International Journal Of
Industrial Electronics Control and Optimization
Print ISSN: 3517-2645
Online ISSN: 3568-2645
Homepage: https://ieco.usb.ac.ir/

An Explicit and Accurate $I-V$ Characteristic for Photovoltaic Modules Based on Piecewise Quadratic Function

Ehsan Moshksar[1]

Faculty of Advanced Technologies, Shiraz University, Shiraz, Iran.[1]
Corresponding author's email: emoshksar@shirazu.ac.ir

Article Info

Article type:
Research Article

Article history:
Received: 20-April-2024
Received in revised form: 22-June-2024
Accepted: 12-July-2024
Published online: 21-Dec-2024

Keywords:
Explicit $I-V$ characteristic,
Linear least square,
Photovoltaic module,
Piecewise quadratic function.

ABSTRACT

Deriving an accurate and simple current-voltage ($I-V$) characteristic for photovoltaic (PV) module is highly significant for condition monitoring, fault detection, and maximizing power production in PV systems. Equivalent circuits consisting of one or more diodes are mostly utilized for $I-V$ curve modelling. However, these models are inherently implicit, relatively complex, and nonlinear in their parameters. Here, a piecewise quadratic function with four different intervals is generated from the measured $I-V$ data. The intervals are chosen such that the best model performance can be achieved, especially at maximum power point (MPP). Each quadratic function is obtained from least square technique according to the experimental data in the corresponding interval. It is easy to obtain the voltage value at MPP from the extracted model, analytically. Also, a suggestion is provided for extending the generated $I-V$ model to the real environmental condition by utilizing artificial neural network. The derived PV module model is highly suitable for maximum power point tracking, monitoring, and fault detection due to its simplicity, explicit structure, and accuracy.

I. Introduction

Recently, there is a high emphasis on the use of renewable energy sources all over the world [1]. In this regard, solar photovoltaic (PV) cells have attracted great attention. By series and parallel combination of solar cells a PV system with desired output power can be achieved [2-4].

Developing an accurate model for PV module is an essential task for improving and optimizing the performance of this system [5]. Also, condition monitoring of PV systems is significant for detecting the possible faults and maximizing power production [6].

The most common approach for PV module identification is to use the measured data from current–voltage ($I-V$) curve [7]. The $I-V$ curve is strongly affected by environmental conditions, such as irradiance (G) and PV module temperature (T). Since the PV model identification is mostly accomplished at standard test condition (STC), i.e., $G=1000$ W/m^2 and $T=25$ ℃, the identified model has to be translated into the actual operating conditions [8]. Some identification techniques consider the whole measured $I-V$ curve data. On the other hand, some methods only consider some specific points such as open circuit $(0,V_{oc})$, short circuit $(I_{sc},0)$, and maximum power point (MPP) (I_{mp},V_{mp}) [9]. Moreover, an accurate and reliable model of $I-V$ curve can be utilized for the fault diagnosis of PV systems [10]. Hence, the precise modelling and analysis of the module $I-V$ is vital for further applications.

Different models have been established to describe the $I-V$ characteristic as accurate as possible, the first of which are the black-box approaches that are based on the conventional artificial neural networks (ANN) [11] and their combination with fuzzy algorithm [12]. In general, these techniques are efficient, but they suffer from some disadvantages. First, a large set of data is required to obtain reliable model which is

not always available. Second, no implicit or explicit mathematical formulations can be achieved for the $I-V$ characteristic. Also, equivalent circuits including single-diode model (SDM) [13, 14], double-diode model (DDM) [15-17], and three-diode model (TDM) [18, 19] are some common approaches for $I-V$ modelling. The SDM is the simplest equivalent circuit model, but with the least accuracy. The TDM has the highest complexity of mathematical relation, but with the highest accuracy. The DDM holds a trade-off between simplicity and prescience of the PV model. However, in all of these three models, current and voltage relations are expressed with inherent implicit formulations and high nonlinearities. Therefore, rapid and accurate estimation of unknown parameters in these circuits' models is a difficult task [20]. It should be noted that the inherent implicitly of equivalent circuits emerged from existence of series resistance (R_s) in these models [21].

Some works have been conducted to generate explicit equations for $I-V$ characteristic and write I as a function of V, or vice versa. The research in [22] can be considered as the first work in this regard. In this work, explicit and accurate functions are derived according to the Lambert W-function for both current and voltage. These equations represent the behavior of the SDM. Although these mathematical expressions have some advantages and explain SDM in an explicit form, they are complicated due to complexity of Lambert W-function. This complexity was revealed in [23] where a model-based maximum power point algorithm was applied for PV module with SDM. Moreover, in this $I-V$ model description, the unknown parameters are still presented in the nonlinear form. In [24, 25], pade approximants have been applied to form explicit $I-V$ relations. In [26, 27], Taylor's series expansion and Chebyshev polynomials have been utilized to express the exponential term of SDM and obtain an explicit analytical description of current. In [28], the mathematical expression $V+R_sI$ in the exponential term of SDM was approximated by cubic polynomial function of voltage V. In [29], an interesting approach has been applied to extract an explicit $I-V$ model for PV systems. The model was obtained according to three parameters including V_{oc}, I_{sc}, and a parameter introduced as shape parameter (S). Despite simplicity in the mathematical form, this method has some disadvantages. The S parameter should be adjusted, iteratively. Hence, small iterative step results in low rate of convergence, which is an issue especially for real time applications. On the other hand, large step lead to inaccurate model. Moreover, the model is nonlinear with respect to S. In [30], the solar cell characteristic curve was approximated by Bezier curve method. The presented model addressed the problems of nonlinearity, complexity, multivariate and multimodal of the characteristic's curve. Although many researches have been conducted to generate mathematical models for PV cell/module, developing more precise and less complicated models is still crucial. Since, some developed models are very complicated and may have implicit mathematical forms. On the other, some other models may not have desirable accuracy for additional investigations.

