A Novel Initial Value Prediction of Curve-Fitting Algorithm for Single-Diode Model of Photovoltaic Modules

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Abstract. In this paper a new initial value prediction of curve-fitting algorithm is presented for extracting the parameters of the single-diode model. Before extracting the parameters of the single-diode model of Photovoltaic (PV) modules, a reform of the equation of the single-diode model has been presented for improving the accuracy of the Single-diode model. And the biggest advantage of the algorithm is the prediction of initial value where Newton-Raphson method utilized to seek the root of initial value objective function. Also, Gauss-Newton iteration method have been applied to seek the optimal value of the algorithm—the least square nonlinear multiple regression. Test on two classic case studies and operational PV cells and modules, the proposed algorithm exhibits substantial improvement in terms of fitting accuracy, where the root-mean-square error is lower than other methods, and reliabilities for practical applications including different types and materials. With these, the proposed method is envisaged to be valuable for practical applications, in which accuracy of the single-diode model is of prime concern.

Keywords: Curve-fitting algorithm, single-diode model, photovoltaic modules.

1. Introduction

For PV systems designers, it is indispensible to develop suitable models to closely simulate the characteristics of PV cells and to simulate, design, evaluate, control and optimize the PV systems effectively [1].

At present, the single-diode model derived from photovoltaic module materials is widely used due to the good balance between the simulation accuracy of model and the complexity of parameters extraction [2]. The equivalent circuit diagram is shown in Figure 1, which composed by independent current sources, diodes, series and parallel resistors. It’s mathematical function can be expressed as equation (1), where \( U_{th} \) is the thermal voltage \( (U_{th} = KTN_e/q) \), \( K \) is the Boltzmann constant, \( T \) is the operating temperature of the photovoltaic module, \( q \) is the electronic charge, \( N_e \) is the number of battery cells in the unit module, and its five characteristic parameters are the photo-generated current \( (I_{ph}) \), the diode reverse saturation current \( (I_0) \), the series resistance \( (R_s) \), the parallel resistance \( (R_{sh}) \) and the diode ideality factor \( (n) \).
The five parameters of the single-diode model are equivalent to different mechanisms in photovoltaic modules: the photo-generated current mainly corresponds to the photovoltaic effect of photovoltaic module materials, and its magnitude depends on the effective luminous flux and the absorption and conversion capacity of the module materials [3, 4]; the equivalent series resistance includes the bulk resistance of the semiconducting material, and the contact resistances between the electrodes, the wiring and semiconducting materials [5-7]; parallel resistance is caused by the leakage current of the p-n junction such as the surface current of the solar cell, the internal fault of the material or the impurity [7]; the diode reverse saturation current relates to diffusion process caused by minority carrier and recombination current [9][8]; and the diode ideal factor represents the adaptation of the photovoltaic module to Shockley diode in its material [9].

According to the amount of sample data used in the process of determining the parameters, the single diode model algorithm can be divided into analytical approach and numerical approach [2]. The method of using the special points (the short circuit point \((0, I_{sc})\), the maximum power point \((V_m, I_m)\) and the open circuit point \((U_{oc}, 0)\) (Fig.2)) provided by manufacturers in datasheets and its mathematical function to solve the characteristic parameters is called the analysis approach, and using a large number or all of measurement data is called the numerical approach, which based on the error between the theoretical data and experiment to be minimized. Despite its simplicity and rapid computations, the error of special point between assumptions and measurement used in the analytical approach often lead to inaccurate and physically unrealistic values [10]. On the optimization algorithm itself, the numerical approach depended on a large amount of data can effectively suppress the influence of measurement noise, so its accuracy is substantially more accurate.

