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Fault diagnosis of power converters in a grid connected photovoltaic system using artificial neural networks

Introduction. *The widespread use of photovoltaic systems in various applications has spotlighted the pressing requirement for reliability, efficiency and continuity of service. The main impediment to a more effective implementation has been the reliability of the power converters. Indeed, the presence of faults in power converters that can cause malfunctions in the photovoltaic system, which can reduce its performance.* ***Novelty.*** *This paper presents a technique for diagnosing open circuit failures in the switches (IGBTs) of power converters (DC-DC converters and three-phase inverters) in a grid-connected photovoltaic system.* ***Purpose.*** *To ensure supply continuity, a fault-diagnosis process is required throughout all phases of energy production, transfer, and conversion.* ***Methods.*** *The diagnostic approach is based on artificial neural networks and the extraction of features corresponding to the open circuit fault of the IGBT switch. This approach is based on the Clarke transformation of the three-phase currents of the inverter output as well as the calculation of the average value of these currents to determine the exact angle of the open circuit fault.* ***Results.*** *This method is able to effectively identify and localize single or multiple open circuit faults of the DC-DC converter IGBT switch or the three-phase inverter IGBT switches.* References 26, tables 4, figures 8.

Key words: **grid connected photovoltaic system, artificial neural network, power converters, open circuit failure of IGBT, fault detection.**

Вступ*. Широке використання фотоелектричних систем у різних застосуваннях висунуло на перший план нагальні вимоги до надійності, ефективності та безперервності обслуговування. Основною перешкодою для ефективнішого застосування була надійність силових перетворювачів. Справді, наявність несправностей у силових перетворювачах може спричинити збої в роботі фотоелектричної системи, що може знизити її продуктивність.* ***Новизна****. У цій статті представлена методика діагностики обриву кола в перемикачах (IGBT) силових перетворювачів (перетворювачів постійного струму та трифазних інверторів) у фотоелектричній системі, підключеній до мережі.* ***Мета****. Для забезпечення безперервності постачання потрібен процес діагностики несправностей на всіх етапах виробництва, передачі та перетворення енергії.* ***Методи****. Діагностичний підхід заснований на штучних нейронних мережах та вилучення ознак, що відповідають обриву кола IGBT-перемикача. Цей підхід ґрунтується на перетворенні Кларка трифазних струмів на виході інвертора, а т акож розрахунку середнього значення цих струмів для визначення точного кута обриву кола.* ***Результати****. Цей метод дозволяє ефективно ідентифікувати та локалізувати одиночні або множинні несправності розімкнутого кола IGBT-перемикача DC-DC перетворювача або IGBT-перемикача трифазного інвертора.* Бібл. 26, табл. 4, рис. 8.

Ключові слова: **фотогальванічна система, підключена до мережі, штучна нейронна мережа, силові перетворювачі, відмова IGBT при обриві кола, виявлення несправностей.**

Introduction. Conventional energy resources remain strategic for energy production, but meeting the world's growing energy needs will be a major challenge in the near future. This is in line with an imminent global energy shortage situation, as well as the depletion of reserves of such energy resources in a way that is dangerous for future generations. At the same time, the use of these energy sources poses a significant environmental risk to the future of our planet due to the release of greenhouse gases. As a result, producing electrical energy from clean, non-polluting, and renewable sources has become a global necessity and a topic of interest in our societies [1, 2].

During the past decade, photovoltaic (PV) energy has become a reliable source of energy, which is based on the conversion of solar radiation into electrical power. In the last decade, solar energy has proliferated and now promises to play a leading role in the current energy transition. The cumulative capacity of the PV installations around the world has increased to reach more than 500 GW [3].

Photovoltaic systems technologies, including power converters, have reached the stage where they can be used in stand-alone, grid-connected or hybrid power systems. In recent years, the evolution of PV systems studies has led to the design of efficient systems [4]. Despite of all this evolution, no system is immune to failures. For this reason, a significant deal of effort is now being put into the monitoring and diagnosis of PV systems. One of the parts most prone to faults in a PV system is the power converters, which includes the DC-DC and the three-phase inverter. These faults, which are mainly caused by the degradation of the switch components such as open circuit faults in IGBT's, can decrease performance and even lead to total unavailability of the PV system. As a result, these faults will reduce the productivity of the system [5].

