Research Article

Application of Wireless Sensor Network Technology Using Intelligent Algorithm in Mismatch Detection of Photovoltaic Power Generation

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The paper was aimed at ensuring the stable operation of the photovoltaic power generation system (PVPGS) and improving the accuracy of automatic mismatch detection. Consequently, this paper presents a PVPGS-oriented mismatch detection system based on wireless sensing technology (WSN). Firstly, the photovoltaic array (PVA) is constructed using a microcontroller, power management chip, nRF24L01, temperature sensor, voltage, and current sensor. Then, a fault detection and localization (FDL) scheme based on the Hampel algorithm is optimized, and Matlab/Simulink implements the PVA simulation model. Finally, several typical mismatch faults are simulated to verify the feasibility of the proposed FDL scheme using the measured voltage and current data. The empirical findings corroborate that the proposed FDL scheme can automatically and regularly collect photovoltaic (PV) electrical characteristic data and quickly and accurately identify and position a mismatch. In the case of a PVA open-circuit fault, the output current loss of the PVA is equal to the sum of the current of the open-circuit fault string in the array during normal operation. When the PVA is short-circuited, the PVA output voltage loss equals the sum of the output voltages of the faulty components in the most serious fault string under normal operation. Overall, the classification accuracy of the proposed FDL scheme is 97.556%. Lastly, the experiment reveals that the classification accuracy of the proposed FDL scheme is 100% for array aging, shadow, and the open circuit. Therefore, the research proposal has a good application prospect.

1. Introduction

With excessive fossil fuel consumption and the intensifying environmental pollution worldwide, renewable energy exploration has been particularly urgent in recent decades. It is fair to say that solar energy resources are universal because there is sufficient sunlight in most parts of the world. It has become the leading alternative energy to traditional fossil energy. Meanwhile, solar energy contributes significantly to space exploration tasks, such as China’s Shenzhou-series spacecraft. Under such backgrounds, photovoltaic power generation (PVPG) has riveted the attention of different fields because of its unique advantages, such as simple configuration, high reliability, zero fuel cost, low maintenance cost, noiselessness, and wear-proof. In particular, PVPG technology is a relatively mature branch in new energy power generation, which the state and the government have vigorously promoted. According to relevant statistics, China’s total PVPG in the first to third quarters of 2019 was 2005 billion kWh, with a year-on-year increase of at least 15%. Moreover, various researches have prospected the utility of PVPG [1, 2]. However, photovoltaic arrays (PVAs) working in a harsh and complex outdoor environment are vulnerable to extreme meteorological elements. These factors easily cause PVAs to age or get open or short circuits, namely, the mismatch failure of photovoltaic modules (PVMs). Mismatch failure may lead to colossal power loss and irreversible damage of PVAs. In extreme cases, it may even induce a fire. At the same time, mismatch faults usually do not generate significant-to-observe fault
current, thus misfunctioning traditional protection devices. Therefore, to help PVMs attain the theoretical service life, it is essential to timely and effectively monitor PVMs and detect and locate their mismatches [3, 4]. Thanks to the arrival of the cheap intelligent device: sensors, it is now possible to fix wireless sensors in inaccessible or dangerous areas to detect and monitor PVM faults. These sensors must be designed to be robust enough to operate independently and stably against external environment factors and be energy-efficient in internal structure. These external and internal factors jointly determine the sensors’ practical service lives. Once activated, each sensor will be responsible for a specific target area, namely, the sensor coverage or the sensing radius (R). On the other hand, artificial intelligence (AI) is proposed as the scientific study of computer simulation of the human thinking process and intelligent behaviors. AI covers such principles as making a machine as smart as a human brain. Essentially, AI is a higher-level application of computer technology or a new technological advancement through the expansion and simulation of information technology. Based on AI and wireless sensing technologies (WSTs), practical application models and devices can complete some data algorithm operations by themselves. Then, the algorithm results can be compared with the results in the database to choose optimal information for specific situations. Therefore, wireless sensors see broader application scenarios, including PVM mismatch monitoring [5].

