A NEW MODELING METHOD FOR PHOTOVOLTAIC MODULES BASED ON

EXTREME LEARNING MACHINE AND I-V CURVES

Hui Yu [1], Zhicong Chen [1*], Lijun Wu[1], Qiao Zheng[1], Peijie Lin [1], Shuying Cheng [1]
1 College of Physics and Information Engineering, Fuzhou University, 2 XueYuan Road, 350116 Fuzhou, China

ABSTRACT

In this paper, a novel rapid modeling method is proposed for solar photovoltaic (PV) modules, which is based on extreme learning machine and current-voltage (I-V) characteristic curves. Firstly, original I-V curves are downsampled to reduce data redundancy, and a simple method is proposed to detect and remove abnormal I-V curves. Secondly, a single hidden layer feedforward neural network is proposed as the model, which is then trained by the extreme learning machine (ELM) algorithm. Finally, the proposed ELM based method is tested using a large dataset of experimental I-V curves provided by the National Renewable Energy Laboratory (NREL). Experimental results show that the proposed ELM based method can shorten the modeling time to 0.2~0.4s, and the root mean square error (RMSE) can reach 0.0484%~0.374%. Compared with other conventional artificial neural network based methods, the proposed method can greatly shorten the modeling time and significantly improve the accuracy and the generalization performance of the modeling for PV modules.

Keywords: PV modules, PV modeling, I-V characteristics, extreme learning machine

1. INTRODUCTION

In recent years, research on photovoltaic cells has become increasingly important due to the need of renewable and clean energy in human society. In the actual power generation system, we usually monitor many parameters of the PV power generation system. Among them, the Current-Voltage (I-V) characteristic curve of the photovoltaic module is an important indicator. By analyzing the I-V curve, we can understand a lot of important information about it, such as open circuit voltage, short circuit current, maximum rated power and module's efficiency [9].

Data-driven artificial neural network (ANN) methods are often used to model PV modules because of their good nonlinear fit. This method uses historical measurement data, learns the network model through ANN algorithm, and uses the trained network model for the prediction of the output current or voltage of the PV module. There are many ANN algorithm is used to modeling PV module. Backpropagation (BP) neural network is used to predict the IV characteristics of the PV module [7], the author uses three characteristics (current, irradiance, cell temperature) to predict the PV module's output voltage and compare it to the radial basis function (RBF) neural network. RBF neural network can be used predict the output current (or voltage) of PV modules [3]. Generalized regression neural networks (GRNN) are also proposed for modeling PV modules [5]. We know that BP neural networks usually require many iterations to find the optimal value, which takes a long time. RBF network is difficult to use in large data scenarios due to the use of kernel functions. The combination of cascaded forward neural network (CFNN) and GRNN are used to model PV module [9], the RMSE is 0.0336 A, but it is more complicated. Three neural networks are used to correct the original irradiance, predict the module temperature, and generate the I-V characterize curve of the PV module [4].

According to the shortcomings in the above work, in this paper, we propose a rapid modeling method for photovoltaic modules based on extreme learning machines and IV characteristics. Compared with other conventional artificial neural network based methods, this method can greatly shorten the modeling time and significantly improve the accuracy and the generalization performance of the modeling for PV modules.

2. ARTIFICIAL NEURAL NETWORK BASED PV MODULE MODELING APPROACH

2.1 Extreme learning machine for I-V curve modeling

Extreme learning machine (ELM) algorithm is a machine learning algorithm based on single-hidden layer feedforward neural networks (SLFNs) proposed by Huang et al. [2] in 2005. When the mapping function of the hidden layer of SLFNs is infinitely differentiable, its learning ability has no correlation with input weight and threshold, only related to the current network structure [1,8]. Therefore, when using the ELM algorithm to fit the neural network, we only need to consider the network structure, and do not need to iteratively update the input weights and thresholds of the network, which avoids the problem that the network training time is too long caused by multiple iterations.
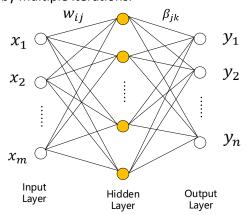

Fig. 1. Network structure of the SLFNs

The working steps of the ELM are as follows:

First, the connection weight W and the threshold b of the neural network are randomly initialized.

