Adaptive neuro fuzzy inference system based method for faults detection in the photovoltaic system

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ABSTRACT

As the case with all electrical and electronic systems, a photovoltaic (PV) system can be exposed to several failures causing it to malfunction; several studies have found that the reliability of the PV systems is highly dependent on the material used for the construction of the PV panels, temperature, humidity and solar radiation. A PV system can have several faults, whether construction type faults, or material and electrical faults caused by climatic conditions. This requires identification, the main objective of which is to provide a tool that can detect and locate these faults in order to guarantee optimal performance of the system, and thus reduce maintenance costs and above all increase productivity by increasing the availability rate facilities in order to have a better performance. The objective of this article is to propose a technique for detecting and locating faults in a PV system, the proposed algorithm is based on adaptive neuro fuzzy inference system (ANFIS). This algorithm is based on the technique of artificial neural networks and fuzzy logic. Nine faults will be examined with simulation results under MATLAB-Simulink in PV system (array, converter DC-DC and battery).

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1. INTRODUCTION

Today, solar energy rhymes with ecology. The technologies for harnessing the sun's rays to make energy have evolved enormously in recent years. The sun is an infinite source of energy and from which we can benefit in abundance. And for a very long time. This passive energy is simply captured by photovoltaic (PV) solar panels [1]. PV solar energy is obtained by the energy of the sun's rays. More precisely, the principle is to transform the energy carried by the photons in the light, into electricity. This is why the PV panels that will harvest them are often installed on roofs, with the best possible orientation. This is where the PV cell come into play. Made of silicon, when exposed to light, it absorbs the energy of light photons. The latter generates a direct electric current which will be converted into alternating current using an inverter. This electricity produced can be immediately used to operate appliances or light [2], [3]. Any solar installation, therefore, requires three elements to ensure the recovery of the rays transmitted by the sun, to then transform them into electricity and distribute them as shown in the Figure 1: i) PV panels, ii) an inverter to convert the electricity obtained into alternating current; This power is controlled by the maximum power point tracker (MPPT) which makes the system always operate at its maximum capacity, and iii) this type of system requires the use of batteries for electricity storage and a charge controller to ensure the durability of the batteries.

The number of solar systems is growing rapidly every year, increasing the need for technicians who know how to operate PV systems effectively and efficiently. Troubleshooting of PV systems usually focuses

on four parts of the system: PV modules, batteries, converters, and junction boxes [4], [5]. Allowing fine diagnosis and detection and localization of faults in a PV installation reduces maintenance costs and above all increases productivity. In this thesis, we are specifically interested in the detection and localization of faults. The objective of this article is to propose a method and an algorithm to detect and locate defects leading to a drop in production [6], [7]. There are several research papers covering this technique; we mention the most important of them.

Bonsignore *et al.* [8] proposed a PV system fault detection method based on the neuro-fuzzy method and using the parameter calculation of PV modules under different operating conditions. Determine the status of the PV system by evaluating and comparing parameters based on thresholds. The study is based on key information containing six parameters under normal and fault conditions, using the synthesis of I-V curves (current-voltage) and their hybrid models; the diagnostic system is able to distinguish between abnormal and normal operating conditions, and at the same time in the absence of noise and interference.

Belaout *et al.* [9] proposed a method for PV system fault detection and classification using multi-class adaptive neuro-fuzzy classifier (MC-NFC). A new classification system based on an adaptive fuzzy neural inference system was proposed based on an experimental data set to generalize performance of fuzzy logic classifiers. The experiments were performed on data collected from PV systems to classify five types of defects. First, in addition to the fully selected original features, features are reduced using fuzzy logic methods. Next, the developed MC-NFC is compared with an artificial neural network (ANN) classifier. Its results show the MC-NFC outperforms ANN classifiers.

The purpose of this method proposed by Kaid *et al.* [10] is to increase the reliability and energy efficiency of the studied solar power station. Based fault diagnosis of PV modules using an adaptive neuro-fuzzy inference method. And predict the expected behavior of the system under study based on the measurements actually collected by the system under study. 120,120 solar panels with an efficiency of 30 megawatts were installed on the 60-hectare land, connected to the 30 kV grid. The obtained results confirm the energy efficiency of the examined system. Experimentally, after the dust storm passed, the limit of normal operation was exceeded, the output power absolutely exceeded 35.5, the output voltage absolutely exceeded 5.6, and the output current absolutely exceeded 1.3. This method allowed to identify faults and make a decision to clean the PV module. In fact, while maintaining the status of operating condition thanks to the proposed approach.

Bendary *et al.* [11] and all proposes a solution for effective fault detection, tracking and resolution. This proposed method is implemented through his development of one of the most artificial intelligence techniques called adaptive fuzzy neural inference systems. The proposed approach is based on linking the measured values of current and voltage to the trained historical values of this parameter, taking into account environmental changes such as radiation and temperature. It is recommended to use two controllers. One detects the faulty string and the other detects the subtle set of faults within the solar array. The model used has a 4x4 PV array configuration connected via multiple switches, four ammeters, and four voltmeters. This study was performed using MATLAB/Simulink, and the simulation results showed the effectiveness of the proposed method in fault tracking, detection, elimination, and transmission in real PV systems [11].

Abbas and Zhang [12] present an intelligent methodology for PV fault detection using adaptive neuro fuzzy inference system (ANFIS). First, this his ANFIS model needs to be trained using research data so that he can employ grid partitioning (GP) and subtractive clustering (SC) strategies to detect and classify PV faults. The performance of the ANFIS SC approach was superior and more accurate than the ANFIS GP approach in predicting and classifying various PV system failures. The AFIS SC approach also performed well when compared to unknown experimental data points that were not found in training.