Several researchers have investigated the behavior of power converters in case of an internal fault and have developed diagnostic and identification methods, focusing in particular on the open circuit failure of IGBT switch. In [6, 7], the authors discuss new approaches based entirely on the artificial neural network (ANN) and the Clarke transformation as a detection tool for locating an interrupt fault of the IGBT switch in a three-phase inverter. In [8, 9], new feature extraction approaches using three-phase load currents are proposed, in [9], the diagnostic method used is based on neural network (NN) that has learned from a database derived from the analysis of the three phase currents. Another study based on discrete wavelet transforms (DWT) and NN for fault detection was proposed in [10, 11]. The presented technique allows the identification of single and multiple faults in IGBTs, where the detection mechanism is based on the analysis of the currents. In [12] the Park's vector technique was presented. The principle of this method is based on the conversion of three phase system (I_a, I_b, I_c) into a two-phase system (I_d, I_q). In this case, the Park contour is a circle whose center is the origin. This contour is considered as a simple and interesting reference index, since these deviations indicate the anomalies that can affect the system. The fixed reference frame is used to evaluate the evolution of currents at the occurrence of open circuits in the inverter. Another diagnostic method proposed in [13-16] is based on calculating the average values of the three phase currents, the absolute mean values are used as primary variables to formulate diagnostic indicators. In [17-20], the authors use fuzzy logic as an expert system for fault detection of open circuit faults in a three-phase inverter, this technique is based on processing and analyzing the load currents. In [21], the author proposes a fault detection technique for three-phase inverters based on monitoring the RMS value and the average values of the three-phase currents.

This paper proposes a technique for detecting and locating the open circuit fault of the IGBT's switches of the power converters in a grid connected photovoltaic system using the ANN assisted by the Clarke transformation. This approach requires the three phase currents (I_a, I_b, I_c) to calculate the Clarke currents as well as the fault angles related to the open circuit faults of the IGBT switch of the DC-DC converter or the three-phase inverter. These features are then fed as inputs into the ANN structure, the resulting output of the ANN is used to identify and locate faults that may exist in the DC-DC converter or the three-phase inverter.

Description of the grid connected photovoltaic system. Figure 1 shows the model of a photovoltaic system connected to the grid through DC/DC boost converter and a three-phase inverter. In this model we have fixed the weather conditions such as incident solar irradiance and temperature.

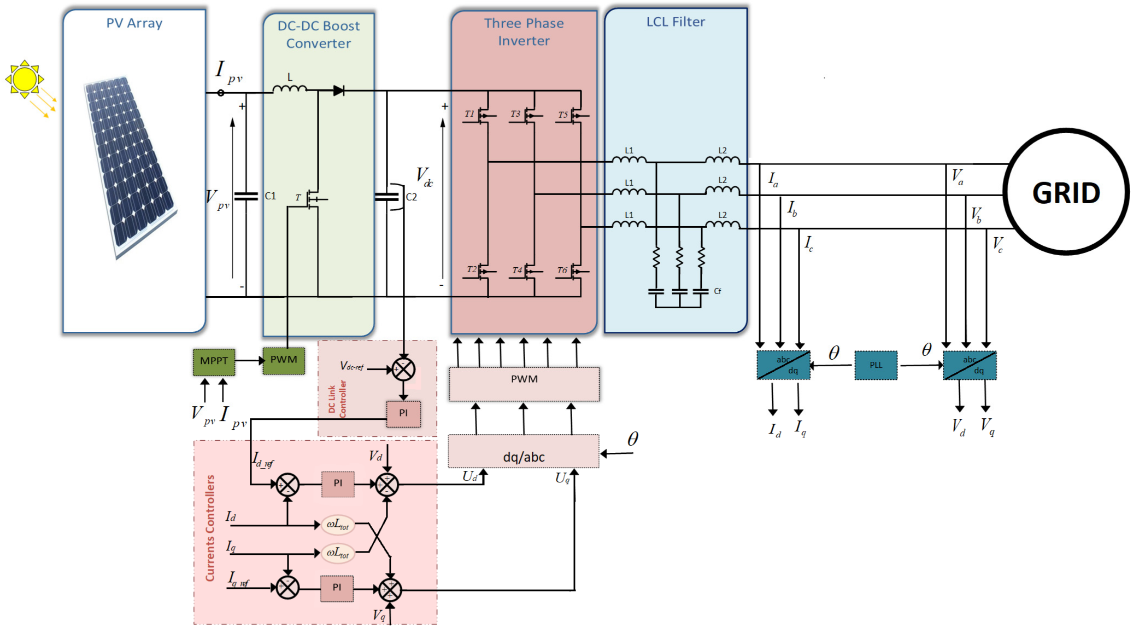

Fig. 1. Grid connected PV system diagram

Photovoltaic cell. The photovoltaic energy results from the direct transformation of rays from the sun into continuous electrical power by means of cells. Thus, to obtain sufficient power, the cells are connected in series and in parallels [2, 22]. The connection between the power source and the distribution grid is provided by a series of power converters. The power stage is an essential element in a photovoltaic system; it is usually formed by a DC-DC converter connected to an inverter via a DC bus.