There have also been abundant studies related to PVPG. To name a few, Satpathy and Sharma [6] studied the sensitivity of PVA topology to local coloring and electrical faults using various electrical parameters based on Matlab/Simulink environment and verified by experimental analysis. Mehmood et al. [7] used switches to reconfigure electrical wiring under different shadow profiles, focusing on improving the performance and efficiency of traditional static photovoltaic systems (PVs). They adopted a metaheuristic algorithm (MHA) and firefly algorithm (FFA) to control the switching mode under nonuniform shadow profile and tracked the highest global peak of multiple switching mode-generated power coefficient (PC). The results provided references for improving the overall PVA performance and efficiency. Nazeri et al. [8] observed that with the rapid decline in the price of solar modules, more residences deploy roof-top solar PVA. They designed a new system: SolarDiagnostics to automatically detect and analyze the damage of roof-top solar PVA at a low cost using the images of roof-top solar PVA. Ko et al. [9] introduced various electrical parameter indexes to study the sensitivity of common PVA topologies to partial shading and electrical faults. It was inferred that given different coloring/faults in the PVA, these indexes would be significantly different. In turn, different PVA topologies would generate different indexes. Additionally, they found that during the minimum (10%) and maximum (90%) system shading, the parallel PVA topology produced as high as 88.95% and 19.48% power of the unshaded scene, respectively. However, when 90% of the system failed, all PVA topologies have generated 11.27% power of the fault-free scenario. Babu et al. [10] used simple population-based optimization algorithms (flow pattern, social simulation, and Rao optimization algorithm) to dynamically reconstruct PVA. Consequently, the power generated by the proposed flow pattern algorithm was 13% higher than that of the social simulation configuration. To sum up, available research on photovoltaic (PV) still has some deficiencies. Firstly, the wired monitoring system is complex and costs tremendously. Secondly, most systems only monitor array level parameters without achieving high-precision monitoring. Thirdly, many systems only monitor the PVA data and cannot detect, locate, and warn the fault automatically. Fourthly, although many wireless monitoring systems combine ZigBee, general packet radio service (GPRS), and other wireless sensing technologies (WSTs), the cost is still relatively high due to many PVMs.

Thereupon, this paper further explores PVA mismatch detection based on the results and shortcomings of previous studies. The present research is organized as follows. (1) It expounds on the working principle of photovoltaic cell (PVC). It establishes the PVC engineering model using the five-parameter method. At the same time, it simulates PVCs’ output characteristics and selects the typical series-parallel PVA topology as the research object. As a result, a 1.5 kW grid-tied photovoltaic power generation system (PVPGS) is built. Finally, the system operation is simulated using Matlab/Simulink. The simulation results are compared with the actual power plant operation outputs to verify the proposed model’s accuracy. (2) This paper analyzes the output characteristics of PVA under open circuit, short circuit, abnormal aging, and shadow shading to determine the fault characteristic parameters and their thresholds preliminarily. (3) It adopts a fault detection and localization (FDL) algorithm based on PVAs’ real-time voltage and current indexes. Then, the real-time data of five parameters are collected to calculate the fault detection threshold under different states. The collected parameters are compared with the measured voltage and current indexes with the defined threshold. Thereby, the fault types are analyzed and judged. As a result, an improved array voltage sensor placement and location method are proposed. The voltage characteristics of each voltage node of the component under different fault conditions are analyzed, and the array location rules are formulated. According to the collected voltage sensor readings and the established positioning rules, the location of the faulty component is determined. A simulation model is established to verify the effectiveness of the proposed method. (4) Using the adopted fault detection and location methods, the hardware object of the detection model is constructed. The model is verified to test the proposed method’s effectiveness and the detection device’s reliability. The innovation of this paper is that the FDL scheme based on the Hampel recognizer is optimized, and Simulink realizes the PVA simulation model.

2. Grid-Tied PVPGS

Grid-tied PVPGS contains no energy storage equipment, thus, has a relatively low cost, and has seen extensive development in China. Thereupon, this paper takes the grid-tied
PVPGS as the research object and implements the PVPGS model. Figure 1 gives the principle of grid-tied PVPGS, and Figure 2 illuminates a simple PVPGS.

