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Review

Artificial Neural Network for Fault Diagnosis of Solar Photovoltaic Systems: A Survey

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Abstract: Solar energy is one of the most important renewable energy sources. Photovoltaic (PV) systems, as the most crucial conversion medium for solar energy, have been widely used in recent decades. For PV systems, faults that occur during operation need to be diagnosed and dealt with in a timely manner to ensure the reliability and efficiency of energy conversion. Therefore, an effective fault diagnosis method is essential. Artificial neural networks, a pivotal technique of artificial intelligence, have been developed and applied in many fields including the fault diagnosis of PV systems, due to their strong self-learning ability, good generalization performance, and high fault tolerance. This study reviews the recent research progress of ANN in PV system fault diagnosis. Different widely used ANN models, including MLP, PNN, RBF, CNN, and SAE, are discussed. Moreover, the input attributes of ANN models, the types of faults, and the diagnostic performance of ANN models are surveyed. Finally, the main challenges and development trends of ANN applied to the fault diagnosis of PV systems are outlined. This work can be used as a reference to study the application of ANN in the field of PV system fault diagnosis.

Keywords: artificial intelligence; fault diagnosis; neural network; photovoltaic; solar energy; review

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1. Introduction

At present, to avoid catastrophic climate change, modern civilization is undergoing an energy transformation in the hope of replacing fossil energy with renewable energy sources [1]. Renewable energy already accounts for a large part of the energy market [2]. In recent decades, solar photovoltaic (PV) energy has rapidly captured a large number of markets due to its global availability, modularity, non-pollution, ease of installation, and affordability. Much progress has been made in the study of PV systems, especially in terms of efficiency, cost, and obtaining maximum available power from PV cells. Nevertheless, PV systems are often subject to a variety of types of faults, which can seriously affect the safe operation and conversion efficiency of the systems [3]. The Energy Audit Report shows an annual energy loss of up to 18.9% due to PV system faults in the UK alone [4]. Furthermore, the fault diagnosis of PV systems also yields numerous economic benefits. Therefore, it is necessary to focus attention on this task.

Faults in PV systems are mainly PV system component faults, which originate from dirty modules, snow cover, local shading, module aging, and basic component manufacturing [5]. The typical faults that occur in PV systems are shown in Figure 1, and can be divided into three types, namely, physical, chemical, and electrical faults. Article 690 of the National Electrical Code (NEC) [6] requires using arc fault circuit interrupters (AFCIs), overcurrent protective devices (OCPDs), fractional fuses (GFDIs), and other devices to protect the PV systems from serious failures in the event of an overcurrent, arc fault, or ground fault. Nevertheless, even if a system is equipped with a protection device, it is likely that one fault will lead to more serious failures if it is not detected and handled in a timely manner [7]. For example, for a common and serious fault, i.e., partial shadowing of a PV module, the available protection devices are largely undetectable [8].

