

The fault diagnosis method of photovoltaic module based on probabilistic neural network

Yongxin Wu^{1,*}, Hu Wang¹, Tingting Guo²

¹China Datang Corporation Science and Technology Research Institute, Beijing, China;

²Department of Physics, College of Sciences, Tianjin University of Science & Technology, Tianjin, China

*Corresponding author e-mail: wuyongxin@cdt-kxjs.com

Abstract. This paper describes a fault diagnosis method of photovoltaic (PV) module, which bases on equivalent circuit module and probabilistic neural network (PNN). The output characteristics of the PV module under normal, dust deposition, abnormal aging and partial shading conditions are simulated by using the equivalent circuit model. The simulated data are used as characteristic parameters to fault type diagnosis. The performance of the fault diagnosis model is evaluated, and the results indicate that the method can detect the fault types correctly.

1. Introduction

The reliability and stability of photovoltaic (PV) module is the key for PV system performance. The PV module may appear some faults in actual application processing, if not detected soon enough, not only reduce output power but may also cause serious damage and fire hazards. Thus the fault diagnosis is crucial and necessary for PV module maintenance.

The accuracy fault diagnosis technology is necessary for improving the performance and reliability of PV systems to achieve higher energy yields. For this propose, several fault diagnosis methods have been studied. Wang et al. proposed an online fault diagnosis method. The fault diagnosis model is based on BP neural network and mathematical model of the PV module. The results indicate that the model is suit for diagnosis various faults, and has high effective and suitability. Due et al. analyzed the output characteristics of PV modules under partial shadow and abnormal conditions, and a fault diagnosis method for PV modules based on the decision tree algorithm is proposed. According to the change of fill factor (FF), the maximum power point voltage (U_{mp}), the maximum power point Current (I_{mp}), open circuit voltage (U_{oc}) and short circuit current (I_{sc}), the state of PV modules can be diagnosed by the decision tree. The experiment results show that the method is feasibility and effectiveness. Chen et al. presented a fault diagnosis method based on PV module power loss and I-V output curve. Through comparing the simulated and measured output power to determine whether there is power loss in the module, and then used the U_{oc} and FF to identify the types of the fault.

The above theoretical and experimental studies have given some fault diagnosis methods, but the actual situation of the fault is very complex, there are still some difficulties to accuracy determine the types of fault.



In fact, due to the complex working environment, the PV module fault presents the complexity and diversity, there are still difficult to accuracy determine the types of fault. Thus, fault diagnosis method needs to be further improvement and development.

In this paper, the output characteristics of PV module under different fault types are simulated by using the equivalent circuit model. The simulated results are used to summarize the principles of PV module output characteristic. The fault diagnosis model base on probabilistic neural network (PNN) is established, and the accuracy and reliability of the model is validated.

The equivalent circuit model

Figure 1 shows the equivalent circuit diagram of solar cells, the mathematical expressions could be express as follows:

$$I = I_{ph} - I_d - I_{sh} \quad (1)$$

$$I_{ph} = \frac{G}{G_{ref}} [I_{sc} + \alpha(T - T_{ref})] \quad (2)$$

$$I_d = I_0 \left(\exp\left(\frac{U + IR_s}{U_t}\right) - 1 \right) \quad (3)$$

$$I_{sh} = \frac{U + IR_s}{R_{sh}} \quad (4)$$

$$I_0 = \frac{I_{sc}}{\exp\left(\frac{U_{oc}}{U_t}\right) - 1} \quad (5)$$

$$I = \frac{G}{G_{ref}} [I_{sc} + \alpha(T - T_{ref})] - I_0 \left(\exp\left(\frac{U + IR_s}{U_t}\right) - 1 \right) - \frac{U + IR_s}{R_{sh}} \quad (6)$$

Where I_{ph} is the photocurrent, and the I_d is the current which through the D diode, I_0 is the diode reverse saturation current, i_s is the current through the parallel resistance, sic is the short circuit current. The $Ouch$ and U are open circuit voltage the output voltage of PV cell, respectively. The $Rash$ is the parallel resistance, and $Rest$ is the series resistance. The q is the unit charge (1.6×10^{-19} C), UT is the thermal voltage of diode (25.9 mV). The $Graf$ and G are the reference solar irradiance at STC (1000 W/m²) and the irradiance at real working condition, respectively. Tre is the temperature of the PV cell at STC (25 °C), and the T is the temperature of working condition, α is the current temperature coefficient.