However, the developing of desirable model is complicated due to inherent nonlinearity of PV characteristic. Moreover, the PV characteristic highly depends on the environmental conditions such irradiance and temperature, which can be considered as another challenge for PV modelling.

In this paper, a piecewise quadratic function consisting of four separate quadratic function is derived to generate an explicit equation for $I-V$ characteristic. For this purpose, the experimental data are extracted non-uniformly from the whole $I-V$ curve (from zero voltage to open circuit voltage) at STC. In fact, more data is considered at the neighborhood of MPP. Intervals are considered as: $0 \le V \le 0.8V_{mp}$, $0.8V_{mp} \le V \le 0.95V_{mp}$, $0.95V_{mp} \le V \le 1.05V_{mp}$, and $1.05V_{mp} \le V \le V_{oc}$. A separate quadratic function is fitted for each interval by linear least square technique. It is shown that the proposed piecewise function simulates the real PV module $I-V$ curve with high accuracy, especially at MPP. Hence, this model can be easily used for maximum power point tracking to maximize energy harvesting from PV system. Moreover, it is suggested that how one can extend the coefficients of the piecewise function to generate another piecewise $I-V$ curve in the real environmental condition by utilizing ANN. The generated model has specific advantages over the equivalent circuits. First, the model defines an explicit relation between current and voltage of any PV module. Second, the generated model is linear in parameter and PV module identification can be easily achieved by simple numerical analysis. Moreover, it has less complexity, but higher accuracy than the equivalent circuit models. The main highlights and novelties of the proposed piecewise quadratic model can be itemized as:

- An explicit and linear in parameters equation for $I-V$ characteristic of photovoltaic module is derived according to piecewise quadratic function.
- The proposed model is highly accurate with unique model's parameters and less complexity compared with equivalent circuits.
- This model can be utilized for maximum power point tracking purpose and any model-based fault detection techniques.
- A reliable suggestion is provided for extension of the derived model to other real environmental conditions by utilizing of artificial neural network.

In the rest of this article, the implicit mathematical $I-V$ characteristic equations for a PV module with diodes equivalent circuits will be given in Section II. Section III

presents a novel approach to generate a mathematical model for PV module with explicit $I-V$ characteristic equation and its extension to other environmental conditions. The results for modelling of the PV module KC200GT with the proposed approach and a comparison with other PV modelling methods are discussed in Section IV. Finally, the conclusion is drawn in Section V.

II. Diodes Equivalent Circuits

The mathematical $\boldsymbol{I-V}$ characteristic equation for a typical PV module is highly nonlinear. Utilization of equivalent circuits consisting of diodes is the most common approach for $\boldsymbol{I-V}$ modelling. In this regard, single-diode model, double-diode model, and three diode model are presented. SDM is the simplest circuit with least amount of accuracy. This model has five unknown parameters that should be estimated for PV model identification. DDM with seven unknown parameters has moderate accuracy and complexity among these three circuits. Finally, TDM with nine unknown parameters has the highest accuracy, but also the highest complexity with respect to the other two circuit models. The schematic representations of these circuit models are shown in Fig. 1. The corresponding $\boldsymbol{I-V}$ characteristics for SDM, DDM, and TDM are written in equations (1) to (3), respectively [14, 16, and 18].

$$I = I_{ph} - I_{01}\left(e^{\frac{V+R_sI}{a_1V_t}} - 1\right) - \frac{V+R_sI}{R_p} \tag{1}$$

$$I = I_{ph} - I_{01}\left(e^{\frac{V+R_sI}{a_1V_t}} - 1\right) - I_{02}\left(e^{\frac{V+R_sI}{a_2V_t}} - 1\right) - \frac{V+R_sI}{R_p} \tag{2}$$

$$I = I_{ph} - I_{01}\left(e^{\frac{V+R_sI}{a_1V_t}} - 1\right) - I_{02}\left(e^{\frac{V+R_sI}{a_2V_t}} - 1\right) - I_{03}\left(e^{\frac{V+R_sI}{a_3V_t}} - 1\right) - \frac{V+R_sI}{R_p} \tag{3}$$

where $\boldsymbol{I}$ and $\boldsymbol{V}$ are output current and voltage of the PV module. $\boldsymbol{I_{0i}}$ and $\boldsymbol{a_i}$ are saturation current and ideality factor of the $\boldsymbol{i^{th}}$ diode ($\boldsymbol{i=1,2,3}$). $\boldsymbol{I_{ph}}$ is photocurrent, $\boldsymbol{R_s}$ is series resistance, and $\boldsymbol{R_p}$ is parallel resistance. Also, $\boldsymbol{V_t}$ is thermal voltage which is proportional to module temperature and number of series cells in the module. Despite accuracy and complexity of these circuit models, they have some common disadvantages. First, all the three equations are expressed in implicit mathematical forms with respect to current and voltage variables. Moreover, these equations generate nonlinear in parameters models for the PV module. Hence, model identification, parameter estimation, and $\boldsymbol{I-V}$ extraction are complicated to achieve by these equivalent circuits.

