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Analysis of Fault Detection and Classification in Photovoltaic Arrays Using Neural Network-Based Methods

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Abstract: Photovoltaic (PV) systems are vital in the global renewable energy landscape because of their capability to harness solar energy efficiently. Ensuring the continuous and efficient operation of PV systems is crucial in maximizing their energy contribution. However, these systems' reliability and safety remain critical because they are prone to various faults, mainly when operating in harsh environmental conditions. This study addresses these issues by exploring fault detection and classification in PV arrays using neural network (NN) -based techniques. A PV array model, consisting of 3x6 PV modules, was simulated using MATLAB Simulink to replicate real-world conditions and analyse various fault scenarios. An open circuit, a short circuit, and a degrading fault are the three types of faults considered in this study. The NN was trained on a dataset generated from the MATLAB Simulink model, encompassing normal operating and fault conditions. This training enables the network to learn the distinctive patterns associated with each fault type, enhancing its detection accuracy and classification capabilities. Simulation results demonstrate that the NN-based approach effectively identifies and classifies the three types of faults.

Keywords: Photovoltaic Arrays, Fault Detection, Fault Classification, Neural Network

1 Introduction

ENERGY is crucial for the economic development and sustained growth of any country. Renewable energy sources are increasingly being recognized as viable solutions for energy production. This shift is attributed to the reduction of conventional energy sources, growing concern regarding the negative environmental impacts of fossil fuel usage, and economic instability resulting from fluctuations in oil and gas prices. Solar photovoltaic technology is becoming a promising alternative due to its abundance, pollution-free nature, noiseless operation, modularity, and ease of installation. The power produced by photovoltaic (PV) systems was reported to have reached approximately 700,000 MW in 2020, as indicated by the International Renewable Energy Agency (IRENA). This milestone reflects an impressive growth trend in the sector over the past decade, demonstrating the potential for further advancements in sustainable energy production. [1].

Despite its advantages, PV systems are susceptible to faults due to prolonged exposure to challenging outdoor environmental conditions. These faults can significantly impact power generation efficiency and quality and even lead to fires. PV module faults are primarily grouped into two main types: permanent and temporary. Permanent faults include defects such as electrical disconnections, wiring issues, delamination, bubbles in cells, ageing, yellowing, scratches, and cell burn marks, which persist over time and may require module replacement. In contrast, temporary faults caused by partial shading, dust, dirt, and snow can be fixed through cleaning and maintenance without module replacement [2], [3]. Common issues, including open-circuit faults, short-circuit faults, and degradation in the direct current

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(DC) section, which may result in considerable power loss and reduced system efficiency in the PV systems, are especially concerning [4],[5],[6]. These faults can disrupt electricity production, shorten the service life of PV modules, and ultimately compromise safety.

Therefore, it is vital to recognize and categorize the types of faults that occur to reduce potential risks to the system. Fault detection involves comparing observational data with simulations to identify potential issues, while fault classification methods categorise fault types and determine their locations for timely intervention [7]. Recent studies by Livera et al., [8] have categorised fault detection and classification methods into visual checks, imaging techniques, and data analysis approaches. While imaging techniques and visual inspections effectively identify a wide range of PV system faults, their cost and real-time capabilities limitations make data analytic methods a more advantageous approach for comprehensive and efficient fault detection in PV systems. Data analytic methods enhance the reliability and performance of PV installations by providing real-time, data-driven, and comprehensive monitoring solutions. This method includes electrical signature analysis, which compares measured and simulated data; numerical methods like Artificial Neural Networks (ANN) or Neural Networks (NN), K-Nearest Neighbors (KNN), Support Vector Machines (SVM) and Principal Component Analysis (PCA), for pattern recognition and fault classification; and statistical analysis techniques that monitor performance through threshold-based methods and control charts to detect abnormalities.

NN has become a powerful tool for improving PV fault detection, owing to its capacity to manage intricate and nonlinear datasets. Studies have shown that NN can achieve high accuracy rates in fault detection, often exceeding 97% [9],[10],[11],[12]. NN-based methods accurately detect and classify various fault types, surpassing traditional approaches and other machine-learning techniques in both accuracy and robustness [13],[14].

