Application of Artificial Intelligence in the Diagnosis of Bypass Diode Faults in Photovoltaic System

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Abstract **-** This paper introduces an intelligent method, based on neural networks, for detecting and classifying bypass diode faults in photovoltaic systems. These faults encompass scenarios where the diode is reversed, open, or short-circuited. The method employs a feed-forward artificial neural network and relies on input data consisting of meteorological and electrical parameters. It offers a simple and efficient approach for detecting and classifying both faulty and normal conditions. The methodology is implemented through simulation using Matlab.

Keywords– Artificial intelligence, Bypass diode, Detection, Neural network, Photovoltaic sytem.

I. INTRODUCTION

Renewable resources, such as solar energy, wind power, geothermal heat, and biomass, are sustainable sources because they can naturally replenish themselves over time. Renewable energies represent an ideal replacement for non-renewable sources like coal and fossil fuels in energy production. Their constant availability, coupled with their clean and cost-effective nature, positions them as the optimal solution to meet the growing global energy demand[1].

In the last few years, significant progress has been made in photovoltaic (PV) systems, driven by their numerous advantages. These systems offer a globally accessible energy source, are environmentally friendly with no pollution or noise, feature straightforward installation processes, and can be seamlessly integrated into buildings. Consequently, there has been a rapid increase in both the quantity and scale of PV systems (PVS) worldwide[2].

Photovoltaic systems can experience various issues related to PV modules, cables, converters, and inverters. Detecting these faults involves several methods, with machine learning techniques being among the prominent approaches [3].

II. PHOTOVOLTAIC SYSTEM MODELING

A) PV cell

A Photovoltaic (PV) cell is a device that converts sunlight or incident light into direct current (DC) based electricity[4]. In this paper the one-single diode is used in simulation since its widely used to describe he electrical behavior of a PV cell and has a rapid responses in simulation environment compared to double–diode model[5]. The equivalent model of single diode solar cell is shown in Fig. 1.

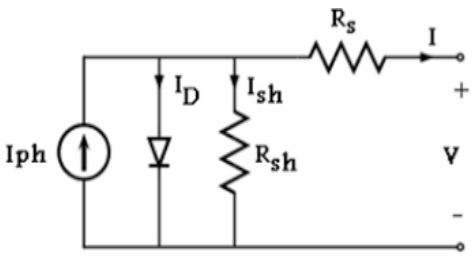

Fig. 1. Equivalent electrical circuit of a single-diode solar cell model

The basic equations which describe the I-V characteristics of the PV model are listed below:

$$I_{ph} = I_D + I_{sh} + I \quad (1)$$

The current in the diode I_d is given by:

$$I_D = I_0 \left[exp\left(\frac{V+R_s I}{V_t a}\right) - 1 \right] \quad (2)$$

The current in the shunt resistor is given by:

$$I_{sh} = \left(\frac{V+R_s I}{R_{sh}}\right) \quad (3)$$

The expression of I can be obtained from equation (1) by :

$$I = I_{ph} - I_d - I_{sh} \quad (4)$$

From equations (2), (3) and (4) the characteristics equation can be described as follows:

$$I = I_{ph} - I_0 \left[exp\left(\frac{V+R_s I}{V_t a}\right) - 1 \right] - \left(\frac{V+R_s I}{R_{sh}}\right) \quad (5)$$

Where the thermal voltage Vt is determined by

$$Vt = \frac{N_s K T}{q} \quad (6)$$

B) PV Module

The electrical characteristics of the photovoltaic module used under standard conditions STC (Temperature Module =25°C, Solar Irradiance=1000W/m^2) are shown in Table 1.

Table 1. Electrical parameters of The PV solarex module MSX60.

Charateristics 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) Characteristics of PV module under STC conditions:

The characteristics of PV module under STC conditions:

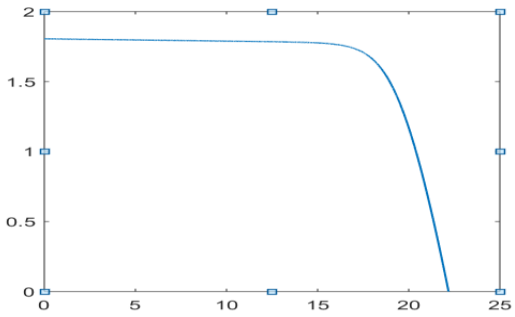

Fig. 2. (I-V) characteristics of MSX60 Module.

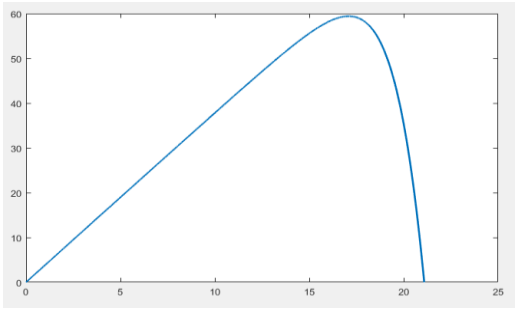

Fig 3. (P-V) characteristics of MSX60 Module.