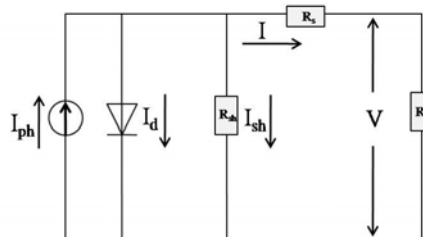


Figure 1. The equivalent circuit of solar cell

PV module consists of many PV cells wired in parallel to increase current and in series to voltage, according to the formula (6), the equivalent mathematical expression of the PV module could be expressed as:

$$I = \frac{N_p G}{G_{ref}} [I_{sc} + \alpha(T - T_{ref})] - N_p I_0 \left(\exp\left(\frac{U / N_s + IR_s / N_p}{U_t}\right) - 1 \right) - N_p \frac{U / N_s + IR_s / N_p}{R_{sh}} \quad (7)$$

Where, the N_s and N_{ap} are the number of series and parallel solar cell, respectively.

The simulation model of PV module is built by using the mat lab/Simulink compiler. The peak power of the module is 320 W, the open circuit voltage (Ouch) is 46.78 V, short circuit current (Sic) is 8.98 A, maximum power point voltage (Ump) and maximum power point current (Imp) are 38.46 V and 8.32 A, respectively. The short circuit current temperature coefficient (α) is 0.00059, and the open circuit voltage temperature coefficient is (β) -0.0033. The Rest of the module is 0.18 Ω . The simulation model diagram of the PV module shows in Figure 2.

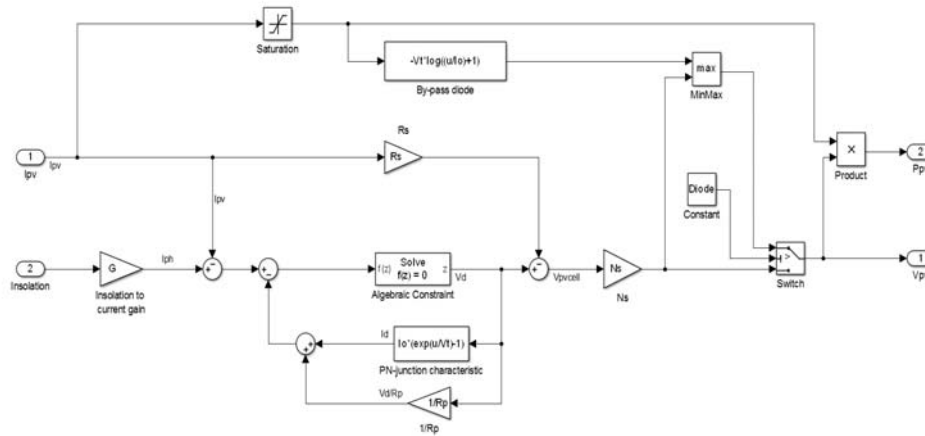


Figure 2. The simulation model of PV module

The output characteristic of PV module at standard test condition (STC) can be simulated by using the simulation model. Due to the effect of the measuring environment, it is difficult to obtain the output characteristic at standard test condition. Thus, it is necessary to change the data of real test environment into standard test condition. The transformation formula as follows:

$$I_{STC} = I + I \left[\left(\frac{G_{ref}}{G} - 1 \right) + \alpha (T_{ref} - T) \right] \quad (8)$$

$$U_{STC} = U [1 + \beta (T_{ref} - T)] - (I_{STC} - I) R_s - K I_{STC} (T_{ref} - T) \quad (9)$$

2. The fault analysis of PV modules

The PV module is directly exposed to work in complex outdoor environment, along with the time increasing, the module unavoidably appears various faults. The common types of fault for PV module are as follows: dust deposition, abnormal aging and partial shading.

2.1. Abnormal aging

The value of series resistance increases significantly when the PV module appears abnormal aging phenomenon, which results the reduction of the maximum power point voltage and the maximum power point current. According to the simulation model of PV model, ignoring the influence of the temperature and external factors on series resistance, the relationship of R_{st} , I_{ph} , I_{mp} and U_{mp} can be expressed as follows:

$$R_s = \frac{U_T \ln \left(\frac{I_{ph} - I_{mpp}}{I_0} + 1 \right) - U_{mpp}}{I_{mpp}} \quad (10)$$

Figure 3 shows the simulated output parameters of PV module with different values of series resistance. It can be seen from the figure, when the value of R_{st} is smaller than 5 Ω , the maximum power point voltage and maximum power point current appear decline, while the open circuit voltage

and short circuit current of the module remain the same. But with the resistance value continues to increase, when the value of R_{st} is above 5Ω , the short circuit current of PV modules shows downward trend. Nevertheless the open circuit voltage remains unchanged. Thus, the O_{uch} , S_{ic} , U_{mp} , I_{mp} , P_{ump} and I-V curve can be used to diagnose the abnormal aging condition.