For the SDM in equation (1), an explicit relation between current and voltage was expressed as follows [22]:

$$I = g(V) = -\frac{V}{R_s+R_p} - \frac{W\left(\frac{R_sI_{01}R_p\exp\left(\frac{R_p\left(R_sI_{ph}+R_sI_{01}+V\right)}{a_1V_t\left(R_s+R_p\right)}\right)}{a_1V_t\left(R_s+R_p\right)}\right)a_1V_t}{R_s} + \frac{R_p(I_{01}+I_{ph})}{R_s+R_p} \tag{4}$$

where $W(.)$ is Lambert *W*-function. It is obvious that relation (4) is complicated and difficult to use, in practice. For example, calculation of the voltage at MPP (V_{mp}) is relatively difficult to achieve as shown in [23]. Moreover, to the best of author's knowledge, no explicit mathematical equations are derived for DDM and TDM.

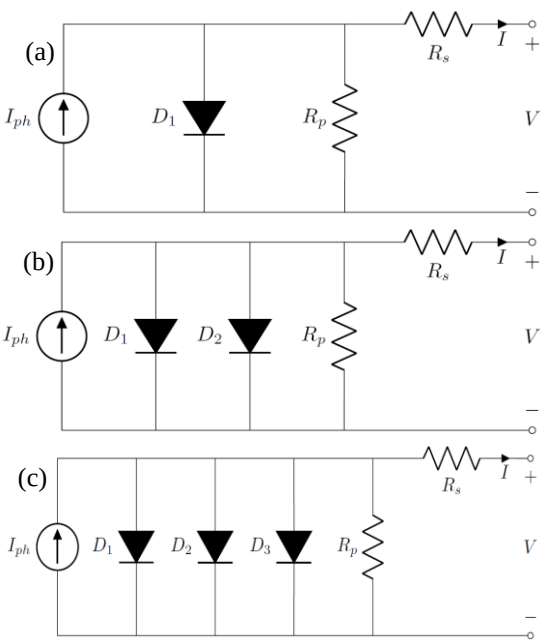

Fig. 1. Equivalent circuits of a PV module: (a) SDM, (b) DDM, (c) TDM.

III. Piecewise Quadratic Function

Here, a novel approach is presented to generate a mathematical model for PV module with explicit and linear in parameter $I-V$ characteristic equation.

In order to establish the $I-V$ curve equation, the experimental data have to be collected from the PV module from zero voltage (short circuit condition) up to its open circuit condition. Since MPP condition is the most significant operating point of the PV module, more data should be allocated to the neighborhood around this point. In general, maximum power extraction is a concerning challenge for researchers due to uncertainty of renewable energy sources,

complex operational constraints, and non-convex cost functions [31].

To generate an explicit and precise $I-V$ characteristic equation, the whole operating conditions of the module are divided into four different ranges. The first interval is related to zero voltage up to $0.8V_{mp}$, which can be shown as $0 \le V \le 0.8V_{mp}$. The second interval can be considered as $0.8V_{mp} \le V \le 0.95V_{mp}$. The third interval consists of MPP and has the highest density of the collected data as $0.95V_{mp} \le V \le 1.05V_{mp}$. The last interval is started from zero and ends at V_{oc}, which can be shown as $1.05V_{mp} \le V \le V_{oc}$. For each interval ($i$), a quadratic polynomial function (f_i) is fitted to the corresponding experimental data by linear regression analysis, which can be written as:

$$I_i = f_i(V) = a_i V^2 + b_i V + c_i, i = 1,2,3,4 \quad (5)$$

Here, ordinary least square method can be applied to estimate the unknown constant coefficients a_i, b_i, and c_i (for $i = 1,2,3,4$). The ordinary least square formula is written as [32]:

$$\theta_i = (X_i^T X_i)^{-1} X_i^T y_i, \qquad i = 1,2,3,4 \quad (6)$$

where θ_i is vector of unknown constants, X_i is a known regressor matrix and y_i is the measured output vector. By applying equation (6) into equation (5), the constant coefficients a_i, b_i, and c_i can be achieved as:

$$\begin{bmatrix} c_i \\ b_i \\ a_i \end{bmatrix} = \begin{bmatrix} n_i & \sum_{j=1}^{n_i} V_{j,i} & \sum_{j=1}^{n_i} V_{j,i}^2 \\ \sum_{j=1}^{n_i} V_{j,i} & \sum_{j=1}^{n_i} V_{j,i}^2 & \sum_{j=1}^{n_i} V_{j,i}^3 \\ \sum_{j=1}^{n_i} V_{j,i}^2 & \sum_{j=1}^{n_i} V_{j,i}^3 & \sum_{j=1}^{n_i} V_{j,i}^4 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{j=1}^{n_i} I_{j,i} \\ \sum_{j=1}^{n_i} V_{j,i} I_{j,i} \\ \sum_{j=1}^{n_i} V_{j,i}^2 I_{j,i} \end{bmatrix}, \quad (7)$$

$$i = 1,2,3,4$$

where n_i, $V_{j,i}$, and $I_{j,i}$ are the number of data points, voltage, and current values in the i^{th} interval, respectively. Hence, the corresponding piecewise quadratic function can be obtained as:

$$I = f(V) = \begin{cases} f_1(V), & 0 \le V \le 0.8V_{mp} \\ f_2(V), & 0.8V_{mp} \le V \le 0.95V_{mp} \\ f_3(V), & 0.95V_{mp} \le V \le 1.05V_{mp} \\ f_4(V), & 1.05V_{mp} \le V \le V_{oc} \end{cases} \quad (8)$$

The main advantage of the least square technique is fast unbiased convergence of the estimated parameters with the lowest variance as verified in [32] for the case of uncorrelated error vector. Therefore, a precise $I-V$ characteristic model is achieved, explicitly and with linear in parameter from.

