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ANFIS-Based Modeling for Photovoltaic Characteristics Estimation

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Abstract: Due to the high cost of photovoltaic (PV) modules, an accurate performance estimation method is significantly valuable for studying the electrical characteristics of PV generation systems. Conventional analytical PV models are usually composed by nonlinear exponential functions and a good number of unknown parameters must be identified before using. In this paper, an adaptive-network-based fuzzy inference system (ANFIS) based modeling method is proposed to predict the current-voltage characteristics of PV modules. The effectiveness of the proposed modeling method is evaluated through comparison with Villalva's model, radial basis function neural networks (RBFNN) based model and support vector regression (SVR) based model. Simulation and experimental results confirm both the feasibility and the effectiveness of the proposed method.

Keywords: ANFIS; modeling; characteristic estimation; photovoltaic module

1. Introduction

For a rapid and reliable photovoltaic (PV) system design, an efficient and accurate PV characteristics simulator is indispensable [1]. PV model is used for obtaining the current-voltage (I-V) or power-voltage (P-V) characteristics by the environmental data, such as solar irradiance and ambient temperature.

During the last few decades, numerous analytical models have been proposed to represent the relations between PV current and voltage [2–4]. These mathematical models are always non-linear as the presence of the silicon PN junction, and the complexity depends on the adopted circuital representation [5]. This kind of model can be divided into two main types, the one-diode and two-diode models. The latter two-diode models have higher accuracy [6,7] but suffer from high computational complexities [8]. And the former type, one-diode model, is the most commonly used mathematical model in the fields of PV modeling as it gives a solution for the tradeoff problems between the simplicity and accuracy [9,10]. The analytical models are easy to implement but a good number of unknown parameters must be identified before using. All the parameters inside the models need to be well determined, otherwise the accuracy of the models reduces [5]. A more complicated model normally results in more parameters in its mathematical formulations along with a higher computational complexity [1,11].

Recently, artificial intelligence (AI) algorithms have been introduced into the fields of PV modeling. Artificial neural network (ANN) based models do not require any physical definitions for PV modules. Since the 1990s, a number of researches presented neural network based systems to predict the optimal operating power points for the PV modules [12,13]. Radial basis function neural network (RBFNN) based PV models were introduced to improve the estimation accuracy [14–16]. Shi et al. [17] proposed a forecasting tool to predict the output power of PV systems using the support vector regression (SVR), which is a regression technique based on the concept of Vapnik's support vector machines (SVM) [18].

The main purpose of this paper is to present a more accurate PV model based on adaptive-network-based fuzzy inference system (ANFIS), which has the capability to approximate a nonlinear function. The proposed ANFIS based model does not need any primary model parameter and the estimation accuracy is verified by applying the model to three PV modules with different technologies (mono-crystalline, poly-crystalline and thin-film) and compared with three different kinds of modeling including Villalva's model, RBFNN model and SVR model. It is envisaged to be useful for the circuit simulation developers and PV system designers who require a simpler and more accurate PV estimation model.

The remainder of this paper is organized as follows. Section 2 introduces the ANFIS method and the proposed ANFIS based PV model. The results and the validated performance of the proposed method are given in Section 3. Section 4 finally summaries this work.

2. ANFIS and PV Modeling

An adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network developed by Jang [19] in 1993. In this section, after a brief introduction of the theory of the ANFIS, we propose a PV model based on the ANFIS technique.

2.1. ANFIS

The ANFIS combines the fuzzy inference and neural network algorithms. It overcomes the limitations of fuzzy inference that the identification procedure of the parameters in membership functions (MFs) is not efficient for complex systems. Recently, ANFIS has been widely used in maximum power point tracking (MPPT) [20], face recognition [21] and object tracking [22].

Considering there are two inputs x, y and one output f, the inputs and outputs of a neural network obey the following rule.

$$\begin{aligned} &\text{If } x \text{ is } A_i \text{ and } y \text{ is } B_i \\ &\text{Then } f_i = p_i x + q_i y + r_i \quad (\, i \in \{1,2\}\,) \end{aligned}$$

where A_i, B_i are fuzzy sets and $\{p_i, q_i, r_i\}$ is the parameter set, which is determined during the training process. f_i are the outputs within the fuzzy region determined by the rules. The architecture of ANFIS is shown in Figure 1.