Hence, NN-based techniques are applied in this research to improve the detection and classification of faults in PV arrays. Using MATLAB Simulink, a PV array with 18 individual modules arranged in a 3×6 configuration was modeled. Three fault types are specifically examined in the study: degradation faults, short circuit faults, and open circuit faults. The neural network was trained on an extensive dataset generated from the MATLAB Simulink model, encompassing data from normal operating conditions and the fault conditions as mentioned above. Through this approach, the study seeks to improve PV array fault detection and classification's accuracy and reliability.

The arrangement of paper is: Section II outlines the modelling of the PV array and faults simulation; Section III highlights the outcomes of fault detection and classification through neural networks. Finally, Section IV presents the conclusion of this paper.

2 Methodology

2.1 PV Modelling

Accurate PV modelling is essential for effective fault detection in PV systems. For its balance of ease of use and reliability, the single-diode model is widely employed and is well-known in PV system modelling [15]. This model includes a photocurrent source, a diode, a series resistance, R_s, and a shunt resistance, R_p, making it a straightforward yet precise representation of a PV cell [16]. PV module design and analysis mostly depend on the single-diode model, which researchers have highlighted for its importance and wide use [17]. Figure 1 presents the electrical circuit corresponding to the five parameters single-diode model. Applying Kirchhoff's law, Eq. (1) determines the output current, I, of the solar cell where I_d is the diode current, I_{PV} denotes the cell photo-generated current, and I_{Rp} is the shunt resistor current [18].

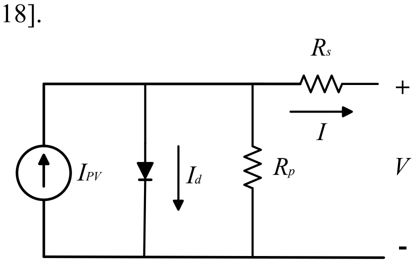


Fig. 1 Single-diode model with 5 parameters

$$I = I_{PV} - I_d - I_{Rp} \tag{1}$$

The diode current, I_d is classified as a non-linear element, characterized by the Shockley equation as presented in Eq. (2). Conversely, the current through the shunt resistor, I_{Rp}, is defined according to Eq. (3).

$$I_d = I_o \left[exp\left(\frac{V + IR_s}{N_s V_t A} \right) - 1 \right] \tag{2}$$

$$I_{Rp} = \frac{V + IR_s}{R_p} \tag{3}$$

Replacing Eq. (2) and Eq. (3) into Eq. (1), the cell of single-diode model is rewritten in Eq. (4).

$$I = I_{PV} - I_o \left[exp\left(\frac{V + IR_s}{N_s V_t A} \right) \right] - \frac{V + IR_s}{R_p} \tag{4}$$

where $V_t = kT/q$ is the junction thermal voltage, k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T (in Kelvin) is the temperature of the p–n junction, q is the electron charge ($1.60217646 \times 10^{-19}$ C), N_s is the count of cells arranged in series, I_o is the leakage current of the diode and the diode ideality factor is represented by A.

Although the manufacturers supplied the electrical characteristics of PV modules under standard test conditions (STC, G=1000 W/m2, T=25°C) to assist in calculations and simulations, these characteristics can deviate from their nominal values in real-world, long-term conditions. Testing fault sample data for different scenarios is impractical due to the inability to control the outdoor operating conditions of actual PV arrays. This provides an accurate and practical approach to modelling PV modules and arrays. The Simulink model of solar cells is the basis for this methodology and has been validated against the data specified by manufacturers of PV modules. The study utilized a PV array consisting of three strings, each made up of six modules connected in series, using eighteen GL-M100 monocrystalline silicon PV modules. Table 1 outlined the details of this module.

Table 1 PV Module GL-M100 specification [19]

Parameters	Symbol	Value
Short Circuit Current	I_{SC}	6.03 V
Open Circuit Voltage	V_{oc}	21.5 V
Maximum Power Current	I_{mpp}	5.71 A
Maximum Power Voltage	V_{mpp}	17.5 V
Maximum Power	P_{mpp}	100 W
V_{mpp} Temperature Coefficient	Υ	-0.5 %
I_{sc} Temperature Coefficient	α	0.06 %
V_{oc} Temperature Coefficient	β	-78 mV
Quantity of solar cells in series	n	36

Solar cells with identical characteristics are combined to form the PV module. A model was initially developed in MATLAB Simulink for the PV module, as depicted in Figure 2, to produce simulation data, including voltage, current and power, as well as current-voltage and power-voltage curves. The current-voltage and power-voltage characteristics at STC from the simulation of the PV module are presented in Figures 3(a) and 3(b). The accuracy of the generated PV module model has been validated through a comparative evaluation of its simulation for Vmpp, Impp, Voc, and Isc against the parameters specified in the manufacturer's datasheet [20]. Table 2 demonstrates a strong correlation between the simulation results and the values provided in the datasheet.