A. MPP of Explicit Characteristic

If one considers the power-voltage ($P-V$) curve at uniform environmental condition, then, there will be a unique MPP. This point is highly desirable and multiple maximum power point tracking (MPPT) algorithms have been implied to extract maximum power form the PV system [33]. At the voltage in which the maximum power occurs, the derivative of power with respect to voltage is zero. In the derived model, the MPP is located in the third interval which is related to $f_3(V)$. Hence, the voltage value at MPP can be achieved as:

$$\frac{dP}{dV} = \frac{d(V \times f_3(V))}{dV} = f_3(V) + V \times \frac{df_3(V)}{dV} = 0 \quad (9)$$

By substitution of $f_3(V) = a_3 V^2 + b_3 V + c_3$ in equation (9), we have:

$$3a_3 V^2 + 2b_3 V + c_3 = 0 \quad (10)$$

Hence, the voltage at MPP can be easily obtained by analytical solution of quadratic polynomial function in equation (10). Finally, by substitution of the calculated V_{mp} in $f_3(V)$, the maximum power current (I_{mp}) will be achieved. This easy computation of V_{mp} is not comparable with the analysis performed in [23] which considered SDM relation in (4) to obtain V_{mp} for the $I-V$ curve.

Unlike circuits' models which have infinite responses for their parameter estimations problem, here, there is only a unique response. Moreover, the proposed piecewise model guarantees only a unique MPP for a uniform environmental condition.

B. Extension to Other Environmental Conditions

In general, the $I-V$ characteristic will be changed according to the variations of G and T. The proposed approach for developing an explicit $I-V$ characteristic can be easily applied at any environmental condition in real time. In other words, one should collect the data from zero to V_{oc} with higher data density around the MPP. Then, dividing the whole voltage working condition into four intervals as in equation (8). Assign a quadratic function to each interval as in equation (5). Finally, the constant coefficients for each interval can be obtained by equation (7). Also, it is possible to achieve the corresponding V_{mp} by solving equation (10). Although this procedure results in a precise and explicit model at any environmental condition, it may not be acceptable for high rate applications such as MPPT. Moreover, this procedure requires to stop the PV module from working at its regular condition to collect the data, which is not desirable.

The ANN is an efficient approach for updating the estimated coefficients in real time ambient condition as shown in Fig. 2. More specifically, the real experimental data have to be collected for an acceptable wide range of environmental condition offline during a total year. Then, a separate

piecewise quadratic function should be assigned for each weather condition according to equation (8). Finally, the ANN should be learned through collected data to realize a black box modelling between G and T as inputs and polynomial coefficients as outputs. This lead to a reliable $I-V$ characteristic model which is applicable for all the environmental conditions. It should be noted that effectiveness of the learned network is related to the reliability, accuracy, and diversity of the collected data.

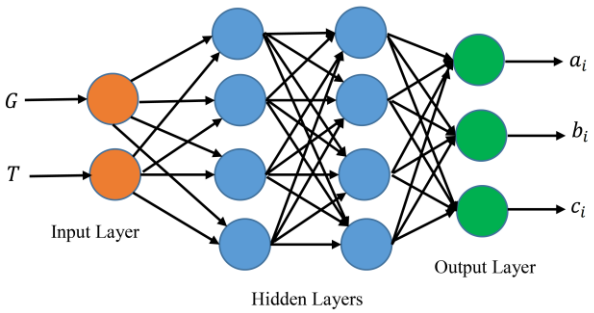

Fig. 2. Schematic representation of the ANN to achieve the model's coefficients for the real G and T values.

A block diagram is provided in Fig. 3 for better interpretation of the established PV model with explicit $I-V$ characteristic based on piecewise quadratic function.

IV. Results and Discussions

Without loss of generality, the popular KC200GT module is considered to validate the effectiveness of the proposed method. It should be noted that this modelling approach can be applied to other PV modules in a similar manner. All the simulations and implementation of the proposed algorithm are developed in MATLAB environment.

First, the experimental data are extracted from module KC200GT at STC. The corresponding data points and the three key working conditions (open circuit, short circuit, and MPP) are illustrated in Fig. 4. It can be observed from this figure that more amount of data is collected in the neighborhood of MPP due to its importance.

All the four quadratic polynomial functions are derived according to the least square technique in relation (7). For the module KC200GT these functions are achieved as:

$$\begin{cases} f_1(V) = -44\times10^{-6}V^2 - 0.0013V + 8.2092 \\ f_2(V) = -0.0154V^2 + 0.6487V + 1.3104 \\ f_3(V) = -0.0663V^2 + 3.1901V - 30.4071 \\ f_4(V) = -0.1639V^2 + 8.5790V - 104.84 \end{cases} \quad (11)$$