According to their own characteristics of algorithms, numerical approach can be divided into deterministic and stochastic algorithms [2]. Based on random optimization technology, stochastic algorithms represented by intelligent algorithm have excellent global search capability and effectively solve nonlinear functions without gradient information and initial values that the starting values of the parameters that are introduced prior to the running of the algorithm. However, stochastic algorithms still have many defects that their convergence times and computational costs are considerably onerous together with, in general, not very high degree of accuracy with respect deterministic algorithms [11]. The gradient-based deterministic methods such as Newton's method, LM method, and curve fitting method has excellent effectiveness in the local search. Choosing appropriate initial value and setting a suitable objective function ensures the effective convergence of the deterministic methods [12].

\[
I = I_{ph} - I_0 \left( \exp \left( \frac{U+IR_s}{nU_{th}} \right) - 1 \right) - \frac{U+IR_s}{R_{sh}}
\]
The curve fitting method of the single diode model is a deterministic method based on the principle of least squares, which mainly includes an initial value prediction method and a least-squares fitting. The initial value prediction method and the least-squares fitting are interrelated. The least-squares fitting depending on the unknown parameters is performed to obtain the optimal parameters but, it clearly needs to start from a guess very near to the optimal solution to ensure, not only its convergence, but also a reduced number of iterations [13]. Among the five unknown parameters of the single diode model, the optimal value of the photo-generated current is very close to the short-circuit current numerically which always be set as the initial value of the photo-generated current [14]; the reverse saturation current of the diode is difficult to assign, and using special points to express the reverse saturation current are often used, which reduces the unknown parameters of the curve fitting method [11, 15]. To the parameters of the series resistance, diode ideality factor, and parallel resistance, it is often assumed in the literature [16, 17], within the empirical range a value is often taken as the initial value called the empirical value method [16, 15, 11, 18]. The empirical value method is widely used but the ranges, materials and structures of photovoltaic cells have been considered negligible among this. Arbitrary of the empirical value method limits the applicability to a certain extent. Another way to predict the initial value of parallel resistance and series resistance is to get the slope information, by linear regression of multiple discrete points and simplify the special point function [13, 16]. Above this initial value prediction method, the value of the diode ideality factor will still be based on the empirical value.

The curve-fitting method mainly determines the performance of the algorithm. Forming the five unknown parameters as the parameters vector of the objective function always to be blamed for the giant number of the diode reverse saturation current of the diode in the Jacobian matrix of the objective function. This determines the extremely small iterative step length of the ideal reverse saturation current of the diode in its inverse matrix (or iteration step size). Even if the iteration below the convergence limits (epsilon), the step length of the ideal reverse saturation current plays a low role in it even not reach the optimal value. So, avoiding the matrix singularity in the solving process of optimization such as chemistry [12], using special points to express the reverse saturation current are often used though sacrificed the accuracy of the curve fitting method which dependent on the numerical accuracy of the special point. To make up the accuracy, additional steps, called Refinement in article [12, 15, 11, 18], achieve the best value by the MATLAB curve fitting toolbox. This Refinement operation take the accurate calculation result as the initial value of the algorithm, otherwise the number of iterations often exceeds the maximum number of iterations.

This paper focuses on the method of parameters extraction, which is gradient-descent based techniques. First of all, the proposed method need to guess initial value as close as possible to the optimal value, so that less iterations to converge and less computational time to cost. Before proposing the initial parameter prediction method, this paper analyzes the influence of five unknown parameters on the performance of the curve fitting algorithm. To overcome the matrix singularity convergence
difficulties, by using some algebraic manipulations, the mathematical equation of the single diode model that was often used in previous works has been altered here by reforming the parameter of the ideal reverse saturation current of the diode. With the aim to show the capabilities of the proposed forms, two classic cases of study are presented which initially proposed in literature [12] and commonly used in literature [13]. Besides, this paper takes measured data as study to test the proposed algorithm in this paper effectiveness of simulating photovoltaic cells, modules and arrays.

2. Extraction of the Single-diode PV model parameters
This section introduces the single-diode model, which mainly includes the classical equation by Lambert W function and the reform of the equation. Then, this paper describes influences of initial value to algorithm and proposes an initial value prediction method.

