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Original Article

Modular Neural Network for Fault Detection and Classification in Photovoltaic System

N. Vidhya[1], P. Rajadurai[2]

[1]*Software Developer & Trainer, Veteran Technology Solution, Tamilnadu, India.*

[2]*Tamilavel Umamaheswaranar Karanthai Arts College, Tamilnadu, India.*

vidhyarsr@gmail.com

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Abstract - Photovoltaic (PV) has become an active and rapidly increasing area of academic and industrial development. Photovoltaic cells in concentrated solar power systems convert solar energy directly to electricity, offering them a top contender for next-generation green power generation. Single and multiple faults occur in grid-connected photovoltaic systems. Severe faults such as high impedance faults, open circuit faults, Partial Shading (PS) and low location mismatch. In this paper, a Principal Component Analysis (PCA) based Modular Neural Network is proposed to identify and classify this type of fault. Applied PCA is employed for feature extraction, which reduces dataset sizes and eliminates the potential of singularity. MNN is capable of detecting small fault movements enhancing the detection of PV models. The proposed method improves the detecting performances by reducing the Missed Detection Rate (MDR) and False Alarm Rate (FAR) in the PV system. The result shows that the PCA-based MNN accurately detect single and multiple errors and the proposed method accurately identifies the fault type with an accuracy of 98.90%. Our proposed method compared with existing methods such as ANN, and KNN.

Keywords - Photovoltaic array, Fault detection, Fault classification, Principal component analysis, Modular neural network.

1. Introduction

The photovoltaic (PV) sectors have shown significant improvement in the production of solar technology as well as the total number of systems. The utilization of solar energy necessitates enhancing a conversion chain's efficacy and maintaining the performance of PV systems. These standards highlight the importance of providing efficient monitoring tools and equipment for PV systems [1]. This has been made feasible by the collaboration of numerous projects aimed at improving the technical qualities of PV plants and developing more effective detecting tools and systems on the other [17]. The usage of monitoring systems in PV systems enables them to operate more efficiently through the collection of indicators regarding their operating conditions. Furthermore, analyzing systems and tools enables the analysis of data, evaluation and detection and recognition of fault occurrences [3, 4]. Detecting devices should track a plant function to ensure more ideal working conditions at all times and detect potential mistakes and malfunctions that could result in performance losses. The PV generator is regarded as a significant element in PV systems. But the element is most vulnerable to errors. In this regard, the PV generator should gain from considerably more intensive tracking, which needs specific attention.

The MNN approach is used in this paper to detect and classify the various defects in a PV system using PCA. The PCA method is utilized to prepare a PV system. The following is an overview of the paper framework: part 2 described a literature survey. Part 3 discusses the modelling of the PV system part 4 shows the performance of the proposed method. Part 5 provides results and discussion which is followed by a conclusion in section 6.

2. Literature Survey

This section explains various surveys related to the fault diagnosis of PV systems studied in recent years. The present state of efficiency and performance of the PV system is discussed and provides an overview of current development

Hu et al. [16] presented the MOPPT approach for integrating large-scale solar (PV) power production into moderate dc systems. The experimental result showed that the laboratory prototype that validates its effectiveness. Abbas et al. [6] presented the Adaptive Neuro-Fuzzy Inference System for PV fault detection and classification. The key drawback is higher cost. Belaout et al. [7] presented the Adaptive Neuro-Fuzzy for fault detection in photovoltaic (PV) arrays. Rao et al. [13] presented the PV array feed data into a neural network for fault detection. In utility-scale PV arrays, simulation findings employing neural networks revealed successfully detecting and diagnosing common defects and shading circumstances such as soiling, short circuits, ground faults, and partial shading. Fazai et al. [9] presented the machine learning method for improved fault detection performance in a PV system. GPR modelling methods based on multi-scale representation perform poorly due to the inadequate separation of noise from key characteristics in the data. To solve the problem of the traditional technique mentioned above, PCA based Modular Neural Network is proposed. Experiments show that this method effectively identifies and classifies defects in a PV system and improves accuracy.