Table 2 Comparative analysis of simulation results and PV module datasheet – PV Module

Parameters	Datasheet	Simulated Data
I_{SC}	6.03 A	6.04 V
V_{oc}	21.50 V	21.50 V
I_{mpp}	5.71 A	5.60 A
V_{mpp}	17.50 V	17.59 V
P_{mpp}	99.925 W	98.59 W

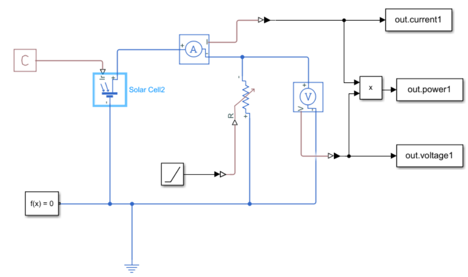
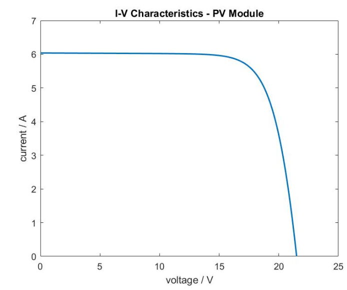


Fig. 2 MATLAB Simulink of PV Module



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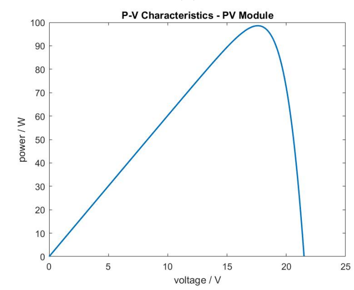


(b)

Fig. 3 Simulation of (a) I-V and (b) P-V response of PV module model

Three arrays were constructed using a total of eighteen PV modules. Each array consisted of six modules, as shown in Figure 4 and Figure 5 [19]. The characteristics of the current-voltage and power-voltage obtained from the simulation of the PV array under STC are shown in Figures 6(a) and 6(b). The simulation results were consistent with the information provided in the datasheet, as indicated by the observations in Table 3. Therefore, the model of the proposed PV array can predict the PV array's performance in this study across standard and defective conditions with sufficient accuracy.

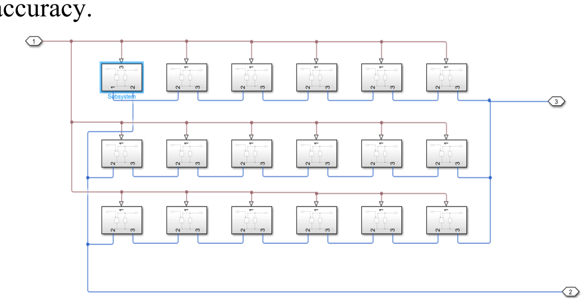


Fig. 4 Simulation of (3x6) PV array

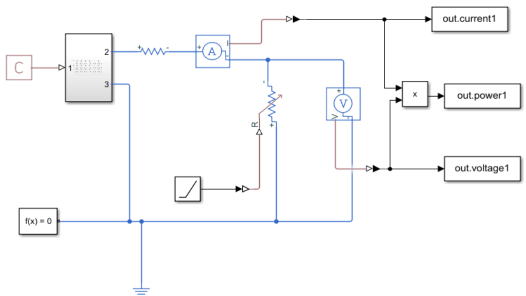
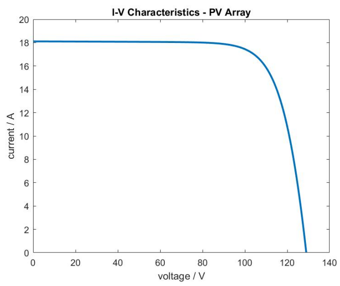
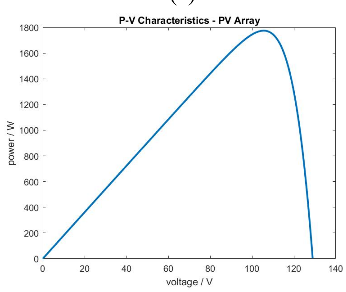