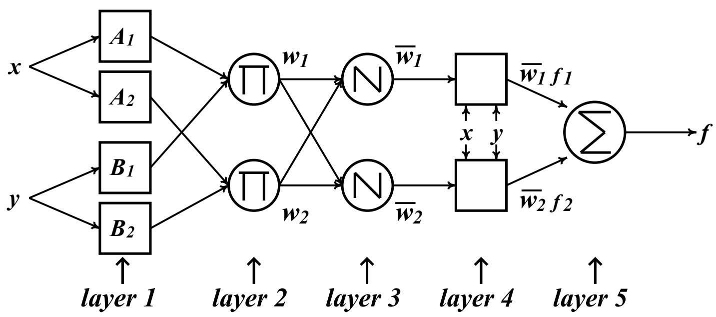


Figure 1. The architecture for adaptive-network-based fuzzy inference system (ANFIS).

Every node in layer 1 has a node function

$$O_i^1 = \begin{cases} \mu_{A_i}(x), & i \in \{1,2\} \\ \mu_{B_{i-2}}(y), & i \in \{3,4\} \end{cases} \quad (1)$$

where O_i^1 is the output of the ith node in the first layer, and $\mu_{A_i}(x)$ or $\mu_{B_i}(y)$ can adopt any fuzzy member function and is usually chosen to be generalized bell function as follows.

$$\left.\begin{aligned} \mu_{A_i}(x) &= \frac{1}{1+|\frac{x-c_i}{a_i}|^{2b_i}} \\ \mu_{B_i}(y) &= \frac{1}{1+|\frac{y-c_i}{a_i}|^{2b_i}} \end{aligned}\right., \quad i \in \{1,2\} \quad (2)$$

where $\{a_i, b_i, c_i\}$ is the parameter set of the generalized bell function.

The general function of layer 2 O_i^2 multiplies the input values, denoted as ω_i.

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i \in \{1,2\} \quad (3)$$

The output of layer 2 need to be normalized, the output of the normalization layer O_i^3 is

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\sum_i(\omega_i)}, \quad i \in \{1,2\} \quad (4)$$

where $\overline{\omega}_i$ is the normalized value of ω_i.

The node function of the nodes in layer 4 O_i^4 is to multiply the outputs of layer 3 and the related supposed function. It can be express by Equation (5).

$$O_i^4 = \overline{\omega}_i f_i = \overline{\omega}_i(p_i x + q_i y + r_i), \quad i \in \{1,2\} \quad (5)$$

The overall output f is the summation of the outputs of layer 4.

$$f = O^5 = \sum_i O_i^4 = \sum_i \overline{\omega}_i f_i \quad (6)$$

There are two fixed layers (layer 2 and 3) and two adaptive layers (layer 1 and 4) in this ANFIS architecture. In layer 1, the parameter set $\{a_i, b_i, c_i\}$ determines the input member function. These parameters are the so-called premise parameters. In the fourth layer, the parameters $\{p_i, q_i, r_i\}$ are related to the first-order polynomial and are the so-called consequent parameters [19].

2.2. The Proposed PV Model

In this paper, the ANFIS based PV model is used to estimate the I-V or P-V characteristics of PV modules under the given environmental conditions. Given the specified solar irradiance and temperature of PV cells, by scanning the voltage of the PV array from zero to the open-circuit voltage of the PV modules, which can be found on manufacturing datasheet, the corresponding predicted current set can be obtained by the proposed PV estimation model.

The architecture for the proposed ANFIS based model is shown in Figure 2. The input data consists of the solar irradiance (G), the ambient temperature (T) and the operating voltage of the PV array (V), while the output is the current (I) of the PV module. The inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate the I-V or P-V nonlinear relations. The algorithm uses a combination of the least-squares and back-propagation gradient descent methods to train the data set.

