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Detection and Classification of Photovoltaic System Faults using Neural Network

***Abstract**. With the growth of solar energy plants and their importance in the world, a fault diagnosis of photovoltaic systems has become an essential task to perform in order to protect the user and PV system components, in addition to increasing energy productivity. This paper presents an efficient neural network method for detecting and classifying different faults in PV system. These faults can occur in a PV array or boost converter. A simple feed forward neural network feed with meteorological parameters (Irradiance and Temperature) together with electrical data (Voltage and Current) has proven its effectiveness to identify common faults in PV system with very high accuracy. This is done by simulation in the Matlab Simulink environment.*

Streszczenie. *Wraz z rozwojem elektrowni słonecznych i ich znaczeniem na świecie, diagnostyka usterek systemów fotowoltaicznych stała się podstawowym zadaniem do wykonania w celu ochrony użytkownika i komponentów systemu PV, a także zwiększenia wydajności energetycznej. W artykule przedstawiono wydajną metodę sieci neuronowych do wykrywania i klasyfikacji różnych uszkodzeń w systemie PV. Te usterki mogą wystąpić w panelu fotowoltaicznym lub przetwornicy podwyższającej napięcie. Proste zasilanie sieci neuronowej ze sprzężeniem zwrotnym z parametrami meteorologicznymi (natężenie promieniowania i temperatura) wraz z danymi elektrycznymi (napięcie i prąd) dowiodło swojej skuteczności w identyfikowaniu typowych usterek w systemie fotowoltaicznym z bardzo dużą dokładnością. Odbywa się to poprzez symulację w środowisku Matlab Simulink.* (***Wykrywanie i klasyfikacja usterek systemów fotowoltaicznych z wykorzystaniem sieci neuronowych***)

Keywords: photovoltaic system, detection Fault, boost converter, neural network.
Słowa kluczowe: instalacja fotowoltaiczna, wykrywanie awarii, przetwornica podwyższająca napięcie, sieć neuronowa

Introduction

In recent years, the world has witnessed a significant growth in photovoltaic systems. This clean energy source and other renewable sources such as wind, ocean thermal, and biomass can be reliable alternative sources compared to fossil fuel sources due to their abundant availability and non-polluting nature. As a result, we see that PV system sizes and numbers have rapidly increased around the globe. [1]–[3].

Fault detection in solar PV systems is an essential function that allows us to prevent or correct any dangerous or undesired states that may occur as a result of the presence of faults. Without the proper detection of faults, these faults could cause a loss in the produced power and may lead to dangerous situations such as fire hazard [4]. Faults in a PV system can occur in PV modules, boost converter, MPPT control, inverter, and battery storage or load charge. A PV panel is an important part in the PV system since it is the power generation unit and any failure in PV modules could have a big impact on the output power, in addition to a reduction in their effectiveness and lifespan. Photovoltaic panels are subjected to a variety of problems, including partial shading conditions, arc faults, short-circuit faults, and open-circuit faults [5].

The majority of these faults stay invisible for a long time, which causes a reduction in energy. In addition, the technician may take a long time and perform many measurements to discover and repair faults [4].

Furthermore, DC-DC converters are also essential for converting the power generated by photovoltaic (PV) modules. They monitor the peak power value (maximum power point) of the device under a variety of climatic situations or load demands. Hence, a malfunction in DC-DC converter components has an impact on the entire PV system and may stop the whole system since it is the link between the PV array and load demand [6]. There are many developing methods to detect faults in PV systems. They are classified as time domain methods; mathematical model analysis methods; thermal infrared detection methods; and artificial intelligence methods. Many artificial intelligence algorithms have demonstrated their effectiveness over the past ten years in controlling, modeling, predicting, and forecasting many aspects of the PV system(Samara & Natsheh, 2020).

Salem and M. A. Awadallah [7] present a methodology to detect and access partial shading based on an artificial neural network using temperature and solar irradiation inputs. A back propagation algorithm with a tan-sigmoid activation function is used on the ANN to determine the shading factor and the number of modules that are under shade in the PV array. This ANN method shows acceptable accuracy with a mean square error range of 0.067 and limited acceptance of testing results.

Y.Meki and A.Melit [8] propose a fault detection method using a neural network to estimate the voltage and current of a PV module under meteorological conditions. The experienced setup has been established and the data like solar irradiance, cell temperature, PV current and voltage have been measured and used to train, validate and test the multilayer perceptron which provided with back propagation method. The performance of the four-layer ANN has shown the effectiveness of this method with a mean square error of about 0.001.