Implementation of DC side control. A DC-DC boost converter is mainly composed of an inductor L, a switch T, a diode and input capacitance C_1 to smooth the output voltage of the PV panel. It is used to extract the maximum power available at the PV array at any time and transfer it. This converter acts as an interface between two elements. It ensures the transfer of the maximum power supplied by the generator via a control action [3, 23].

A maximum power point tracker (MPPT) control associated with a DC-DC converter, allows a PV array to be operated to produce the maximum of its power whatever the weather conditions (temperature and irradiation), the converter control places the system at the maximum operating point. A power converter controlled by an MPPT will optimize the photovoltaic conversion chain. In this paper a Perturb and Observe algorithm is employed (Fig. 2) because of its simplicity and easy implementation [3, 23].

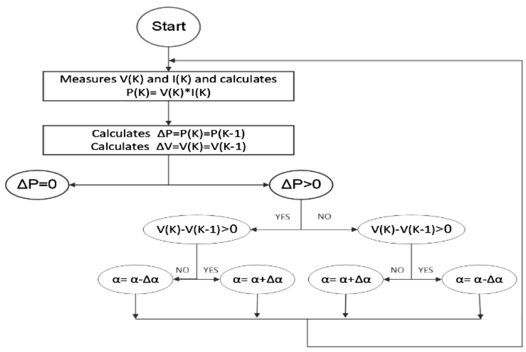

Fig. 2. Flowchart of Perturb and Observe algorithm

Implementation of AC side control. A two level three-phase inverter is used for converting the DC energy into AC energy, where the six switches (T1-T6) are employed in the main circuit of the inverter. The DC bus C_2 is the link between the two converters and its purpose is to act both as a power storage element and a filter [24].

To achieve stable operation of the system, the voltages and currents in the system must be monitored and controlled. This is accomplished by implementing the control part [24, 25].

Figure 1 presents a control strategy for a three-phase inverter connected to grid; this control technique includes two numbers of control loops. Voltage control is provided to maintain the DC link voltage constant; the boost converter is controlled by the duty cycle of the MPPT. Then the voltage measured from the boost V_{dc} is compared to the reference voltage $V_{dc\text{–}ref}$. For the voltage control a PI controller is employed [24, 25].

The three-phase currents of the inverter (I_a, I_b, I_c) and the grid voltages (V_a, V_b, V_c) are transformed into to dq reference frame (I_d, I_q) and (V_d, V_q). To obtain a unit power factor in a grid-connected PV system, the current reference $I_{q\text{–}ref}$ is considered to be zero. The output from the voltage controller is the current reference $I_{d\text{–}ref}$. The voltage reference for the PWM is the PI current controller's outputs which are given by [24, 25] in (1):

$$\begin{cases} U_d = V_d - \omega \cdot L_{tot} \cdot i_q + \left(K_p + \dfrac{K_i}{s} \right) \cdot \left(i_{d-ref} - i_d \right); \\ U_q = V_q + \omega \cdot L_{tot} \cdot i_d + \left(K_p + \dfrac{K_i}{s} \right) \cdot \left(i_{q-ref} - i_q \right), \end{cases} \tag{1}$$

where U_d, U_q are the dq desired voltage references; ω is the angular frequency of the grid; K_p, K_i gains of the PI controller; L_{tot} refers to $L_1 + L_2$.

Grid synchronization. One of the most critical issues with grid-connected PV systems is the synchronization between the PV system and the grid. The phase angle θ of the grid voltage vector is the main output of the synchronization algorithm. In this paper it is extracted using phased locked loop. The phase angle used to control the three-phase inverter switches, calculate and control active and reactive power, and convert feedback variables (grid voltage and current) to a reference frame [22, 24].

The fault diagnosis approach. The reliability of power converters has always been a major concern in many power applications such as power generation. It is worth mentioning that these converters are particularly sensitive to faults in their power components IGBT's, which can be broadly can be classified as open circuit faults and short circuit faults. In our work, we focus on the open circuit fault; such a fault can lead to secondary failures in other converter components, which can lead to high repair costs [5].