In the ANFIS architecture shown in Figure 2, the consequent parameter set is $\{p_i, q_i, r_i, s_i\}$ according to the dimension of the input vector $\{G, T, V\}$. The outputs of the specified rule f_i are as follows.

$$f_i = p_i G + q_i T + r_i V + s_i \tag{7}$$

After completing the training phase, the aforementioned premise and consequent parameters, and the final weights ω_i of the nodes are found and then stored in matrixes of real numbers. Thus, the learned model can be used to get the predicted results as follows.

$$I = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i (p_i G + q_i T + r_i V + s_i)}{\sum_i \omega_i} \tag{8}$$

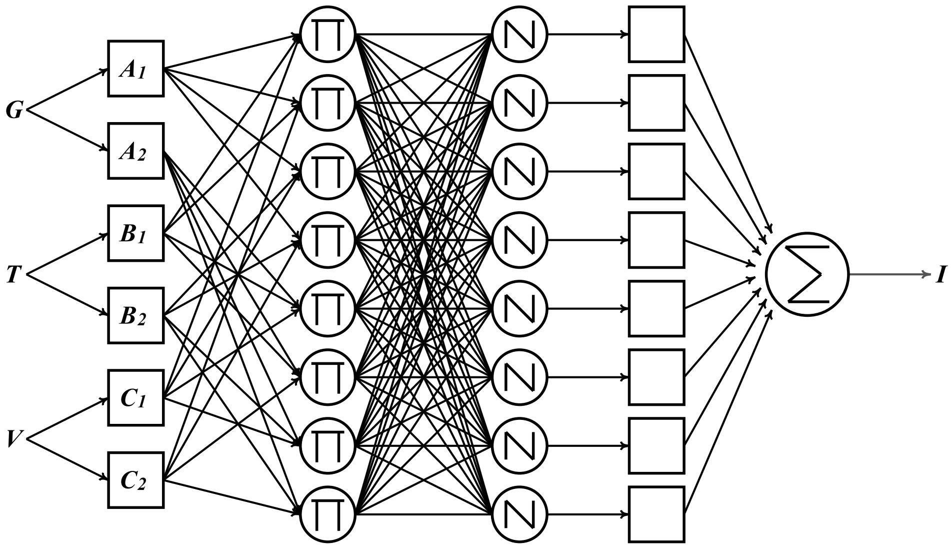


Figure 2. The ANFIS architecture for the proposed photo-voltaic (PV) model.

3. Results

In this section, the performance of different estimation models are evaluated by four statistical indicators including root mean squared error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE) and coefficient of determination (R^2). The mathematical expressions of these three indicators are given as follows.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{I}_i - I_i)^2} \tag{9}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{I}_i - I_i| \tag{10}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{I}_i - I_i}{I_i}\right| \tag{11}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{I}_i - I_i)^2}{\sum_{i=1}^{n}(\hat{I}_i - \bar{I}_i)^2} \tag{12}$$

where $\hat{I}_i$ is the predicted current of PV modules, I_i is the measured one and $\bar{I}_i$ is the mean of the measured ones.

RMSE is frequently used to measure the differences between the values predicted by the model and the related experimental data. MAE is a quantity used to measure how close the predictions are to the experimental data. MAPE is also used to measure the errors but it differs in values from module to module because the short-circuit current varies from different PV models. R^2 evaluates how well the predicted data fits the measured one. $R^2 = 1$ indicates that the predicted values and the measured values are perfectly fitted, while $R^2 = 0$ indicates that the predicted values do not fit the measured values at all.

All the simulations are carried out in MATLAB 2016a (http://www.mathworks.com) environment running on an Intel(R) Core(TM) i7-4850HQ 2.30 GHZ CPU with 16 G RAM. Gaobo GSMT-H-3A100 solar module tester is applied to measure the I–V experimental data. A comparative experiment has been performed among the four different estimation models including Villalva's model [6], RBFNN model, SVR model and the proposed ANFIS model, using three PV modules with different technologies. Villalva's model is one of the most successful models in the field of PV modeling. Therefore, the proposed method was compared with Villalva's model. The technical parameters at the nominal environment of the three PV modules used in this manuscript are listed in Table 1.

Table 1. Technical parameters of PV modules at 25 °C, AM 1.5, 1000 W/m^2.