A novel method proposed by [9] to identify faults in PV systems using only two parameters(solar irradiance and output power). The shading and non-shading states are determined using a radial basis function (RBF). The authors propose four different methodologies, including data normalization and mapping of solar irradiance against output PV power. The proposed method shows an accuracy range of from 96.5% to 98.1% in the four different cases.

M.Chouay and M.Oussaid [10] present a fault diagnosis technique that uses artificial neural networks and I-V characteristics that can detect and locate eight different faults in PV modules, PV arrays, and bypass diodes using artificial neural networks and the analysis of I-V characteristics. The method used consists of two algorithms: the first one based on I-V characteristics to indicate the fault that affects I-V properties, whereas the second method is based on the ANN approach to detect faults that affect I-V characteristics. The results of simulation indicate that each algorithm has good performance individually, and the proposed method can predict and identify faults with a 94.5% correct classification.

Considering the preceding studies, developing methods and algorithms to detect and identify defects in PV systems is a critical task for safety, time consumption, and the conservation of energy produced in large-scale power plants. However, the majority of artificial intelligence studies have focused on the diagnosis of PV faults rather than boosting faults. This paper proposes a method relying on an artificial neural network that can detect and classify PV faults in conjunction with boost faults using limited voltage and current sensors.

Open-circuit and short-circuit defects are the most common switch failures in boost converters. Practically, the short-circuit fault leads to a huge excess of current, while the open-circuit fault results in a subsequent failure in the power conversion [11].

The proposed algorithm can detect a variety of faults, including electrical faults (open circuit and short circuit) in PV panels and boost converters, as well as partial shading situations. The suggested method needs only the sensors of current and voltage at the entry and exit of the boost converter device, which are already there. The simulation results show the efficiency of this approach under all scenarios of failure situations. Therefore, the basic contribution of this work is to diagnose faults related to PV panels and boost converter with high efficiency using an artificial neural network enabling the identification of multiple electric faults in a PV system with a low-cost experiment. This work looks to identify faults that may occur in the PV array or boost converter. Referring to Table 1, nine possible cases are studied.

Table 1.Fault classification

Fault classification	**Symbol**
Normal Operation	F0
One open-circuit PV module.	F1
Two open-circuit PV modules	F2
One short-circuit PV module	F3
Two short-circuit PV modules	F4
Faulty string	F5
Partial shading	F6
An open circuit fault in the MOSFET converter	F7
A short circuit fault in the MOSFET converter	F8
Disconnection of the PV array	F9

PV system modeling

Modeling of PV Module:

MSX60 PV Solarex Module was chosen in our study for simulation using Matlab Simulink.

The table below shows the electrical characteristics of the PV module MSX60 under standard conditions (STC) (Temperature Module = 25°C, Solar Irradiance = 1000W/m2). [13]

Table 2. Electrical parameters of the PV Solarex Module MSX60

Characteristics of MSX60 PV Module	
Voltage in open circuit (Voc)	21.1V
Optimal operation voltage(Vmp)	17.1V
Short circuit current (Isc)	3.8A
Optimal operating current (Imp)	3.5A
Maximum power (Pmax)	60W
Temperature coefficient of Voc	-(0.038±10) %/°C
Temperature coefficient of Isc	(0.065±5) %/°C
NOCT	47°C
Number of series cells (Ns)	36
Operating Temperature	25°C

The characteristics of PV module under STC condition are shown in Fig.1

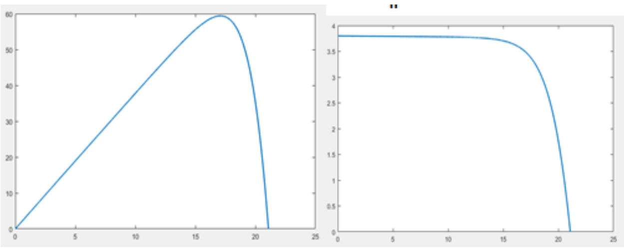

Fig.1. P-V and I_V Characteristics of the PV module under STC conditions

PV array:

The proposed system in our study consists of six panels arranged in two parallel stings, each of which contains three modules linked in series. Fig. 2 depicts the PV array configuration. Bypass diodes are wired in parallel with the modules to create an alternative path of electricity when there is a shaded panel. This minimizes the heat gain and reduces current loss. However, blocking diodes are connected in series with panels to prevent the backward flow of current when there is a faulty string in the PV array("No Title," n.d.).