Figure 3 dissects the working principle of the PVC. The n-type semiconductor is usually on the PVC bright side, and the dark is a p-type semiconductor. The carrier diffusion occurs near the interface due to the concentration difference of p-type and n-type semiconductors, forming an n-to-p built-in electric field. The light shines on the surface of the PVC and is absorbed inside. In p-type silicon and n-type silicon, photons with sufficient energy can excite electrons from valence band to conduction band to produce electron-hole pairs. Electrons and holes are separated under the action of the internal electric field. Therefore, a positive and negative voltage will be generated in the p-region and the n-region as the photovoltage. Then, the p-region and n-region can be wired, and the load is concatenated to form a complete circuit. Thereby, the current will flow through the load, resulting in voltage drop and power output on the load [11].

PVCs are wired together and then encapsulated into PVMs. The cascaded or parallelly connected PVMs form the actual PVA. Based on this, the voltage, current, and power will be output, which meets the requirements of grid-tied PVPGS. Figure 4 demonstrates the equivalent circuit of PVC.

The output characteristic equation (CE) of the PVC in Figure 4 can be calculated by

\[ I = I_{ph} - I_0 \left( 1 - \frac{q(V + IR_s)}{AKT} \right) - \frac{V + IR_s}{R_sh}, \]  

(1)

In Equation (1), \( I \) is current, \( I_{ph} \) indicates the PVC-generated current. \( I_0 \) means the saturation current. \( q, K, A, T, R_s, \) and \( R_{sh} \) stand for electron charge, Boltzmann constant, the diode ideality factor, the absolute operating temperature of the battery, string equivalent resistance, and the parallel equivalent resistance, respectively.

The mathematical calculation of PVC simulation is shown:

\[ I = I_{ph} \left( 1 - C_1 \left[ \exp \left( \frac{V}{C_2 V_{oc}} \right) - 1 \right] \right), \]  

(2)

\[ C_1 = \left( 1 - \frac{I_m}{I_{SC}} \right) \exp \left( - \frac{V_m}{C_2 V_{oc}} \right), \]  

(3)

\[ C_2 = \left( \frac{V_m}{V_{oc}} - 1 \right) \left[ \ln \left( 1 - \frac{I_m}{I_{SC}} \right) \right]^{-1}, \]  

(4)

\[ \Delta T = T - T_{ref}, \]  

(5)

\[ \Delta S = \frac{S}{S_{ref}} - 1, \]  

(6)

\[ I_{SC} = I_{SC} \times \frac{S}{S_{ref}} (1 + \alpha \Delta T), \]  

(7)

\[ I_m = I_m \times \frac{S}{S_{ref}} (1 + \alpha \Delta T), \]  

(8)

\[ V_{oc}' = V_{oc}(1 - \gamma \Delta T) \ln \left( \frac{V + \beta \Delta S}{V_{oc}} \right), \]  

(9)

\[ V_m = V_m(1 - \gamma \Delta T) \ln \left( \frac{V + \beta \Delta S}{V_{oc}} \right), \]  

(10)

\[ R_s = \frac{C_2 V_{oc}}{C_1 I_{SC}} \exp \left( - \frac{V_m}{C_2 V_{oc}} \right) = \frac{V_m}{I_m}, \]  

(11)

\[ I_m' = V_m' \ln \left( \frac{e + \beta \Delta S}{V_{oc}} \right), \]  

(12)

\[ I_m = I_m \times \frac{S}{S_{ref}} (1 + \alpha \Delta T). \]  

(13)

In Equations (2)–(13), the open-circuit voltage, the short circuit current, the maximum power point voltage, and the maximum power point current are \( V_{oc}, I_{SC}, V_m, \) and \( I_m \). \( I, I_{ph}, T, \) and \( R_s \) are the current, the photogenerated current, the battery’s absolute operating temperature, and the series equivalent resistance.

Common PVA structures can be divided into series, parallel, and SP (hybrid) structures. The PVMs in the array first form a branch in series and then form each group in series and parallel [12, 13]. The schematic diagram of the SP structure is described in Figure 5.