The values obtained from the statistical analysis are a correlation coefficient R of 0.9989, a root mean square error (RMSE) of 0.0383, and a coefficient of determination R^2 of 0.9978. These obtained results demonstrate that the AFIS SC framework can accurately perform excellent diagnostics for PV array failures. The block radius is 0.6 [12].

Mansouri *et al.* [13] propose an ANFIS-based method for fault detection in PV systems. In this method, control is exercised using two tests. First, the fault is detected by calculating the difference between the ANFIS-estimated power and the generator power, and the inverter is isolated by shutting off the affected branch using a controlled switching element, completely shutting off the power supply. Second, the consistency between generator voltage and current, and between open-circuit voltage and short-circuit current. This is estimated by ANFIS to determine open circuit and short circuit conditions. For simulations MATLAB/Simulink was used and was experimentally validated against panels with different power ratings and technical installations older than five years using the DS1104 dSPACE control board.

This paper presents an intelligent faults diagnosis algorithm for PV installations based on adaptive fuzzy neural inference control. We need to reveal Initially a simulated estimate of the I-V curve to obtain the open circuit voltage and short circuit current along with the output current and voltage values from the inverter and the battery. The model we used contains a Iph (current source) which represents the sunshine received by the cell and a diode

to model the PN junction of the cell. The series resistance (Rs) and the shunt resistance (Rsh) represent the non-ideal state of the cell. The series resistance represents the resistivity of the material in which is made the cell, the contact resistance between metal and semiconductor and the resistance interconnection between cells. Parallel resistance represents all paths that the leakage current traverses, either parallel to the cell or at the edge of itself. It results usually from crystal damage or impurities in or near the junction [14], [15]. The mathematical equations of a single diode electrical circuit as shown in the Figure 2, it is 4 equations with two unknowns (I and V) and parameters [16]. And these parameters we summarize them in the Table 1.
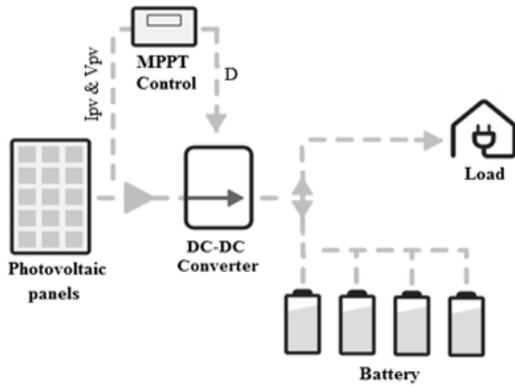
Figure 1. PV system
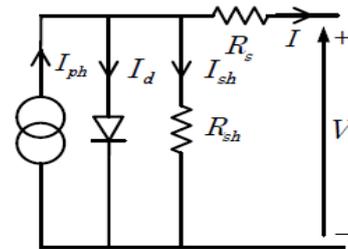
Figure 2. Simplified model of a PV cell

$$I = I_{ph} - I_0.\left[\exp\left(\frac{q.(V+I.R_S)}{n.K.N_S.T}\right) - 1\right] - I_{sh} \tag{1}$$

$$I_{ph} = I_{SC} + K_i.(T - 298).\frac{G}{1000} \tag{2}$$

$$I_0 = I_{rs}.\left(\frac{T}{T_n}\right)^3.\exp\left[\frac{q.E_{g0}\,.\left(\frac{1}{T_n}-\frac{1}{T}\right)}{n.K}\right] \tag{3}$$

$$I_{rs} = \frac{I_{sc}}{\exp\left(\frac{q.V_{oc}}{n.N_S.K.T}\right)-1} \tag{4}$$

Table 1. The parameters of PV module

Parameters	Its meaning
Iph	the Photo-current
Isc	the short circuit current
Ki=0.0032	the short circuit current of cell at 25 °C
T	the operating temperature
Tn=298 K	the normal temperature
G	the solar irradiance in W/m²
q=1,6.10-19	the electron charge
Voc	the open circuit voltage
n=1.3	the ideality factor of the diode
K	the Boltzmann's constant (J/K)
Eg=1.1 eV	the band gap energy of semiconductor
Ns	the number of series cells
Np	the number of parallel cells
Rs	series resistances
Rp	Parallel resistances

A simulation of a PV system composed of 16 PV modules (4 strings) connected to a load R is built on the MATLAB/Simulink environment. The characteristic of the PV solar which has 36 cells, where the power maximum generated is approximately 52 W at a maximum voltage of 21.9 Volt, in standard conditions (25 °C and 1,000 W/m²). Figure 3 shows the block diagram of PV system studied. The component power is constructed using the Simulink System Library and consists of a solar panel, a buck converter with control that includes an MPPT algorithm, a battery, and a load [17]. The static current-voltage (I-V) and power-voltage (P-V)