Figure 3 shows the procedure for diagnosing open circuit failures that may affect the different power converters (DC-DC converter and three-phase inverter) is based on the following steps:

- application of the Clarke transformation on the three-phase currents of the three-phase inverter;
- extraction of information from the Clarke transformation;
- implementation of ANN as diagnosis method;
- identification of open circuit fault of IGBT switch.

For the feature extraction approach, the suggested defect diagnosis system takes into account the inverter output current signals. After applying the Clarke transformation to convert these three-phase currents to two-phase currents, a feature extraction technique is employed to extract the most efficient characteristics of the operating system. The system's characteristics are then determined for various operational scenarios (with and without faults). The values of the feature vectors in distinct fault instances are recorded in a fault table. This table is then used to train the ANN that will be utilized to detect and diagnose open circuit faults in the grid-connected photovoltaic system's power converters.

The extracted characteristics. The system of (2) shows the three phase currents of the inverter output:

$$\begin{cases} I_a = I_{\max} \cdot \sin(\omega \cdot t); \\ I_b = I_{\max} \cdot \sin(\omega \cdot t - 2 \cdot \pi/3); \\ I_c = I_{\max} \cdot \sin(\omega \cdot t + 2 \cdot \pi/3); \end{cases} \tag{2}$$

where $I_{\max}$ is the maximum amplitude of the current.

Applying the Clarke transformation on the system allows us to obtain the system of equation (3) [7]:

$$\begin{cases} i_\alpha = \dfrac{2}{3} \cdot i_a - \dfrac{1}{3} \cdot i_b - \dfrac{1}{3} \cdot i_c; \\ i_\beta = \dfrac{1}{\sqrt{3}} \cdot \left(i_b - i_c \right), \end{cases} \tag{3}$$

where i_α, i_β are the Clarke currents.

The average currents in the two axes (α and β) can be calculated using the following equations [7]:

$$\begin{cases} i_{\alpha mean} = \sum\limits_{j=1}^{N} \dfrac{i_\alpha(j)}{length(i_\alpha)}; \\ i_{\beta mean} = \sum\limits_{j=1}^{N} \dfrac{i_\beta(j)}{length(i_\beta)}, \end{cases} \tag{4}$$

where N defines the number of samples.

The calculation of the angle that corresponds to the open circuit fault in each switch is given by [7]:

$$\theta_f = \tan^{-1}\left(\frac{i_{\alpha mean}}{i_{\beta mean}} \right). \tag{5}$$

The range of the angle in each fault condition in the different T_i switches is shown in Table 1 [12, 26].

Table 1

The open circuit angle in each switch of the power converters

State	θ_f	State	θ_f
Healthy	[0, 2π]	T1 and T5	[π/2, 5π/6]
T1	[π/2, 3π/2]]	T1 and T6	[5π/6, 3π/2]
T2	[0, π/2] or [3π/2, 2π]	T2 and T3	[0, π/6] or [3π/2, 2π]
T3	[0, π/6] or [7π/6, 2π]	T2 and T4	[π/6, 2π]
T4	[π/6, 7π/6]	T2 and T5	[0, π/2] or [11π/6, 2π]
T5	[0, 5π/6] or [11π/6, 2π]	T2 and T6	[3π/2, 11π/6]
T6	[5π/6, 11π/6]	T3 and T5	[0, π/6] or [11π/6, 2π]
T	[0, 2π]	T3 and T6	[7π/6, 11π/6]
T1 and T3	[7π/6, 3π/2]	T4 and T5	[π/6, 5π/6]
T1 and T4	[π/2, 7π/6]	T4 and T6	[5π/6, 7π/6]

The architecture of the ANN used. The ANN system is built up of neurons with identical structures that are linked together in a manner comparable to the human nervous system's cells. It consists of a series of layers coupled in such a way that each neuron receives its input from the output of the one before it. The neurons of the input layer are connected only to the next layer while the neurons of the hidden layers have the particularity of being connected to all the neurons of the previous layer and of the next layer [10].

The input layer of our neural network has three neurons ($i_{\alpha mean}$, $i_{\beta mean}$ and θ_f), whose job is to send the input values to the hidden layer, which has 15 neurons, and the output layer, which has six neurons (Fig. 4). The system's intended output is binary (1 or 0).