Internationally, SP-structured PVS is the most widely used because of its low cost, simple connection, and actual need-oriented flexible construction. Yet, such a structure also has some disadvantages. For instance, a single component mismatch might induce the failure of other directly connected components, thus reducing the output power. The SP-structured PVA can guarantee appropriate output voltage, and the overall PVS can normally work upon a single open-circuit string (series-connected set of cells or modules). The proposed FDL algorithm is mainly aimed against such scenarios [14, 15]. The paper takes the PVM in the roof grid-tied PVS of the Solar Energy Research Institute as an example and implements the PVM simulation model through Matlab/Simulink. Table 1 details the PVM parameters.

Most large PVAs are installed in remote depopulated zones with dramatic climate change and harsh environments. Hence, in the long-term run, PVAs are prone to various faults. Among them, a mismatch is most commonly found in PVAs. Mismatches can be permanent or temporary, and their causes can be summarized as follows. (1) Temporary mismatch is caused by local shadow or nonuniform temperature on the PVA. (2) Permanent mismatch is induced by open circuit and aging/degradation of PVM or PVM strings [16, 17].

3. PVA-Oriented Online Monitoring System (OMS) Overall Design

3.1. OMS Demand Analysis. Aiming at some shortcomings of the current PVA-oriented OMS, this paper designs a set of low-cost and low-power PVA-oriented OMS. The
proposed PVA-oriented OMS can monitor the PVM and PVA parameters in real-time, manage the PVM with high precision, and detect, locate, and warn of the mismatch of PVM strings. The functional requirements of the PVA-oriented OMS can be dissected as follows. (I) Data acquisition and transmission. Then, to monitor PVM and PVA on the host, the proposed OMS first collects PV parameters and transmits them to the host software. At the same time, to detect PVM mismatch, the module parameters need to be analyzed and processed to ensure the accuracy and timeliness of data. Then, the collected parameters are transmitted to the host through the communication carrier. This section selects two-level WSN. Since PVAs are designed for a permanent operation in complex and harsh environments, it is crucial to ensure the reliability of sensor nodes’ communication [18–21]. (II) Data monitoring center display. The host should be designed with a monitoring interface to display the working voltage and current, component backplane, temperature, PVA voltage and current, ambient illumination, and single component temperature in the PVA in real-time and locates mismatched components on the screen. Meanwhile, the host interface should be simple and easy to understand to reduce the workload of maintenance personnel, and the electrical and environmental parameters of the PVPGS shall be stored in the database to prevent data loss in case of system power or network failure [22–24]. (III) Positioning of mismatched components. Further, to locate the mismatched strings and PVMs in the actual PVAs, this paper first strives to design an FDL algorithm for PVPGS mismatch. Therefore, it is necessary to simulate and verify the designed FDL algorithm to ensure its feasibility and then apply the proposed FDL algorithm to measure PV parameters to position mismatch faults (namely, the position function). Next, the feasibility of the FDL algorithm is verified on the simulation model to apply the proposed FDL algorithm to the actual PVAs. This paper uses the proposed PVA simulation model to simulate the mismatch to verify the proposed FDL algorithm. There are many types of PVAs [25–27]. The simulation experiment connects 5 × 3 components in series and parallel. Figure 6 views the schematic diagram of the PVA mismatch simulation.

3.2. FDL Algorithm Design. Outliers are usually defined as the distinctive data in the data set. A data set \(x_i, i = 0, 1, 2, \ldots, n\) contains a reference value \(x_0\), change scale \(\zeta\), and threshold \(\alpha\). If Equation (14) holds, the statistical anomaly rule will judge \(x_i\) as outliers.

\[
|x_i - x_0| > \alpha\zeta. \tag{14}
\]

The upper and lower limits of the outlier labelling rule (OLR) are \(x_0 + \alpha\zeta, x_0 - \alpha\zeta\). Assuming that PV strings have the same output current under similar environmental conditions, if a string current significantly deviates from the normal, the PV string with poor performance is labeled a mismatched string, so the string current can be used for positioning mismatch. Accordingly, some FDAs or technologies based on string current are proposed. Then, based on the current string characteristics, the paper proposes a PVA outlier detection (OD) algorithm combining “threshold method Hampel identifier (HI)” for mismatch detection and location [28–30].