Module	STP265S-20	KC200GT	TS-150C1
Technology	mono-crystalline	poly-crystalline	thin-film
P_{MAX} (W)	265.05	200.14	149.96
V_{OC} (V)	38.1	32.9	64.5
I_{SC} (A)	9.22	8.21	3.61
V_{MPP} (V)	30.5	26.3	46.0
I_{MPP} (A)	8.69	7.61	3.26
K_V (V/K)	−0.130	−0.123	−0.187
K_I (A/K)	5.53×10^{-3}	3.18×10^{-3}	3.61×10^{-4}
N_{CS}	60	54	100

Figure 3 depicts the median deviation of the current predicted by four different modeling methods from the measured values of operating current of three PV modules with varied technologies. The red circle below the unit-slope straight line indicates that the estimated current is smaller than the measured one, and vice versa.

As can be seen in Figure 3, the estimation results from RBFNN model are much more accurate than those from Villalva's model, but some red circles can be found to deviate from the unit-slope straight line, indicating that some errors still exist in the estimation phase. Besides, it is hard to distinguish the prediction performance of SVR model and the proposed ANFIS model from Figure 3.

Figure 4 shows the I-V curves of three PV modules predicted by different modeling approaches along with the measured ones obtained by solar module tester. The left three figures in Figure 4 depict the overall views of the estimation results from four models versus the experimental I-V curves and the right three ones give the details of the appointed areas marked with red rectangles in the overall views. The most important point for solar cells is the maximum power point, thus, these selected regions contain the corresponding maximum power points. It is observed that the estimated I-V curves from the proposed ANFIS model are relatively close to the measured ones among all the modeling methods.