3. Modelling of a PV System

A technique is used in this research to build temperature and the connection between S and R. For the electrical activity of the solar, this method utilizes the single diode method. A series and parallel resistances, a current source, and a diode make up this circuit. [10] Kirchhoff's current law can be used to calculate the voltage currents I (V) relationship of PV.

$$I = I_{ph} - I_D - I_{Rsh} \quad (1)$$

Finally, the power flow of a PV module is expressed as a function of irradiation and temperature.

$$I = I_{ph}(G, T) - I_s(T) \times \left(\frac{V + IR_S(T)}{e^{V(T)A(T)}} \right) \quad (2)$$

The results reveal that the suggested simulation model can accurately simulate the PV module's manufacturer-specified properties. G and T have linear temperature variations of 3.144×10^{-3}ohm/°C and 4.72×10^{-3}/°Crespectively.

4. Proposed PCA-Based Modular Neural Network in PV System

Single and multiple faults occur in grid-connected photovoltaic systems. To detect this kind of fault in a PV system, Principal Component Analysis (PCA) based Modular Neural Network (MNN) is proposed. The proposed method detects the performances by reducing the MDR and FAR. The result shows that the PCA-based MNN accurately detect single and multiple errors and the proposed method accurately identifies the fault type with an accuracy of 98.90%. Figure 1 depicts the block diagram for the proposed method.

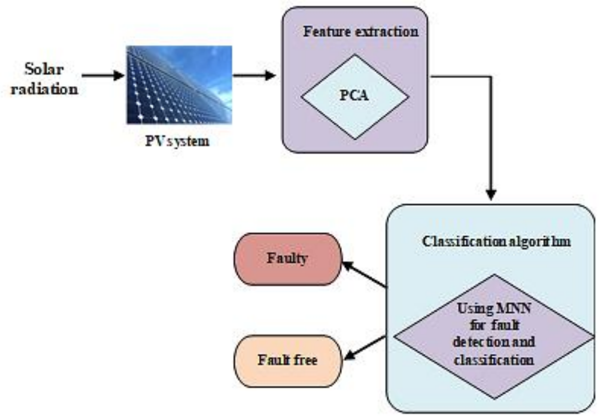

Fig. 1 Block diagram of fault detection using the proposed PCA-based MNN classifier

4.1. Principal Component Analysis for Feature Extraction

PCA is an information multimodal method often employed in the monitoring process [11]. The PCA model is derived from data representing processes obtained under typical operating conditions. The data matrix m variables containing N observations and m variables are called X∈ $R^{N\times m}$. Eigenvalue reductions are provided by:

$$\Sigma = \frac{1}{x} N^T N \tag{3}$$

$$= [\widehat{M} \quad \widetilde{M}] \begin{bmatrix} \widehat{\Lambda} & 0 \\ 0 & \widetilde{\Lambda} \end{bmatrix} [\widehat{M} \quad \widetilde{M}] \tag{4}$$

Where $\widehat{M} \in R^{m\times n}$ and $\widetilde{M} \in R^{m\times(m-n)}$ are the initials n and final (m-n) eigenvectors of Σ, respectively.

The following is a decomposition of the data matrix N:

$$\text{N}= \widehat{N} + \widetilde{N} \tag{5}$$

The modelled and un-modelled variations of the data matrix N are denoted as $\widehat{N}$and$\widetilde{N}$, respectively.

$$\hat{x}(t) = \widehat{M}\widehat{M}x(t) = C_n x(t) \tag{6}$$

4.2. Modular Neural Network

Our Modular Neural Network (MNN) is a deep learning neural network with learning that has a separate sequence of intermediary components that comprise a module that operates under a specific design. Individual network module output is received as input by this intermediate, which aids in the computation of the final output, which is resolved using a tangential activation function. It improves efficiency by connecting units in a way that grows exponentially when more separate networks are added.

V neurons contribute to the input layer, where v is the dimension of the input variable at time t.

$$\pi(t) = [\pi_1(t), \dots, \pi_v(t)]^T \tag{7}$$

The activation function:

$$M_i(\pi(t), a_i) = e^{\left(\frac{-\|\pi(t)-a_i\|}{c_i^2}\right)} \tag{8}$$

Where a_i and c_i are the ith neuron centre and radius respectively.