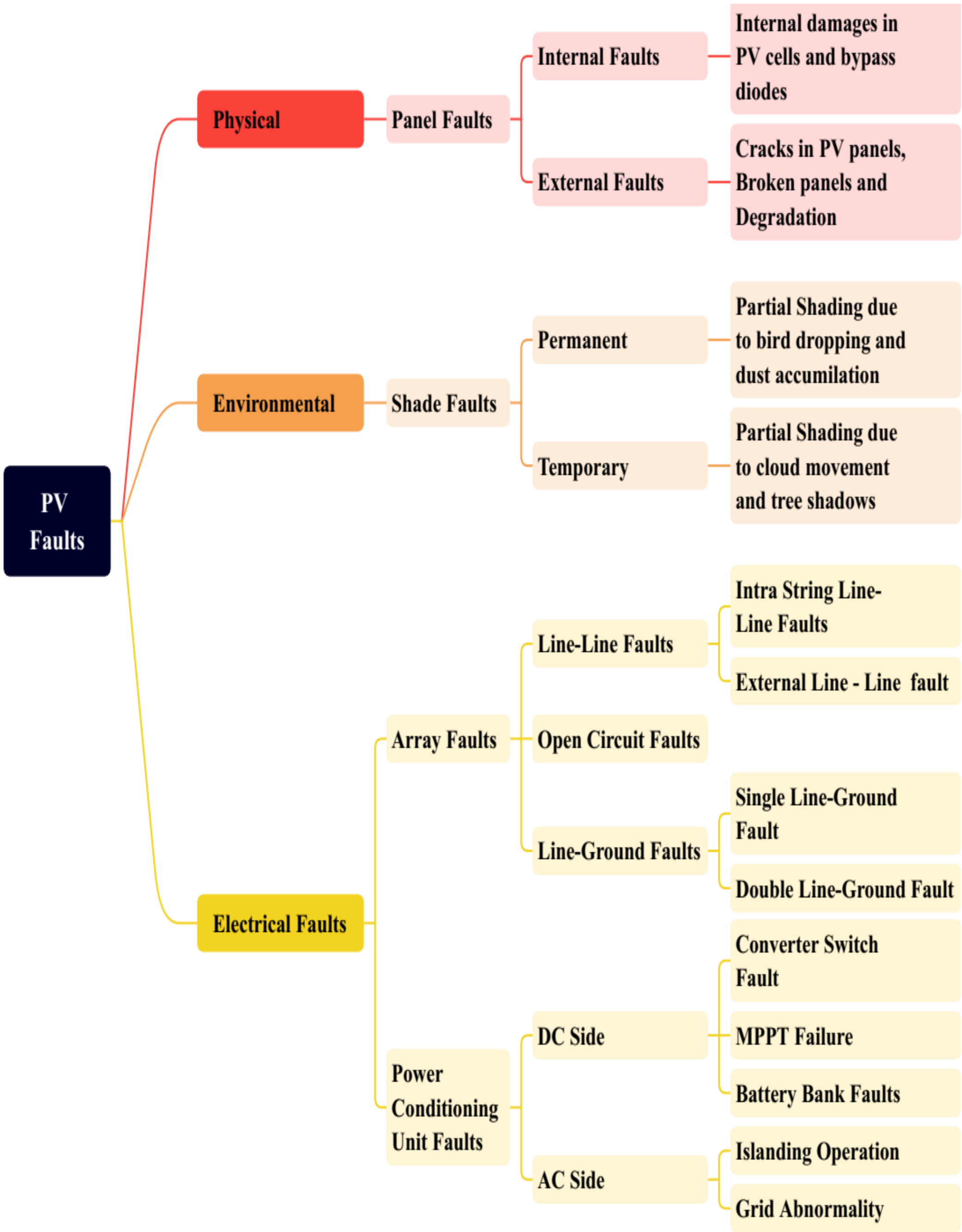

Figure 1. Classification of faults in PV systems.

Hence, in order to identify and diagnose various faults of PV systems in an effective and timely manner, researchers have proposed many methods. In general, there are two kinds of fault diagnosis methods, i.e., the electrical method, and the thermal and visual method [9]. The visual and thermal method is preferable for small PV plants, whereas the electrical method is more applicable to the monitoring and diagnosing of PV systems [10,11]. The electrical method can be further classified into statistical and signal processing (SSPA), voltage and current measurement (VCM), power loss analysis (PLA), I–V curve characterization (I–VCA), and artificial intelligence techniques (AIT) [12–15]. SSPA identifies faults by analyzing signals such as power data in a time series. This method has a high correct diagnostic rate but requires many pre-processed data and a complex analysis process. PLA achieves this by analyzing the output power loss on the DC side of PV systems, which reduces the computational and simulation costs, but does not distinguish the exact type of fault. The VCM detects the occurrence of faults by measuring the relevant voltage and current data, and comparing them with those in normal operation. This method is intuitive and simple, but the diagnostic accuracy is not high. The I–V curve can reveal the changes in a PV module. The module changes when different faults occur, and the faults can be identified by comparing the curve under the same external conditions. Fault analysis using I–VCA is intuitive and can help verify the health of a PV module during commissioning, but small changes in the fill factor can lead to a loss in the reliability of diagnostic results. In addition, the type of fault cannot be accurately identified if the I–V curves corresponding to the faults are very similar to each other. AIT achieves automatic fault diagnosis by analyzing a large amount of data. Compared with other methods, AIT has a wider scope of application, not only for electrical parameters, but also for images and other information. Moreover, it possesses many merits such as simple implementation process, high diagnostic accuracy, low cost, accurate classification of fault types, and better diagnostic performance for complex faults.

Some reviews have been conducted of PV system fault detection and diagnosis during the decades of the rapid development of PV systems. The authors in [16] reviewed the imaging-based defect detection techniques for PV modules, such as the visual inspection technique and IR-thermography imaging technique, and highlighted the advantages and limitations of the basic measurement methods. In [17], an overview of the conventional methods applied for the fault diagnosis of PV systems was provided, but it did not provide a detailed analysis of the performance of the mentioned methods. In [18], various failure modes of PV modules during grid connection were reviewed and an overview of the PV system fault diagnosis techniques applied in microgrids was provided. In [19], the AIT-based PV system fault detection and diagnosis methods were surveyed. In [20], the architecture and data acquisition systems applied to PV fault diagnosis systems were reviewed.

In summary, the existing literature reviews of PV system fault diagnosis generally include a variety of techniques and are relatively extensive and comprehensive. Unlike them, this survey focuses on the application of an artificial neural network (ANN) to PV system fault diagnosis. It concentrates on one fault diagnosis method instead of all techniques. ANN is a pivotal AIT and has been widely used in numerous areas of power systems, such as insulated equipment fault diagnosis in power grids [21], current harmonic suppression [22], economic dispatch [23–26], fault diagnosis of power systems [27–41], load prediction [42–45], and voltage stability analysis [46–50], due to its strong self-learning ability and good generalization performance. In addition, ANN-based fault diagnosis of PV systems has also shown excellent performance. When applied to PV system fault diagnosis, ANN can perform automatic fault analysis using a data-driven mechanism for different inputs, such as electrical parameters and images. Therefore, it can handle complex problems more proficiently compared to other methods [51]. As a whole, it has high fault tolerance and can handle high volumes of fault statistics to accurately identify the faults that occur in PV systems.

In this survey, we compile the literature published in recent years on ANN-based fault diagnosis of PV systems, classify the existing ANN models, and analyze their fault diagnosis performance. Then, we outline the main challenges in the fault diagnosis of PV systems, and finally summarize some potential development directions for ANN in solving this challenging issue.

The remainder of this paper is structured as below: Section 2 reviews the application of ANNs to different problems of PV systems. Section 3 introduces various types of ANNs in the fault diagnosis of PV systems. Section 4 compares the features of the literature. Section 5 outlines the main challenges. Lastly, Section 6 concludes this work and provides future prospects.

2. Application of ANNs in PV Systems

ANNs have been applied in various fields to resolve complex practical projects [52]. An ANN has a highly competitive edge. First, it has a strong self-learning capability via learning from training samples, which can be predicted and generalized after training; second, it is robust and has a high level of fault tolerance; third, it can find the optimal solution at high speed [53–56]. Due to these merits, the ANN has been broadly used in a variety of areas of PV systems.