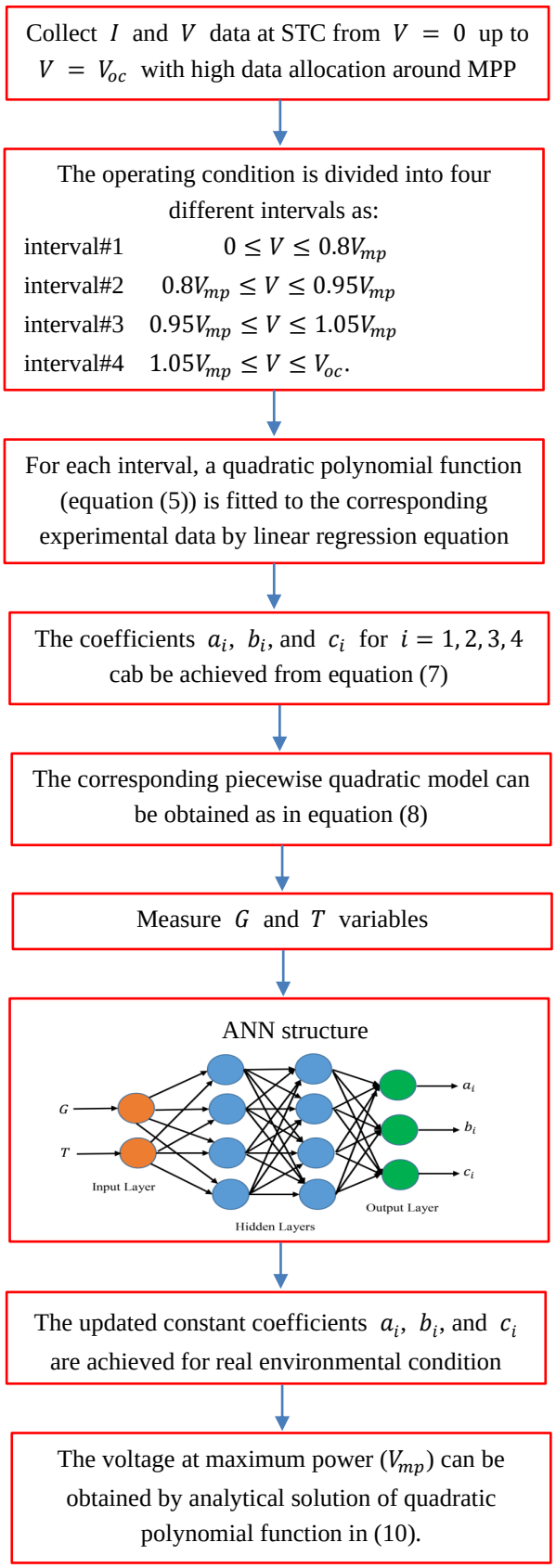

Fig. 3. A simple block diagram of the proposed piecewise quadartic model with an analytical procedure to find MPP

The established model in equation (11) can be easily generated in MATLAB by the command "polyfit(Vi,Ii,2)" where Vi and Ii are measured voltage and current data at the interval number i (i=1,2,3,4).

These polynomial functions are depicted in Fig. 5 for the whole operating condition, i.e., $0 \le V \le V_{oc}$. This figure verifies that each quadratic function has desirable performance at its corresponding voltage interval.

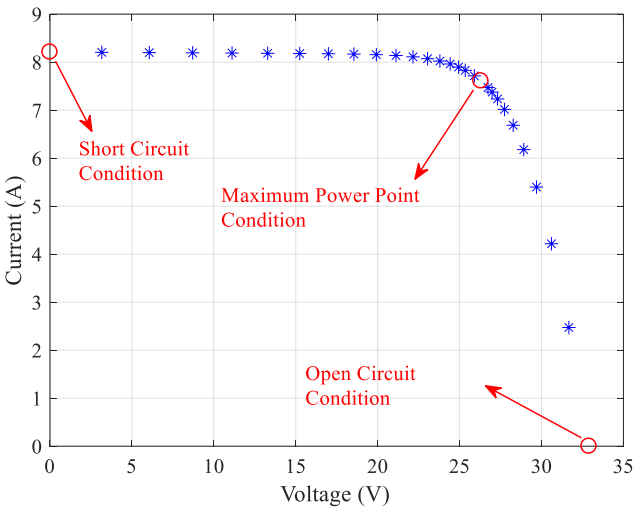

Fig. 4. Experimental data from $I-V$ characteristic of module KC200GT at STC.

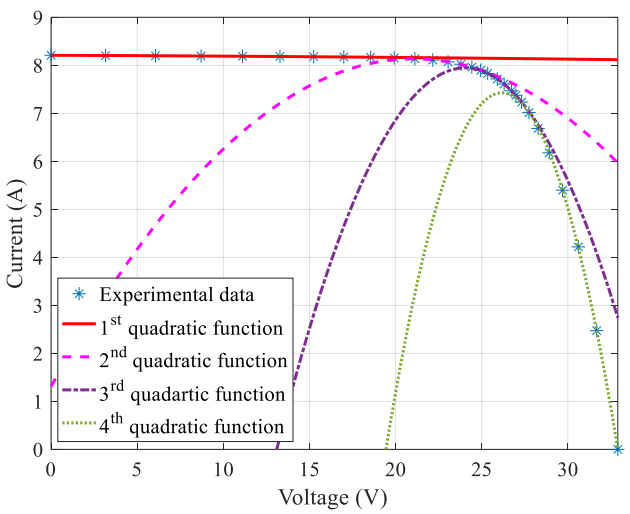

Fig. 5. Four extracted polynomial functions for the total operating condition $0 \le V \le V_{oc}$.

By considering each polynomial at its own extracted interval from equation (8), the derived $I-V$ characteristic can be obtained as it is illustrated in Fig. 6. It can be observed from this figure that a reliable model is achieved for the PV module all over its operating condition. To quantitatively verify the effectiveness of the proposed model, the root mean square error (RMSE) between the simulated current (I) from equation (11) and the measured experimental current (I_m) is calculated as [19]:

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}\left(I_{mj} - I_j\right)^2}{N}} \quad (12)$$

where N is the number of total experimental data. For the corresponding KC200GT module, we have $RMSE = 0.0068$ which is a very small value.