In the HI method, let \(x_0 = \bar{x}, \zeta = S, \) and \(\alpha = 3\). \(\bar{x}\) is the sample mean, and \(S\) represents the mean absolute deviation (MAD) estimation. Unlike the sample mean, the HI method refers to sample mean \(\bar{x}\), and its mathematical expression read

\[
|x_i - \bar{x}| > aS, \quad S = 1.4826 \text{median} \{|x_i - \bar{x}|\}. \tag{15}
\]

At present, the most widely used multilayer feedforward neural network is the backpropagation neural network (BPNN). The BPNN topology includes the input, hidden, and output layers. BPNN can be divided into signal forward
transmission and error backpropagation. The signal passes through the input layer to the hidden layer and, finally, to the output layer. By comparison, the error is fed back from the output layer to the input layer through the hidden layer to adjust the weight and offset between layers [31, 32]. The transfer function is also a critical factor in BPNN. The derivative Sigmoid function is usually used, and the tanh (hyperbolic tangent), rectified linear units (ReLU), and softmax functions can also be used. The Sigmoid function of unipolarity $f(x)$ is calculated by Equation (16), and the BPNN weight and bias adjustment are expressed by

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

$$\Delta w_{jk} = \eta \delta_k y_j = \eta (d_k - o_k) o_k (1 - o_k) y_j,$$

$$\Delta V_{ij} = \eta \left( \sum_{k=0}^{r} \delta_k w_{jk} \right) y_j (1 - y_j) x_{ij}.$$  

In Equations (17) and (18), $\eta$, $w_{jk}$, and $(\delta_k, d_k, o_k)$ represent the given learning rate, the weight connection parameter, and the intermediate variable, respectively.

So far, the HI method is most robust against outliers (robust against up to 50% outliers), so it can detect outliers in theory. Occasionally, the HI method may trigger false alarms under normal conditions. For example, due to poor module packaging process, module power deviation, and other reasons, the electrical performance of different PV strings cannot be absolutely consistent. Therefore, there must be output current deviation between different strings. A microscopic variance often leads to a stricter OLR. Therefore, there may be normal data points in the suspicious outliers.

### Table 1: PVM parameters.

| Serial number | Parameter   |
|---------------|-------------|
| $V_{OC}$      | 45.2 V      |
| $I_{SC}$      | 5.6 A       |
| $V_m$         | 36.5 V      |
| $I_m$         | 5.2 A       |
| $P_m$         | 190 W       |

![Figure 3: Working principle of PVC.](image3.png)

![Figure 4: Actual PVC equivalent circuit.](image4.png)

![Figure 5: SP structure.](image5.png)
Figure 6: Mismatch simulation. (a) Short circuit. (b) Abnormal aging. (c) Local shadow. (d) Open circuit.
outside the upper and lower limits calculated by the HI method, resulting in a false alarm. Against this problem, this section determines the dispersion rate threshold as 5% to determine the suspicious abnormal value with false alarm [33]. Figure 7 presents the flowchart of the optimized HI algorithm.

Figure 7: Optimized HI algorithm flow.

4. Design of PVM-Oriented Wireless OMS Node

This section selects the mixed signal processor (MSP) 430G2553 launchpad as the PVM-oriented wireless OMS node. Its working voltage is between 1.8 and 3.6 V, and the instruction cycle time is only 625 ns. 16-bit multifunctional hardware multiplication and direct memory access (DMA) gives MSP430G2553 more decisive data operation and processing ability than general single-chip microcomputer (SCMC), such as 51 SCMC. The structure of the PVM-oriented wireless OMS node built by MSP430G2553 is drawn in Figure 8.

This section constructs the resistance-based voltage-divider voltage acquisition module for the PVM-oriented OMS node. At the same time, the standard high-precision resistance with an error rate of 0.01% is used to improve the voltage acquisition accuracy. Secondly, the DS18B20 sensor is selected to measure the temperature of the PVM-oriented OMS node. Thirdly, this section uses nRF24L01 to realize data communication, including data sending and data receiving. Here, the first-level wireless transceiver...
process uses the enhanced short burst function of nRF24L01. Figure 9 unveils the flow of nRF24L01 data sending and receiving.