2.1. The Reform Single-diode PV model
The well-known single-diode equation is shown in Eq. (1), which can be expressed by Eq. (2) using the Lambert W function.

\[ I = \frac{R_s(I_{ph}+I_0)-U}{R_{sh}+R_s} - \frac{nU_{th}}{R_s} \text{LambertW} \left( \frac{R_sR_{sh}}{nU_{th}(R_s+R_{sh})} \exp \left( \frac{R_sR_{sh}(I_{ph}+I_0)+R_{sh}U}{nU_{th}(R_s+R_{sh})} \right) \right) \]  

(2)

In extracting the parameters of the single-diode model, all the parameters of the PV are used as the parameters vector of the objective function, and the diode reverse saturation current is expressed in exponential form \( I_0 = e^t \), where the parameter \( t \) corresponded to \( I_0 \) mathematically, because of the different orders of magnitude of five parameters. The parallel resistance is used in the calculation in the form of parallel conductance \( G_{sh} = 1/R_{sh} \). At the same time, Eq. (1) and Eq. (2) can be rewritten as Eq. (3) and Eq. (4).

\[ I(I_{ph}, t, R_S, G_{sh}, n, U) = I_{ph} - \exp(t) \left( \exp \left( \frac{U+IR_S}{nU_{th}} \right) - 1 \right) - (U + IR_S)G_{sh} \]  

(3)

\[ I(I_{ph}, t, R_S, G_{sh}, n, U) = \frac{(I_{ph}+\exp(t)-UG_{sh})}{R_sG_{sh}+1} - \frac{nU_{th}}{R_s} \text{LambertW} \left( \frac{R_s\exp(t)}{nU_{th}(G_{sh}R_s+1)} \exp \left( \frac{R_s(I_{ph}+\exp(t))+U}{nU_{th}(R_sG_{sh}+1)} \right) \right) \]  

(4)

Considering the five parameters of model in Eq.(4), we denote \( \pi \) the vector of unknown parameters, namely \( \pi = [I_{ph}, t, R_S, G_{sh}, n] \). An objective function \( S(\pi) \) is defined over \( \pi \), subjected to Eq. (5), as the squared difference between the experimental and the theoretical data:

\[ S(\pi) = \sum_{k=1}^{N} (I_k - I_k^{exp})^2 \]  

(5)

Where \( N \) is total number of available points, \( I_k^{exp} \) is the \( k \)th sample out of \( N \) experimental current data samples and \( I_k \) is the \( k \)th sample of the theoretical current. The current Root Mean Square Error (RMSE) given by Eq. (6):

\[ \text{RMSE} = \sqrt{\frac{S(\pi)}{N}} = \sqrt{\frac{\sum_{k=1}^{N}(I_k-I_k^{exp})^2}{N}} \]  

(6)

RMSE is accounting for the accuracy of the curve fitting algorithm, which the smaller represents the more accurate result of algorithm.

2.2. Prediction of Initial value
In previous literature, the prediction of initial value is always simple, vague, subjective or even arbitrary [1]. With the improvement of the accuracy of extraction, the increasing of the dimension of
The objective function needs an initial value very near to the optimal value, not only its convergence and time-consuming, but also a capability that can be proved to have the effectiveness of simulating photovoltaic cells, modules and arrays.

In this section, we will analyze the influence of five parameters, compare the parameters’ influence degree on convergence of algorithm, and put forward a universal initial value prediction method.

2.2.1. Influence of initial value. Aim to test the influence of initial value of parameters on the curve-fitting algorithm, two classic or typical case studies commonly used in the literature includes the measurement data of a 57mm diameter commercial (R.T.C, France) silicon solar cell and a solar module composed of 36 polysilicon cells in series (Table 1) given in reference [12]. The way to get the best numerical results of curve fitting method are given in reference [18, 13], through it the best value of two case studies which based on the Eq. (2) shows in Table 2.

| Type | $U_{oc}(V)$ | $I_{sc}(A)$ | $U_{m}(V)$ | $I_{m}(A)$ | Pcs | N | T(°C) |
|------|-------------|-------------|-------------|-------------|-----|---|--------|
| Cell | 0.5728      | 0.7603      | 0.4507      | 0.6894      | 1   | 26| 33     |
| Module | 16.778     | 1.030       | 12.649      | 0.912       | 36  | 26| 45     |