D) Photovoltaic Array Configuration

The proposed system in our study consists of six panels arranged in two parallel stings, each of which contains three modules linked in series. Bypass and blocking diodes are used to protect the whole system. Fig. 4 depicts the PV array configuration.

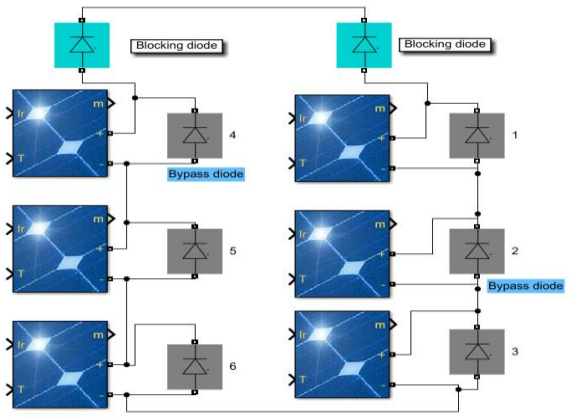

Fig. 4. PV array configuration.

E) Photovoltaic System Sizing

The circuit diagram of the suggested autonomous photovoltaic system as described in Fig. 5 contains a PV array, a boost converter with an MPPT control unit, and a resistive load.

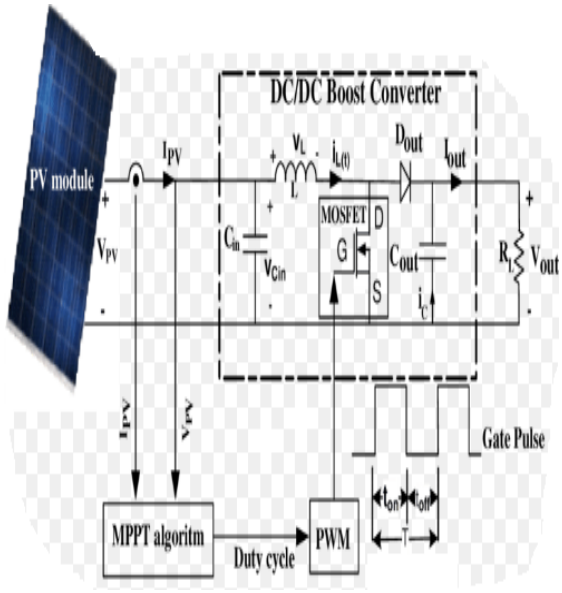

Fig. 5. Block diagram of PV system using boost converter [6].

The boost converter's parameters are calculated using [7, 8], and the resulting values are presented in the table below :

Table 2. Boost converter parameters.

Patameter	Value
F (frequency)	20KHz
R (resisstive load)	200Ω
α (duty cycle)	0.806
L (inductance)	0.27mH
Cin (input capacitance)	220µF
Cout (output capacitance)	22µF

III. PV FAILURES

A) Bypass diodes

External bypass diodes are typically installed in parallel with a photovoltaic (PV) module or a group of cells. Their primary purpose is to establish an alternative electrical pathway for the generated current when shading occurs, thereby preventing it from passing through the shaded cell. This function plays a crucial role in maintaining the efficiency of the series string by constraining the development of reverse bias voltage across partially shaded cells, thus reducing the amount of electrical power that can be absorbed by the shaded cell. The key requirements for these diodes include having two critical attributes: a low forward voltage and rapid switching capabilities. This is why Schottky diodes, known for their semiconductor-metal junctions, are the preferred choice for integration into solar modules. Additionally, for bypass diodes, it is imperative that they exhibit minimal leakage current[9].

In this paper, we focus on failures related to bypass diodes. These failures can be classified into three cases:

1. One bypass diode is reversed.
2. One bypass diode is short-circuited.
3. Partial shading (PS) with one bypass diode disconnected

In addition to these failures, we also identify normal and partial shading cases in this work.

B) Curves under STC conditions

Using MATLAB, we can obtain different I-V and P-V curves that represent the cases discussed earlier. Fig.6 and Fig.7 describe how power and current can decrease, with the amount of reduction varying from one case to another.

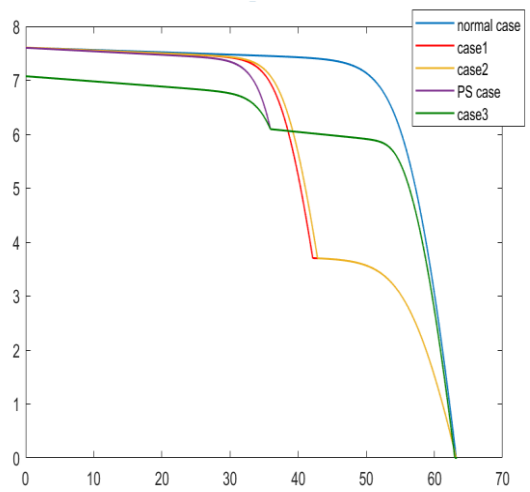

Fig. 6. (I-V) characteristics of PV system in different cases.