Fig. 5 MATLAB Simulink circuit for I-V characteristics testing



(a)



(b)

Fig. 6 Simulation of (a) I-V and (b) P-V response of PV array model

Table 3 Comparative analysis of simulation results and PV module datasheet – PV Array

Parameters	Datasheet	Simulated Data
I_{SC}	18.09 A	18.11 V
V_{oc}	129.00 V	128.96 V
I_{mpp}	17.13 A	17.03A
V_{mpp}	105.00 V V	105.57 V
P_{mpp}	1,798.65 W	1,797.86 W

2.2 PV Fault Simulation

Before detecting faults in the PV array, fault characteristics and data collection are facilitated through simulations of PV system faults. This data is crucial for NN's training, validation, and testing. The study focused on three main types of faults in PV systems: open circuit, short circuit, and degradation faults. Open circuit faults occur when there is a break in the electrical circuit, preventing current flow. In contrast, short circuit faults happen when an unintended connection allows excessive current flow, potentially causing overheating and damage to system components. Degradation faults involve a gradual decline in PV system performance over time due to environmental conditions, material wear, and ageing, impacting long-term efficiency and reliability. For each mentioned fault, the current-voltage curve performance will be analysed in MATLAB Simulink under STC.

The open circuit condition is represented by the serial connection of a high resistance value resistor of 100 kΩ in the string, as illustrated in Figure 7 [21]. This will eventually cause the string to be isolated from the PV array. Open-circuit faults and their impact on current-voltage and power-voltage characteristics are illustrated in Figure 8. An open circuit significantly reduces the short-circuit current and the output power. The gradient of the current-voltage characteristic exhibits minimal variation, but the open-circuit voltage remains constant.

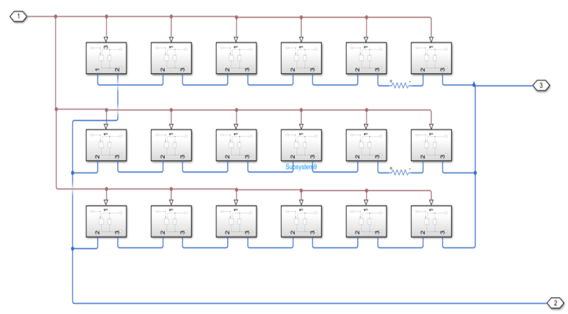
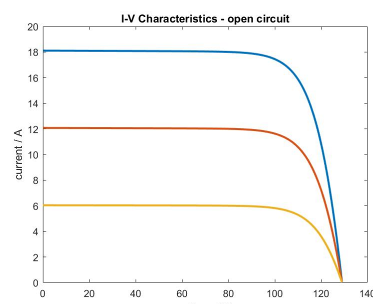
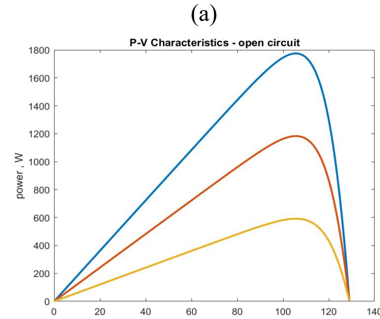


Fig. 7 Simulation of an open circuit fault



(a)



(b)

Fig. 8 Simulation of (a) I-V and (b) P-V response of PV array model under open circuit fault

The short circuit effect is modelled by adding resistors in parallel with the relevant modules with infinite resistance, as described in Figure 9. The analysis of the current-voltage and power-voltage characteristic curves presented in Figure 10 indicates that the occurrence of a short circuit cause a decline in the maximum power output of the PV array and the open circuit voltage, while the short circuit current remains unchanged.