characteristics of the solar field can be used to describe it. Figure 4 depicts the I-V and P-V characteristics of a PV field under typical operating conditions.
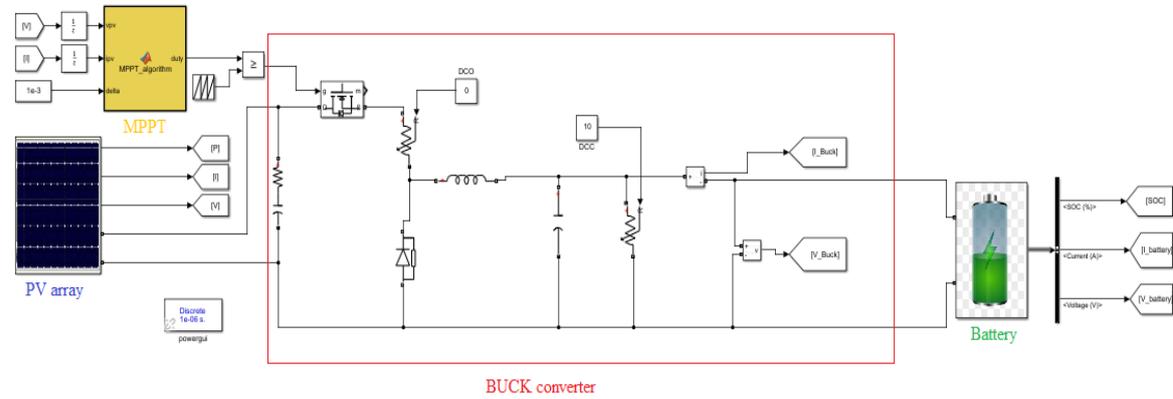
Figure 3. The PV system studied
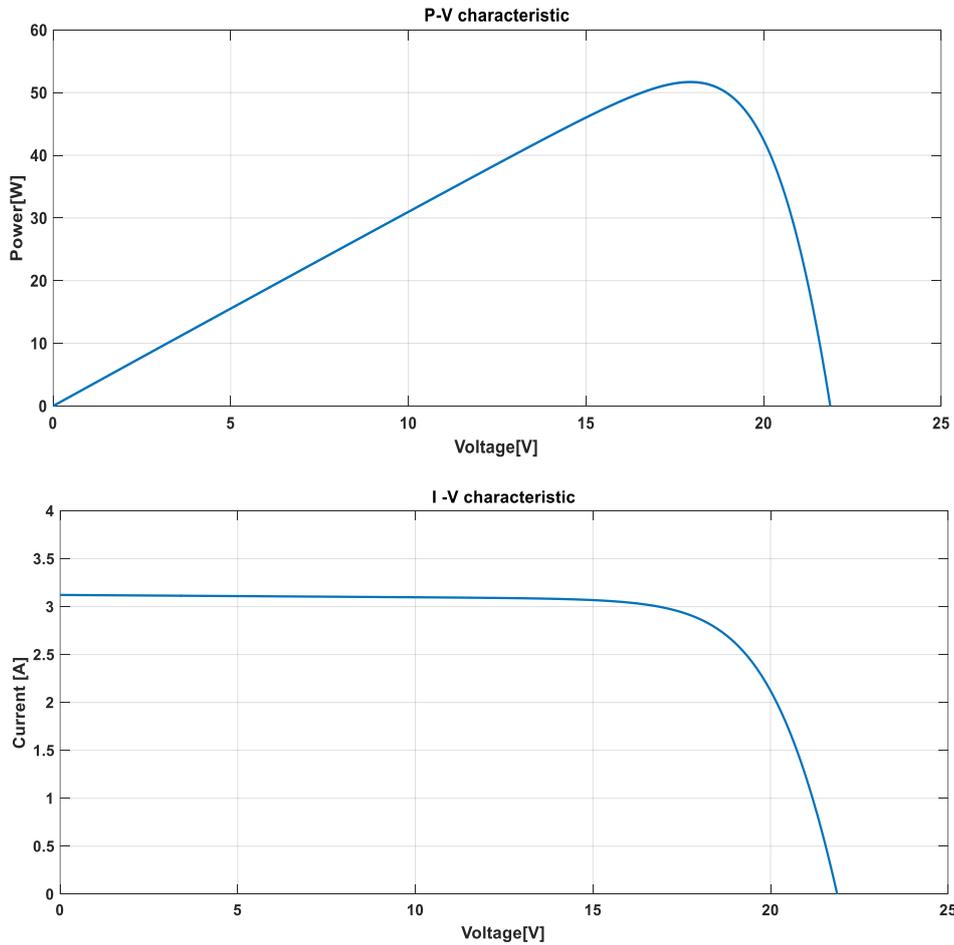
Figure 4. P-V and I-V characteristics

PV systems can be subject to several faults during their operation, and two main types can be distinguished [18], [19]:

−   Permanent faults (degradation, short-circuit, and open circuit).
−   Temporary defects (partial shading, and accumulation of dust).
There are many faults in the PV system. We present in the Table 2 some of the different faults that we can find in the PV system and which are detected.

Table 2. Faults occurring in the examined PV system

Components	Faults	Fault code
PV array	Shading	01
	Temperature increase	02
	Series resistances	03
	Shunt resistances	04
	Interconnection faults	05
Buck	Open circuit	06
Converter	Short circuit	07
	MP controller failure	08
Battery	Charging failure	09

2.   METHOD

Neuro-fuzzy systems combine the benefits of two complementing methods. Knowledge can be well represented by fuzzy systems. Due to neural networks' ability to learn, the integration of neural networks within these systems enhances their performance. In contrast, the addition of fuzzy rules to neural networks explains the meaning of the network parameters and makes it easier for them to be initialized, which significantly reduces the amount of time needed to calculate their identification [20], [21].

ANFIS, or systems adaptive neuro-fuzzy inference uses five layers of a neural network of the multilayer perceptron (MLP) type. Where each layer represents the realization of a single stage of a Takagi-Sugeno type fuzzy inference system. We have a fuzzy inference system with five inputs and one output [22], [23].

In fact, the input selection was obtained by using the parameters available from the data set of I-V and P-V characteristics and Vc and Vb obtained by simulations of the few solar system faults, including the maximum power (Pmax), the short circuit (Isc) and the open circuit voltage (Voc) output of the PV generator with the converter voltage (Vc) and the battery voltage (Vb). The selected P-V and I-V and Vc and Vb curves represent different values (Pmax, Isc, Voc, Vc, Vb) of each default. The selection of the hidden layers is obtained using a simulation of the defaults [24].

The modification of I-V and P-V characteristics can be expected when there is a change in the state of the PV field caused by a change in the operating condition (sunshine, temperature, series resistances, shunt resistances and interconnection faults) or by the appearance of one or more faults in the field. Figure 5 shows the different signals of the PV system in normal function with the effect of witch faults. Figures 5(a) and 5(b) show the shape of an I-V and P-V characteristics of a PV field in faulty operation (faults 01 to 05) compared with that in normal operation. In this test, each defect is introduced into the model of the PV array. The object of this test is to check the maximum power and short circuit voltage and open circuit voltage when varying the operating condition.