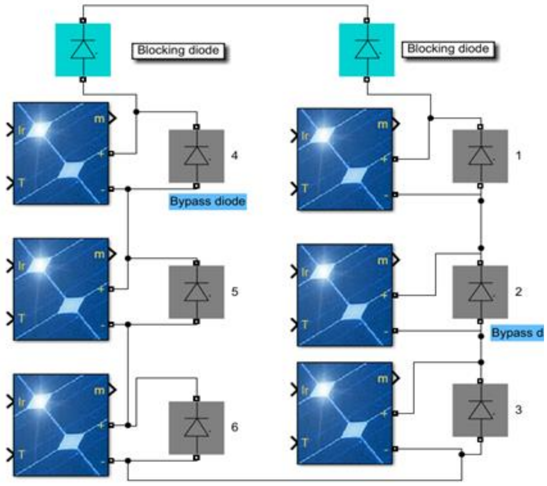

Fig.2. PV array configuration

Photovoltaic System

The boost converter connects the PV array to the resistive load. Five components are required: a diode, a switching device, a capacitor, an inductor and a load resistance. In the simulation, a standard power diode and a power MOSFET switching device are utilized because they are frequently used for low to medium power applications. The frequency is selected at F=20 KHz and the load resistance is set to R=200Ω using [15]. Other components are selected using the following equations [16].

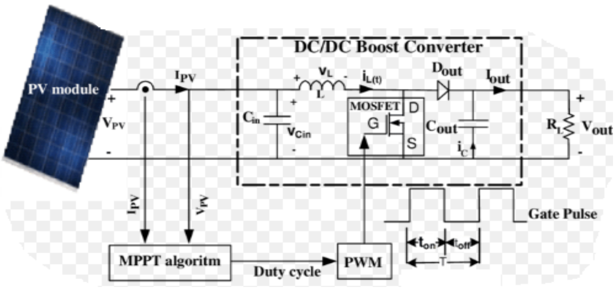

Fig.3. Block diagram of PV system using boost converter

Where α is the duty ratio of the boost converter.
The table below shows all the parameters needed to design boost converter:

$$L \geq \frac{\alpha(1-\alpha)^2 R}{2F} \quad (1)$$

$$C_0 \geq \frac{\alpha}{0.02 \times F \times R} \quad (2)$$

$$C_{in} \geq \frac{\alpha}{8 \times F^2 \times L \times 0.01} \quad (3)$$

Table 3.Fault classification

Fault classification	Symbol
F	20KHz
R.	200Ω
α	0.806
L	0.27mH
Cin	220µF

PV array faults:

Our system is subjected to three different faults with bypass diode in the PV array as illustrated in Fig.4.

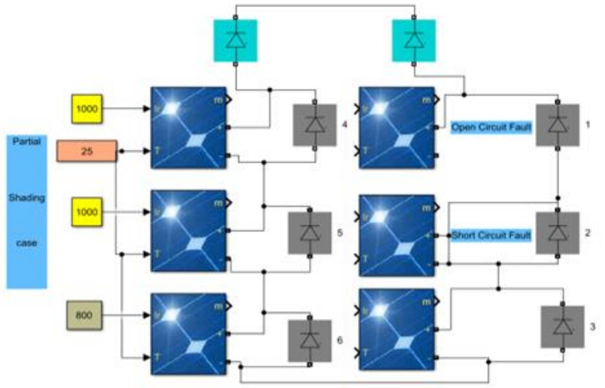

Fig.4. Multiple faults in PV array

The open circuit fault can occur due to a break in the wires, a bad connection, or a loose terminal [17], in which case the open voltage remains close to its normal value while the current and power values are reduced [18].

Short circuit: it is mainly due to bad wiring in a PV string.

Partial shading: a partial shading fault occurs when a part of the PV array is shaded while the other part is normally exposed to the solar energy due to passing clouds, adjacent buildings, towering trees and so on, with a resulting power reduction [19]. Partial shading states are numerous. In this paper, we consider a case where one module or two modules are under shade with a shading factor of 10% to 25% in one module.

Faulty string: it could happen because all the modules of a string are open or short-circuited. As a result, this string will be isolated from the system due to the presence of a blocking diode.