(1) Energy supply forecasting. In essence, the intermittent nature of different renewable energy sources is derived from volatile climatic conditions. In this context, the complexity of matching power sources and loads makes it difficult to determine energy supply options, but the use of an ANN can be a good solution to this problem. In general, forecasting models for energy supply based on historical data can be achieved using temperature, solar radiation, date, humidity, and operating hours as inputs for an ANN [57–63].
(2) Performance prediction of collector systems. The performance prediction model mainly includes a mathematical model of collectors and an ANN prediction model. In general, the instantaneous flow rate of the medium inside the solar collector, temperature data including inlet temperature, ambient temperature, etc., radiant illumination, and heat collection area are mainly used for the mathematical model of the collector. The medium outlet temperature is generally set as the ANN's input [64–69].
(3) Maximum power point tracking (MPPT). MPPT maximizes the output power of PV systems to maximize the energy conversion efficiency. The cell temperature and the prevailing irradiance are often used as input parameters for the ANN. In addition, the voltage inverse can be also used as an input to improve the MPPT performance by black-boxing the ANN internally [70–77].
(4) Solar radiation prediction. Solar radiation prediction is heavily affected by the weather, and using an ANN to solve this problem is an accurate and applicable approach. In general, latitude, longitude, altitude, sunshine rate, and month are often used as inputs for the ANN-based prediction model [78–84].
(5) Determination of PV system size. Accurate sizing of PV systems ensures that the system produces the right amount of power to satisfy the load demand with low costs. Generally, peak insolation data, total electricity, and the maximum value of load consumption are usually used as inputs for the ANN to determine the system size [85–90].

3. Fault Diagnosis of PV Systems with ANN

Section 2 summarizes the application of ANN models in most widely used areas of PV systems, except for the area of fault diagnosis. This section provides an overview of the basic principles and structures of the most commonly used ANN models in the area of fault diagnosis, in addition to their research progress in this area.

3.1. Multi-Layer Perceptron Neural Network (MLP)

MLP usually enables gradient algorithms based on backpropagation to train the network by minimizing the error between the actual output and the expected output [91]. Its structure is shown in Figure 2.

The outcome of the enhanced layer is:

$$O = g(\boldsymbol{wx} + \boldsymbol{b}) \tag{1}$$

where x is the input; w, b denote the weight and bias, respectively; and g is the activation function, which generally uses the sigmoid function and tanh function.

The outcome of the i-th hidden layer is:

$$O_i = g(O_{i-1}) \tag{2}$$

The output of the last layer is given by:

$$f(x) = \sum_{i=2}^{n} G(b^{(i)} + w^{(i)}(g(b^{(i-1)} + w^{(i-1)}O_{i-1}))) \quad (3)$$

where G is generally a SoftMax function.

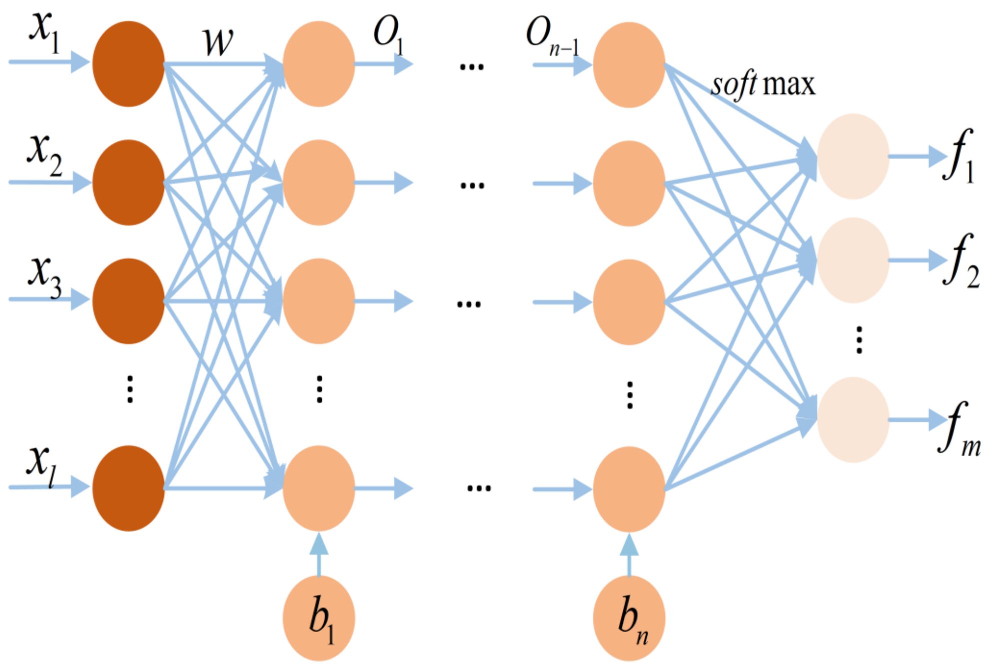

Figure 2. Architecture of MLP.

In [92], Mekki et al. used MLP to estimate the output voltage and current under variable operating conditions using two parameters, i.e., cell temperature and solar irradiance, to achieve the fault diagnosis of PV systems.