Figure 5(c) shows buck converter output with charging normal operation compared with faulty operation (faults 06 to 08), the purpose of this test is to check the voltage of output converter. Figure 5(d) shows battery voltage with charging normal operation compared with faulty operation (fault 09), the aim of this test is to check the voltage of battery.

The neuro-fuzzy method is based on comparing five parameters (Pmax, Voc, Isc, Vc, Vb) with their normal values. The values for the mentioned parameters for each defective condition are shown in Table 3. Then, the comparison of all values is calculated by (5):

$$C_{i=} \frac{val_{default\_i}}{val_{normal\_i}} \tag{5}$$

where val_{normal_i} is the value of normal system and $val_{default\_i}$ is the value of failed system. The result of comparator system has to be input of ANFIS controller.

The suggested method is based on the study of a set of output values from the PV system ($C_{Pmax}, C_{Voc}, C_{Isc}, C_{Vc}, C_{Vb}$), in both normal (healthy) and problematic (faulty) operation. Based on a comparator system, the performance of the neuro-fuzzy technique is evaluated. The proposed technique is summarized in the diagram shown in Figure 6.

(a)

(b)

(c)

(d)
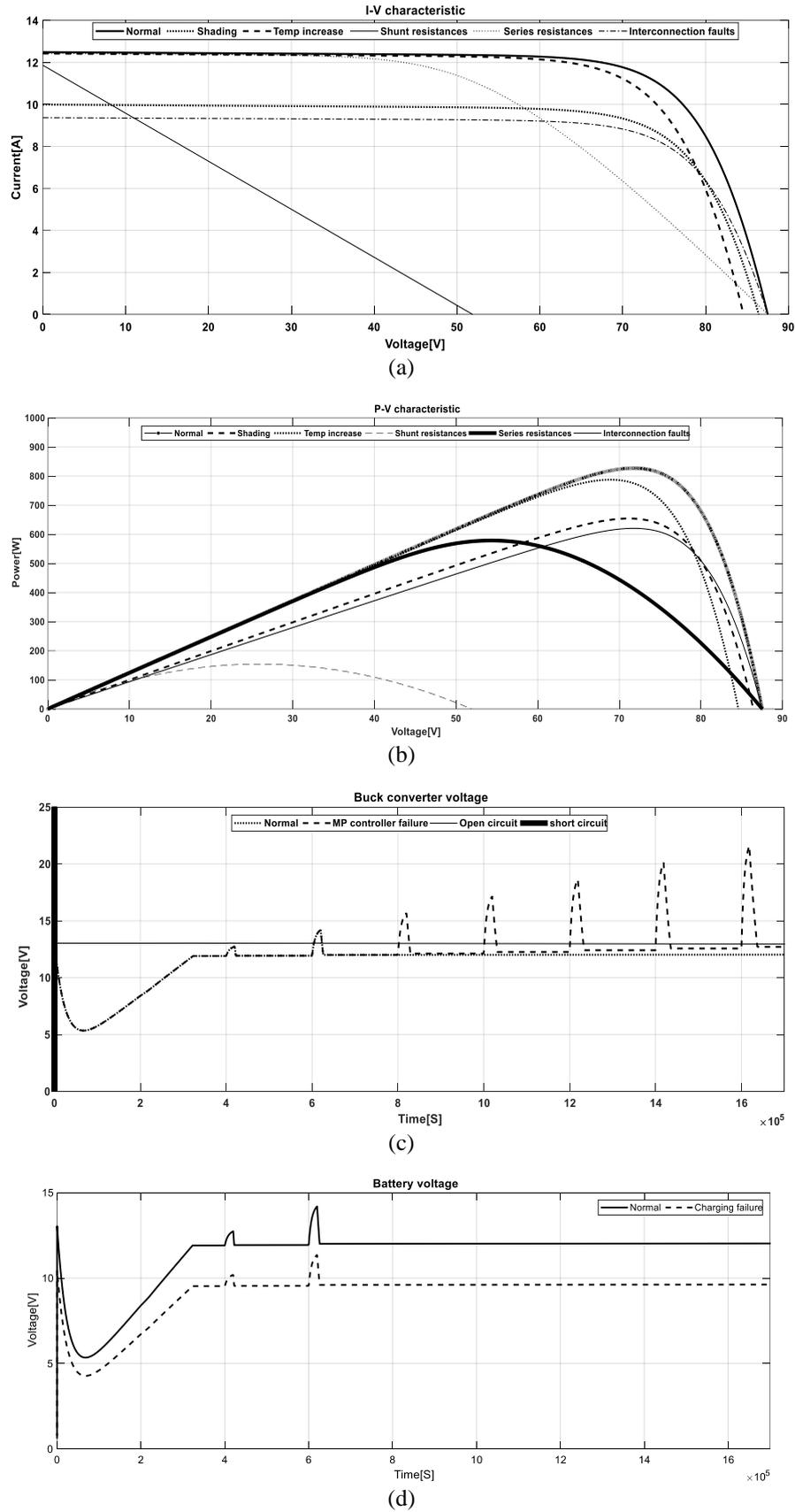
Figure 5. The different signals of the PV system (a) I-V characteristic of PV faults, (b) P-V characteristic of PV faults, (c) buck converter output with charging faults, and (d) battery voltage with charging fault