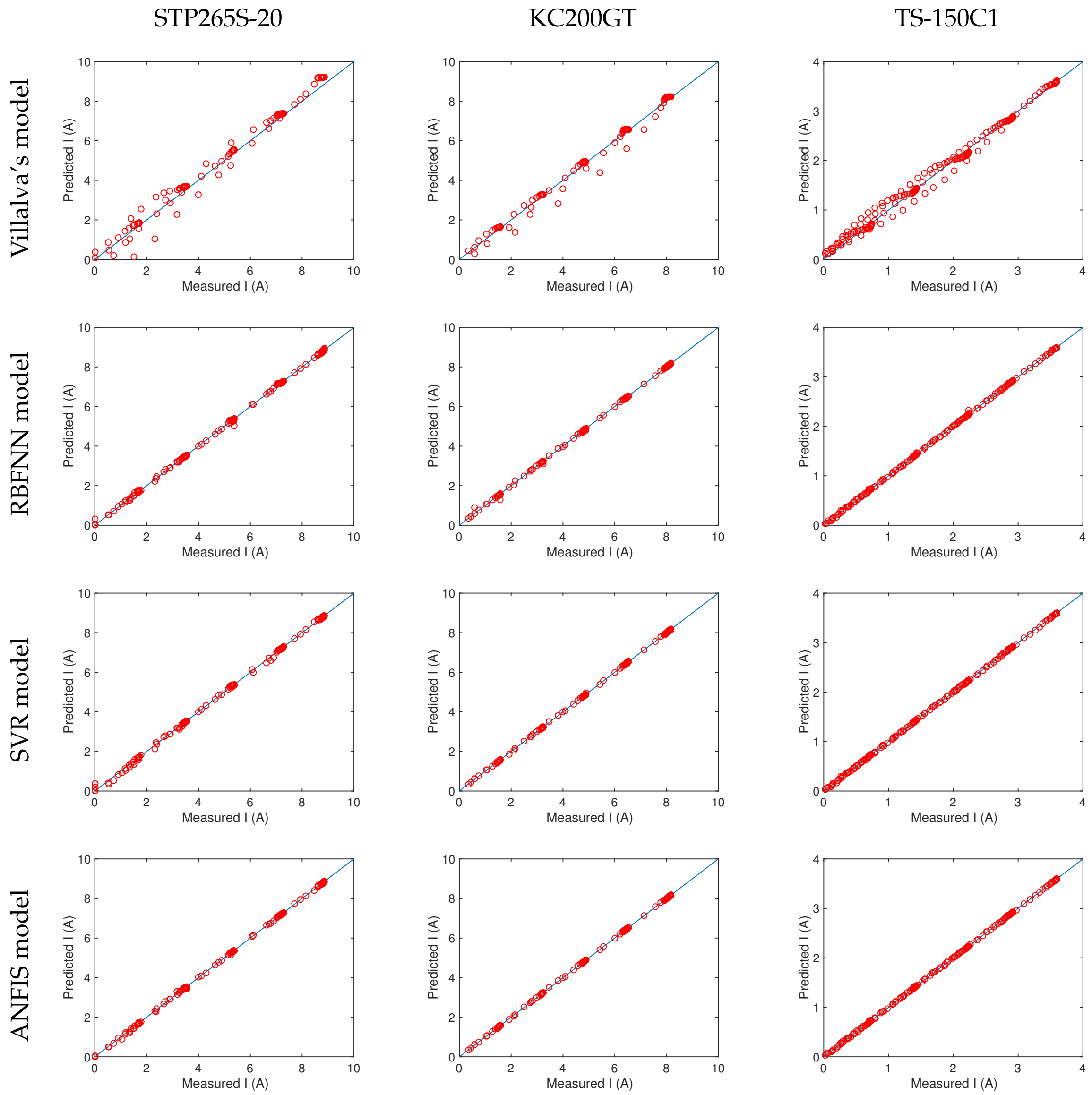


Figure 3. Operating current predicted by different models versus the measured data.

Furthermore, Table 2 lists the best results of involved mathematical indicators for the mentioned three PV modules over 100 runs of four given estimation models. As can be seen, considering the values RMSE and MAPE, the results of these two indicators from the analytical approach (Villalva's model) are much higher than that from the ANFIS model. The RMSE value of Villalva's model is nearly 20 times of that of the proposed model. Meanwhile, the R^2 value of the later three AI-algorithm-based models are all close to 1, while the Villalva's method's R^2 is much lower. Overall, the proposed ANFIS model obtains the lower values of RMSE/MAPE and higher R^2 value, which indicates that the proposed ANFIS model has the most accurate estimation capability among four modeling methods.