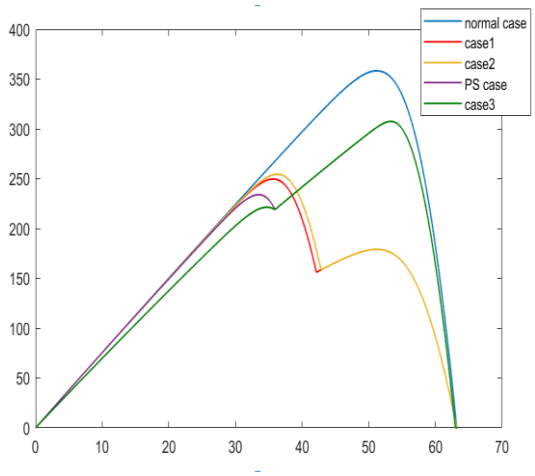

Fig. 7. (P-V) characteristics of PV system in different cases.

IV. APPROACHES AND RESULTS

A) Artificial Neural Network

Artificial neural networks (ANNs) are computational models inspired by the human brain. ANNs consist of interconnected nodes called neurons, linked by weighted connections. They find common application in tasks such as image processing and data classification. Neural networks primarily excel at learning intricate nonlinear function mappings through iterative training and self-adjustment techniques. Unlike traditional mathematical problem-solving, ANNs offer approximations to solutions based on input data characteristics. ANNs are adept at simplifying complex natural systems with high precision, making them valuable for generating simplified models from extensive input datasets [10, 11].

B) Methodologies and techniques

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[12]. Fig.8 illustrates illustrates a simple MLP neural network structure.

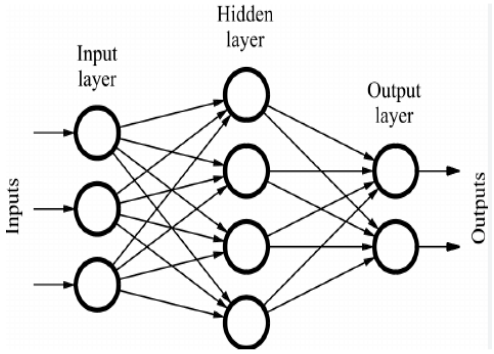

Fig. 8. Simple multi-layer perceptron architecture.

In this work, 240,000 data points were generated by simulating the system in MATLAB/Simulink. Each data point includes information on solar irradiance, ambient temperature, voltage array, and current array. Of these data points, 80% were used for training the neural network to update its weights and biases. The remaining 20% of the dataset was reserved for testing the MLP model, allowing us to compare the estimated output with actual data.

A three-layer ANN having 10 neurons in the hidden layer with a hyperbolic tangent activation function trained by Levenberg-Marquardt back propagation algorithm is used in this work. The 4 inputs of dataset are normalized to [-1 1] whereas outputs are represented in five digits of binary code.

C) Results and discussion

In Matlab, we employed automatic learning to achieve a very low error rate, which was accomplished after 30 iterations. The cofusion matrix is illustrated in Fig. 9, while Fig.10 displays the best validation performance.

The results obtained indicate that this approach demonstrates strong performance in identifying and categorizing both normal and faulty states. all predictions for the five proposed classes are accurate, demonstrating the effectiveness of this artificial neural network (ANN) model for classifying inverted bypass faults in addition to open and short-circuit bypass faults under varying meteorological conditions.

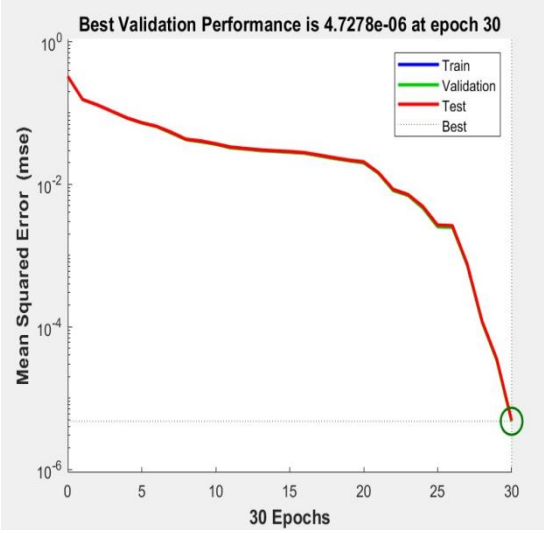

Fig. 9. Representation of the confusion matrix for the ANN model.

Fig. 10. Best validation performance graph.

IV. CONCLUSION

The paper presents a method based on the ANN of the PV system for detecting and classifying electric faults. According to the results obtained from simulation, we can say that this methodology is effective and reliable to classify the proposed faults. Hence, this ANN topology can be developed to cover different faults electrical faults.It could be applicable in real experiment.

V. REFERENCES

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