Inverse modelling of PV power prediction based on GA method

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Abstract. Traditional modelling methods are generally forward modelling, that is, the basic parameters of photovoltaic cells provided by manufacturers need to be known before in order to calculate the power output of photovoltaic cells. However, the traditional modelling method is no longer applicable to complex situations, such as if manufacturer parameters are not available, or if the original manufacturer parameters are inaccurate due to prolonged usage. In this study, a new inverse modelling method is proposed, which uses genetic algorithm (GA) to identify the internal parameters of photovoltaic cell equation and solve the equation by Gauss-Seidel iterative method. The experimental test was conducted in Wuhan, China. The results show the root mean square error is only 1.34V and 2.66V for two-day tests, which demonstrated the effectiveness of the proposed method.

1. Introduction
With increased attention towards the effective usage of PV cells [1-3], many mathematical models had been derived to predict the power output of them. These includes models such as the ideal model, the one-diode model and the two-diode model [4]. However, in order for the IV equation to be accurately used, a set of 5 basic parameters must be provided, by the manufacturer or an otherwise similar source. Under these standard conditions, the electric output of the PV system can be calculated through the IV equation [5]. This method is generally reliable when used under regular circumstances. However, when applied under more complicated circumstances, this model is not accurate. If the manufacturer does not provide the necessary parameters, it may be impossible to calculate the power output accurately. In addition to this, many of the manufacturer-provided parameters can be degraded after long-term usage of the PV cells, rendering the calculations inaccurate. As such, an alternate method of inverse modelling was proposed to target this issue.

In this paper, we aim to create an inverse model for the power output of PV cells, through the use of genetical algorithms. By measuring the PV cells’s power output under a known level of temperature and solar radiation, we are able to plot an IV curve based upon these pieces of data. Utilizing genetical algorithms (GA), we then generate random groups of 5 parameters and input them into the model, in which the parameters that generate a power output most similar to the actual value will be selected. This process is then repeated until a set of parameters fit into the range of acceptable error. Those parameters will then be adopted for the output predictions for PV cells.
2. Literature review
The mathematical modelling of PV panel is an important topic currently with rapid development of solar energy. Considering that the internal parameter of solar cell is crucial to the performance prediction of PV panel, lots of researches have been devoted to the parameter’s extraction of solar cells based on experiments [5] or other simulation methods [6]. At present, there are mainly two methods to extracting five parameters of PV. One is the analytical method, which makes use of the key points of I–V characteristics of photo-voltaic module to simplify the model [7]. The second method is the numerical method, which requires a lot of measured I–V data compared with the analytical solution method for sampling several key points. Some research papers have discussed some statistical algorithms to extract five parameters, such as improved stochastic evolutionary algorithm [8], adaptive differential evolutionary algorithm [9], particle swarm optimization algorithm [10], following the basic idea of “establishing objective function–determining initial value–iterative calculation”. These methods are sensitive to initial values and prone to be trapped in local minima.

3. Method
3.1. Five-parameter model of PV panels
The mathematical modelling of PV panels generally adopts the one-diode model of PV cells. This model aims to converts the many complicated physical processes that occur within a PV cell into a simple electrical circuit. The one-diode model in specific consists of an ideal current source wired in parallel with a single diode, with resistors added in series and in parallel to better represent the internal mechanisms of solar cells.

The one-diode model of PV cells is used in conjunction with the I-V equation (1) [5], which calculates the power output of PV panels. The I-V equation can be used to draw the I-V curve, which plots voltage output against current output in a PV cell. In this equation, Iph represents the photocurrent, I0 represents the diode saturation current, Rs represents the series resistance, Rp represents the parallel resistance, and Vt represents the diode thermal voltage, calculated with the formula Vt=nNsKT/q. For the diode thermal voltage, Ns is the number of solar cells in series; K is Boltzmann’s constant (-1.380653×10^{-23} J/K); q is the absolute value of electron’s charge (-1.60217646×10^{-19} C); T is the temperature of the junction (K); n is the diode ideality factor.