Secondly, according to the input data, calculate the value of each output neuron in each SLFNs. Assuming that the hidden layer neuron activation function is $g(x)$, then the value of the first output neuron after the input matrix X passes through the neural network is $t_1 = \sum_{i=1}^{l} \beta_{i1} g(w_i x_j + b_i)$. It can be seen that when the neural network inputs the j-th sample, the network output value is:

$$t_j = \begin{bmatrix} \sum_{i=1}^{l} \beta_{i1} g(w_i x_j + b_i) \\ \sum_{i=1}^{l} \beta_{i2} g(w_i x_j + b_i) \\ \vdots \\ \sum_{i=1}^{l} \beta_{im} g(w_i x_j + b_i) \end{bmatrix}$$

Therefore, the predicted value of the network output is $T = [t_1, t_2, \ldots, t_Q]$, assuming that the output of the implicit layer of the neural network is H, then:

$$H = \begin{bmatrix} g(w_1 x_1 + b_1) & g(w_2 x_1 + b_2) & \ldots & g(w_l x_1 + b_l) \\ g(w_1 x_2 + b_1) & g(w_2 x_2 + b_2) & \ldots & g(w_l x_2 + b_l) \\ \vdots & \vdots & \ddots & \vdots \\ g(w_1 x_Q + b_1) & g(w_2 x_Q + b_2) & \ldots & g(w_l x_Q + b_l) \end{bmatrix}$$

Finally, using the ELM fitting algorithm, calculate the hidden layer and output layer weight β of the SLFNs,

and $\beta = H^+ T'$ is calculated by the least squares method, where H^+ is the pseudo-inverse matrix of the matrix H, matrix T' is transpose matrix for T. Through the above calculation, a network model with parameters W, b and β can be obtained.

2.2 Original experimental data processing

In the process of modeling and validation, the measured data sets of solar panels provided by the National Renewable Energy Laboratory (NREL) were used. The data set contains output characteristics of solar panels made of six materials, such as Single-crystalline silicon (x-Si), Multi-crystalline silicon (m-Si), Cadmium telluride (CdTe), Copper indium gallium selenide (CIGS), Amorphous silicon (a-Si), heterojunction with intrinsic thin-layer (HIT) under different environmental parameters. Solar panels are installed in Golden, Colorado. Data collection time is from August 14, 2012 to September 24, 2013.

2.2.1 Linear sampling of current and voltage

In the original data set, each I-V characterize curve contains nearly 200 data points. In order to reduce the redundancy of the data points and reduce the amount of calculation, we use a method of uniformly sampling the current value and the voltage value respectively. The number of data points contained in each I-V curve in the data is reduced to 50 points. Using this method can not only reduce data redundancy, reduce the amount of calculation, but also ensure that the data is representative and does not lack some important data features of the I-V characteristic curve.

The principle of uniform sampling of current and voltage is as follows. Record the open circuit voltage V_{oc} and short circuit current I_{sc} of each measured I-V curve. Uniformly take 30 voltage points in the interval [0 V_{oc}], the interval between adjacent resample points is $\frac{V_{oc}}{30}$, and record the resampled voltage vector $[V_1, V_2, \ldots, V_c, \ldots, V_{30}]$, V_c is the resampled voltage value of the c-th point, and the current value corresponding to the point is obtained by linear interpolation method:

$$I_c = \frac{(V_c - V_{c-1}) \times I_{c+1} + (V_{c+1} - V_c) \times I_{c-1}}{V_{c+1} - V_{c-1}}$$