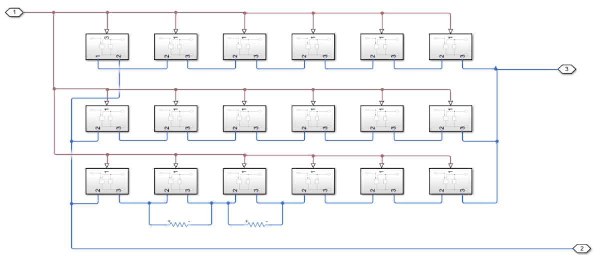
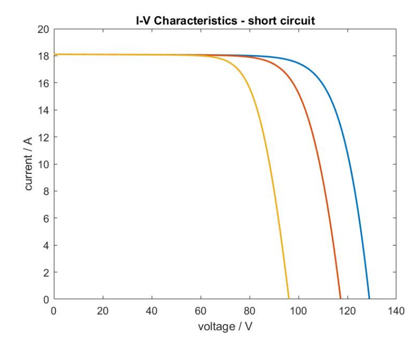


Fig. 9 Simulation of short circuit fault

The simulation of PV Array degradation is achieved by connecting a resistor to the load in a series configuration, as shown in Figure 11. Resistors of 1Ω and 2Ω were utilized to simulate varying degrees of degradation [22]. The rise in series resistance notably alters the current-voltage characteristic gradient. It reduces the output power of the PV array while the open-circuit voltage and short-circuit current remain unaffected, as seen in Figure 12.



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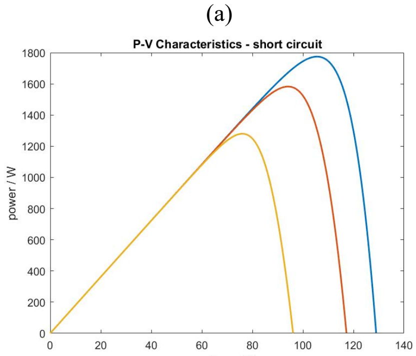


(b)

Fig. 10 Simulation of (a) I-V and (b) P-V response of PV array model under short circuit fault

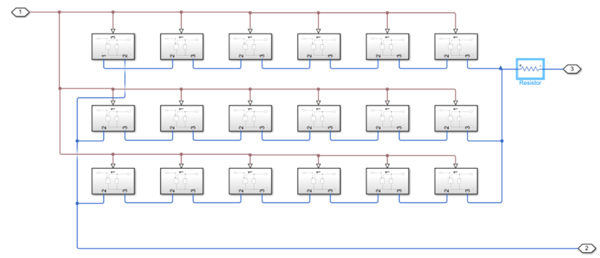
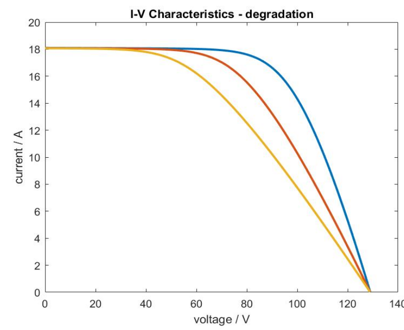


Fig. 11 Simulation of degradation fault



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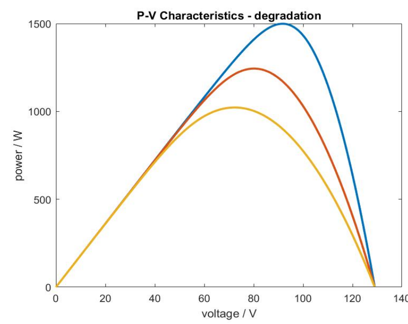

(b)

Fig. 12 Simulation of (a) I-V and (b) P-V reponse of PV array model under degradation fault

2.3 Development of Neural Network (NN)

Developing an NN-based fault detection system involves comprehensive data collection and pre-processing to ensure the availability of high-quality and representative data for training. The data used for training the NN is obtained from PV fault simulations conducted in MATLAB Simulink. These 19,993 datasets of temperature, irradiance, current, voltage and power form the basis for training the neural network, allowing it to learn and identify patterns related to normal operations and three fault conditions: open circuit, short circuit, and degradation. In this work, one-hot encoding, or 1-of-N encoding, is used to classify normal and three types of faulty PV Array. It involves converting each categorical variable into a binary format [23], [24]. This binary was then used as a target for NN, as in Table 4. Normal condition or no fault had been classified as target 1000, while target 0100 is for open circuit fault. Meanwhile, target 0010 is for a short circuit fault, and

0001 is for a degradation fault.