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

\[
\begin{align*}
\text{eq1} & \quad I_{ph,STC} - I_{0,STC} \left[ \exp \left( \frac{V_{STC}}{V_{t,STC}} \right) - 1 \right] - \frac{V_{STC}}{R_{p,STC}} = 0 \\
\text{eq2} & \quad I_{ph,STC} - I_{0,STC} \left[ \exp \left( \frac{I_{ph,STC}R_{p,STC}}{V_{t,STC}} \right) - 1 \right] - \frac{I_{ph,STC}R_{p,STC}}{R_{p,STC}} - I_{n} = 0 \\
\text{eq3} & \quad I_{ph,STC} - I_{0,STC} \left[ \exp \left( \frac{V_{m} + I_{ph,STC}R_{p,STC}}{V_{t,STC}} \right) - 1 \right] - \frac{V_{m} + I_{ph,STC}R_{p,STC}}{R_{p,STC}} - I_{n} = 0 \\
\text{eq4} & \quad R_{p,STC} + \frac{V_{t,STC}R_{p,STC}}{I_{ph,STC} + I_{0,STC}R_{p,STC} \times \exp \left[ \frac{V_{m} + I_{ph,STC}R_{p,STC}}{V_{t,STC}} \right]} - V_{m} = 0 \\
\text{eq5} & \quad R_{p,STC} + \frac{V_{t,STC}R_{p,STC}}{I_{ph,STC} + I_{0,STC}R_{p,STC} \times \exp \left[ \frac{I_{ph,STC}R_{p,STC}}{V_{t,STC}} \right]} - R_{p,STC} = 0
\end{align*}
\]

There are 5 unknown parameters in the I-V equation, and these 5 parameters are I_{ph}, I_{0}, R_{s}, R_{p} and n. The 5 unknown variables within the IV equation can be calculated by substituting the 5 parameters of solar cells into the equation, according to the condition at open voltage point Voc, short-current point Isc, max working power point (Vmpp, Imp), and the slope of I-V curve. By substituting these parameters into the IV equation for important points on the IV curve, the unknowns in the IV equation can be calculated through a system of equations (2) [11, 12]. The 5 parameters under standard testing
condition \( G=1000\text{W/m}^2, T=25\text{C} \) can be solved. After that, five parameters under general conditions with arbitrary solar radiation \( G \) and PV temperature \( T \) input, can be derived based on five extrapolated equations. Finally, the I-V equation under general condition is obtained, which can be solved numerically to get the current and voltage output dynamically.

### 3.2. Parameter extraction through GA

As mentioned in the introduction, the IV-equation (1) derived from the 5-parameter model of PV panels can be used to calculate the predicted power output from PV cells at a given solar radiation level \( G \) and temperature \( T \). This requires knowing the baseline 5 parameters (under standard testing condition) given by the manufacturer. However, in most modelling situation, the 5 parameters are unknown, while the solar radiation, temperature, and power output can be measured to assist with parameter identification.

Due to the nature of the IV equation, the 5 parameters cannot be calculated accurately through algebraic manipulation if the only known variables available are \( G \), \( T \), and \( I \). Hence, the proposed method in order to model and calculate these 5 parameters are through the usage of genetic algorithms (GA).

Similar to evolutionary biology, as the GA process repeats, the accuracy and quality of the results will also increase. Hence, the 5 parameters can be calculated within a very accurate margin of error when the experimental power output is already calculated. This actually is a process of optimization and searching for the best matching parameters. The optimization problem is described in Equation (3), in which the subscript “simu” and “exp” means simulation and experimental data; the subscript “stc” means standard testing condition. This optimization problem is to be solved by GA method. As the equation shows, those five parameters have very different ranges. Those parameters have very weak physical meaning in reality because the creation of those parameters is based on equivalent circuit.

\[
\begin{align*}
\text{min} & \left\{ \frac{1}{m} \sum_{i=1}^{m} (I_{\text{simu} - i} - I_{\text{exp} - i})^2 \right\} \\
\text{solve} & \left\{ \begin{array}{l}
I_{\text{simu} - i} = I_{ph} (G, T, I_{ph\text{-stc}}) - I_{0\text{-stc}} (G, T, I_{0\text{-stc}}) \times \\
\exp \left[ \frac{V + IR_{p\text{-stc}} (G, T, R_{p\text{-stc}})}{V (n_{stc})} - 1 \right] - \frac{V + IR_{p\text{-stc}} (G, T, R_{p\text{-stc}})}{R_{p\text{-stc}} (G, T, R_{p\text{-stc}})} 
\end{array} \right. \\
I_{sc} & \leq I_{ph\text{-stc}} \leq I_{sc} + 0.2, \quad 10^{-9} \leq I_{0\text{-stc}} \leq 10^{-6} \\
0 & < n_{stc} < 1 \\
0 & < R_{p\text{-stc}} < 20 \\
100 & < R_{v\text{-stc}} < 2000 
\end{align*}
\]

### 3.3. Experimental test

The aim of this experiment is to test the validity of the inverse model for PV power output. By testing the power output and measuring the solar radiation and temperature at the same time, the 5 parameters can be extracted through the usage of GA. The power output of the solar cell under certain \( G \) and \( T \) conditions can then be predicted with the 5 parameters and the I-V equation, through which we can test the model’s accuracy.