Subsequently, to monitor the real-time state of each PVA component, each OMS sensor node’s parameters are transmitted to the host Data Management Center (DMC) for unified display and storage and then used to judge mismatch. Accordingly, all OMS node parameters are collected synchronously and then sent to the routing node of the PVA for the following communication. Although the star network has only terminal and coordination nodes, it has high reliability and scalability with a small network scale. Therefore, the PVS-oriented OMS node adopts the star topology and signifies in Figure 10.

Further, to realize the mismatch detection and positioning of PVM, it is necessary to collect each PVM parameter simultaneously. The software design flow of the PVM-oriented OMS node is plotted in Figure 11. First, it initializes the external device and then lets the OMS node enter the low-power mode to save energy consumption (EC). When receiving the trigger acquisition signal from the routing node, the interrupt pin will be set low, and the OMS node will exit the low-power mode. Then, it collects the component voltage and backplane temperature and sends the parameters to the routing node of sub-PVAs. Afterward, the PVM-oriented OMS node enters the low-power mode and waits for the next round of data acquisition commands.

5. Data Source and Lab Environment Configuration

Subsequently, the algorithm’s feasibility is verified using the PVA simulation model to ensure that the proposed FDL algorithm can be applied to the actual PVAs. Therefore, this paper uses the designed PVA model to simulate the mismatch and obtains the simulation data to verify the proposed FDL algorithm. There are many kinds of PVAs. This section designs a PVA topology through series and parallel connection of $6 \times 3$ components. The number of components is large, and the same mismatch type contains many permutations and combinations, which will increase the difficulty of mismatch detection. To this end, the simulation experiment refines and simulates different mismatch types according to PVA string to improve the positioning accuracy. Specifically, the ambient illumination is $1,000 \text{ W/m}^2$, and the ambient temperature is set to $25^\circ \text{C}$. The sampling rate is 100 per second, and each mismatch fault occurs at the third second through the switch. Altogether, 800 pieces of simulation data are obtained under normal conditions. For short-circuit fault, 1,600 pieces of simulation data are obtained by setting the number of short-circuit components in a PVA string to 1 and 2. For open-circuit fault, 800 pieces of data are obtained by simulating a $10 \text{k}\Omega$ resistor in series in a group of strings. Aging includes component aging and component string aging, and the aging resistance is set to 22. Overall, 1,600 pieces of data are obtained. Local shadow
simulates the situation of one shadow and two shadows by setting the illumination of several components in a group of strings to 300 Wm, and 600 pieces of data are determined.

6. Simulation Verification of FDL Algorithm

Figure 12 describes the simulation results of the FDL algorithm.

As signified in Figures 12(a) and 12(b), under normal operations, the component’s maximum and minimum string currents are 5.7A and 5.5A. Then, the first string of PVA is detected using the improved HI method, finding that the component voltage is within a reasonable range, and the PVA operates stably. Figures 12(c) and 12(d) corroborate that under a single-component short circuit, \( I_1 \) decreases rapidly, and the voltage of the failed component becomes 0. Therefore, a mismatch occurs in the fifth block of the first string of PVA. Figure 12 indicates that the current \( I_1 \) of the block (e) and (f) changes similar to block (c) and (d) at the moment of the short circuit. However, the instantaneous current decreases faster because of the two short-circuited components, and it takes longer to recover to a stable state. Thus, it is inferred that a mismatch occurs at the fourth and fifth components of the first string. Figures 12(g) and 12(h) suggest that the aging occurs in the fourth block of the first string. Also, when the PVA has an open circuit, the output current loss of the PVA equals the sum of the current of the open-circuit mismatched string in the PVA during normal operation. When the PVA is short-circuited, the loss of the PVA output voltage equals the sum of the output voltage of the mismatched components in the most seriously mismatched string under normal operation. In case of abnormal aging, the PVA outputs between the output voltage of short-circuit mismatch with the same number of mismatched components and the output voltage in normal operation.

7. Wireless Communication Test

Figure 13 manifests the communication test results.

