Fault diagnosis and operation and maintenance of PV components based on BP neural network with data cloud acquisition

Zhongfeng Wang\textsuperscript{1,2}, Ligang Li\textsuperscript{1,2}, Xiao Yang\textsuperscript{3,5}, Ming Guan\textsuperscript{4}, Yanan Li\textsuperscript{4} and Bowen Zhou\textsuperscript{3}

\textsuperscript{1} Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China;
\textsuperscript{2} Institutes for Robotics and Intelligent Manufacturing, Chinese Academy of Sciences, Shenyang 110016, China;
\textsuperscript{3} Northeastern University, Shenyang 110000, China;
\textsuperscript{4} State Grid Liaoning Electric Power Co. Ltd. Anshan Electric Power Supply Company, Anshan 114000, China.

\textsuperscript{5} Email: 490078420@qq.com

Abstract. In order to improve the power generation efficiency of photovoltaic systems and to reduce the cost of manual maintenance, this paper proposes a fault diagnosis and operation and maintenance method based on BP neural network with data cloud acquisition. The causes of short circuit and abnormal aging failure of photovoltaic modules are analyzed. BP neural network fault diagnosis model is established in Matlab, combined with the mathematical model of photovoltaic components to simulate the output of various faults, performing sample training on the fault diagnosis model. The data collected by the distributed photovoltaic information processing and data analysis system platform is used as the input data of the neural network. According to the diagnosis result, reasonable suggestions for PV module operation and maintenance are provided from the aspects of component maintenance, photovoltaic panel cleaning, dip angle change, etc. Simulation results verify the correctness and effectiveness of the proposed method.

1. Introduction

With the increasing development of social production, the demand for energy is increasing, and the global energy crisis is also growing. Solar energy is clean, pollution-free and sustainable. In recent years, with the continuous maturity and popularization of photovoltaic power generation technology, the price of photovoltaic modules has been declining, and its application fields and scale have been continuously developed and expanded. Photovoltaic modules are prone to various failures due to their long-term outdoor harsh working environment. If the fault cannot be detected and processed in time, it will directly affect the normal power generation of the photovoltaic system, and even cause accidents such as fire disaster.

At present, the maintenance of photovoltaic power plants mostly adopts the method of manual inspection, and the electrical parameters of the photovoltaic modules are detected block by block to judge whether the components are normal or not. However, most of the photovoltaic modules are
installed at the top of the roof, which requires a lot of manpower and material resources. Therefore, the fault diagnosis of photovoltaic modules is of great significance.

There are many troubleshooting methods for PV modules, mainly infrared image analysis [1], according to the principle that the working temperature of the PV module is different between normal and fault, and the type of fault is judged by analyzing the captured infrared image. The multi-sensor detection method [2] determines the type of fault by analyzing the data measured by the sensor; however, although infrared image analysis and multi-sensor detection can perform on-line detection, for large-scale photovoltaic systems, a large number of infrared cameras and sensors are required, increased cost of photovoltaic systems. The capacitance measurement method for ground [3] is to determine the disconnection position of the photovoltaic circuit by measuring the value of the capacitance to the ground connected in series in the photovoltaic circuit. The time domain reflectometry [4] analyzes the shape and delay time of the returned signal by injecting a pulse into the photovoltaic circuit. However, the ground capacitance method and the time domain reflection analysis method are only applicable to off-line detection and series photovoltaic circuits.

In this paper, the fault diagnosis equivalent model of PV modules is established, and three PV module faults are analyzed. A fault diagnosis method for photovoltaic modules based on BP neural network is proposed. The data collected by the distributed photovoltaic information processing and data analysis system platform is used as the input data. The diagnostic result is the output data of the neural network. According to the diagnosis result, reasonable suggestions for PV module operation and maintenance are proposed from the aspects of component maintenance, photovoltaic panel cleaning, dip angle change, etc. Finally, the proposed fault diagnosis method is verified by simulation analysis.