Table 4 Neural Network output target

Fault Description	Target			
	Y1	Y2	Y3	Y4
No-Fault	1	0	0	0
Open Circuit	0	1	0	0
Short Circuit	0	0	1	0
Degradation	0	0	0	1

During the training phase of the NN, 15 hidden neurons are selected based on the performance values obtained from the training process, as illustrated in Figure 13 and Figure 14. Table 5 presents the evaluation metrics for various neural network configurations utilized in the study. The objective of selecting the optimal number of layers is to identify the configuration that achieves the lowest performance value, ideally close to zero or the smallest among the recorded values. This demonstrates that the PV system is capable of detecting faults with a high degree of accuracy and efficiency.

Table 5 Neural Network performance value

Hidden Layers	Performance	Hidden Layers	Performance
5	0.0571	11	0.0259
6	0.0460	12	0.0230
7	0.0372	13	0.0367
8	0.0360	14	0.0327
9	0.0241	15	0.0156
10	0.0276	16	0.0260

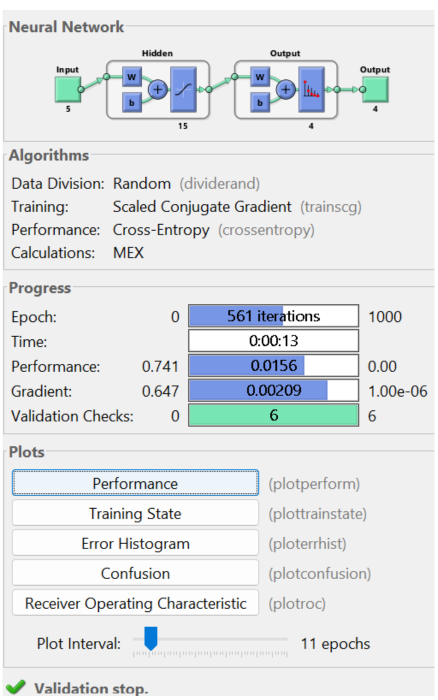

Fig. 13 Neural Network training result

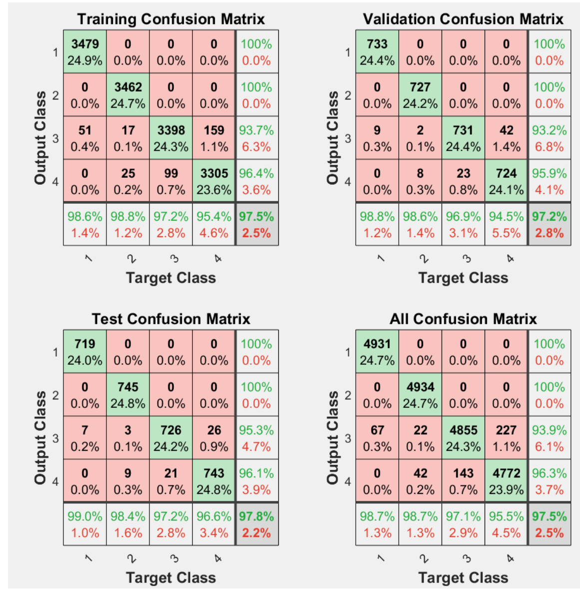

Fig. 14 Confusion Matrix

3 Results

Assessing the capability of the chosen NN architecture, configured as 5-15-4, to detect and classify photovoltaic (PV) faults, a simulation is executed within the MATLAB Simulink environment, as illustrated in Figure 15. A set of five randomly selected data points from the collected dataset is used as inputs for the NN simulation. The simulation allows the NN model to process and evaluate the data using selected inputs, mimicking the network's behaviour in real-world scenarios. The simulation outputs in Table 6 indicate the network's predictions or classifications of faults within the PV system. It was found that the neural network successfully classified no fault and open circuit conditions. However, in classifying short circuit and degradation, the neural network was less accurate initially. This situation improved as the voltage levels increased.