Table 3. Neuro-fuzzy console values for each defective condition

Faults	Pmax[W]	Isc[A]	Voc[V]	Vc[V]	Vb[V]	Type of fault
00	827.1	12.480	87.508	13.578	13.578	No faults
01	654.1	9.990	86.415	13.578	13.578	Shading 800 w/m^2
02	787.4	12.423	84.582	13.578	13.578	Temperature increase
03	578.6	12.428	87.508	13.578	13.578	Series resistances 2.21
04	153.9	11.863	51.871	13.578	13.578	Shunt resistances 4.15405
05	620.3	9.365	87.508	13.578	13.578	Interconnection faults
06	827.1	12.480	87.508	13.043	13.578	Open circuit
07	0.06693	12.480	87.508	infinity	undetermined	Short circuit
08	827.1	12.480	87.508	19.268	13.578	MP controller failure
09	827.1	12.480	87.508	13.578	11.269	Charging failure

Each parameter (Pmax, Voc, Isc, Vc, Vb) of normal and failed systems is calculated, after that comparator system run for obtain the values ($C_{Pmax}, C_{Voc}, C_{Isc}, C_{Vc}, C_{Vb}$) are shown in Table 4. The result depends first on C_{Pmax} in other words the power maximum generated by failed system and Ci others values. Then, the neuro-fuzzy controller is started [25]. The diagram of the proposed neuro-fuzzy algorithm of fault detection is illustrated in Figure 7.
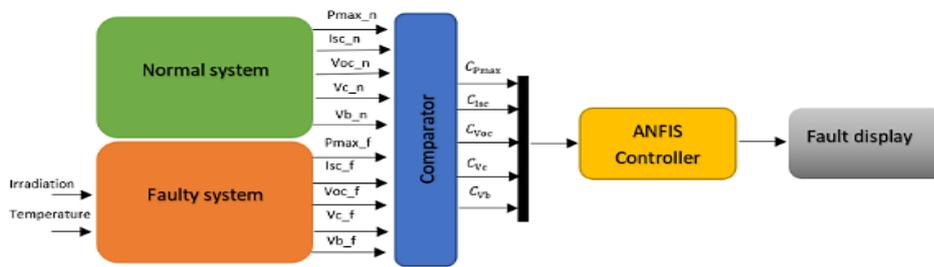
Figure 6. General structure of the proposed technique
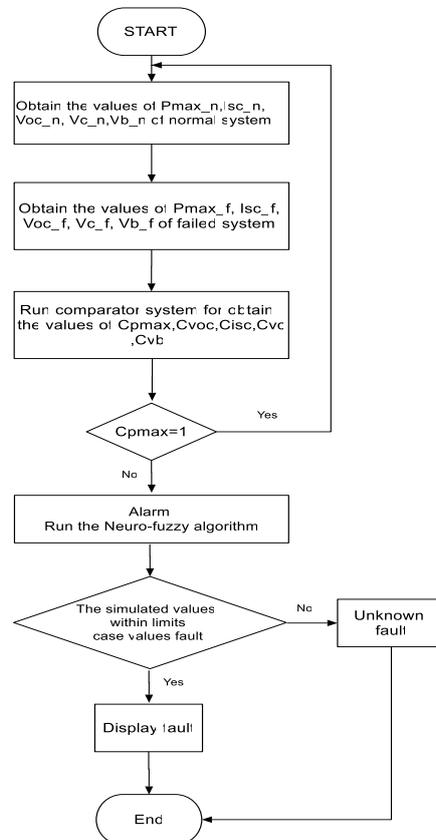
Figure 7. Flowchart of the proposed neuro-fuzzy algorithm for fault detection

Table 4. Values for each defective condition

Parameter fault	C_{Pmax}	C_{Isc}	C_{Voc}	C_{Vc}	C_{Vh}
0	1	1	1	1	1
1	0.790835449	0.800480769	0.987509713	1	1
2	0.952000967	0.995432692	0.966563057	1	1
3	0.699552654	0.995833333	1	1	1
4	0.186071817	0.950560897	0.592757234	1	1
5	0.749969774	0.750400641	1	1	1
6	1	1	1	0.960598026	1
7	8.09213E-05	1	1	736485.4912	0
8	1	1	1	1.419060245	1
9	1	1	1	1	0.8299455

3. RESULTS AND DISCUSSION

The ANFIS method is a technique for optimizing fuzzy type inference systems Takagi Sugeno proposed by Jang [26]. This uses to adjust the system settings; the least squares method combined with the gradient descent method. This method is based on the use of multilayer networks. Figure 8 shows the structure of the evaluation decision-making stage ANFIS. The architecture consists of five main layers [27], each layer consisting of a number. The number of nodes is dis-tributed as follows: 5-30-6-6-1.
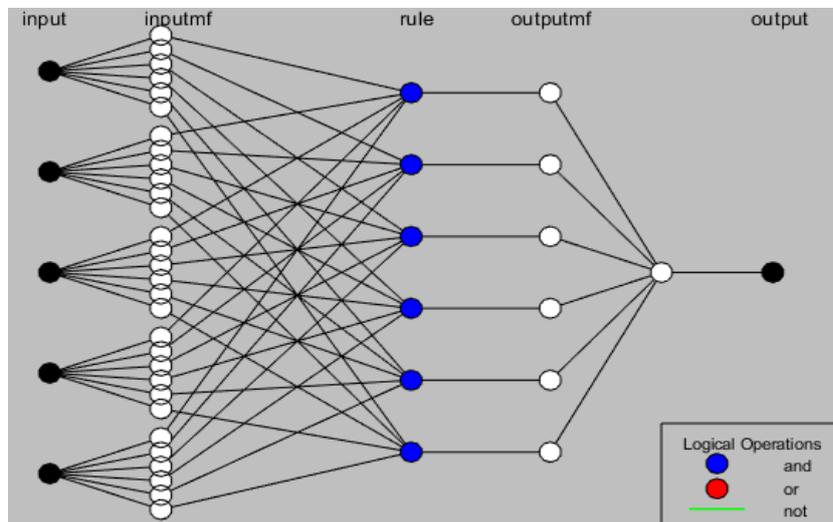
Figure 8. Architecture of ANFIS

Layer 1: each node i in this layer has a membership function in the Gaussian form and is a square node as shown in (6).

$$O_i^1 = U_{A_i}(x) = e^{-(\frac{x-m_i}{\alpha_i})^2} \tag{6}$$

Where m_i is the center of the membership function and α_i its width.