Using the single variable method to change only one parameter value of Table 2 by weighting as the initial value of the lsqnonlin function of MATLAB optimization toolbox can record its iterations (Table 3) which from the latest initial value return to the optimal value.

| $I_{ph}(A)$ | $I_{0}(µA)$ | $R_s(Ω)$ | $R_{sh}(Ω)$ | $n$ | RMSE          |
|-------------|-------------|-----------|-------------|-----|---------------|
| Cell        | 0.7608      | 0.3102    | 0.0366      | 52.86| 1.4770       | $0.7730 \times 10^{-3}$ |
| Module      | 1.0324      | 2.5189    | 1.2390      | 745.64| 1.3174      | $2.0465 \times 10^{-3}$ |

The impact that $R_s$ and $n$ has on the objective function is clearly visible in Table 3 that the iterative process is indeed highly sensitive to small changes. Consequently, an inappropriate value attained in the process of the optimization was very likely to cause the divergence of the algorithm [13] and time-consuming. It is clearly observed that the iterations of five parameters has difference in value, and the descending order can be expressed by Eq. (7). Besides, bearing in mind, it is more difficult to return for the initial value of $R_s$ is more greater than optimal value. On the country, the initial value of...
parameter $n$ has an opposite characteristics that the iteration increasing caused by the decreasing of the initial value of $n$. The tendency of $R_{sh}, I_0, I_{ph}$ could be overlooked compared to $R_s$ and $n$. Here is a bold assumption that taking a smaller initial value of $R_s$ and a greater initial value of $n$ let the algorithm return to the optimal value as soon as possible.

$$n > R_s \gg R_{sh} > I_0 > I_{ph} \quad (7)$$

2.2.2. Prediction of initial value. The initial values assigned to the extracted parameters, which have different difficulties in the process of manipulation, affect the convergence of the method. This section introduced the prediction of five parameter of the reform single diode model.

(1) To the parameter $I_{ph}$

First of all, considering the influence of the initial value of $I_{ph}$ in algorithm, the initial value was always set to the short-current ($I_{sc}$) numerically [19].

(2) To the parameter $R_{sh}$ or $G_{sh}$

For decreasing the influence of $R_{sh}$, the parameter form of the objective function which changed into parallel conductance ($G_{sh}$) has less influence in process of extraction by MATLAB Optimization toolbox. Experiment with the lsqnonlin function, it was founded that the more greater initial value of $G_{sh}$ corresponded to the less number of iterations (Table 4).

| Table 4. The iterations of $G_{sh}$ of MATLAB Optimization Toolbox. |
|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| Weights                 | +50%        | +30%        | +20%        | +10%        | +5%         | +2%         | +0%         | -2%         | -5%         | -10%        | -20%        | -30%        | -50%        |
| iterations              | 2           | 2           | 2           | 2           | 2           | 1           | 2           | 2           | 2           | 2           | 3           | 3           | 4           |

It is clearly visible in Table 3 that the iterations of $G_{sh}$ has less iterations due to the greater initial value, which indicated that the initial value of $R_{sh}$ should be less than the optimal value. What the most difficult of prediction was we never know the optimal value, but we could find the range of parameter by Eq. (1). Taking the derivative of Eq. (1) with respect to $U$, and re-arranging the resulting expression as Eq. (8).

$$\frac{dl}{du} = \frac{-1}{R_{sh}} \left(1 + \frac{R_s}{R_{sh}} \frac{l_0 R_s}{n U_{th}} \exp \left(\frac{U + l_0 R_s}{n U_{th}}\right) \right) \quad (8)$$

Where the term $R_s/R_{sh}$ may be neglected since it is assumed that $R_{sh} \gg R_s$ and at the short circuit point Eq. (9) can be easily verified.

$$\frac{l_0 R_s}{n U_{th}} \left(\exp \left(\frac{l_{sc} R_s}{n U_{th}}\right) - 1 \right) \ll 1 \quad (9)$$