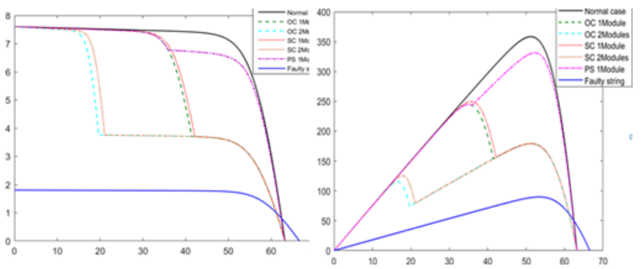

Fig.5. I-V and P-V characteristics of PV array under different faults

Faulty PV array: this fault could happen due to a break in wires or bad connection as a result the PV array could be disconnected from the boost converter.

Open circuit and partial shading cases trigger the bypass diodes, which affects the power generating output of the PV arrays. Fig. 7 describes the effect of the faults related to the PV array on the P-V and I-V curves.

OC: open circuit fault
SC: Short circuit fault
PS: Partial Shading

Boost converter faults:

As mentioned before the electrical faults in boost converter are going to study in this paper are open and short circuit in MOSFET:

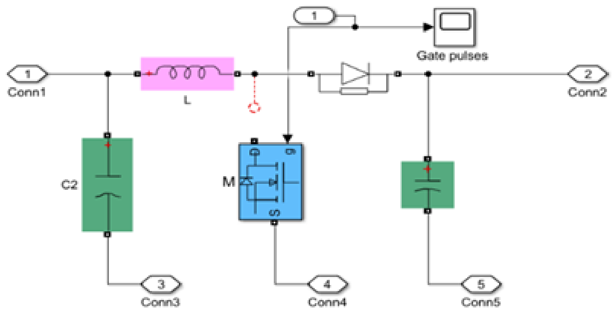

Fig.6. Open circuit fault for boost converter

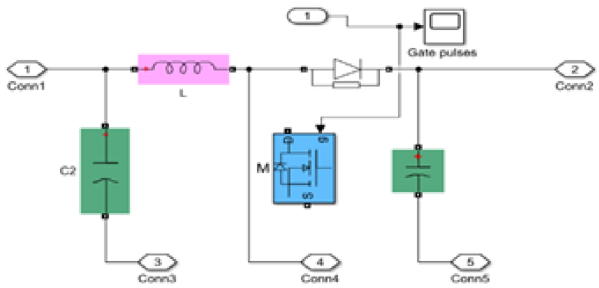

Fig.7. Short circuit fault for boost converter

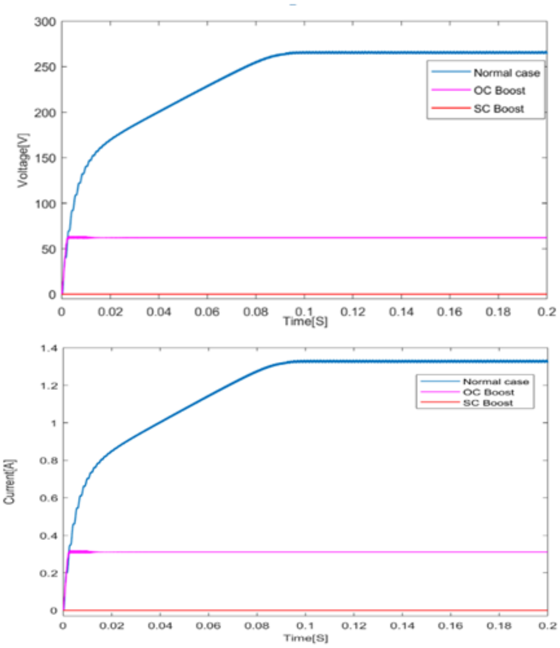

Fig.8. Simulation results of the PV array voltage and current under open-circuit and short-circuit MOSFET faults

In normal case, at STS conditions, the voltage reaches up to 250 volts, whereas the current drops to 1.3 amps. For an open circuit switch fault (OC Boost), there is no IGBT, so the current will flow without MPPT work, which leads to maximum PV voltage. For a short-circuit switch fault (SC Boost), no current will flow through the load, hence we get zero voltage and current. The resulting Matlab/Simulink model's V and I curves for the two cases, in addition to those obtained from the normal situation, are shown below (Fig.8).

Methodologies and techniques used:

Artificial Neural Network:

Artificial neural networks are essentially computing models that mimic the processes of the human brain. ANN is made up of several nodes called neurons joined by weighted connections. It is usually applied in image processing, classifying data. The primary function of neural network is to learn complicated nonlinear function mapping using sequential training methods and self-adaptation. ANNs do not really solve the problem, like in mathematics, but instead provide an approximation of a solution based on the characteristics of the processing data[11]. A neural network application can generate a simple model to user from a complicated natural system with high accuracy using a large number of inputs[20].