Layer 2: the weights of the rules are the outputs of this layer, and they are produced by merely multiplying the entries in each cell as shown in (7).

$$W_i = U_{A_i}(x) \times U_{B_i}(x) \times U_{C_i}(x) \times U_{D_i}(x) \times U_{E_i}(x) \tag{7}$$

Layer 3: the normalization of the rule weights is represented by this layer. It determines the proportion between the weight of the i ruler and the total weight of all the rulers as shown in (8).

$$\overline{W}_i = \frac{W_i}{\Sigma_i W_i} \tag{8}$$

Layer 4: each node i in this layer is a node which is calculated as shown in (9).

$$O_i^4 = \overline{W}_i \times f_i = \overline{W}_i \times (p_i x + q_i x + r_i) \tag{9}$$

Layer 5: the cell at this layer adds up all the input signals and outputs a value that roughly corresponds to the desired function as shown in (10).

$$O_i^5 = \sum_i \overline{W}_i \times f_i \tag{10}$$

ANFIS uses hybrid learning algorithm is shown in Figure 9. The role of learning is the adjustment of fuzzy inference system parameters. These are therefore the premises parameters and consequent parameters. In other words, the learning process is used to optimize the premise parameters (membership function parameters) and the consequence parameters (the output coefficients) [28], [29].
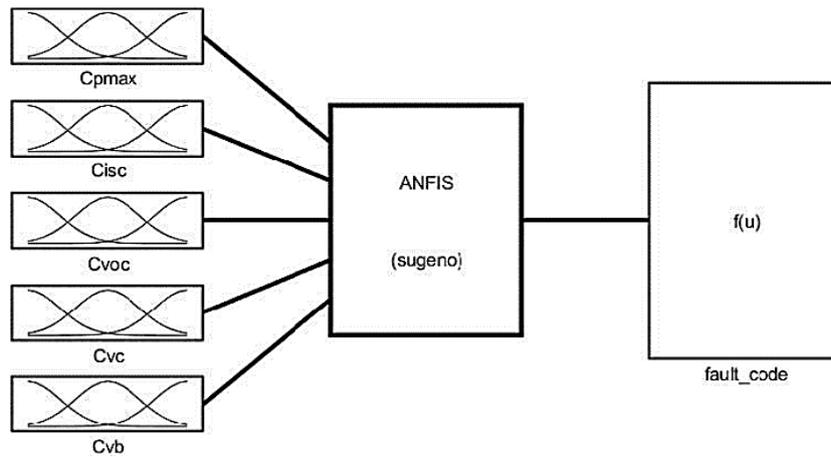
Figure 9. System ANFIS 5 inputs, one output

The learning procedure of the ANFIS system can be done in two phases as indicated: the first aims to adjust the premise parameters while keeping the consequent parameters fixed using the error gradient backpropagation method. With this method we calculate the gradient of the error to adjust each parameter (weight), linked to the nodes by calculating the squared difference E between the predicted output and the observed output [26]:

$$E_k = \sum (d_i - x_{L,i})^2 \tag{11}$$

where N(L) is number of neurons in the L layer, d_i is desired output vector component and $x_{L,i}$ is ANFIS real output vector component.

For each parameter α_i are modified as shown in (12):

$$\Delta \alpha_i = -\eta \frac{dE}{d\alpha_i} \tag{12}$$

where η is the learning step (positive constant).

In the second phase by adjusting the consequent parameters while keeping the premises parameters fixed, this operation is done by the method of least squares, we might argue that the latter's goal is to reduce the gap between the anticipated model and the observed data [30], [31]. The learning of neuro-fuzzy systems in general is a phase which makes it possible to determine or modify the parameters of the system, in order to obtain an optimal combination. Utilized experimental data for training and testing purposes to enhance system intelligence and achieve realistic simulation results [32].

The input data is set several times throughout the training operation to ensure good decision-making and to lessen the estimation fault. To adapt, several iterations are necessary. Figure 10 is illustration of the ANFIS for PV fault detection state, Figure 10(a) shows training data, Figure 10(b) shows training error with 100 epochs and Figure 10(c) shows FIS output with the training data.

(a)

(b)