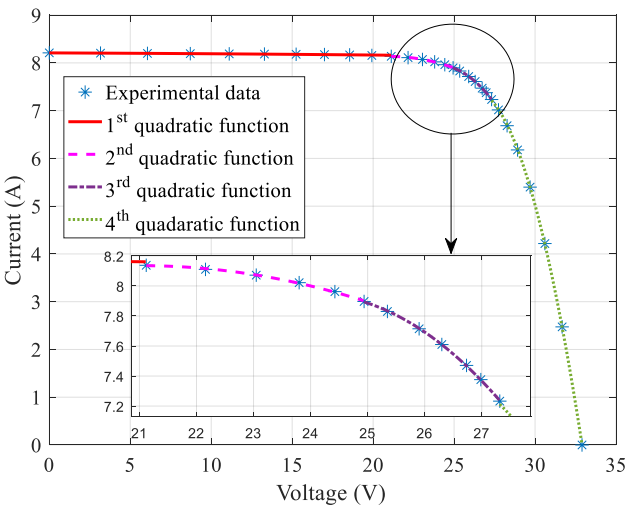

Fig. 6. Explicit piecewise quadratic function for $I-V$ characteristic at STC.

In order to investigate the preciseness of the proposed explicit function at MPP, the $P-V$ curve is illustrated in Fig. 7. For quantitative investigation, the third quadratic function ($f_3(V)$) which consists of MPP is considered again. It can be concluded from equation (10) that $-0.1989V^2 + 6.3802V - 30.4071 = 0$. By solving this quadratic equation for V, the maximum power voltage is achieved as $V_{mp} = 26.2546$ V. Substitution of the calculated V_{mp} in $f_3(V)$ results in obtaining $I_{mp} = 7.6468$ A. These calculated values are very close to the real values specified in the module's datasheet. Hence, the results show the effectiveness of the proposed $I-V$ curve model at MPP.

A. *Comparison with Other Methods*

In order to verify the capability of the proposed approach, a comparison is provided with some recent methods including SDM [13], DDM [15], and TDM [19]. First, the generated $I-V$ curve from each method and the corresponding experimental data for the module KC200GT are illustrated in Fig. 8.

According to Fig. 8, for $V < V_{mp}$, the proposed method and the SDM has the best performance while the proposed method is still slightly better. The performance of the TDM is worse than SDM and DDM has the worst behavior for lower voltages. In the neighborhood of MPP, the proposed method and TDM

has the best fitness with experimental data. However, the proposed approach shows slightly better fit with measured data. After these two methods, DDM has a better performance compared with SDM. Interestingly, all the four approaches have a desirable performance at the MPP itself. However, it should be noted that achieving MPP can be easily accomplished analytically by the proposed method (equation (10)). On the other hand, analytical calculation of MPP in SDM is relatively complicated and it is almost impossible for DDM and TDM. For $V > V_{mp}$, the piecewise quadratic function has the best modelling potential. After the designed approach, TDM and DDM has reliable performances, respectively. Finally, SDM has noticeably the lowest accuracy among all the four modelling methods.

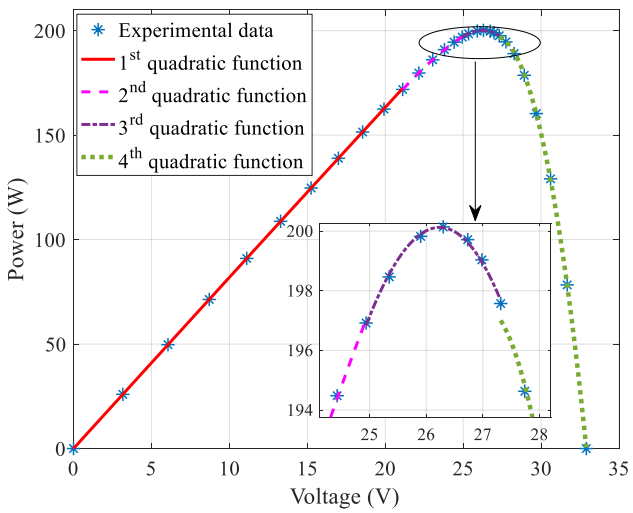

Fig. 7. Explicit piecewise quadratic function for $P-V$ characteristic at STC.

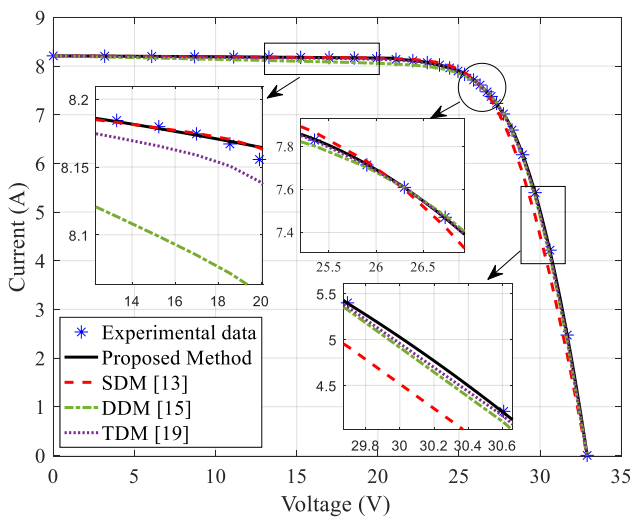

Fig. 8. Comparison between different approaches for $I-V$ characteristic at STC.

From the above discussion, one can conclude that the proposed method represents more reliable and accurate model with respect to circuit models at all operating conditions. For better insight on the performance of each method some quantitative and qualitative analyses are provided in Table 1. The quantitative indices are RMSE, maximum absolute current error (CMAE), maximum absolute power error (PMAE), maximum absolute current error at MPP (CMAE-MPP), and maximum absolute power error at MPP (PMAE-MPP). The qualitative indices include number of unknown parameters, linearity of model with respect to parameters, rate of modelling, complexity, and reliability.