The experiment will involve the setup of a conventional PV panel, which will be connected to a controlled-resistance resistor, in a sunny condition. There will also be a pyranometer and a thermal couple placed in the same location as the PV panel in order to measure temperature and solar radiation. During the experiment, the temperature and the solar radiation will be measured at consistent intervals in conjunction with the voltage output of the solar cells.
The experiment will be conducted through a time period of sunny day conditions. A PV panel will be exposed to the sun, along with a pyranometer and a thermal couple in the same area. The pyranometer will be set out in the sun, while the thermal couple will be attached to the back of the solar panel for a more precise measurement. This is to ensure that the solar radiation received by PV and temperature of the PV panel is accurately measured. The data that the pyranometer and thermal couple are logging will be processed by a data logger, which transmits the information into a computer at set intervals. The PV panel itself will be connected to a resistor with a set load, and a voltmeter will be used to measure the power output at regular intervals. For a clearer representation of how the experiment was set up, refer to Figure 1.

![Experimental setup diagram]

Figure 1. The pictures of experimental testing rig.

4. Results and discussions

4.1. Parameter extraction

There are 101 data of G, T and V. It is divided into two groups and each has 50 data (group 1) and 51 data (group 2). There are 3 sets of calculation for parameter extraction: (1) using group 1 as training data and group 2 as validation data; (2) using group 2 as training data and group 1 as validation data; (3) using whole 101 data as training data and 101 data as validation data.

By adopting the GA algorithm coupled with PV model structure, the five parameters of PV under standard testing condition are identified and listed in Table.1. When performing this GA, all five parameters are searching in a certain range: 0<Iph<4.88, 10-9<I0<10-5, 0<Rs<50, 1000<Rp<10000, 1<n<2. The error for each set of parameter extraction result is checked by RMSE. It is interesting that the whole RMSE in third test (using 101 data) is in between the first and second test. In addition, the extracted five parameters are also in between the first and second test.

We can see that the result of the first test using group 1 data is less accurate compared to the rest. The reason is the measurement in the first half has not captured the variation of voltage with increasing solar radiation due to a measurement error. However, the overall error is quite small, which can indirectly show the robust of proposed method and algorithm.
4.2. Model validation
After parameter extraction, those results will be imported into PV model and the simulated data are to be compared with data in other groups.

(1) Using group 1 as training data and group 2 as validation data: we used the five-parameter extracted from group 1 and solar radiation and temperature data measured from 12:50 to 17:00. Then the simulated voltage outputs and measurements during 12:50 to 17:00 are compared in Figure 2. It shows a good agreement between experimental measurement and simulation results with very small RMSE=1.34V.

The simulation data, had some fluctuation at lower or higher points in comparison to the experimental data curve, but they share the same overall trend and are very similar. This can largely confirm the accuracy of PV model and the extracted five parameters in this case.

(2) Using group 2 as training data and group 1 as validation data: The five parameters extracted based on group 2 data are used as inner parameter in PV model and then we compared the simulation voltage with measurements from 8:40 to 12:45. It should be noted that, in Figure 3, with the exception for one wrong data point in the experimental measurement, the rest data are in good agreement with simulation data, with RMSE=2.66. It is important to note that although there are incorrect data points in experiment, the simulation is able to ignore this wrong data in calculation, due to the robust design of GA. This comparison results not only can demonstrate the model and method accuracy, but also proved the robustness of the proposed method.

(3) Using the entirety 101 data as training data and 101 data as validation data: Finally, the 101 data are used in the comparison in order to check the accuracy of the proposed method and model. As Figure 4 shows, the simulation and experimental data are in good agreement with a very small RMSE=1.93. The simulation was again able to ignore the wrong data in measurement.

![Figure 2](image1.png)  ![Figure 3](image2.png)

**Figure 2.** The comparison between experimental and simulation data in group 1 test.  
**Figure 3.** The comparison between experimental and simulation data in group 2 test.
5. Conclusions
In this study, an inverse modelling method for PV panel is proposed based on parameter identification through GA. In conducting this experiment, our goal was to discover a more accurate way to mathematically model the power output of solar cells through the use of GA in inverse modelling. The main conclusions are given below:
1) The results demonstrate clearly that this model is successful in what it sets out to do, as the comparison between the simulation data and the experimental data were highly matched. The results show the root mean square error is only 1.34V and 2.66V for two-day tests, which demonstrated the effectiveness of the proposed method.
2) In addition to this, the usage of GA was able to make the model extremely robust, as the model was able to ignore wrong data points, forming correct simulated data despite the errors in the training group data.

With the rising need of solar power in modern society, the adopt of a more accurate model to predict PV cell power output is very important, especially after degradation due to age or the lack of clear parameters from the producer. Considering the precision and robustness that this model was able to achieve, this proposed model can be applied for management of solar power plant, optimal operation of integrated energy system integrated with solar system etc.

![Figure 4](image-url)

Figure 4. The comparison between experimental and simulation data from the combination of group 1 and group 2 test.

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