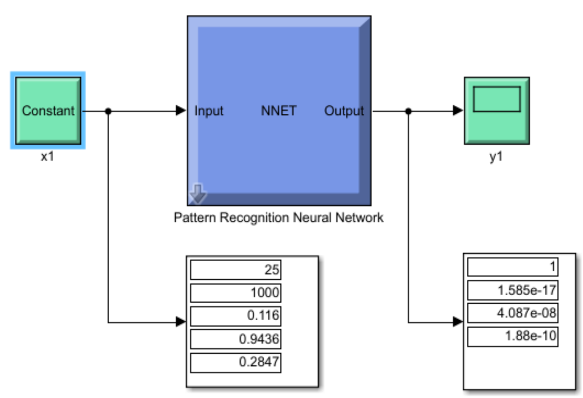

Fig. 15 Simulation of NN model

Table 6 Neural Network analysis for different faults type

Input of NN					Target Output of NN				Analysis
T (°C)	G (W/m^2)	Current (A)	Voltage (V)	Power (P)	NN1	NN2	NN3	NN4	
25	1000	0.25551	0.0035	0.0016	1	7.69x10^{-32}	6.6x10^{-8}	2.93x10^{-19}	No Fault
25	1000	0.2542	0.5413	0.2602	1	8.47x10^{-28}	2.58x10^{-8}	9.73x10^{-13}	
25	1000	0.2022	0.8790	0.8790	0.9997	1.44x10^{-25}	0.0003	5.42x10^{-10}	
25	1000	0.116	0.9436	0.9436	1	1.59x10^{-17}	4.09x10^{-8}	1.88x10^{-10}	
25	1000	0.0877	0.9568	0.2536	1	1.05x10^{-11}	1.19x10^{-7}	1.489x10^{-6}	
25	1000	0.5529	0.8563	0.7432	8.05x10^{-11}	0.9543	0.0457	4.33x10^{-7}	Open Circuit Fault
25	1000	0.4667	0.9062	0.6853	2.17x10^{-51}	1	5.23x10^{-55}	1.54x10^{-12}	
25	1000	0.3983	0.9301	0.6209	9.25x10^{-50}	1	1.37x10^{-57}	3.75x10^{-7}	
25	1000	0.2877	0.9578	0.5021	1.15x10^{-48}	1	5.24x10^{-58}	3.04x10^{-5}	
25	1000	0.1815	0.9781	0.3781	2.95x10^{-37}	0.9995	6.81x10^{-54}	0.0005	
25	1000	0.9975	0.3755	0.5426	0.0030	3.56x10^{-5}	0.4488	0.5481	Short Circuit Fault
25	1000	0.4698	0.8636	0.6565	1.32x10^{-7}	1.11x10^{-5}	0.9977	0.0023	
25	1000	0.2231	0.8941	0.3938	0.0008	3.46x10^{-19}	0.9992	1.39x10^{-7}	
25	1000	0.0581	0.911	0.2066	5.92x10^{-14}	1.94x10^{-52}	1	8.768x10^{-37}	
25	1000	0.0260	0.2066	0.1692	1.76x10^{-14}	1.81x10^{-53}	1	6.54x10^{-40}	
25	1000	0.9956	0.3606	0.5201	0.0026	3.36x10^{-5}	0.4433	0.5541	Degradation Fault
25	1000	0.9866	0.4964	0.7110	0.0007	0.0007	0.2441	0.7544	
25	1000	0.7078	0.7603	0.8126	6.30x10^{-10}	1.00x10^{-5}	1.96x10^{-8}	1	
25	1000	0.4541	0.8529	0.6310	5.50x10^{-6}	3.86x10^{-8}	0.0004	0.9996	
25	1000	0.1795	0.9370	0.3598	3.70x10^{-5}	2.62x10^{-5}	1.06x10^{-16}	0.9999	

4 Conclusions

This research explored the ability of neural network-based techniques for the detection and classification of faults in PV arrays, explicitly focusing on open circuits, short circuits and degradation faults. Simulations conducted in MATLAB Simulink demonstrated the models' ability to accurately predict and classify various fault conditions with 97.5% accuracy, highlighting their reliability and effectiveness. The results confirm that neural networks can effectively distinguish between normal operations and different fault scenarios in PV arrays, enhancing system efficiency and reliability. Future studies might focus on enhancing the models by incorporating additional fault types, advanced neural network architectures, and real-time deployment in operational PV systems to validate practical applicability.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Arizadayana Zahalan contributed to the original draft preparation, software and simulation, analysis, and revise and editing. **Ernie Che Mid** and **Noor Fazliana Fadzail** were responsible for idea and conceptualization and methodology. **Samila Mat Zali** provided supervision and verification of the work.

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