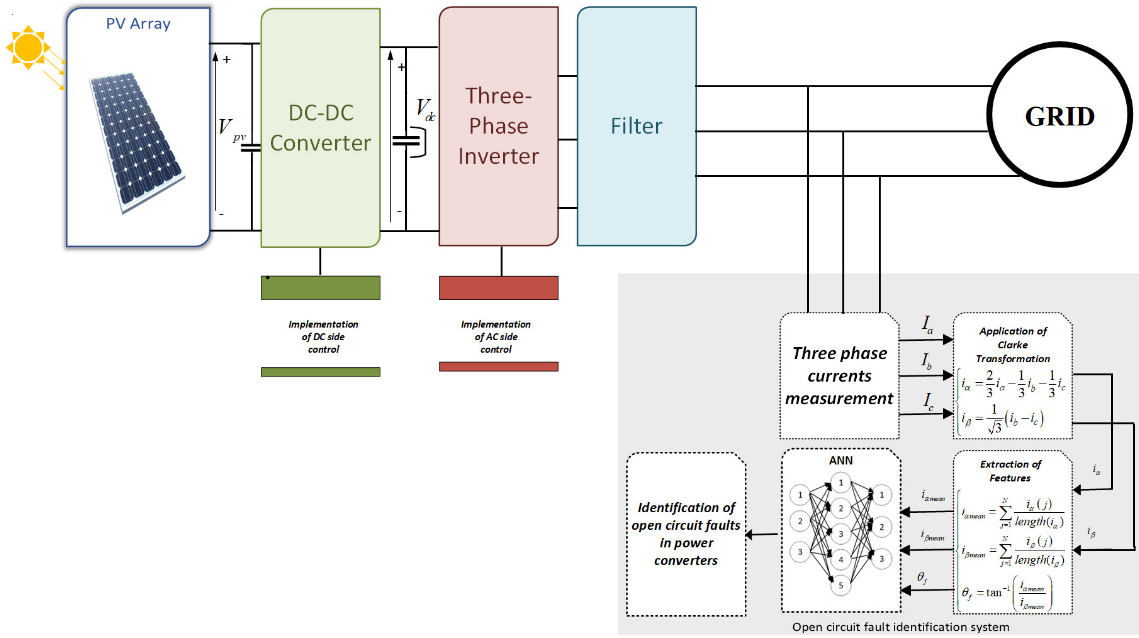

Fig. 3. Diagram of the proposed diagnostic system

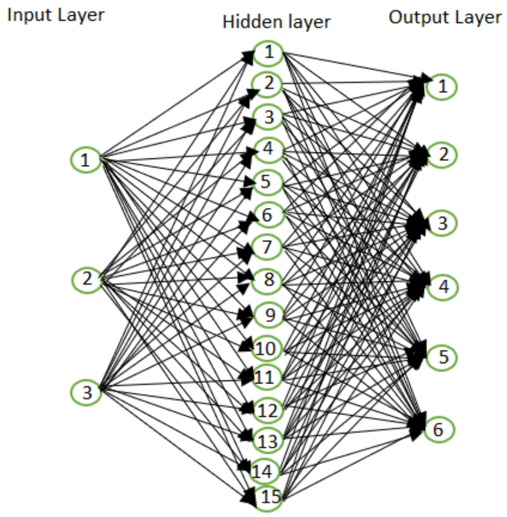

Fig. 4.The architecture of the ANN used

The desired output for the different possible fault cases at the IGBT switches of the two power converters is shown in Table 2.

Table 2

Classification of open circuit faults

State	Output	State	Output
Healthy	[0 0 0 0 0 0]	T1 and T5	[1 0 0 0 1 0]
T1	[1 0 0 0 0 0]	T1 and T6	[1 0 0 0 0 1]
T2	[0 1 0 0 0 0]	T2 and T3	[0 1 1 0 0 0]
T3	[0 0 1 0 0 0]	T2 and T4	[0 1 0 1 0 0]
T4	[0 0 0 1 0 0]	T2 and T5	[0 1 0 0 1 0]
T5	[0 0 0 0 1 0]	T2 and T6	[0 1 0 0 0 1]
T6	[0 0 0 0 0 1]	T3 and T5	[0 0 1 0 1 0]
T	[1 1 1 1 1 1]	T3 and T6	[0 0 1 0 0 1]
T1 and T3	[1 0 1 0 0 0]	T4 and T5	[0 0 0 1 1 0]
T1 and T4	[1 0 0 1 0 0]	T4 and T6	[0 0 0 1 0 1]

Validation of diagnosis method. In this part a validation of the efficiency of the developed method for the detection of the open circuit faults of power switches integrated in the power converters (DC-DC converter and three-phase inverter). A simulation of normal and faulty operation was carried out in MATLAB / Simulink environment. The normal case and all possible fault combinations are manually fed into the system, the ANN is used for the learning process, and the generated code is implemented in our simulation system.