At the same time, Eq. (8) can be expressed as Eq. (10), which means the slope of $I$-$U$ curve at the short circuit point correspond to the value of $R_{sh}$ relatively. Consequently, we can easily achieve an approximate range of $R_{sh}$ (Fig. 3), and the minimum of $R_{sh}$ can be expressed by Eq. (11). According to conclusion of the iterations of $G_{sh}$, this paper sets the initial value of $G_{sh}$ as Eq. (12).

$$\frac{dl}{du} |_{U_{sc}} = -\frac{1}{R_{sh}} \quad (10)$$

$$R_{sh, min} = \frac{U_m}{l_{sc} - l_{m}} \quad (11)$$
Voltage source
Operation region
Current sources
operation region
Voltage source
Operation region

Figure 3. The approximate range of $R_{sh}$ on the I-U curve.

(3) To the parameter $I_0$, $R_s$ and $n$

In order to simplify the complexity of the initial value prediction and the initial value of parameter $G_{sh}$ has been given, the component of Eq. (3) included the parameter $G_{sh}$ can be neglected and the Eq.(3) described as Eq. (13) which called as four-parameter model or simplify of the single diode model, not tired in words here. The most advantage of Eq. (13) it can be solved by three special point only would mostly simply the complexity of the process of prediction. Experimenting with the Newton–Raphson method later on, it was found that the parameters ($R_s$ and $n$) have small changes corresponding to the neglect, by the way, and the changes are positively corresponded to the assumption of Table.3.

$$I = I_{ph} - I_0 \left( \exp \left( \frac{U+IR_s}{nU_{th}} \right) - 1 \right)$$

At the short circuit point ($0, I_{sc}$) and the open circuit point ($U_{oc}, 0$),

$$I_0 = \frac{I_{sc}}{\left( \exp \left( \frac{U_{ac}}{nU_{th}} \right) - \exp \left( \frac{I_{sc}R_s}{nU_{th}} \right) \right)}$$

$$I_{ph} = I_0 \left( \exp \left( \frac{U_{ac}}{nU_{th}} \right) - 1 \right)$$

At the maximum power point ($U_m, I_m$), we can rearrange the non-linear Eq. (16) by substituting the parameters of $I_0$, $I_{ph}$ by Eq. (14) and Eq. (15) as Eq. (17).

$$f = \left[ I_{ph} - I_0 \left( \exp \left( \frac{U_m+IR_s}{nU_{th}} \right) - 1 \right) - I_m \right]$$

$$\left[ I_0 (I_mR_s-U_m) \exp \left( \frac{U_m+IR_s}{nU_{th}} \right) + I_m \right]$$

$$\left[ I_0 (I_mR_s-U_m) \exp \left( \frac{U_m+IR_s}{nU_{th}} \right) + I_m \right]$$
\[ f = \left[ \frac{t_{sc} \left( \exp \left( \frac{u_{sc}}{nU_{th}} \right) - \exp \left( \frac{u_m + l_m R_s}{nU_{th}} \right) \right) - I_m}{nU_{th} \left( \exp \left( \frac{u_{sc}}{nU_{th}} \right) - \exp \left( \frac{t_{sc} R_s - u_m}{nU_{th}} \right) \right) \exp \left( \frac{u_m + l_m R_s}{nU_{th}} \right) + I_m} \right] \]  \tag{17}

Eq. (17) are definite equations whose independent unknown parameters are \( R_s \) and \( n \). And even if the initial value of Eq. (17) is far away from the optimal value, it can converge to the optimal value by some more iterations.

2.3. Parameters extraction with the Newton–Raphson method

The popular Newton–Raphson method is known to offer an elegant method of locating the roots of non-linear equations. The curve fitting algorithm this paper introduced which based Newton–Raphson method includes the method of initial value prediction and the parameter extraction method.