In Figure 13, A, B, and C are mean zero barrier, 120 m module spacing, and 120 m module spacing separated by a wall, respectively. Apparently, when there is no obstacle between two nRF24L01 modules, the packet loss rate (PLR) is 0. Under 120 m spacing and 120 m spacing separated by a wall, the PLR of the nRF24L01 modules is 0 and 20%. By comparison, when there are no obstacles between two ZigBee modules, the PLR is 0. Under 120 m spacing and 120 m spacing separated by a wall, the PLR of the ZigBee modules is 0 and 6.67%.

8. Discussion of Experimental Results

Compared with the algorithm by Shestopalova et al. [34], this paper adopts the outlier detection algorithm combined with the “threshold method-Hampel identification method” to detect and position mismatch faults. This allows real-time and rapid detection without human intervention. It is expected to be portable and can be used for real-time condition monitoring of outdoor power stations. Field
Figure 12: Simulation verification of FDL algorithm. (a) and (b) represent the experimental results of the PVA under normal working conditions, (c) and (d) indicate the experimental results of the PVA under a single-component short circuit, (e) and (f) refer to the experimental results of the PVA under bicomponent short circuit, and (g) and (h) denote the experimental results of component aging.
measurement and analysis results have proven the proposed FDL method’s excellent detection performance. It can locate faulty strings using normal string information. Compared with the manner presented by Pan et al. [35], the present proposal can understand the system operating parameters in real time, pinpoint the fault causes, and make correct decisions. Meanwhile, the present proposal can locate and track the fault location in time and realize rapid fault response and long-term stable operation of the system. Unlike the algorithm by Wan et al. [36], the present model has adopted an FDL method based on the real-time voltage and current of PVAs. It uses real-time state parameters to judge the PVA faults. Besides, an improved voltage sensor placement method for array fault location is also proposed. Lastly, the current scheme allows real-time and rapid detection without human intervention compared with Evik and Akta’s [37] technique. It is expected to be portable and can be used for real-time condition monitoring of outdoor power stations. Thus, the present PVA-oriented FDL method can realize the integrated management of PVAs. Overall, large numbers of field measurement and analysis results corroborate that the proposed PVA-oriented FDL

Figure 13: Communication test results. (a) and (b) indicate nRF24L01 communication test results and (c) and (d) signify the ZigBee communication test results.
method has a good detection effect. It can more effectively use the information of a normal string to locate the fault string.

9. Conclusions

The aim is to monitor better and automatically warn against PVM faults. A PVPGS-oriented mismatch detection system is proposed based on WST. The proposed PVPGS-oriented mismatch detection system includes photovoltaic modules, component sensor nodes, array routing nodes, and host computer and data management software. Specifically, the component sensor node collects the component parameters. It sends them to the array routing node in the form of polling through the first stage nRF24L01 star network. After receiving the component parameters and collecting the component string parameters, the array routing node uses the second-level ZigBee mesh network to transmit them to the sink node connected to the host computer. Then, upon receiving the PV parameters forwarded by the sink node, the upper computer’s data management software analyzes, stores, and visualizes the data. At the same time, an FDL algorithm is proposed and verified in the simulation model to realize the mismatch component location and early warning function. Further, fault diagnosis simulation analysis of grid-tied PVPGS is carried out by Matlab/Simulink. It is proved that the proposed FDL method can effectively identify four typical array faults. Meanwhile, it can identify the number of open-circuit fault strings and fault components in the most seriously short-circuited fault string of the PVA. The proposed FDL method directly judges mismatches by obtaining the total output voltage and current of the PVA. Moreover, it has a simple implementation process, low cost, and broad applicability to various scenarios. Lastly, there are still some deficiencies: (1) The designed detection device is tested and verified in the 1.5 kW grid-tied PVPGS. It has not been detected and analyzed in the actual large-scale PVPGS. Thus, the research results lack generalization on large-scale power stations. (2) The proposed FDL algorithm only studies a single type of fault in the PVA. Hence, there is a need to explore further the proposed FDL method’s feasibility in multiple faults cooccurrence. (3) The designed fault detection device does not involve communication and storage systems. The follow-up research is expected to consider adding the communication and data storage systems to remotely display the working state and record the historical data in real time.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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