And then we can get 30 voltage resampling points (V_c, I_c). The same method is used to resample the current value, and 20 current value points are uniformly taken in the interval [0 I_{sc}], the interval between adjacent current sampling points is $\frac{I_{sc}}{20}$, and the resampled current vector $[I_1, I_2, \ldots, I_d, \ldots, I_M]$, where I_d represents the

current of the d-th current resampling point, and the corresponding voltage value obtained by linear interpolation method is:

$$V_d = \frac{(I_d - I_{d-1}) \times V_{d+1} + (I_{d+1} - I_d) \times V_{d-1}}{I_{d+1} - I_{d-1}}$$

So, we can obtain 20 current resampling points (V_d, I_d). The obtained 50 resampled points are sorted and combined according to the magnitude of the voltage value, and the resampled I-V curve is obtained.

2.2.2 Shadow curve processing

During the working process of solar panels, it is inevitable that the output characteristics will be unstable due to the obscuration of dark clouds, leaves and flying objects. In this situation, the I-V characteristic curve appears as a shadow curve, and this shadow curve belongs to abnormal data, which is very disadvantageous for modeling and prediction. Since abnormal data can have a dramatic effect on the prediction, we must remove the shadow curve before modeling the I-V curve. This paper proposes a shadow curve culling method based on the slope of the I-V curve, which determines the slope between adjacent points and determines the abnormal curve when the slope is abnormal. We know that the normal I-V curve is shown in Fig. 2. During the gradual increase of voltage from 0, the slope of the curve changes very little, and the slope value is close to 0. In the near-V_{oc} portion, the slope of the I-V curve approaches negative infinity. During this process, the slope of the curve is gradually decreasing. In Fig. 2, the slope between the open circuit voltage point and the short circuit current point is K_0, the slope near the short circuit current point is K_1, and the slope near the open circuit voltage point is K_2, then $K_2 < K_0 < K_1$. Since the slope trend between two adjacent points is constantly decreasing over the entire I-V curve, according to this rule, we set a simple criterion to determine the shadow curve:

Step1: Traversing the uniformly sampled I-V curve, assuming that the current point is P_i, the slope between P_i and P_{i-1} is calculated as KP_i (Fig. 3).

Step2: Calculate the slope between P_i and P_{i+1} as KP_{i+1}.

Step3: Judging the calculation result, if $KP_{i+1} < K_0$ and $KP_i > K_0$, it can be determined as a shadow curve.

Step4: In order to eliminate influence of tiny noise points, the slope between P_i and P_{i-2}, P_i and P_{i+2} can be calculated separately and then compared with K_0. Taking the intersection of the two experimental results, the shadow curve can be well filtered out.
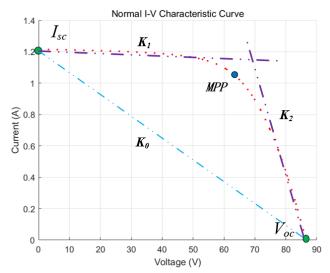

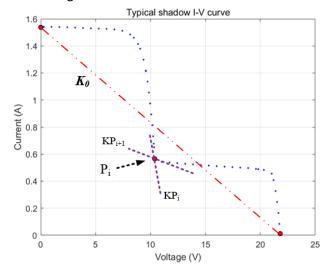Fig. 2. Normal I-V characteristic curve

Fig. 3. Typical shadow I-V curve

2.2.3 Downsampling

In original dataset, the distribution of data samples is very uneven (Fig. 5). When the sample distribution of some intervals is obviously too much or too little, it will cause over-fitting or under-fitting of the model. For unevenly distributed data, we use the method of grid sampling to downsample the data samples, on the one hand avoiding the non-uniformity of the sample, and on the other hand, reducing the sample size while maximally including the hidden features of the sample. The specific steps of grid sampling are as follows:

Step1: Set the irradiance sampling interval and range to sample the measured I-V curve in the grid.

Step2: Set the sampling interval and range of the cell temperature, and sample the temperature of the I-V curve obtained in step 1.

