolo, and S. Defreitas, or higher order models.

[32] A. M. A. Oteafy, J. N. Chiasson, and S. Ahmed-Zaid. Development of a similar non-iterative method for the full SDM, i.e., with $R_s$, or higher order models.

[33] A. M. A. Oteafy. Fast Online Parameter Identification of PV modules.

[34] J. Chiasson. Modeling and high performance control of electric machines, volume 26. John Wiley & Sons, 2005.

[35] A. M. A. Oteafy, J. N. Chiasson, and S. Ahmed-Zaid. Development of a similar non-iterative method for the full SDM, i.e., with $R_s$, or higher order models.

[36] A. M. A. Oteafy, J. N. Chiasson, and S. Ahmed-Zaid. Development of a similar non-iterative method for the full SDM, i.e., with $R_s$, or higher order models.
[35] Y. Chen, Y. Yao, and Y. Zhang. A robust state estimation method based on socp for integrated electricity-heat system. IEEE Transactions on Smart Grid, 12(1):810–820, 2020.

[36] G. Grandi, A. Ienina, and M. Bardhi. Effective low-cost hybrid led-halogen solar simulator. IEEE Transactions on Industry Applications, 50(5):3055–3064, 2014.

AHMED M. A. OTEAFY (Senior Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from Kuwait University, and the Ph.D. degree in electrical and computer engineering from Boise State University, ID, USA, in 2011. He is currently an Assistant Professor with Alfaisal University, Riyadh, Saudi Arabia, and the Director of the Joint Smart Grids and Electric Vehicles Research & Development Center (JSEC). His research interests are in the fields of Smart Power Grids and Electric Machines: Modeling, parameter identification, control, and design of Cyber Physical Power Systems, generators and motors. Specifically, large synchronous generators, induction motors, switched reluctance machines, battery-energy storage systems, and DC Microgrids. He is also developing R&D testbeds for DC microgrids, active battery pack balancing, and a Boeing-funded solar car project.

ABDULRAHMAN ABOMAZID (Member, IEEE) was born in Riyadh, Saudi Arabia, in 1995. He received his Bachelor of Engineering (B.Eng.), in the field of Electrical Engineering, from Alfaisal University, Riyadh, Saudi Arabia, in 2018. He joined the Joint Smart Grids and Electric Vehicles Research & Development Center (JSEC), Alfaisal University, in 2018 as a research assistant and as of 2019 remains an affiliate member. He received the MASc degree in Electrical Engineering and Computer Science from the Lassonde School of Engineering, York University, Ontario, Canada in 2021. Since September 2019, he has been working as a Research Assistant and Teacher Assistant at the Department of Electrical Engineering and Computer Science (EECS) at York University. His current research interests are in energy conversion, microgrids, and renewable energy systems integration.

ARAM S. MONAWAR (Member, IEEE) is an instructor of Electrical Engineering at Alfaisal University. She completed her bachelors in Electrical Engineering with First Honors from Alfaisal University in 2018. Afterwards, she went on to pursue an MS in Electrical and Computer Engineering from Georgia Institute of Technology, Atlanta, Georgia, USA, awarded in 2020. Her technical focus was in the area of Systems and Control. She was a research assistant at the Joint Smart Grids and Electric Vehicles R&D Center (JSEC) for two years. In addition to the experience of working with the DC Microgrid cyber-physical energy systems, she was a 5-year senior member of the Alfaisal Solar Car Project.

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