The initial value prediction method define the unknown parameter vector \( \beta = [R_s, n] \), the residual \( (F_k = f_{2 \times 1}) \) and the Jacobian matrix \( (J_k = \frac{\partial F_k}{\partial x} = \frac{\partial F_k}{\partial R_s} \frac{\partial F_k}{\partial n})_{2 \times 2} \), and we set the empirical initial value that initial value \( \beta_0 = [0.3, 1.2] \) as the initial value of Eq. (17) and \( \varepsilon = 10^{-6} \), depicted graphically as a flow-chart in Fig. 4.

\[ t_0 = \log_e (I_0) \]  \tag{18}

As we introduced in section 2, the parameter extraction method, which based on the Gauss–Newton method that an iterative method for least square of regression parameters in nonlinear regression model, was defined by the vector of unknown parameters \( x = [I_{ph}, t, R_s, G_{sh}, n] \), the residual \( (F_k \text{ as Eq. (19)}) \) and the Jacobian matrix \( (J_k \text{ as Eq. (20)}) \).

\[ F_k = (I_k - I_k^{exp})_{N \times 1} \]  \tag{19}
\[ J_k = \frac{\partial F_k}{\partial x} = \left[ \frac{\partial F_k}{\partial \phi}, \frac{\partial F_k}{\partial \tau}, \frac{\partial F_k}{\partial R_{sh}}, \frac{\partial F_k}{\partial \eta} \right]^{N \times 5} \] (20)

Among the method, the iteration step \( d_k \) can be calculated by Eq. (21) and the process depicted graphically as a flow-chart in Fig. 5, where the \( G_{sh0} \) are calculated by Eq. (12).

\[
d_k = \left( f_k^T \cdot J_k \right) ÷ \left( f_k^T \cdot F_k \right) \] (21)

Figure 5. Flow chart of the parameter extraction method.

3. Numerical results

In order to validate the proposed approach in Section 2, first of all, two classic case studies provided in reference [12] (shown in Sec. 2.1) and commonly used in the literature are selected in order to perform a comparative evaluation against the best documented solutions. Besides, the data, which measured under approximate standard conditions according to the test and measurement specifications, in this paper include photovoltaic modules and arrays which belong to monocrystalline and polycrystalline silicon photovoltaic modules.

3.1. Classic Case Study #1: PV module and Cell

In order to compare the performance of the proposed method, the simulation results are compared with reference [2, 13, 11, 18]. The results are shown in Table 5 and the error of current in Table 6.

| Type        | Proposed | MTALAB | Ref. [11] | Ref. [18] | Ref. [13] | Ref. [2] |
|-------------|----------|--------|-----------|-----------|-----------|----------|
| \( I_{ph}(A) \) | 0.7608   | 1.0324 | 0.7608    | 1.0324    | 0.7608    | 1.0324   |
| \( I_{sc}(A) \) | 0.3107   | 2.5129 | 0.3104    | 2.5155    | 0.3102    | 2.5189   |
| \( R_{sh}(\Omega) \) | 0.0365   | 1.2393 | 0.0366    | 1.2392    | 0.0366    | 1.2390   |
| \( R_{s}(\Omega) \) | 52.8898  | 744.7142 | 52.8700 | 745.1759 | 52.8590 | 745.6431 |
| \( n \) | 1.4753   | 1.3155 | 1.4752    | 1.3156    | 1.4770    | 1.3174   |

Table 5. The results of case studies.
In Table 5, the proposed represents the curve fitting method proposed in this paper, and MATLAB represents the parameter results obtained by using Isqnonlin function of MATLAB optimization toolbox based on Eq. (2).