In [93], the identification of eight types of faults in PV arrays was achieved by comparing the simulated data of I–V characteristics with the corresponding attributes obtained from actual measurements. The inputs to the MLP include V_{OC}, V_{mmp}, and I_{mmp}. In the output layer, each neuron represents one fault class. The correct classification rate of the MLP-based model can reach 90.3%. In [94], Rao et al. used the SoftMax activation function in the output layer for classifying faults, and the diagnostic accuracy reached 99% in the noiseless case. In [95], Li et al. designed a signal strength metric to approximate the arc distance and used data augmentation (DA) to extend the dataset to enhance the robustness of MLP; this approach can be used to protect smart buildings with PV systems from accidental tripping. In [96], UI-Haq et al. developed a combination of a scaled conjugate gradient algorithm (SCG) and MLP. It considered different configurations of thin-film and polycrystalline PV technologies, and was able to diagnose and classify PV system fault segments with 99.6% accuracy in 0.08 s. In [97], Khelil et al. integrated a backpropagation neural network (BPNN) in MLP to recognize and pinpoint short-circuit faults and open string faults in PV generators. It can identify the faults quickly and accurately.

3.2. Radial Basis Function (RBF) Neural Network

An RBF neural network consists of three layers: input, hidden, and output, as shown in Figure 3. The hidden layer uses the RBF as an activation function and calculates the output using the Euclidean distance between the center and the input. Its output layer is a linear layer [98]. With the hidden layer, the patterns can be transformed from a low-dimensional space of the input vector to a high-dimensional space, as given below:

$$f(x) = \sum_{p=1}^{P} w_p \varphi(\|x - x^p\|) \tag{4}$$

where P is the output node; w_p is the output weight; and φ is the RBF, which generally uses a Gaussian function:

$$\varphi_i(x) = \exp(-\frac{\|X - c_i\|}{2\sigma_i{}^2}) \tag{5}$$

where c_i denotes the center and σ_i denotes the width.

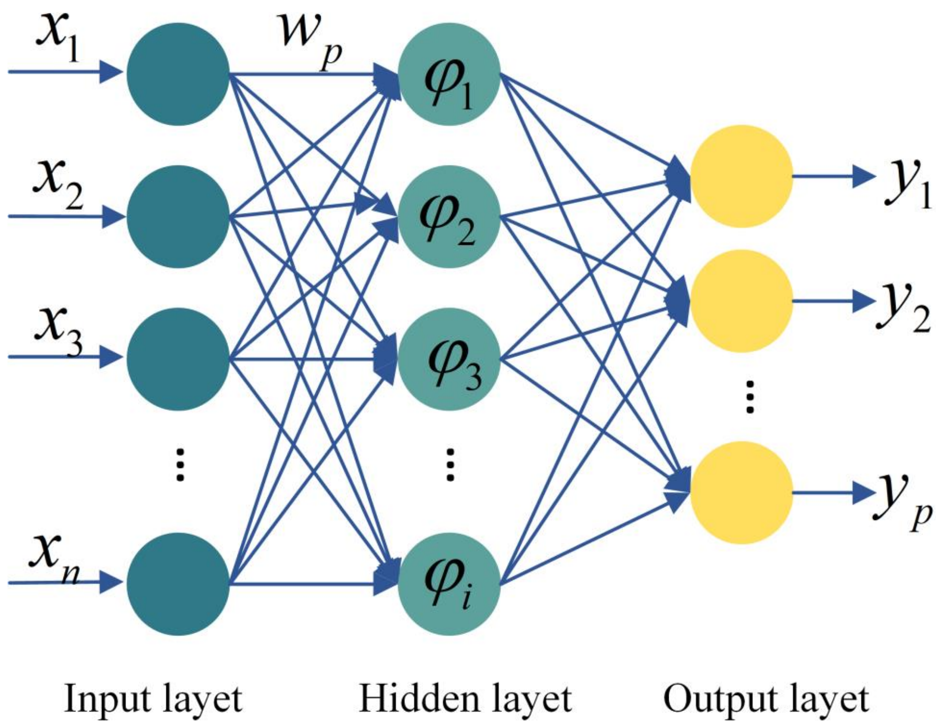

Figure 3. RBF network structure.

In [93], Chine et al. identified the fault type of PV arrays using an RBF neural network by comparing simulated attributes (short circuit current, output current, open circuit voltage, output voltage, the number of MPPs in the I–V characteristic) with actually measured attributes. The center and width were determined using the *K*-means algorithm. The correct classification rate based on the RBF-based model reached 68.4%. In [99], Dhimish et al. detected the faults of PV systems by creating an RBF neural network and Mamdani and Sugeno fuzzy logic system. The method was effective and accurate in diagnosing different faults, such as faults in modules and faults caused by shading. It could locate them with a diagnostic accuracy of up to 92.1%. In [80], Hussain et al. developed an RBF-based PV fault diagnosis system using solar irradiance and output power. This method was also applicable for PV systems installed at remote locations. Compared with the MLP, it had the merits of higher accuracy and better robustness, and needed fewer computational resources. In [97], Khelil et al. used RBF neural networks to recognize and pinpoint the majority of common faults in PV generators, such as the short-circuit fault and open string fault. In the test cases, all the fault types were classified correctly.

3.3. Probabilistic Neural Network (PNN)

The PNN operates on the basis of the Bayesian minimum risk criterion. It can classify data sets with less samples and does not require adjustment of weights, thus it is faster to train [100]. Its structure is presented in Figure 4. The number of neurons in the hidden layer is the same as the number of training samples, and the hidden layer output can be expressed as:

$$Out\_1 = \exp(-\frac{\|X - c_i\|}{2{\sigma_i}^2}) \tag{6}$$

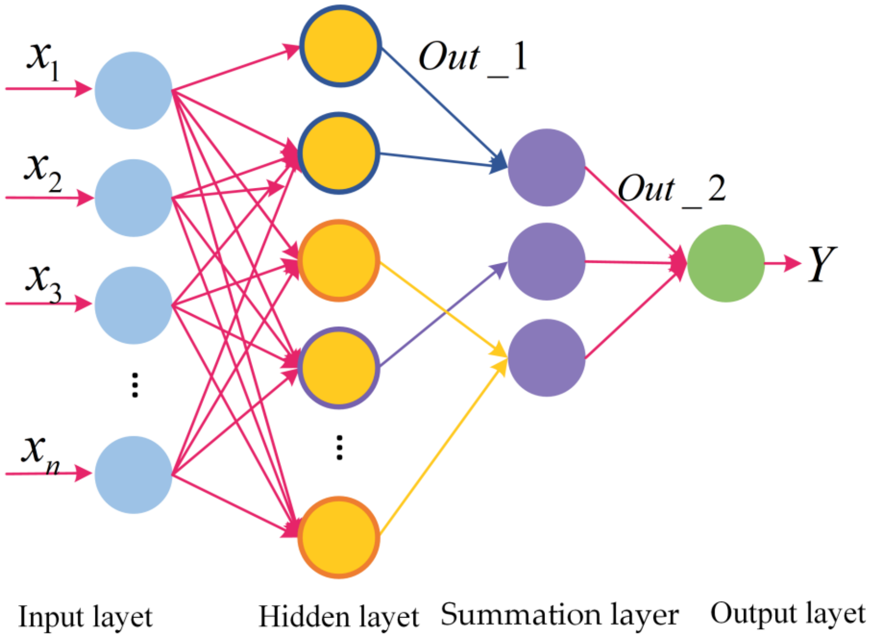

Figure 4. PNN network structure.

The third layer is the summation layer, which carries out a weighted average of the outcomes of the neurons belonging to the same class in the hidden layer. The output is:

$$Out\_2 = \frac{1}{m_i(2\pi)^{n/2}\sigma^n}\sum_{i=1}^{m_i} Out\_1_i \tag{7}$$

where m_i is the number of samples in the same category.

The output layer is used to maximize the outputs of the summation layer, as given below:

$$F = \max\{Out\_2_i\} \tag{8}$$

In [101], Akram et al. designed a PNN-based diagnostic model for PV systems for real-time monitoring and fault classification of frequent faults; the model can accurately respond to the characteristics at different temperatures. In [102], Garoudja et al. extracted the parameters of PV modules using the artificial bee colony algorithm, and used PSIM to experimentally simulate and validate the PV arrays. Then, a PNN-based diagnostic model with historical data was constructed, and the outcomes demonstrated that the method had a better diagnostic efficiency in both the presence and absence of noise. In [103], Zhu et al. proposed the integration of the Gaussian kernel function into the fuzzy c-means algorithm (GK-FCM), which is based on the input data without artificial prior knowledge, and can still train the model even if the input data is not of high quality. The combination of the GK-FCM and PNN, using clustered data as input, was utilized for fault identification of PV arrays.

For the problem of similar characteristics of I–V curves for the PV fault state and fault-free state in winter, Bashet et al. proposed using the PNN to train the collected normal data and fault data, and the model showed an excellent performance in terms of accuracy [104]. In [97], PNN neural networks were used for the most common faults in PV devices.

3.4. Deep Neural Networks (DNN)

Compared to the above-mentioned traditional ANN models that have been widely used in the PV system fault diagnosis, DNNs seem to have better prospects with the scale expansion of PV systems and the increase om data volume and fault complexity. This sub-section surveys some commonly used DNN models in this area.

3.4.1. Convolutional Neural Network (CNN)

CNNs are more complex than other neural networks. A CNN has a structure of input–convolution and pooling–fully connected–output, as illustrated in Figure 5. A CNN is more capable of processing data and can be used for image classification [105]. Taking LeNet-5 as an example, the input layer transforms the image into a pixel matrix, and the convolutional layer acquires local features of the image by performing convolutional operations on the input feature map and the convolutional kernel. Its output is:

$$Z^{l+1} = [Z^l \otimes w^{l+1}](m,n) + \mathbf{b} = \sum_{k=1}^{K_l} \sum_{x=1}^{f} \sum_{y=1}^{f} [Z_k^l(s_0 m + x, s_0 n + y) w_k^{l+1}(x,y)] + b \quad (9)$$

where $(m,n) \in \{0,1,\ldots L_{l+1}\}$; L_{l+1} is the scale of Z^{l+1}; $Z(m,n)$ is the pixel; K is the number of passes in the eigenmap; f is the convolution kernel size; and s_0 is the convolution step size.

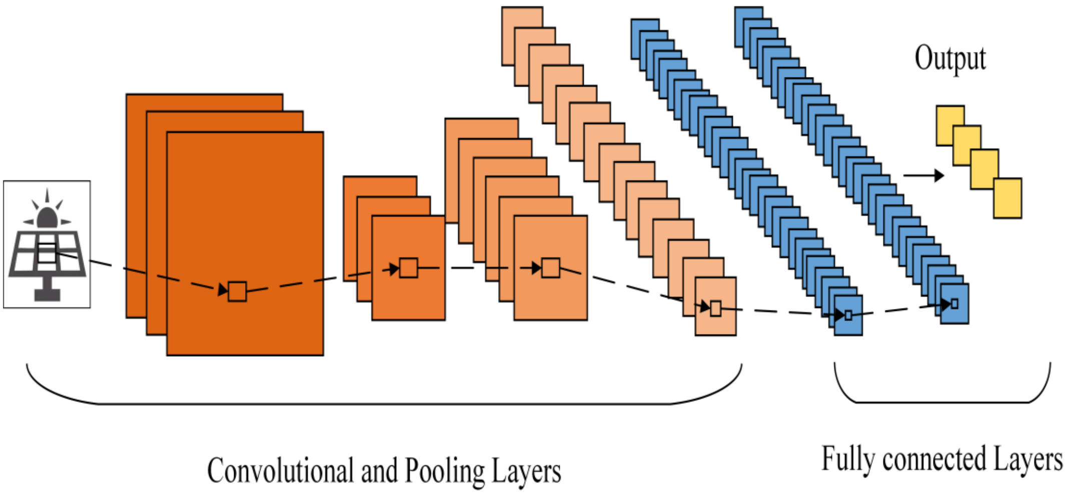

Figure 5. CNN architecture.