TABLE 1 COMPARISON BETWEEN DIFFERENT PV MODELLING APPROCHES

Comparison indices	Proposed method	SDM [13]	DDM [15]	TDM [19]
RMSE	0.0068	0.1777	0.0628	0.0189
CMAE	0.0187	0.5151	0.1208	0.0554
CMAE-MPP	9.7e-04	0.0077	6.7e-04	3.2e-05
PMAE	0.5298	15.7651	3.8250	1.6962
PMAE-MPP	0.0255	0.2017	0.0176	8.4e-04
Parameters No.	12	5	7	9
Complexity	Very low	Low	High	Very high
Convexity	Yes	No	No	No
Simulation time	Very low	Low	High	Very high
Linear in parameters	Yes	No	No	No

It can be observed from Table 1 that the piecewise quadratic model has the highest accuracy among all the other methods considering the whole operating condition. However, at MPP specifically, DDM and TDM lead to more accurate model. But as previously discussed, analytical calculation of MPP from DDM and TDM is almost impossible. Hence, this specific preciseness is ineffective in practice.

From qualitative points of view, the proposed approach results into a model with very low complexity regardless of its 12 number of unknown parameters. Unlike the circuit models, the piecewise quadratic model is represented linear with respect to its parameters. Hence, it is easy to obtain the unknown parameters with common techniques such as linear least square. By the assumption of the known parameters, the simulated $I-V$ curve from the piecewise quadratic function can be rapidly generated in MATLAB environment. However, numerical simulation of $I-V$ curves for circuit models is much slower. Therefore, the piecewise quadratic model is highly desirable for real time applications of PV systems such as MPPT and fault detection. Moreover, the solution of estimated parameters for the proposed method is unique. On the other hand, all the circuit models lead to non-convex problems for their parameters' estimations. In other words, they all have non-unique solutions. Hence, the piecewise quadratic approach results in more reliable PV model with respect to equivalent circuits.

V. Conclusions

It is important to generate precise and simple model for a typical PV module. This task can be accomplished by using the measured data form $I-V$ characteristic. Although the equivalent circuits are popular modeling approaches, they result in models with an implicit mathematical structure and nonlinear in parameters forms. Hence, this leads to a highly complex, nonlinear, and non-convex model, in which the unknown parameter estimation is difficult and time consuming. These disadvantages may reduce the application of these equivalent circuits, in practice.

In this work, a piecewise quadratic function including four different quadratic functions is generated from the measured $I-V$ data at standard test condition (STC). The interval of each quadratic function is selected such that, the derived model is accurate and relatively simple. One of the intervals is allocated only to the MPP and its small neighboring. Hence, the generated model has high reliability at MPP and it is suitable for model-based maximum power point tracking algorithms. Moreover, the extracted model has high preciseness in all other operating conditions, verified by $RMSE = 0.0068$. Besides, the generated model has an explicit mathematical structure where all the parameters appear in the linear mathematical form. These advantages lead to a model which is desirable for maximum power point tracking, monitoring, and fault detection. Finally, one suggestion was provided to extend the derived model to the other ambient conditions through utilization of ANN.

REFERENCES

[1] A. A. Zamani, M. Shafiee, and M. Sajadinia, "Optimal self-tuning fractional order fuzzy load frequency control considering sustainable energy sources and electric vehicle," International Journal of Ambient Energy, vol. 44, pp. 2170-2184, 2023.

[2] M. A. Hasan and S. K. Parida, "An overview of solar photovoltaic panel modeling based on analytical and experimental viewpoint," Renewable and Sustainable Energy Reviews, vol. 60, pp. 75-83, 2016.

[3] J. Farzaneh and A. Karsaz, "Application of Improved Salp Swarm Algorithm Based on MPPT for PV Systems under Partial Shading Conditions," International Journal of Industrial Electronics, Control and Optimization, vol. 3, pp. 415-429, 2020.

[4] M. Sajadinia, "An adaptive virtual inertia control design for energy storage devices using interval type-2 fuzzy logic and fractional order PI controller," Journal of Energy Storage, vol. 84, Part A, p. 110791, 2024.

[5] R. Daxini, Y. Sun, R. Wilson, and Y. Wu, "Direct spectral distribution characterisation using the Average Photon Energy for improved photovoltaic performance modelling,". Renewable Energy, vol. 201, pp. 1176-1188, 2022.

[6] K. Lappalainen, M. Piliougine, S. Valkealahti, and G. Spagnuolo, "Photovoltaic module series resistance identification at its maximum power production," Mathematics and Computers in Simulation, 2023.

[7] K. Lappalainen, M. Piliougine, and G. Spagnuolo, "Experimental comparison between various fitting approaches based on RMSE minimization for photovoltaic module parametric identification," Energy Conversion and Management, vol. 258, p. 115526, 2022.

[8] H. K. Viljakainen, K. Lappalainen, and S. Valkealahti, "A novel procedure for identifying the parameters of the single-diode model and the operating conditions of a photovoltaic module from measured current–voltage curves," Energy Reports, vol. 8, pp. 4633-4640, 2022.

[9] F. J. Toledo, V. Galiano, J. M. Blanes, V. Herranz, and E. Batzelis, "Photovoltaic single-diode model parametrization: An application to the calculus of the Euclidean distance to an *I –V* curve," Mathematics and Computers in Simulation, 2023.

[10] Y. Liu, K. Ding, J. Zhang, Y. Lin, Z. Yang, X. Chen, Y. Li, and X. Chen, "Intelligent fault diagnosis of photovoltaic array based on variable predictive models and I–V curves," Solar Energy, vol. 237, pp. 340-35, 2022.