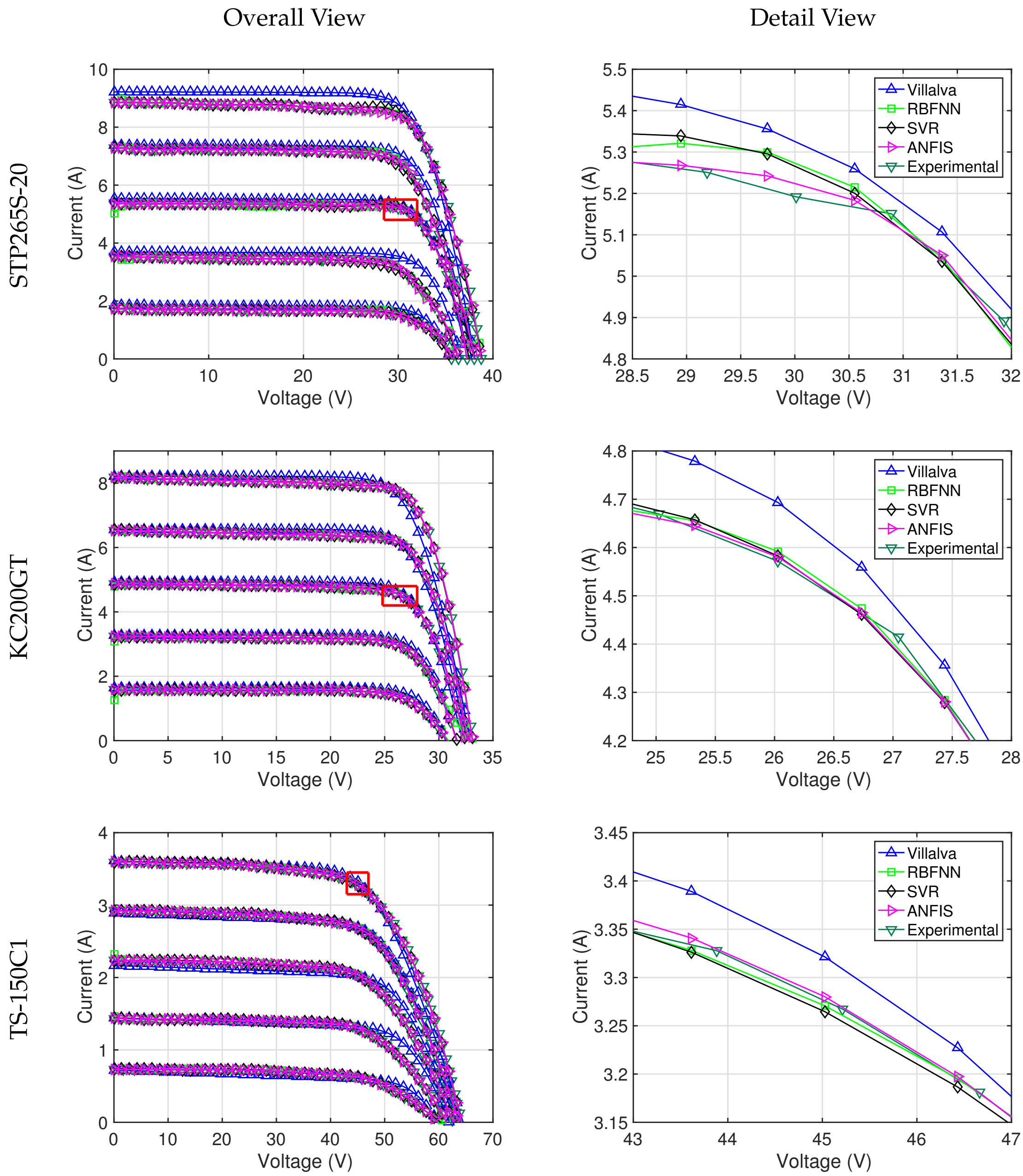


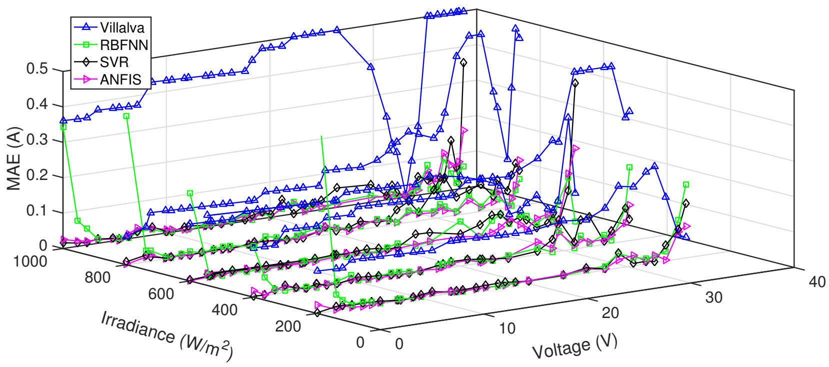
Figure 4. Current-voltage (I-V) curves obtained by different estimation models.

Table 2. Best results in 100 runs of different models.

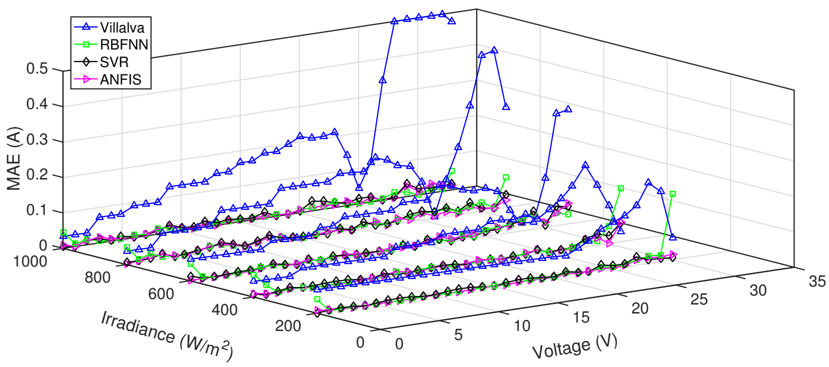
Method	**STP265S-20**			**KC200GT**			**TS-150C1**		
	RMSE	**MAPE**	**R^2 (%)**	**RMSE**	**MAPE**	**R^2 (%)**	**RMSE**	**MAPE**	**R^2 (%)**
Villalva's model [6]	0.6754	11.859	94.50	0.2032	0.0499	99.27	0.1007	0.1386	99.04
RBFNN model *	0.0458	1.9232	99.97	0.0381	0.0071	99.97	0.0414	0.0204	99.71
SVR model †	0.0574	3.1932	99.95	0.0145	0.0037	99.99	0.0105	0.0150	99.99
ANFIS model	0.0280	0.7363	99.99	0.0123	0.0026	99.99	0.0079	0.0109	99.99