The MNN output is generated by combining the outputs of the networks that have been enabled in the integration layer. MNN's output expression can be written as:

$$x_i(t) = \sum_{j=1}^{i} \gamma_j x_{ji} (\pi(t)) \tag{9}$$

Two objective functions are used to address genetic optimization: the FAR and MDR. A MOO system with two variables is created to select the best smoothing settings for MNN. This approach allows you to trade off the three metrics. As a result, using this strategy, you may choose the best vector that reduces MDR and FAR, as shown below.

$$\overrightarrow{E_d} = min_{E_{d\epsilon R^N}} [FAR(E_d), MDR(E_d)] \tag{10}$$

The objective function is defined as follow:

$$\text{Maximize (fit(i))} = \text{sum (P)} + \left(\frac{E}{W}\right) \tag{11}$$

5. Result and Discussion

The specification and settings required for the PCA-based MNN simulation are listed below. A MATLAB solar PV simulation is utilized, and it is linked to the actual grid. Experimental results are proved through the modular neural network. The advantage of the latest soft computing technique for modelling PV systems has been used in this research. Table 1 shows that the Parameter values adopted by dataset collection

Table 1.Parameter values adopted by dataset collection

parameters	Value
Irradiance	100 to 1200 W/ m^2
Temperature	0 to 55 C
Mismatch	30% to 100%
Partial shading	30% to 100%
High impedance values	20, 40, 80, 100 and 200Ω

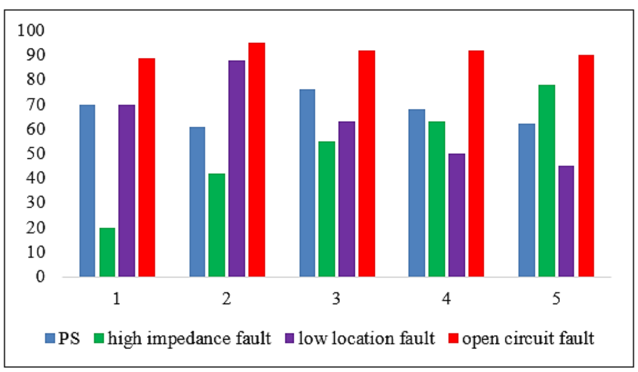

Fig. 2 Performance of fault detection and classification

The performance of the fault detection and classification is analyzed in Fig. 2. The four faults (i.e., high-impedance partial shading (PS), the low location fault and open-circuit fault (OC).

5.1. Performance Metrics

In classification, accuracy is the most commonly used evaluation metric. As demonstrated in figure 3, the proposed technique has an accuracy of 98.90 %.

$$\text{Accuracy} = \frac{TP}{(TP+FP)}$$

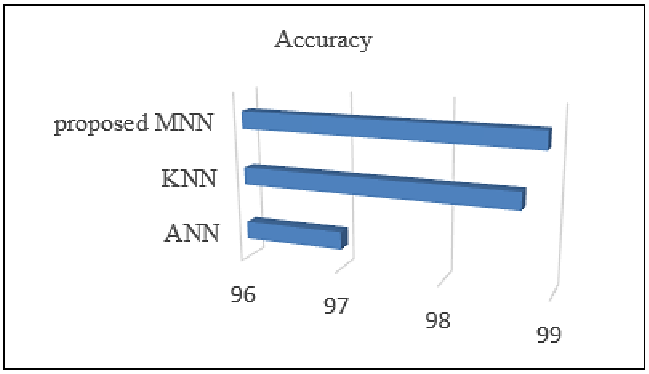

Fig. 3 Graphical representation of accuracy with existing and proposed method MNN

Table 2. MDR and FAR evaluation

Fault	**ANN**		**KNN**		**Proposed MNN**	
	MDR	**FAR**	**MDR**	**FAR**	**MDR**	**FAR**
1	0.92	11.0765	0.76	10.7240	0.20	1.7024
2	1.56	56.1214	1.20	44.276	0	2.25
3	1.20	40.18421	1.18	34.2241	0.60	2.145

The current methods include ANN and KNN. In the case of many faults, we can show that the suggested method improves existing approaches in terms of rates of false alarms and missing detection. The MNN technique outperforms ANN and KNN in terms of false alarm rates and missed detection in Table 2.

6. Conclusion

A PCA-based Modular Neural Network approach is proposed in this paper. The PCA model is used to calculate the residual, and the MNN is used to detect a fault. The established PCA-based MNN technique is used to detect a fault in PV systems by tracking the number of parameters in simulations. Furthermore, under severe conditions, PV array faults based on detection and classification methods were done for four scenarios (PS, high impedance fault, low location fault, and open circuit faults). Rates of false alarms (FAR) and missed detections (MDR) are used to assess detection capability. Because of the 98.90% of accuracy, the proposed method is suitable for real-time implementation.

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