Table 6. The current error of case studies.

| Cell          | Module                           |
|---------------|----------------------------------|
| $U(V)$ | $I_{\text{exp}}(A)$ | $|I - I_{\text{exp}}|(mA)$ | $U(V)$ | $I_{\text{exp}}(A)$ | $|I - I_{\text{exp}}|(mA)$ |
| -1.9426       | 1.0345  | 1.22762 | -0.2057 | 0.764 | 0.14946       |
| 0.1248        | 1.0315  | 1.00497 | -0.1291 | 0.762 | 0.70215       |
| 1.8093        | 1.03    | 1.78267 | -0.0588 | 0.7605| 0.87377       |
| 3.3511        | 1.026   | 0.08951 | 0.11052 | 0.7605| 0.34550       |
| 4.7622        | 1.02    | 0.20618 | 0.0464  | 0.76  | 0.96095       |
| 6.0538        | 1.018   | 3.85492 | 0.1185  | 0.759 | 0.98925       |
| 7.2364        | 1.0155  | 3.73668 | 0.1678  | 0.757 | 0.04570       |
| 8.3189        | 1.014   | 1.54895 | 0.2132  | 0.757 | 0.91517       |
| 9.3097        | 1.01    | 0.26730 | 0.2545  | 0.7555| 0.47765       |
| 10.2163       | 1.0035  | 3.35532 | 0.2924  | 0.754 | 0.40265       |
| 11.0449       | 0.988   | 3.49657 | 0.3269  | 0.752 | 0.82726       |
| 11.8018       | 0.963   | 2.98740 | 0.3585  | 0.7465| 0.80534       |
| 12.4929       | 0.9255  | 1.71804 | 0.3873  | 0.7385| 1.58463       |
| 12.649        | 0.912   | 1.10305 | 0.4135  | 0.728 | 0.57381       |
| 13.1231       | 0.8725  | 1.05765 | 0.4373  | 0.7065| 0.52593       |
| 14.2221       | 0.7265  | 2.13147 | 0.459   | 0.6755| 0.09967       |
| 14.6995       | 0.6345  | 2.21423 | 0.4784  | 0.632 | 1.00185       |
| 15.1346       | 0.5345  | 0.98792 | 0.496   | 0.573 | 0.82529       |
| 15.5311       | 0.4275  | 0.72973 | 0.5119  | 0.499 | 0.53898       |
| 15.8929       | 0.3185  | 0.64809 | 0.5265  | 0.413 | 0.48487       |
| 16.2229       | 0.2085  | 1.51077 | 0.5398  | 0.3165| 0.66154       |
| 16.5241       | 0.101   | 3.38462 | 0.5521  | 0.212 | 0.01673       |
| 16.7987       | -0.008  | 0.61680 | 0.5633  | 0.1035| 0.86326       |
| 17.0499       | -0.111  | 0.01241 | 0.5736  | -0.01 | 0.70169       |
| 17.2793       | -0.209  | 0.39903 | 0.5833  | -0.123| 1.36133       |
| 17.4885       | -0.303  | 2.10843 | 0.59    | -0.21 | 0.89832       |

Table 6 reports the experimental values of voltage and current and the corresponding error in terms of current, obtained by using the algorithm and objective function Eq. (4). The maximum absolute error of all the 26 available measurements is lower than 3.855 and 1.585mA for the cell and module respectively, whereas the mean absolute error is about 1.692mA and 0.678mA. A further comparison with the results proposed in literature is discussed to emphasize the simulation accuracy (Table 7). Table 7 resumes the results of the most recent works about two classic case study with some kind of manipulations or recomputing (or Refinement) [11, 13, 18]. Bearing in mind, Refinement operation would neglect the difference of the result and reach to the optimal value finally, and the proposed method of this paper have no need to refine by “lsqnonlin” algorithm.
Table 7. The results of evaluation parameters.

|               | Cell          | Module                |
|---------------|--------------|-----------------------|
| Proposed      | 0.7730062689 | 2.04653469954648      |
| MTALAB        | 0.7730075565 | 2.04653593182236      |
| Ref.[11]      | 0.773009395  | 2.0465409             |
| Ref.[18]      | 0.773006272 | 2.0465456             |
| Ref.[13]      | 0.773006272 | 2.0465347             |
| Ref.[2]       | 0.81291      | 2.422747              |

From Table 7, this proposed method successfully extracted the module’s and cell’s parameter values of the measurement data in the classic case studies, which proves that the curve fitting method proposed in this paper is available for photovoltaic modules and cells. It can be seen that the proposed method has the smallest evaluation value, that is, the more accurate result. The evaluation parameters obtained by the MATLAB lsqnonlin function are higher than the proposed method in this paper. The parameter epsilon that described the convergence of the method is hardly sensitive to the relatively small diode reverse saturation current iteration step size. Therefore, rearranging the form of the diode reverse saturation current could let each parameter value to be more sensitive to evaluation parameter.