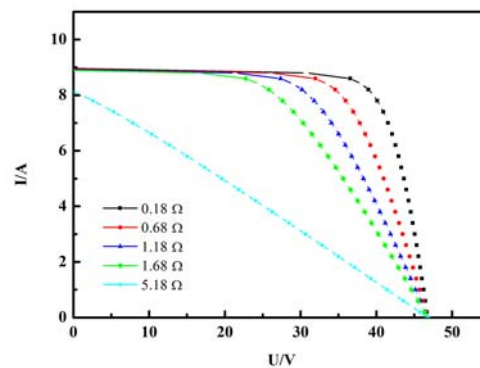


Figure 3. The output characteristic varied with changing of series resistance value

2.2. Dust deposition and partial shading

The dust deposited on the surface of PV module, which results in reducing of the solar radiation intensity and output power decreases. The simulate result of the dust impact on the output characteristic of PV module at strand test condition are shown in Figure 4. As shown in the Figure, there is a line relationship between short circuit current and solar radiation intensity, and the influence of solar radiation intensity to open circuit voltage is not significantly. Due to decline of the maximum power point current, which cause the maximum output power decrease.

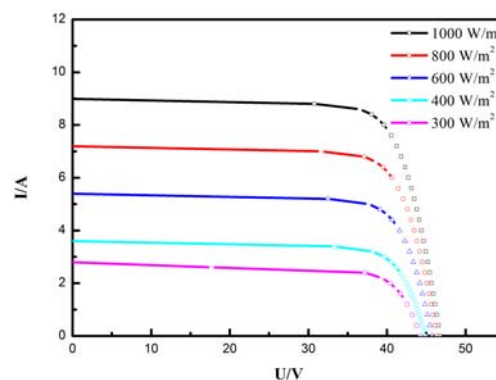


Figure 4. The impact of dust deposition on the output characteristic of PV module

The output power curves of PV module under multiple solar cell shaded conditions are shown in Figure 5. As can be seen from the Figure 5, due to the effect of the bypass diode, the output current of the module is a piecewise function, the I-V curve of the PV module exhibits multiple gradients and multiple extreme values under the different partial shading conditions, which make it is difficult to find any extreme value of the curve as the maximum output power point. The above results indicate the open circuit voltage and shot circuit current do not change when the PV module is shaded. Thus, the open circuit voltage, shot circuit current and I-V curve are used to diagnosis the fault of partial shading.

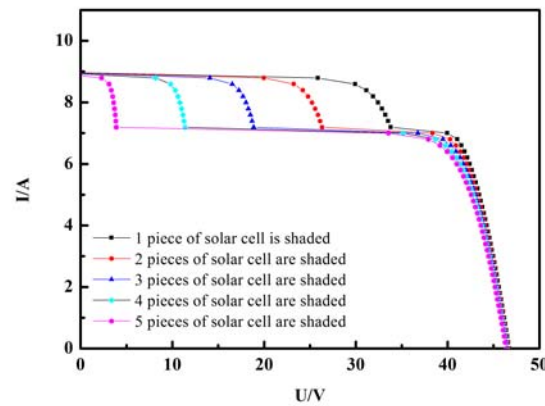


Figure 5. The I-V and output power curves of PV module under different partial shading condition.

3. The Probabilistic Neural Network

The probabilistic neural network is consisted of input layer, hidden layer and output layer, the structure of the neural network is shown in Figure 6. For fault diagnosis of PV module, the input layer is used to receive the output power curves of PV module for fault diagnosis. The number of neurons is same as the length of the input vector. Use x to express an input sample, which dimension is d , so $x=(x_1, x_2, x_3, \dots, x_d)$. The hidden layer is the fault category. The neurons number of each category has the same number as the input sample, ω is the category, c is the total number of categories, where, $\omega=(\omega_1, \omega_2, \omega_3, \dots, \omega_c)$. The input layer and the hidden layer are connected by a Gaussian function for obtaining the degree of matching between each neuron in the hidden layer and each neuron in the input layer. The summation layer sums up the matching degree of each class, and then averages the values to get the corresponding problem categories of the input samples. The number of neurons in the summation layer is the same as the hidden layer, and the expression as follows:

$$y_i(x, \sigma) = \frac{1}{N_i (2\pi)^{\frac{d}{2}} \sigma^d} \sum_{i=1}^{N_i} \exp\left(-\frac{(x-x_i)(x-x_i)^T}{2\sigma^2}\right) \quad (11)$$

Where N_i is the number of sample, which category belong to it, σ is the smoothing factor; I is the j central vector of the I type.