The role of the pooling layer is to make a selection of key features on the outcomes of the previous layer.

$$A_k^l(m,n) = g(Z_k^l(m,n)) \quad (10)$$

where g is the excitation function, and generally uses the Rectified Linear Unit (ReLU).

The fully connected layer scales the input features into a one-dimensional matrix and outputs the classification results by combining with the SoftMax classifier in the last layer.

In [106], Deitsch et al. used a CNN and SVM to diagnose the surface of PV cells during the panel manufacturing process to determine if there was damage. In [107], Gao et al. combined a residual-gated recurrent unit (Res-GRU) and CNN to diagnose faults in PV arrays. The model had strong anti-interference capability and did not require manual feature extraction. It had a high fault diagnostic rate, not only for single faults but also for mixed faults, with classification accuracy up to 98.61%. For physical fault detection of PV plants, Espinosa et al. developed a CNN model to analyze the RGB images to reduce the workload and time required to detect whether there is a fault in large-scale PV systems. The model can output three fault categories and no-fault cases, and the average correct rate was 70% [108]. In [109], Aziz et al. proposed to apply wavelet transform (CWT) to capture 2-D scale maps from PV systems, and then used a CNN to extract features to perform fault diagnosis for PV system components. In [110], Manno et al. used a CNN to achieve high accuracy in identifying the presence of hot spot faults in PV panels by analyzing the thermal image of PV systems. It achieved 100% fault identification for test images and improved the resolution of remote fault images. To address the issue that the CNN may not be able to correctly diagnose the conventional faults under low radiation conditions or other complex operating conditions, a two-channel CNN was proposed [111]. The results showed that the method can correctly diagnose faults that occur under complex conditions.

3.4.2. Stacked Auto Encoder (SAE) Network

SAE is a type of DNN that is trained greedily by stacking multiple autoencoders. In SAE, two adjacent layers are connected at the beginning and end, and layer-by-layer, as shown in Figure 6 [112]. Each autoencoder contains encoders and decoders that transform the input to obtain representative features, i.e.,

$$h = f\theta(x) = s(wx + b) \tag{11}$$

$$\tilde{x} = g\theta'(y) = s(w'h + b') \tag{12}$$

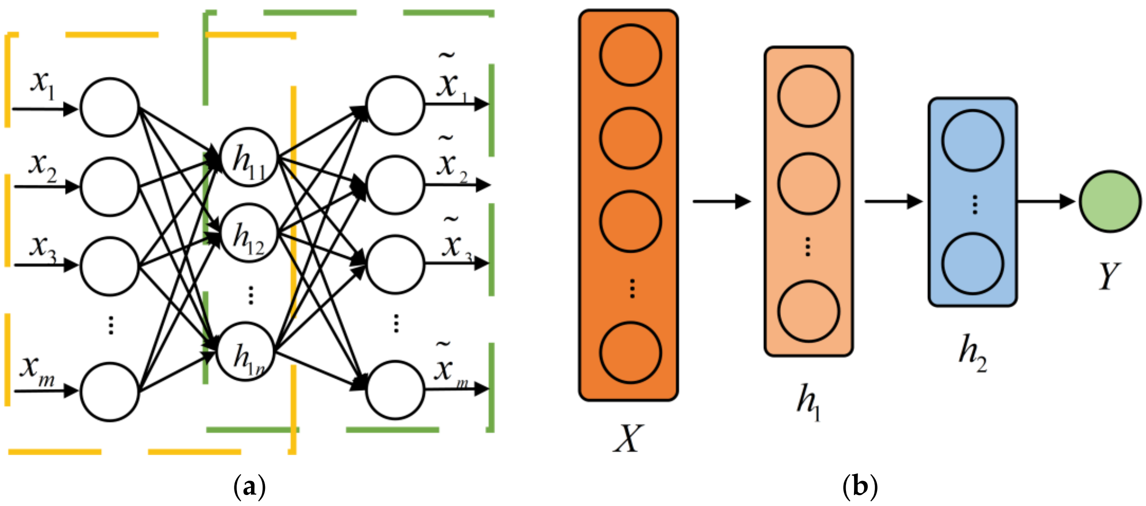

Figure 6. (**a**) Automatic encoder structure; (**b**) SAE structure.

In [113], Thirukovalluru et al. demonstrated the robustness of SAE by comparing the engineer's hand-designed features and SAE's extracted features for fault diagnosis. In [114], Manohar et al. proposed a sparse auto-encoder to distinguish similar I–V curves of PV array faults and symmetrical line faults. In [115], Liu et al. adopted a clustering algorithm combined with SAE to diagnose faults occurring in PV systems. It first used the SAE to obtain accurate I–V characteristics and achieved feature dimensionality reduction using a strategy t-SNE, and then used the affiliation function for fault diagnosis. This method gained a correct diagnostic rate of 97.12% and 98.56% on two experimental datasets, respectivel.