3.2. Case Study #2: PV module and array

Once the accuracy of the proposed method has been demonstrated, the method has been applied to model some operational modules and arrays I-V curves available. The output data volume of the photovoltaic module data measurement system is large, and the data needs to be preprocessed. According to the voltage-source and current-source theory, the sample data should be selected to meet the practical significance with different attributes. The selection rule of the sample data in this article is to select data points at similar current intervals in the voltage source area, relatively at similar voltage intervals in the current source area, and try to balance the number of points. And the result (Table 8) of the proposed method in PV module and array shows the advantage of the proposed method in operational PV and array. In Table 8, EGZL is an array of PV which composed by 22 PV modules of EG-250P60-C.

Table 8. The result of the proposed method in PV module and array.

| Type         | Material | $N$ | $M$   | MATLAB RMSE($\times 10^{-3}$) | Proposed RMSE($\times 10^{-3}$) | Time(s) |
|--------------|----------|-----|-------|-------------------------------|---------------------------------|---------|
| JKM315PP-72  | Module   | 72  | Polysilicon | 24.5826                      | 24.5725                         | 51.4612 |
| RSM72-156P   | Module   | 72  | Polysilicon | 27.0783                      | 27.0757                         | 36.0688 |
| EG-250P60-C  | Module   | 60  | Polysilicon | 15.3679                      | 15.3669                         | 24.2397 |
| JKM280M-60   | Module   | 60  | crystalline | 23.6853                      | 22.0802                         | 54.9174 |
| RJT325M-72   | Module   | 72  | crystalline | 24.8307                      | 24.7330                         | 65.3419 |
| EGZL Array   | Array    | 63  | Polysilicon | 18.3694                      | 18.3676                         | 24.1105 |

From Table 8, this proposed method successfully not only its convergence successfully, but also a capability that it can be proved to have a lower evaluation value of simulating photovoltaic modules and arrays. Again, the evaluation parameters proved the accuracy of the form of the diode reverse saturation current. There are two different types of PV modules in the measured data which are commonly applied in the actual project.

The elapsed time using the proposed method is shown in Table 8 on a computer with Intel Core i7-4710 2.50 GHz processor, 8 GB RAM and Windows 10 Professional 64-bit operating system. At the two case studies, the consuming-time is 11.8515 (s) and 11.0549 (s) respectively. Hence, the computation of the proposed method compared to other methods is small relatively.
4. Conclusions
In this paper, a new initial value prediction of curve-fitting algorithm to extract the parameters of the reform single diode model is presented. The main idea is to first predict the initial value through three the special points on the I-V curve points exactly and second reform the parameter of the ideal reverse saturation current of the diode to achieve best fit. Hence, the accuracy involved are relatively improved.

In this work, Newton-Raphson method, which often used for finding successfully better approximations to the roots of a real valued function, is utilized for finding three initial value through the simplified single-diode model. And in the main section of the method, Gauss-Newton iteration method, which is known for a basic iterative method for least square of regression parameters in nonlinear regression model, is described here to find the optimal value of the single diode model with the reform of the objective function. When compared to other relevant parameter extraction methods, the proposed method exhibits substantial improvement in terms of fitting accuracy. Tests on the PV Cell and module of two classic case studies at standard environmental condition indicate that the proposed method is more accurate and on different technologies (i.e. monocrystalline, polycrystalline) and different types (i.e. cell, module, array) at operational condition indicate that the proposed method is reliable and suitable for practical applications. With these, the proposed method is envisaged to be valuable for practical applications where fast and reliable extraction of the PV cell/module/array parameters is required.

Acknowledgments
This work was financially supported by NJCIT Natural Science Foundation key projects of young teacher fund. (No. YK20170701)

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