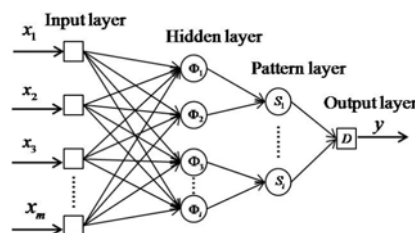


Figure 6. The structure of Probabilistic Neural Network

4. Results and discussion

The mat lab software is used to build the fault diagnosis model, and the equivalent circuit models are established by using mat lab/Simulink to obtain I-V curve, O_{uch} , S_{ic} , I_{mp} and U_{mp} of PV module under different fault types. The simulate results are used as fault diagnosis parameters for PNN model. The accuracy and practicability of fault diagnosis model are verified by experiment data. Three fault PV modules are selected as the research object. The simulated and measured I-V curves are shown in Figure 7-9, the specific parameters and diagnosis results are shown in Table 1, respectively.

According to the figure 7, the simulated and measured curves are fitting well. The fault diagnosis result indicates that two pieces of solar cell of the PV modules are shaded, and the shading ratios are 30%.

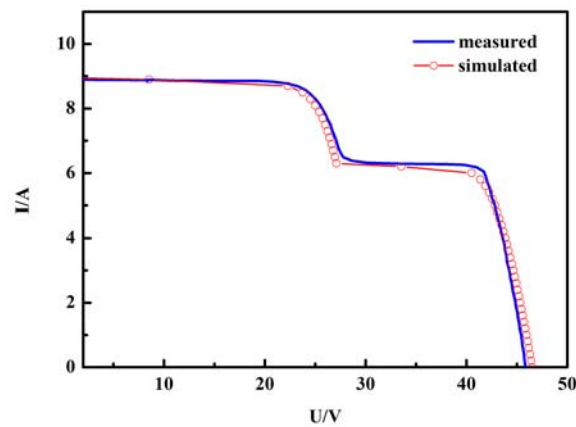


Figure 7. The measured and simulated curves of PV module under partial shading

Figure 8 shows the matching result of simulated and measured curves for PV module, which surface is covered by dust. The simulated curve and measured curve exhibit same variation trend. The simulated result indicates that dust deposition causes the solar radiation, which receives by PV module decreases 5%.

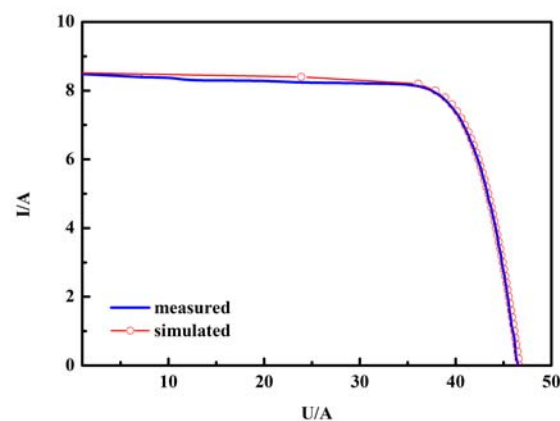


Figure 8. The measured and simulated I-V curves under dust deposition condition.

Figure 9 shows the simulated and measured curves of abnormal aging PV module. The simulated result indicates that the series resistance value of abnormal aging PV module increases from 0.18 to 0.23.

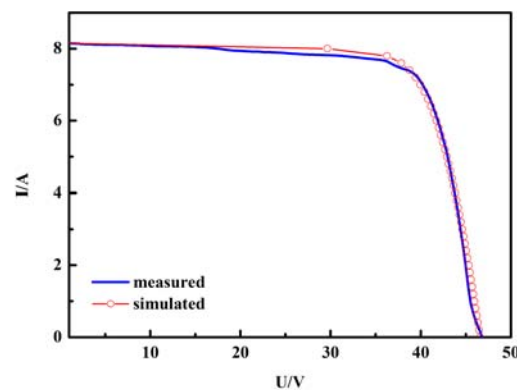


Figure 9. The measured and simulated IV curves of abnormal aging PV module

From the above results, it can be seen that the fault diagnosis results for the PV module samples are correct. Therefore, it can be proved that the fault diagnosis method, which bases on PNN network and PV module equivalent circuit model can diagnosis the fault types, and can accurately simulate the electrical characteristics of PV modules.