2. PV module fault diagnosis model and fault type analysis

2.1. Fault diagnosis equivalent model of photovoltaic modules

Photovoltaic power generation system is a device that converts solar energy into electrical energy according to the photovoltaic effect, the equivalent model [5] is shown in Figure 1.

![Figure 1. Photovoltaic module equivalent model.](image)

The current equation of the photovoltaic module [6] is:

\[
I = I_{ph} - I_0 \left( \exp \left[ \frac{q(U+IR_s)}{AKT} \right] - 1 \right) - \frac{U+IR_s}{R_{sh}}
\]  

(1)

\(U\) means the voltage across the load; \(I\) means the load current; \(I_{ph}\) means photogenerated current; \(I_0\) means diode reverse saturation current; \(A\) means diode influence factor; \(R_s\) means battery series resistance; \(R_{sh}\) means battery shunt resistor; \(T\) means absolute temperature of the battery; \(K\) means Boltzmann constant \((1.38*10^{-23} \text{J/K})\); \(q\) means charge constant \((1.6*10^{-19})\).

2.2. Fault type analysis of photovoltaic modules

It is assumed that a photovoltaic module is made up of 48 photovoltaic cells in series, and each of the 16 photovoltaic cells is connected in parallel with a bypass diode. As shown in Figure 2 [7], where \(I\) is the current flowing through the photovoltaic module.
There are three common types of faults in photovoltaic modules, namely short circuit, open circuit and abnormal aging. The following three types of faults are analyzed in detail.

2.2.1. **Short circuit fault**. As shown in Figure 3, the output characteristic curve of the number of short-circuited photovoltaic cells is different. When the short-circuit fault occurs in the photovoltaic module, the output current of the component remains unchanged, and the maximum power point voltage and open-circuit voltage are reduced.

The analysis chart can be seen as follows: When a component has a short-circuit fault, its maximum power point voltage and open circuit voltage are linearly related to the number of battery short circuits, and decrease as the number of battery short circuits increases. The voltage value can be obtained by the following formula:

\[
U_{\text{in}} = \frac{48 - n_s}{48} U_0
\]

\(U_0\) means maximum power point voltage or open circuit voltage value of PV modules during normal operation; \(U_{\text{in}}\) means maximum power point voltage or open circuit voltage value of the PV module in the event of a short circuit fault; \(n_s\) means the number of shorted batteries, \(n_s \in [1, 48]\).

**Figure 2.** Photovoltaic battery equivalent model.

**Figure 3.** Short circuit condition output characteristic curve.

**Figure 4.** Short circuit condition output characteristic curve.
2.2.2. Open circuit fault. Figure 4 shows the output characteristic curve when the PV module is broken. When the PV module is open. The output current of the component $I = 0$. The magnitude of the voltage depends on the number of bypass diodes turned on.

The analysis chart shows the following law, the open circuit voltage becomes larger as the number of diode conduction increases. Formula (1) can be changed:

$$I_{ph} = I_0 \left[ \exp \left( \frac{qU_{DC}}{AKT} \right) - 1 \right] + \frac{U_{DC}}{R_{sh}}$$  \hspace{1cm} (3)

$U_{oc}$ means Open circuit voltage.

2.2.3. Abnormal aging failure. When the PV module is abnormally aged, the internal series resistance value may increase and the internal parallel resistance value may decrease. The series equivalent resistance of the photovoltaic module has the following relationship:

$$R_s = 4R_{sc} + R_1 + R_2 + \cdots + R_n$$  \hspace{1cm} (4)

$R_s$ means photovoltaic module series resistance, $R_{sc}$ means single photovoltaic cell internal resistance, $R_n$ means abnormal aging component series resistance value. Figure 5 shows the resistance output characteristic curves of different resistance values in series.