(c)
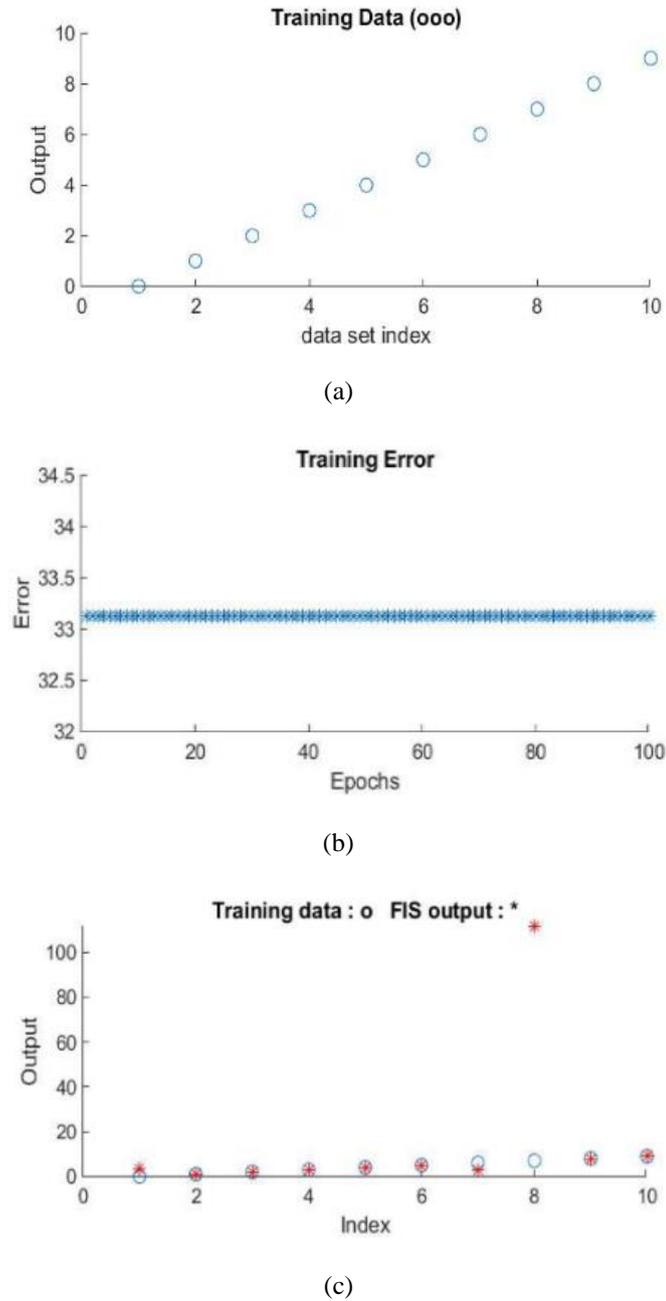
Figure 10. Illustration of the ANFIS for PV fault detection state (a) training data, (b) training error with 100 epochs, and (c) red stars indicate FIS output, fully tracked the blue circles that represent the training data

We use five membership functions (C_{Pmax}, C_{Voc}, C_{Isc}, C_{Vc}, C_{Vb}) and one for output (default code) as shown in the Figure 11 with six diverse clusters for the input, Figures 11(a) to 11(e) for each variable and introduce six inference rules that can satisfactorily generalize the fault condition output. The fuzzy thinking mechanism diagram of ANFIS is shown in Figure 12. Sixteen rules conditional control the operation where the columns represent the five inputs and one output data. It can be seen from the figure that if C_{Pmax}=0.5, C_{Isc}=0.875, C_{Voc}=0.796, C_{Vc}=3.68 $\times 10^5$, C_{Vb}=0.5, then fault code=0.113 are respectively predicted by ANFIS approach. And the Figure 13 shows the ANFIS surfaces viewers. These results approve the capability of the ANFIS algorithm to detect PV faults with high and speed accuracy under every irradiance and temperature conditions.

(a)

(b)

(c)

(d)