Table 1. Measured and simulated output characteristic of PV module under different fault types

Sample	Measured/simulated	Sic	Ouch	Imp	Ump	PMAX	Types of fault
1	simulated	8.54	46.53	6.00	40.50	243.02	partial shading
	measured	8.84	46.83	6.15	42.02	258.42	
2	simulated	8.4	46.67	7.8	38.89	303.36	Dust deposition
	measured	8.48	46.52	7.92	38.64	301.26	
3	simulated	8.16	46.58	7.6	37.83	287.56	Abnormal aging
	measured	8.14	46.74	7.30	39.54	288.76	

5. Conclusion

In this paper, a fault diagnosis method of PV module is proposed. The method bases on equivalent circuit model and probabilistic neural network, the equivalent circuit model of PV modules under different fault types are established, and the corresponding electrical parameters are selected as the fault characteristic parameters for Fault diagnosis analysis. The method has high accuracy and feasibility.

Acknowledgments

This work was financially supported by the multi-energy complementary key technology research project of China Dating Corporation (NO. DTJT2017-119), and the research fund of Tianjin University of Science & Technology (NO. 20323)

References

- [1] HUANG Zhijia, LIU Dongfang, ZHANG Guozhi. Design and analysis system of barn photovoltaic power generation[J]. Energy Conservation Technology, 2010, 28(161): 257-161.
- [2] CAO Yan, SONG Xiaolin, ZHOU Yihuan, et al. Probe into distributed photovoltaic power generation system in electric vehicle charging stations[J]. Shanxi Electric Power, 2012(9): 20-23.
- [3] Santiago Silvestre, Aissa Chouder, Engin Karatepe. Automatic fault detection in grid connected PV systems[J]. Solar Energy, 94 (2013) 119–127.

- [4] Santiago Silvestre, Sofiane Kichou, Aissa Chouder, Gustavo Nofuentes, Engin Karatepe. Analysis of current and voltage indicators in grid connected PV (photovoltaic) systems working in faulty and partial shading conditions[J]. *Energy* 86 (2015) 42-50.
- [5] Yagi Y, Kishi H, Hagihara R, Tanaka T, Kozuma S, Ishida T, et al. Diagnostic technology and an expert system for photovoltaic systems using the learning method[J]. *Sol Energy Mater Sol Cells* 2003(75):655-63.
- [6] W. Chine, A. Mellit, V. Lughi, A. Malek, G. Sulligoi, A. Massi Pavan. A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks[J]. *Renewable Energy*, 90 (2016) 501-512.
- [7] Kuei-Hsiang Chao, Sheng-Han Ho, Meng-Hui Wang. Modeling and fault diagnosis of a photovoltaic system[J]. *Electric Power Systems Research* 78 (2008) 97–105.
- [8] WANG Yuanzhang, LI Zhihua, WU Chunhua, ZHOU Diqing, FU Li. A Survey of Online Fault Diagnosis for PV Module Based on BP Neural Network[J]. *Power System Technology*, 2013 37(8):2094-2099.
- [9] XULi-juan, WUCHun-hua, WANGYuan-zhang, LIZhi-hua. Survey of fault diagnosis for PV modules based on decision tree[J]. *Advanced Technology of Electrical Engineering and Energy*, 2017 36 (6) :83-88.
- [10] CHEN Yuhang, YAN Tengfei, XIE Tian, WEN Ying, LIANG Rui. A Novel Fault Diagnosis Method of Photovoltaic Module Based on Power Loss and U-I Characteristics[J]. *Electric machines & control application*, 2016, 43(11):92-97.
- [11] Dan Yangqing, Liu Wenying, Zhu Yanwei. Matlab simulation of pv array and analysis of output efficiency under partial shading[J]. *ACTA ENERGIAE SOLARIS SINICA*, 2013, 34(6):997-1001.
- [12] CHEN Ling, HAN Wei, ZHANG Jingwei. PV Module Fault Diagnosis Based on Data Fusion[J]. *Power System Technology*, 2017 41(6):1864-1872.