* RBFNN model uses the tool embedded in MATLAB 2016a; † SVR model uses the SVM tool provided by LIBSVM [23].

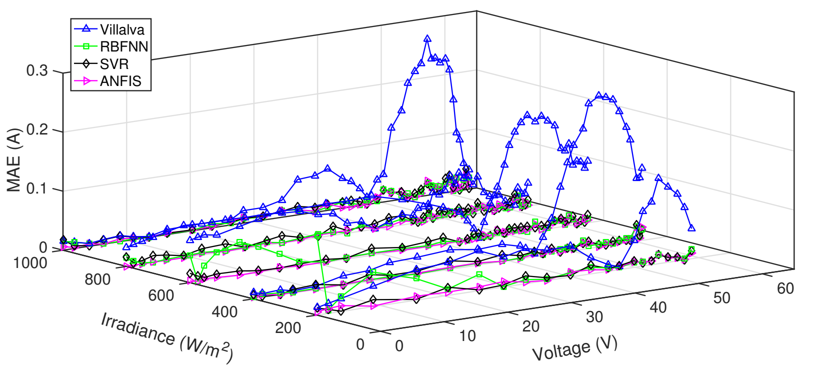
The best prediction results over 100 times only show the optimal predicting capability of each model. Figure 5 further estimates the average prediction performance of different modeling methods over 100 times. Among the four PV models, the ANFIS model shows the lowest MAE in most cases, which is just 7.34% of that for Villalva's model in average. It is observed that significant errors usually occur in Villalva's model when the operating voltage is approaching the open-circuit voltage. Both SVR and ANFIS models obtain good estimation capabilities, yet small errors can be found at the open-circuit points. The MAE value for the estimation results from ANFIS model is 32.9% and 50.0% lower than that from SVR model and RBFNN model in average, respectively.



(**a**)



(**b**)



(**c**)

Figure 5. The comparison of mean absolute error (MAE) values over 100 runs for the module (**a**) STP265S-20 (**b**) KC200GT (**c**) TS-150C1. (The MAE value above 0.5 A is shown as 0.5 A in the figure).

Especially, thin-film modules exhibit both time dependent degradation and annealing behavior, which make device analyses more complicated. The simulation of the initial device performance works fine while the degradation behavior of thin-film modules requires a more detailed analysis.

4. Conclusions

In this paper, an adaptive-network-based fuzzy inference system (ANFIS) based estimation model has been proposed to predict the electrical characteristics of various types of PV modules.

The proposed method has the capability of obtaining I-V or P-V curves based on environmental data. The accuracy of the proposed model has been evaluated by PV modules with different technologies. Three modeling approaches, including Villalva's model, RBFNN model and SVR model, have been used to benchmark the proposed ANFIS model. The simulation results show that the I-V curves predicted by the proposed model are relatively close to those measured data and the improvement on the prediction accuracy of the proposed PV estimation model also can be reflected by its lowest RMSE, MAPE and highest R^2. The robustness of the proposed model is validated by comparative study on performance test of PV models by using different environmental conditions.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AM	air mass
P_{MAX}	maximum power (W)
V_{OC}	open circuit voltage (V)
I_{SC}	short circuit current (A)
V_{MPP}	maximum power point voltage (V)
I_{MPP}	maximum power point current (A)
K_V	temperature coefficients of open circuit voltage (V/K)
K_I	temperature coefficients of short circuit current (A/K)
N_{CS}	number of cells in series

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