Step3: If there is a value in the grid of two samples, the I-V curve data is saved.
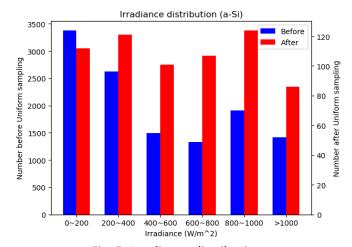
Fig. 5. Irradiance distribution

2.2.4   Modeling

Although many factors affect the output of PV module, the two most important factors are cell temperature and irradiance. Since photovoltaic modules of different materials have different absorption ranges for the spectral bands, using the same instrument to measure irradiance of different photovoltaic modules may cause deviations. Therefore, we use short-circuit current corrected irradiance to model the I-V curve of the photovoltaic module, thus avoiding the deviation caused by the irradiance measurement process.

For each data point obtained, the irradiance, cell temperature, and voltage are the input of the network, and the current is used as the network output. A single hidden layer feedforward neural network is established, and the network parameters are calculated using an extreme learning machine fitting algorithm. Finally, the test set data is input into the trained network, and the output current value of the network is obtained and compared with the actual current value to evaluate the error of the model we built.
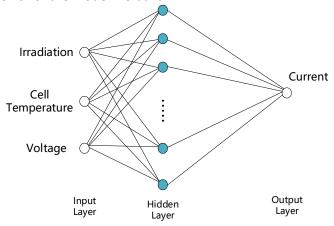

Fig. 6. Actual Network structure

2.3   Experimental Result

2.3.1   Hyperparameter verification

In this paper, we compare the effect of different number of hidden layers on prediction accuracy. Obviously, the accuracy of the model will increase when the number of neurons in the hidden layer increases, but the amount of calculation will increase due to the increase of parameters, which will lead to an increase in network training time. Fig.7 shows the network prediction error and training time for different hidden layer neurons. In order to balance the model prediction accuracy and training time, we chose the hidden layer neurons between 150 and 200.
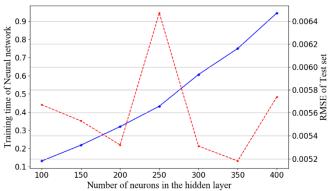

Fig. 7. Performance comparison of the number of neurons in different hidden layers

In the process of modeling with the ELM algorithm, there is another parameter that we need to choose, that is, the activation function of the hidden layer. We test three activation functions. The experimental results are shown in Table 1.

In the actual modeling, we use the commonly used sigmoid activation function, its expression is:

$$g_{(x)} = \frac{1}{1 + e^{-x}}$$

Table 1. The impact of different activation functions

Activation Function	Sigmoid	Sin	SoftPlus
Training Set	4.89E-03	4.86E-03	4.83E-03
Validation Set	4.99E-03	4.85E-03	4.94E-03
Test Set	5.40E-03	5.26E-03	5.39E-03
Training Time	0.228s	0.207s	0.236s

2.3.2   Compared with other algorithms

Through the above experiments, we obtained the optimal hyperparameters of the neural network fitted by the ELM algorithm, and verified the feasibility of short-circuit current and cell temperature as network input characteristics. In this section, we use a variety of other

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algorithms and ELM algorithm to compare the advantages of the proposed modeling method.

In this part, BPNN, GRNN and Support Vector Regression (SVR) are used respectively. For these algorithms, after experimental verification, the following parameters are selected: the number of BPNN hidden layer neurons is set to 100, the SPREDA value of GRNN is set to 0.05, the SVR algorithm uses the best performance Gaussian kernel, and the eplison loss function value is set to 0.05.

In this work, Matlab software was used as the establishment of neural networks and ELM algorithm fitting. At the same time, the solar cell data of the six materials mentioned were used to test the accuracy of various algorithms and model training time. The experimental results are shown in Table 2.