A multi-layer perceptron (MLP) is a well-known artificial neural network model that functions as a universal approximator for continuous functions that are not linearly separable. An LMP consists of an input layer, which receives the problem's inputs; hidden layers, which describe the relationship between the problem's inputs and outputs using synaptic weights; and an output layer, which shows the solution to the problem. The most common uses of MLPs are prediction, pattern classification, and approximation. Figure 10 illustrates a simple MLP. Common neural network types include feed-forward methods, which means data flows in the forward direction from the input layer to the output layer. A feed-forward neural network model is made up of three essential parts: a group of neurons with different network weights; a linear combiner to add the input signals; and an activation function that sets the values of output neurons to a certain limit[21]. Fig.9 illustrates a simple multi-layer perceptron used in this study.

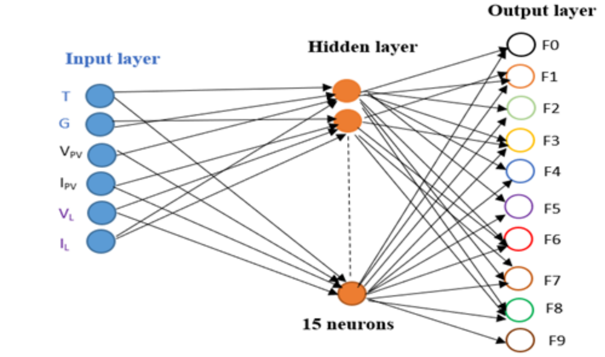

Fig.9. Construction ofANN fault classification faults

The database and ANN-designed model:

In this study, we constructed a database from the simulation of our system using Simulink/Matlab. The parameters used in this database are shown below:

T: The temperature of the module

G:The irradiance of the module

Vpv: The voltage entry of the boost converter

Ipv: The current entry of the boost converter

V_L=The voltage of the resistive load

I_L=The current of the resistive load

The meteorological data used range from 400 to 1100 W/m^2 of uniform solar irradiance and 25 to 45 °C of temperature. In each case, forty-eight situations are simulated under various meteorological conditions. Then one thousand points are taken from the permanent state of every instance simulation.At the end of the data collection, 576000 samples are obtained from all possible scenarios, containing the corresponding output represented by nine digits. This

Dataset is divided into two parts as follows:

- 70% of samples are used to train the neural network in order to build the model by adopting the network weights and bias.
- 30% of samples are used to test and validate the trained model by making comparison between the desired outputs (Targets) and the generalized ones(ANN outputs) and measure the accuracy of the system

Each feature of the input data are normalized within [–1 1] interval using the following equation :(4)

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min})} + y_{min}$$

Where xε{x_{min},x_{max}} and yε{y_{min},y_{max}} is the original input data and y is the mathching normalized value with y_{min} = 1 and y_{max} = +1 [22].

We have chosen a simple multilayer perceptron with six input neurons corresponding to the features used in the dataset (G,T ,Vpv,Ipv, VL, IL) to feed the network or hidden layer. This last layer has 15 neurons with a tangential sigmoid type activation function (its output range is between-1 and 1). The network is trained using pattern recognition neural networks and the Levenberg-Marquardat algorithm, which is considered the best algorithm for training the data after testing different algorithms to update the bias and weights of the network in order to reduce the error between the targets and the output of this neural network. The output layer corresponds to the ten different output cases (one normal case and eight faults, as described in the table in Section 2).

Results and discussion:

Using Matlab, we perform automatic learning for the chosen ANN model until we obtain a very small mean square error (MSE) with a smaller gradient value. Figure 10 illustrates the ANN model used with its results after 80 iterations. Figure 11 displays the MSE value, which is an optimal value.

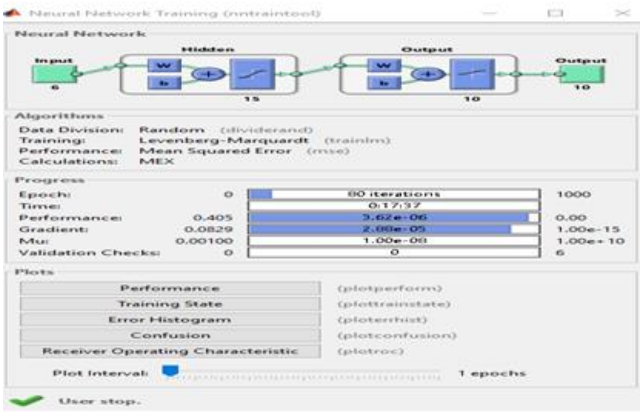

Fig.10. Neural network model

The confusion matrix is a famous performance measure for solving classification problems. It can be used for both binary and multiclass classification problems

Confusion matrices represent the difference between expected and actual values. The result "TN" refers to "True Negative" and represents the number of negative cases that were correctly identified. "TP" refers to "True Positive" and represents the number of positive cases that were successfully identified. "FP" refers to the number of true negative cases that were incorrectly identified as positive, while "FN" represents the number of true positive examples that were classified as negative.