(e)
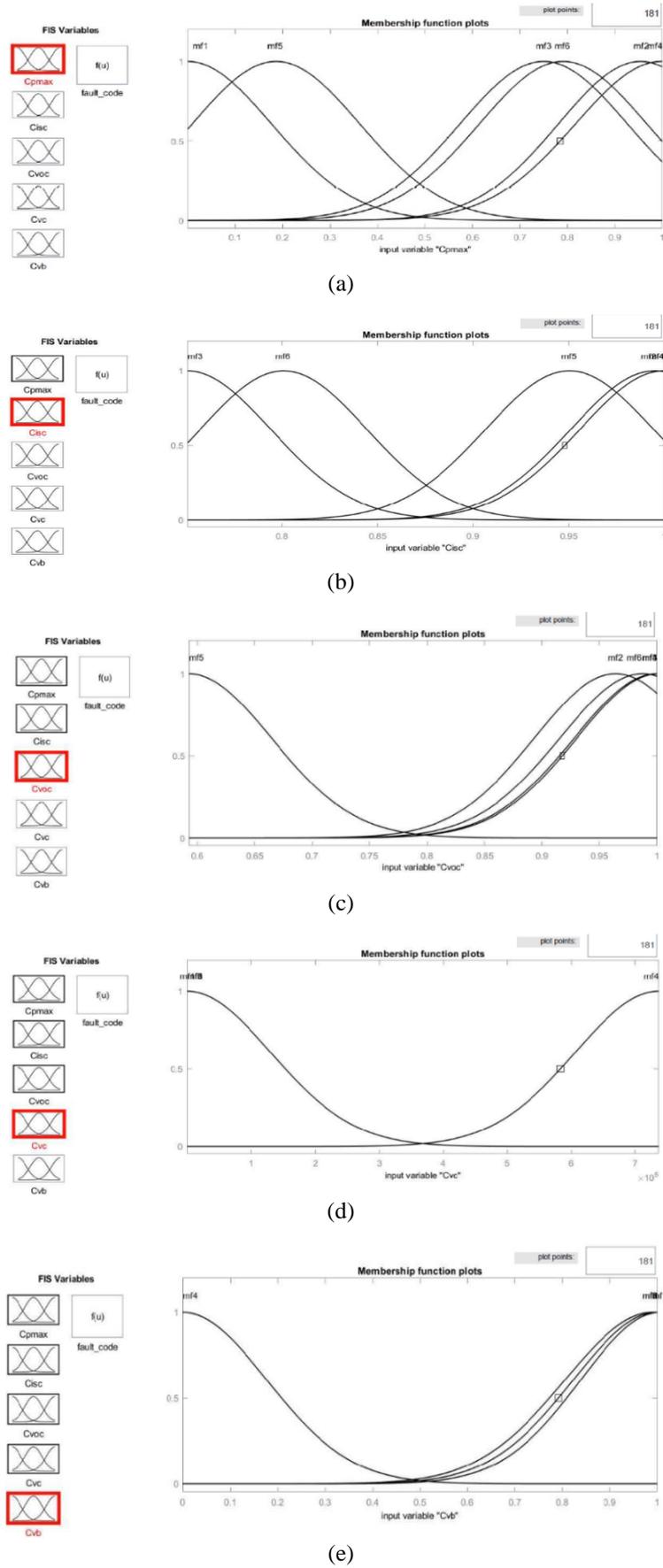
Figure 11. MFs with six diverse clusters for the input (a) C_{Pmax}, (b) C_{Isc}, (c) C_{Voc}, (d) C_{Vc}, and (e) C_{Vb}
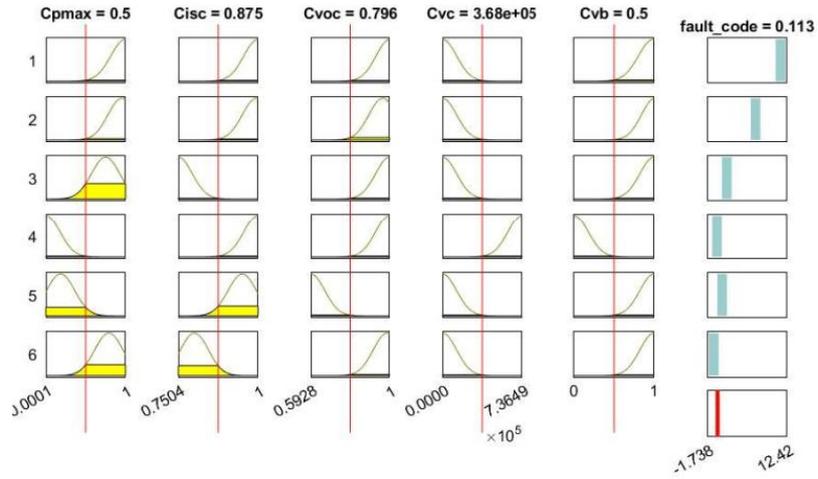
Figure 12. The fuzzy thinking mechanism diagram of ANFIS
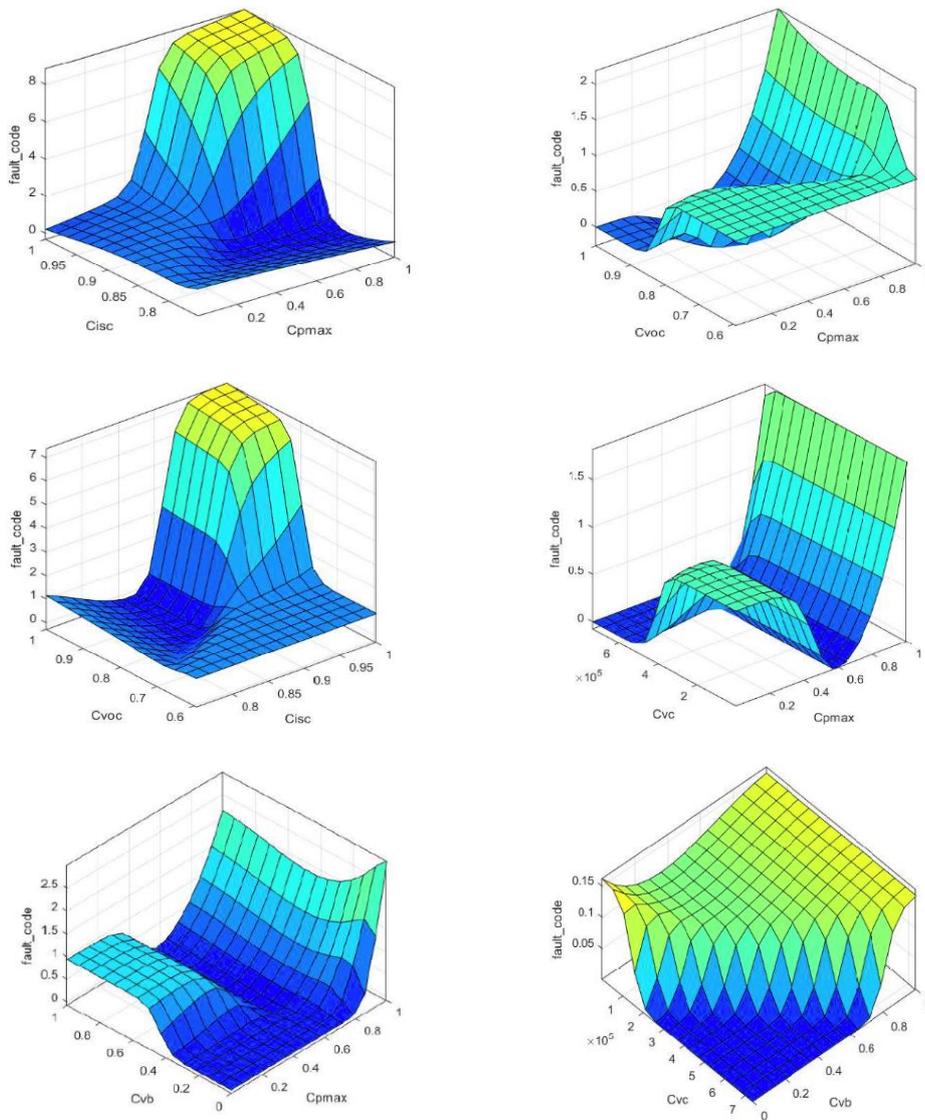
Figure 13. The ANFIS surfaces viewers

4.   CONCLUSION

We have presented, in this paper, an algorithm of a fault detection and localization system of PV system based on control by ANFIS model of neuro-fuzzy networks, the learning of this model was done after several attempts to arrive at an optimal architecture and minimize the number of model parameters. The retained architecture of ANFIS with five inputs and six Gaussian-type membership functions. This new intelligent algorithm to detect nine faults in the PV system. The study and analysis of the results obtained show that the smart method made by the ANFIS algorithm achieves better prediction performance with homogeneous and reliable results.

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