Table. 2. Experimental result

Data Set	Algorithm	Training Time (s)	Training Set RMSE	Verification Set RMSE	Test Set RMSE
aSi	BPNN	105.63	7.187E-03	7.259E-03	2.481E-02
	GRNN	22.14	1.216E-02	1.341E-02	1.583E-02
	SVM	6.67	3.479E-02	3.484E-02	3.497E-02
	ELM	**0.196**	**8.481E-03**	**8.454E-03**	**9.116E-03**
CdTe	BPNN	159.60	3.951E-03	4.206E-03	5.711E-03
	GRNN	24.56	1.487E-02	1.704E-02	1.721E-02
	SVM	6.49	3.161E-02	3.156E-02	3.097E-02
	ELM	**0.278**	**4.847E-03**	**4.958E-03**	**5.556E-03**
CIGS	BPNN	101.86	1.699E-02	1.794E-02	2.952E-02
	GRNN	21.20	5.336E-02	5.836E-02	6.103E-02
	SVM	15.51	5.280E-02	5.276E-02	5.120E-02
	ELM	**0.184**	**1.920E-02**	**1.892E-02**	**2.379E-02**
Hit	BPNN	107.52	3.453E-02	3.485E-02	4.089E-02
	GRNN	30.52	1.556E-01	1.663E-01	1.579E-01
	SVM	28.19	6.732E-02	6.791E-02	6.386E-02
	ELM	**0.365**	**3.740E-02**	**3.740E-02**	**3.997E-02**
mSi	BPNN	82.56	1.000E-02	1.032E-02	1.155E-02
	GRNN	23.85	7.104E-02	7.495E-02	7.818E-02
	SVM	19.46	6.536E-02	6.625E-02	6.666E-02
	ELM	**0.371**	**1.209E-02**	**1.211E-02**	**1.328E-02**
xSi	BPNN	89.21	2.026E-02	2.124E-02	4.103E-02
	GRNN	18.74	1.094E-01	1.173E-01	1.202E-01
	SVM	14.25	4.912E-02	4.960E-02	5.019E-02
	ELM	**0.284**	**2.310E-02**	**2.352E-02**	**2.335E-02**

Fig. 8 shows the comparison between the actual measured data and the predicted data. It can be seen that the proposed method has a better fitting effect.

2.4 Discussion

It can be clearly proved from the experimental data that using the ELM fitting algorithm to model the I-V curve of the PV module can greatly shorten the network training time. The time required for BP neural network to process the same data is about 380 times that of ELM, GRNN is about 90 times that of it, and the relatively short SVM algorithm is about 50 times that of ELM algorithm.

It is worth noting that although the BP neural network performs well on the training set and the verification set, the generalization error on the test set does not perform well. It shows that ELM algorithm has better generalization performance than BP neural network. It can be concluded that the ELM-based rapid modeling method proposed in this paper has higher precision, faster network training, and strong generalization performance. It is more suitable for application in engineering practice to predict the I-V characteristic curve of photovoltaic module in real time.
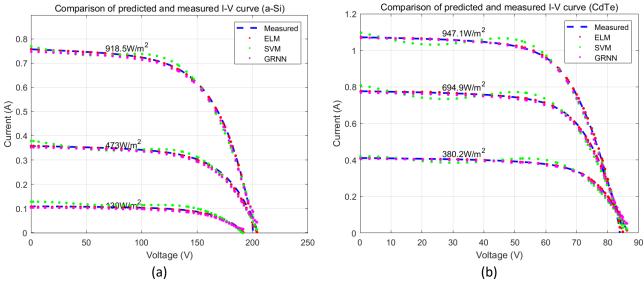
Fig. 8. Fitting results of different algorithms

3.   CONCLUSIONS

In this paper, a novel rapid modeling method is proposed for photovoltaic modules, which is based on ELM and IV characteristics. Experimental results show that the proposed ELM based method can shorten the modeling time to 0.2~0.4s, and the root mean square error (RMSE) can reach 0.0484%~0.374%. Compared with other AI algorithm based methods (including BPNN, GRNN and SVM), this method can greatly shorten the modeling time and significantly improve the accuracy and the generalization performance of the modeling for PV modules. In addition, it can be applied for modeling of various solar panels made of different materials.

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