3.4.3. Other DNNs

In addition to the aforementioned DNNs, some other DNNs have also been developed for the fault diagnosis of PV systems. In [116], Chen et al. extracted the features of I–V curves, and combined them with cell temperature and ambient irradiance to form the input of a deep residual network (ResNet). In [117], Appiah et al. presented an approach for extracting meaningful characteristics from the original incoming data using a long short-term memory (LSTM) network. It inputted the extracted key features into a SoftMax classifier to identify faults. In [118], a genetic algorithm was adopted to evaluate the initial weight and deviations of a deep belief network. The optimal network can diagnose faults such as abnormal aging, local shading, and ground short circuit. Although the training time was long, it had a high fault diagnostic rate.

3.5. Other Neural Networks

In addition to the above commonly used neural network models applied in PV system fault diagnosis, other neural network models have also been utilized for fault diagnosis. In [119], Jazayeri et al. designed a detection ANN (DANN) using a large amount of health and fault data as input, and two SoftMax classifiers for the output layer. The experimental outcomes demonstrated that the overall training and testing accuracy of DANN could reach 99.8%. Since it is hard to acquire labeled samples of fault data from actual onsite trials, the authors in [120] extracted key points from realistic scenarios and measured I–V curves, and applied the kernel-based extreme learning machine (KELM) to diagnose faults of PV systems. The simulation outcomes demonstrated that the model had good accuracy and excellent generalization performance. In [121], Hwang et al. obtained the open-circuit voltage based on the duty cycle and combined the Multilayer Neural Network (MNN) and Adaptive Resonance Theory 2 Neural Network (ART2 NN) for fault diagnosis of PV panels. This method did not require additional power calculations for the initial estimation of solar panel faults. In [122], Natsheh et al. proposed modeling the PV system as a tree-like hierarchical structure, and used a fuzzy nonlinear autoregressive network with external inputs (NARX) to judge the exact PV system faults by diagnosing possible faults, classifying faults, and identifying the source of faults in three independent operations. The method was highly accurate in identifying faulty PV panels and could be monitored via Wi-Fi.

4. Comparative Analysis

The above survey shows that different ANN models have been applied to the fault diagnosis of PV systems. In this section, we further provide a tabular summary of all the literature regarding the enumeration of ANN models applied to PV system fault diagnosis. Through the analysis in Table 1, the following points can be summarized:

(1) Although MLP and PNN are more frequently used in this area, CNN has been the most frequently used ANN during the past three years. In addition, the frequency of using DNN models for PV system fault diagnosis has increased significantly in the past five years.
(2) Both climate data (solar irradiance and temperature) and electrical parameters (voltage and current) are the most common input attributes for ANN models. The CNN utilizes additional image information as part of the inputs in addition to climate data and electrical parameters.
(3) The diagnosis of types of faults using ANN models mainly focuses on the PV array side, including strings and modules. These faults mainly include short circuit faults, open circuit faults, masking faults, and mixed faults. In addition, some studies have also focused on arcing faults, soiling, module mismatch, etc.
(4) DNN models for identifying complex faults occurring in PV systems have greater potential as they are better able to extract valid features from the original input with less data cost.
(5) Overall, the ANN has shown good accuracy in identifying and classifying different faults in PV systems. The correct rates are over 90% in the vast majority of cases.

Table 1. Summary of application of ANNs to PV system fault diagnosis.

Ref	ANN Type	Year	Input	Fault Type	Correct Rate
[92]	MLP	2016	Solar irradiance, cell temperature, PV current, and voltage	Photovoltaic module shading failure	-
[93]	MLP	2016	Solar irradiance and PV module temperature	Short-circuit fault, diode fault, disconnection fault, connection resistance fault, shadow fault	90.3%
[94]	MLP	2019	Voc, I_d, V_{max}, I_{max}, T_m, module irradiance, fill factor, γ, and power	Ground fault, arc fault, module shadow, module temperature change (change temperature), dirty, short circuit	99%
[95]	MLP	2020	Images	Arc fault	-
[96]	MLP	2020	Irradiance, T, I_d, Voc, and peak power	Module mismatches, short circuits, open circuits, and fault combinations in multi-fault scenarios	99.6%
[97]	MLP	2021	I–V characteristics of cell T, solar radiation, V_{mmp} and I_{mmp}	Short circuit failure, broken circuit fault	97.27%
[93]	RBF	2016	Solar irradiance and T_m	Short circuit failure, diode failure, breakage failure, connection resistance failure, shadow failure	68.4%
[99]	RBF	2017	Power ratio and voltage ratio	Normal operation, 1–4 optical multiplex module failure, shading failure, PV string failure, MPPT device failure	92.1%
[97]	RBF	2020	I–V characteristics of cell T, solar radiation, V_{mmp} and I_{mmp}	Short circuit fault, broken circuit fault	97.27%
[80]	RBF	2021	Solar irradiance and output power	PV string failure, 1–9 PV modules, and PV string disconnection failure	97%
[101]	PNN	2015	Irradiation, temperature, maximum power point voltage, current, power	Short circuit fault, open circuit fault	98.53%
[102]	PNN	2017	Module temperature, tilt irradiance, maximum power point voltage, current	Healthy systems, multiple modules in a string break circuit, and one string disconnected from the array	98.19%
[103]	PNN	2018	Voc, I_d, V_{mmp} and I_{mmp}	Normal, short circuit fault, open circuit fault, abnormal aging, masking fault	92.48%
[104]	PNN	2020	Current, voltage, irradiation level and temperature data	Permanent masking, hot spot failure, line failure, aging	100%
[97]	PNN	2021	I–V characteristics of Tc, solar radiation, V_{mmp} and I_{mmp}	Short circuit fault, open circuit fault	100%
[106]	CNN	2019	Solar cell electroluminescence image	Defects on the surface of photovoltaic modules	88.42%
[109]	CNN	2020	Images	Partial masking and high impedance failure, low location mismatch, line failure, aging	73.53%
[107]	CNN	2020	I–V curve, temperature, and irradiance	Short circuit, partial shadow, abnormal aging, mixed fault	95.23%
[108]	CNN	2020	RGB images	Free of faults, cracks, shadows, and dust	70%