[11] Z. Chen, Y. Chen, L. Wu, S. Cheng, P. Lin, and L. You, "Accurate modeling of photovoltaic modules using a 1-D deep residual network based on I-V characteristics," Energy Conversion and Management, vol. 186, pp. 168-187, 2019.

[12] A. Chikh and A. Chandra, "Adaptive neuro-fuzzy based solar cell model," IET Renewable Power Generation, vol. 8, pp. 679-686, 2014.

[13] M. H. Qais and S. M. Muyeen, "A novel adaptive filtering algorithm based parameter estimation technique for photovoltaic system," IEEE Transactions on Energy Conversion, vol. 37, pp. 286-294, 2022.

[14] J. Xu, C. Zhou, and W. Li, "Photovoltaic single diode model parameter extraction by dI/dV-assisted deterministic method," Solar Energy, vol. 251, pp. 30-38, 2023.

[15] K. Chennoufi, M. Ferfra, and M. Mokhlis, "An accurate modelling of PV modules based on two-diode model," Renewable Energy, vol. 167, pp. 294-305, 2021.

[16] F. F. Liu, S. C. Chu, C. C. Hu, J. Watada, and J. S. Pan, "An effective QUATRE algorithm based on reorganized mechanism and its application for parameter estimation in improved photovoltaic module," Heliyon, vol. 9, p. e16468C, 2023.

[17] A. Şentürk, "A new recursive method based on datasheet information to calculate the double diode model parameters of commercially available photovoltaic modules," Renewable Energy, vol. 227, p. 120507, 2024.

[18] H. Rezk and M. A. Abdelkareem, "Optimal parameter identification of triple diode model for solar photovoltaic panel and cells," Energy Reports, vol. 8, pp. 1179-1188, 2022.

[19] A. M. Shaheen, A. R. Ginidi, R. A. El-Sehiemy, A. El-Fergany, and A. M. Elsayed, "Optimal parameters extraction of photovoltaic triple diode model using an enhanced artificial gorilla troops optimizer," Energy, vol. 283, p. 129034, 2023.

[20] T. N. Olayiwola and S. Choi, "Superellipse model: An accurate and easy-to-fit empirical model for photovoltaic panels," Solar Energy, vol. 262, p. 111749, 2023.

[21] L. E. Mathew and A. K. Panchal, "An exact and explicit PV panel curve computation assisted by two 2-port networks,"

Solar Energy, vol. 240, pp. 280-289, 2022.
[22] A. Jain and A. Kapoor, "Exact analytical solutions of the parameters of real solar cells using Lambert *W*-function," Solar Energy Materials and Solar Cells, vol. 81, pp. 269-277, 2004.
[23] E. Moshksar and T. Ghanbari, "A model-based algorithm for maximum power point tracking of PV systems using exact analytical solution of single-diode equivalent model," Solar Energy, vol. 162, pp. 117-131, 2018.
[24] S. Lun, C. Du, G. Yang, S. Wang, T. Guo, J. Sang, and J. Li, "An explicit approximate I–V characteristic model of a solar cell based on pade approximants," Solar Energy, vol. 92, pp. 147-159, 2013.
[25] A. K. Das, "An explicit *J–V* model of a solar cell using equivalent rational function form for simple estimation of maximum power point voltage," Solar Energy, vol. 98, pp. 400-403, 2013.
[26] S. Lun, C. Du, T. Guo, S. Wang, J. Sang, and J. Li, "A new explicit *I–V* model of a solar cell based on Taylor's series expansion," Solar Energy, vol. 94, pp. 221-232, 2013.
[27] S. Lun, T. Guo, and C. Du, "A new explicit I–V model of a silicon solar cell based on Chebyshev Polynomials," Solar Energy, vol. 119, pp.179-194, 2015.
[28] Y. Mahmoud, M. Abdelwahed, and E. F. El-Saadany, "An Enhanced MPPT Method Combining Model-Based and Heuristic Techniques," IEEE Transactions on Sustainable Energy, vol. 7, pp. 576-585, 2016.
[29] N. Boutana, A. Mellit, S. Haddad, A. Rabhi, and A. M. Pavan, "An explicit I-V model for photovoltaic module technologies," Energy Conversion and Management, vol. 138, pp. 400-412, 2017.
[30] M. Louzazni and S. Al-Dahidi, "Approximation of photovoltaic characteristics curves using Bezier Curve," Renewable Energy, vol. 174, pp. 715-732, 2021.
[31] M. Shafiee, A. A. Zamani, and M. Sajadinia, "Using Improved DDAO Algorithm to Solve Economic Emission Load Dispatch Problem in Presence of Wind Farms," International Journal of Industrial Electronics, Control and Optimization, vol. 6, pp. 161-169, 2023.
[32] R. A. Johnson and D. W. Wichern, "Applied Multivariate Statical Analysis," Pearson Printice Hall, Upper Saddle River, 6th ed., 2002.
[33] M. Rahideh, A. Ketabi, and A. H. Niasar, "Maximum Power Point Tracking Using a State-dependent Riccati Equation-based Model Reference Adaptive Control," International Journal of Industrial Electronics, Control and Optimization, vol. 3, pp. 115-124, 2020.

Ehsan Moshksar was born in Shiraz, Iran in 1985. He received the B.Sc. and M.Sc. degrees in Electrical Engineering from Shiraz University, Shiraz, Iran, in 2008 and 2011, respectively, and the Ph.D. degree in Chemical Engineering from Queen's University, Kingston, ON, Canada, in 2015. He is currently an Assistant Professor in the School of Advanced Technologies, Shiraz University, Shiraz, Iran. His research interests include nonlinear systems, adaptive control, parameter estimation, and real-time optimization with application to electrical, mechanical, and chemical systems.