Analysis of the output characteristics of components when abnormal aging can be seen as follows:

1) When the external series resistance increases, the maximum power point voltage of the component gradually becomes smaller.

2) When the external series resistance increases, the maximum power point current of the component gradually becomes smaller.

3) The open circuit voltage of the component is not affected by the external resistor value.

![Figure 5. Abnormal aging condition output characteristic curve.](image)

When the external temperature, light intensity and other parameters change, the calculation formula for $I_{ph}$ and $I_0$ is [8]:

$$I_{ph} = I_{sc} \left( \frac{S}{1000} \right) + C_T(T - T_{ref})$$  \hspace{1cm} (6)

$$I_0 = I_{STC}\left( \frac{T}{T_{ref}} \right)^3 e^{\frac{E_g}{k}\left( \frac{1}{T_{ref}} - \frac{1}{T} \right)}$$  \hspace{1cm} (7)

$I_{sc}$ means Short circuit current; $S$ means Light intensity; $C_T$ means Temperature coefficient; $T$ means Absolute temperature; $T_{ref}$ means Absolute temperature under standard conditions; $I_{STC}$ means Reverse saturation current in standard state; $E_g$ means Energy band energy.

When the PV module is operating at the maximum power point, formula (1) can be changed:

$$I_m = I_{ph} - I_0 \left\{ \exp \left[ \frac{q(U_m + I_m R_s)}{A KT} \right] - 1 \right\} + \frac{U_m + I_m R_s}{R_{sh}}$$  \hspace{1cm} (8)

$U_m$ and $I_m$ means Voltage and current for the maximum power point of the component.
Deriving formula (7), at the maximum power point, according to:

\[ \frac{dU}{dT} \bigg|_{P=P_m} = - \frac{U_m}{I_m} \]

(9)

\[ U_T \text{ means Thermal voltage, and its expression is:} \]

\[ U_T = \frac{kT}{q} \]

(10)

The simultaneous formula (2) ~ (8) can get the maximum power point voltage of the component \( U_m \), Maximum power point current \( I_m \), Short circuit current \( I_{sc} \), and Open circuit voltage \( U_{oc} \).

3. BP neural network fault diagnosis model

In recent years, BP neural network has developed rapidly [9]. BP network is a multilayer feedforward neural network, composed of input layer, hidden layer and output layer, as shown in Figure 6. Multi-layer feedforward network trained by error inverse propagation algorithm, fastest descent method, according to adjusting the weights and thresholds of the network through backpropagation errors, minimize the square of the network error. When there are enough hidden layers and hidden nodes, it can estimate any nonlinear mapping relationship with good generalization ability[10].

According to the analysis, this paper sets the internal parameters of the input layer of the PV module fault diagnosis model. They are the component maximum power point voltage \( U_m \), the maximum power point current \( I_m \), the short-circuit current \( I_{sc} \), and the open circuit voltage \( U_{oc} \). Corresponding output of four diagnostic results, respectively, normal, short circuit, open circuit, abnormal aging. The fault output definition table is shown in Table 1.

![Figure 6. BP neural network structure.](image)

| Component status     | O1 | O2 |
|----------------------|----|----|
| Normal               | 0  | 0  |
| Short circuit        | 0  | 1  |
| Open circuit         | 1  | 0  |
| Abnormal aging       | 1  | 1  |

The function used in this paper is the tansig function, and the output of the hidden layer is:

\[ H_j = \frac{1}{1+e^{-\frac{\beta}{2}(x_j+b_j)}} \]

(10)

The output of the output layer is:

\[ O_k = \sum_{j=1}^{l} H_j w_{jk} + b_k \]

(11)
The connection weights and thresholds are extracted from the trained neural network, and the online fault diagnosis of the program implementation component can be written according to the structure of the neural network.