Table 1. *Cont.*

Ref	ANN Type	Year	Input	Fault Type	Correct Rate
[110]	CNN	2021	Thermal image	Hot spot failure, masking failure, battery damage	100%
[111]	CNN	2021	Current and voltage electrical time series diagram	Partial shadow condition, open circuit fault, line fault	99.6%
[114]	SAE	2018	Grayscale images	Array failure, symmetrical line failure	100%
[115]	SAE	2021	Residuals between I–V and P–V curves	Short-circuit faults, degradation faults, local shadows, and concurrent faults	98.5%
[116]	ResNet	2019	I_d, Voc, V_{mmp} and I_{mmp}	Short-circuit faults, open-circuit faults, degradation faults and local shadows	99.940, 95.778%
[117]	LSTM	2019	I, V, P	Line-line fault, Hot spot fault, Normal condition	100%
[118]	DBN	2020	Voc, I_d, V_{mmp} and I_{mmp}	Normal operation, ground short, series break, local shading, and abnormal aging	95.73%
[119]	DANN	2017	Photovoltaic module output power and irradiance	Masking effect, dirt or dust accumulation on the module surface	99.8%
[120]	ELM	2017	Voc, I_d, V_{mmp}, I_{mmp}, photocurrent, saturation current, ideal factor, series resistance, parallel resistance	Short circuit failure, Degradation fault, broken circuit fault, Partial shading condition	100%
[121]	ART2NN and MNN	2018	Open Circuit Voltage	Battery board failure	100%
[122]	NARX	2020	Voltage, current, temperature, irradiance	23 types of faults in 8 PV panels	98.2%

5. Discussions

The rapid development of PV systems has been accompanied by the frequent occurrence and increasing complexity of system failures, which can lead to huge losses in energy conversion. This study reviews the ANNs most recently used for PV system fault diagnosis. The applications of ANNs in power systems, such as for load forecasting, fault diagnosis, economic dispatch, and system control, in addition to fault diagnosis, such as power forecasting, sizing, and MPPT, are briefly described.

ANN-based fault diagnosis of PV systems is generally based on historical data. Relevant data and images, such as those relating to voltage, current, power, and I–V curves, are usually employed as inputs for ANNs. The type of faults can be determined by comparing the network output with the actual fault-related data. Results have shown that common ANNs such as MLP, RBF, and PNN can diagnose faults quickly and accurately. In addition, DNNs including CNN, SAE, ResNet, LSTM, and DBN have also been widely applied in this field. They can automatically extract features of the input data, reduce the data dimensionality, and diagnose common and mixed faults more accurately. Moreover, there is also literature on adding intelligent algorithms to ANNs for training relevant structural hyperparameters; this improves the diagnosis performance compared to ANNs alone, but a longer time may be required to optimize the hyperparameters.

6. Conclusions and Future Works

The application of the latest ANNs in PV system fault diagnosis was reviewed. These ANNs include traditional MLP, RBF, PNN, etc., and, more recently, CNN, SAE, ResNet, LSTM, DBN, etc. Their basic principles and structures were introduced. The input attributes of ANN models, including climate data, and electrical and image parameters, were outlined.

In addition, the types of faults and the diagnosis performance of ANN models were surveyed. In summary, this study can be used as an introductory reference for the initial learning of fault diagnosis of PV systems using ANNs, providing a suitable entry point for researchers, in addition to facilitating a systematic understanding of the field. Furthermore, it can also serve as a reference guide for evaluating the potential of ANN models for PV system fault diagnosis.

Although different ANNs have exhibited excellent performance in this field, the following challenges still remain:

(1) Most of the existing fault detection and diagnosis techniques based on ANNs were tested in experiments and have not been practically applied in engineering.
(2) The training of ANNs requires a large number of labeled samples, but it is often challenging to obtain enough actual fault data. In addition, the cost of acquiring valid raw data is high.
(3) The PV systems are subject to a large amount of interference during the operation process, resulting in a large amount of noise in the operation data. Determining how to filter the noise and improve the authenticity of the data source is worthy of attention.
(4) The performance of ANNs is seriously affected by the network hyperparameters, and it is not easy to obtain accurate hyperparameters, especially for DNNs.
(5) The training of ANNs frequently suffers from under-fitting and over-fitting.

Based on the current challenges of applying ANNs to PV system fault diagnosis, some possible directions for this field are summarized by combining the cutting-edge research techniques:

(1) For the existing ANNs in fault diagnosis, the training time cost is a large problem. These ANNs can be combined with the embedded system of digital signals to achieve real-time diagnosis, maximizing the effectiveness of the fault diagnosis system.
(2) Using ANNs alone cannot identify some complex faults and some faults with similar characteristics. In this context, although they can discover the existence of faults, identifying the exact type of faults is challenging. For this, combining ANNs with other diagnosis methods is a potentially effective approach.
(3) For some PV plants in remote areas, it is costly to conduct fault detection. UAVs can be used to locate faults and combined with IoT technology to achieve monitoring of PV systems to improve the quality of diagnosis.
(4) It is often challenging to extract a large number of labeled samples, and there may be noise in realistic fault data. Some deep learning techniques and data cleaning techniques can be integrated with ANNs to achieve fault diagnosis.
(5) To increase the fault tolerance of ANNs, some architecture search methods, including evolutionary algorithms, can be hybridized with common training methods to identify accurate structure hyperparameters.

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