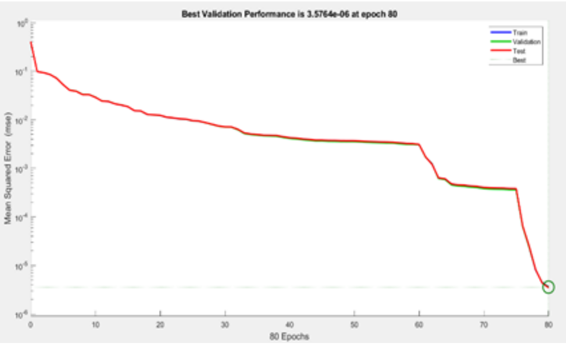

Fig.11. The mean square error

Accuracy (ACC) and precision (P) are the most commonly used performance measures after applying classification based on these parameters. These performance measures are calculated based on the values in the confusion matrix. The following equations are used to determine the accuracy (A) (see Equ. 5) and precision (P) (see Equ. 6) of the model based on the confusion matrix[23].

$$A = \frac{TN + TP}{TN + FP + FN + TP} \tag{5}$$

$$P = \frac{TP}{TP + FP} \tag{6}$$

Figure below shows the Confusion Matrix Obtained after performing classification (Figure 12)

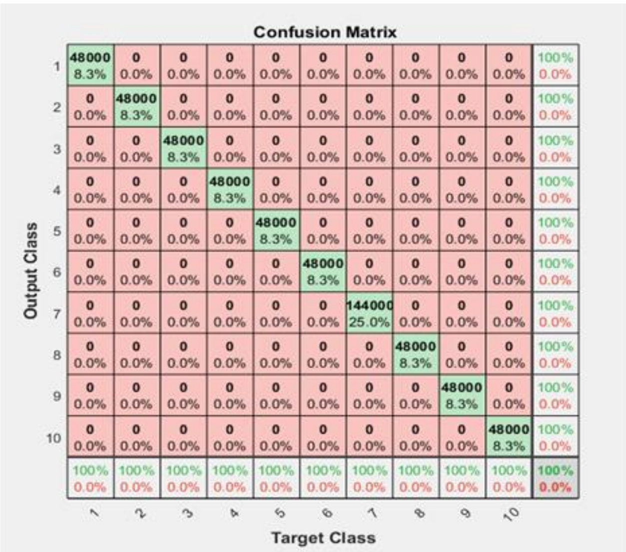

Fig.12. Confusion matrix for the ANN model

Observing Figure.13. we notice that 100% of predications are correct and 0% are faulty classifications. Using the confusion matrix and the equations above, we can calculate the accuracy and the precision of the constructed neural network that gives us: Accuracy = 100 % and Precision = 100%.

These results show that all possible nine output classes are well identified using the available input data with 100 % accuracy. The high efficiency of the ANN model demonstrates that it is the best approximation of the model to classify the different desired cases of the PV system using irradiance and temperature parameters in addition to the measured voltage and current values at the entry and exit of the boost converter.

Conclusion:

This paper presents an efficient neural network method used to detect and classify multiple faults in PV systems. The used ANN has proven its effectiveness in classifying all studied cases with a performance that reaches 100% based on climatic and electric data.

In this study, we have taken partial shading cases as non-uniform solar irradiation situations. Therefore, other cases are treated under uniform solar irradiation. Moreover, the partial shading factor may vary on the PV modules, so we notice that the different shading ratios in different numbers of panels cause similarity in the output data. As a result, we gather all partial shading cases into one case.

In future work, this neural network could be implemented in the real world to validate the model proposed in this study with a smaller number of voltage and current sensors, and it can also be useful for large-scale systems. This artificial methodology can also be extended to diagnose other PV system faults at the level of PV arrays, such as mismatch faults, ground faults, bridging faults, etc., boost converter or charging load.

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