4. Photovoltaic module efficiency monitoring and operation and maintenance method

4.1. Photovoltaic panel efficiency monitoring
Considering the natural resource indicators, electricity indicators, energy consumption indicators, equipment operation level indicators and economic benefit indicators in distributed photovoltaic systems, and the influencing factors of each indicator, a new energy system efficiency evaluation index system based on cloud data analysis is established for distributed photovoltaic systems to calculate various indicators.

4.2. Photovoltaic panel operation and maintenance method and operation and maintenance recommendations
When the fault diagnosis system has a short circuit, open circuit, abnormal aging fault alarm, repair the PV module according to the fault prompt. When there is no fault alarm and the power generation efficiency is low, operation and maintenance are performed according to the abnormality index. Photovoltaic panel operation and maintenance recommendations is shown in Table 2.

Table 2. Photovoltaic panel operation and maintenance recommendations.

| Operational indicator | Device status | Operation and maintenance advice |
|-----------------------|---------------|----------------------------------|
| Discrete rate $H$     | $10\% \leq H \leq 20\%$ | Equipment operation needs to be improved |
|                       | $20\% \leq H$     | Equipment must be improved       |
| Photovoltaic efficiency $\eta$ | $\eta \leq 75\%$ | Check the PV array for more than half an hour |
|                       | $\eta \leq 85\%$ | Cleaning photovoltaic panels (cleaning methods is shown in 4.3.2) |
| Weather detector      | $S < -5^\circ C$ | Snow removal, deicing           |
| temperature $S$       | $R < K$          | Adjust the angle of the Photovoltaic panel |
| Sunshine hours $R$    |                | (The best tilt angle is shown in 4.4) |
| Photovoltaic panel angle | $S > T$        | Check the inverter status and check the combiner box broken or not |
|                       | $R > K$         |                                  |
| Confluence box current $I$ | $I = 0$       |                                  |

4.3. Photovoltaic panel cleaning and maintenance

4.3.1. The impact of photovoltaic panel pollution. The photovoltaic panels have been in the field for a long time, and dust and other debris will fall on the glass, and a large amount of dust or dust will settle
for a long time, which will weaken the penetration of sunlight. At the same time, the surface temperature of the photovoltaic panel is increased to affect the efficiency of photovoltaic panel power generation. When the dust on the surface of the solar energy is serious, the difference before and after cleaning is 5.7%. If the long-term cleaning is not carried out, the difference in the amount of dirt generated in the surface of the photovoltaic panel can reach more than 10%.

4.3.2. Photovoltaic panel cleaning method. (1) Artificial dry-cleaning photovoltaic panels. (2) Manually washed photovoltaic panels. (3) Construction vehicle cleaning photovoltaic panel. (4) Smart photovoltaic panel cleaning robot.

4.4. Photovoltaic panel best inclination
The main factors affecting the optimal tilt angle of photovoltaic panels include: 1) Latitude, the difference in latitude affects the variation of the solar elevation angle, which affects the optimal inclination of the photovoltaic panel. 2) Radiation distribution per month, the amount of radiation in a year is more concentrated in the month with a higher sun height, which will make the optimal dip angle larger, and vice versa. 3) Straight ratio, direct radiation has directionality, while scattered radiation is isotropic, so their respective proportions in total radiation also have a certain influence on the optimal tilt angle.

The best inclination recommendations for each region are shown in Table 3.

Table 3. Best inclination recommendation.

| Angle level | Area                                           | Remarks                                      |
|-------------|------------------------------------------------|----------------------------------------------|
| 15°         | Yunnan, Guangxi, Guangzhou, Fujian             | The optimal installation angle of each city is not completely for the corresponding angle level, depending on the local latitude and longitude. |
| 20°         | Hunan, Jiangxi, Guizhou, Zhejiang, Sichuan     |                                              |
| 25°         | Shanghai, Anhui, Henan, Hubei, Sichuan         |                                              |
| 30°         | Tibet, Shaanxi, Shandong, Henan                |                                              |
| 35°         | Beijing, Tianjin, Gansu, Qinghai, Ningxia, Shandong, Hebei, Shanxi |                                              |
| 40°         | Xinjiang, Inner Mongolia, Liaoning, Jilin      |                                              |
| 45°         | Inner Mongolia, Jilin, Heilongjiang            |                                              |

5. Simulation analysis

5.1. Data collection
The correctness of BP neural network data acquisition is directly related to the accuracy and reliability of online fault diagnosis results of PV modules. The data source of this paper is from the distributed photovoltaic information processing and data analysis system platform[11].

Distributed PV information processing and data analysis system platform data acquisition device host computer reads PV inverter data through GPRS. The Modbus communication protocol based on RS485 serial port is adopted. When the device realizes data communication between the smart meter and the GPRS-DTU and the touch screen, the Modbus protocol is adopted, and the Modbus protocol is a common language applied to the electronic controller. Through this protocol, controllers can communicate with each other and between controllers via the network and other devices.

In the distributed photovoltaic information processing and data analysis system platform, the photovoltaic component data can be directly collected, thereby calculating the maximum power point
voltage, the maximum power point current, the short-circuit current, and the open circuit voltage of the photovoltaic panel according to the formula.

In this paper, the input layer of the PV module online fault diagnosis model is the maximum power point voltage, the maximum power point current, the short-circuit current, and the open circuit voltage, corresponding to 4 output results. Specific parameter training methods can be found in the literature [12].

5.2. Simulation results and analysis

According to the operating characteristics of electric vehicles and thermal storage electric boilers, a model of power grid peak shaving strategy based on electric vehicles and thermal storage electric boilers is established. The model uses particle swarm optimization to search for the optimal value. The conditional treatment method realizes the functions of electric vehicles and thermal storage electric boilers participating in power grid peak shaving. Through the simulation of the daily load curve of a certain regional power grid, the simulation results show that when the electric vehicle and the thermal storage electric boiler participating in the peak shaving of the power grid reach a certain scale, a better peak shaving effect can be obtained, and the fluctuation of the grid load can be effectively suppressed. Increasing the economics and stability of the grid operation will correspondingly reduce the peak reserve capacity required by the grid.

A simulation model of the PV module is established in Matlab based on the external characteristics of the PV module [13] to draw fault diagnosis data. The BP neural network training data is changed by changing the temperature, internal series resistance and external series resistance in the Matlab equivalent model. In this paper, 500 sets of training samples with temperature range of 10~50°C and illumination intensity range of 200~900W/m² were recorded. 30 groups collected on the distributed PV information processing and data analysis system platform as test samples input into the neural network program, observe whether its output is in line with expectations. The output data of the neural network is shown in Figure 7.

According to the simulation diagram, the output is mainly distributed in four areas. The lower left corner represents 20 groups of normal data. The upper left corner represents 4 sets of short circuit fault data. The lower right corner represents 3 sets of open circuit fault data. The upper right corner represents three sets of abnormal aging fault data.

![Neural network fault diagnosis](image)

**Figure 7.** Neural network fault diagnosis.

6. Conclusions

This paper establishes a fault diagnosis and operation and maintenance method for BP neural network based on data cloud acquisition. Firstly, the PV module data is collected through the distributed PV information processing and data analysis system platform, and the fault diagnosis parameters are obtained according to the calculation (the maximum power point voltage, the maximum power point
current, the short-circuit current, and the open circuit voltage). Different types of faults are diagnosed and classified by BP neural network fault diagnosis model. The correct rate of fault diagnosis is 95%. According to the fault diagnosis results and the indications of the operation indicators, the rationalization of the PV module operation and maintenance is given from the aspects of component maintenance, photovoltaic panel cleaning, and dip angle change. The simulation results show that the BP neural network fault diagnosis algorithm can accurately and clearly identify the fault type, and demonstrate the effectiveness and feasibility of this method.

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