The simulation of the system was carried out using the parameters presented in Table 3.

Table 3

The parameters of the studied system

Parameters	Values
Number of modules in series	15
Number of modules in parallel	16
The desired power, kW	51.156
Capacitor C_1, F	$6.7586\cdot10^{-5}$
Capacitor C_2, F	$5.5\cdot10^{-3}$
Inductor L, H	$3\cdot10^{-3}$
Boost frequency, kHz	5
DC-link voltage, V	700
Inverter frequency, kHz	10
Parameters of LCL filter: L_1, H L_2, H C_f, F	$4.1897\cdot10^{-4}$ $2.5138\cdot10^{-4}$ $5.0886\cdot10^{-5}$
Grid frequency, Hz	50

Simulation results. Figure 5 shows the simulation results in the healthy state and in the presence of an open circuit fault. An operation in faulty mode due to an open circuit fault on the IGBT T4 will cause the loss of the negative half-wave of the current of phase B. In another way if there is no opening of the IGBT T4 and T5 will cause a loss of positive alternation in the current of phase C.

The inputs to the system diagnostic block consist of the following characteristics ($i_{\alpha mean}$, $i_{\beta mean}$ and θ_f). The information of each scenario for the healthy case and the defective cases is summarized in Table 4.

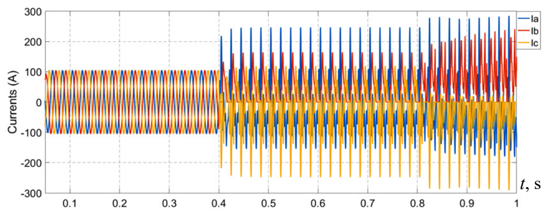

Fig. 5. Three phase currents in healthy and faulty mode

Table 4

Diagnostic indicators values

States	Parameters $i_{\alpha mean}$, $i_{\beta mean}$, θ_f		
Healthy	0.0004039	–0.004703	274.91
T1	–39.14	9.166	166.8
T2	39.17	–9.186	346.8
T3	11.59	–38.45	286.77
T4	–11.6	38.53	106.8
T5	27.52	29.37	46.86
T6	–27.49	–29.43	227
T1 and T3	–16.8	–82.43	258.5
T1 and T4	–96.12	6.134	176.3
T1 and T5	–63.08	55.82	138.5
T1 and T6	–53.36	–80.41	236.4
T2 and T3	96.23	–6.064	356.396
T2 and T4	16.89	82.44	78.42
T2 and T5	53.35	80.32	56.41
T2 and T6	63.04	–55.78	318.45
T3 and T5	79.83	26.65	18.46
T3 and T6	42.88	–86.38	296.4
T4 and T5	–42.68	86.35	116.3
T4 and T6	–79.76	–26.61	198.5
T	–0.003302	–0.000994	196.8

Neural network learning outcomes. Learning is a crucial stage in the deployment of a neural network, in which the network's behavior is modified until the desired behavior is achieved. The software MATLAB was used to do automatic learning until a very small squared error was acquired. The ANN learning base is presented in the form of table. It is represented by classes of vectors, where each class represents a type of functioning (healthy and defective), and each vector is represented by the sampled values.

The best learning performance obtained thanks to a good choice of the ANN structure and after several learning tests. The learning performance of the ANN used is evaluated by the root mean square error. In our case, the ANN reached a value of $9.1656 \cdot 10^{-21}$ after 28 iterations, as shown in Fig. 6.

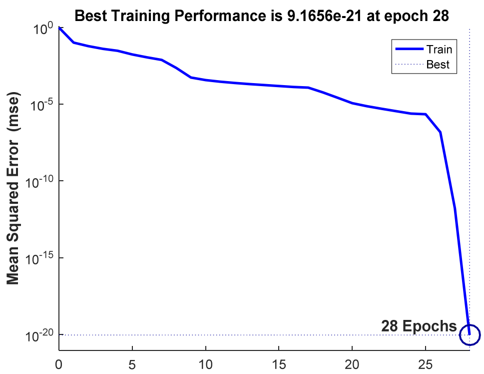

Fig. 6. Performance of the ANN

Once the ANN has been constructed (Fig. 7) and its training has achieved satisfactory performance, we move on to the step of comparing the target outputs to the simulation results. The results of the ANN test are shown below in Fig. 8.

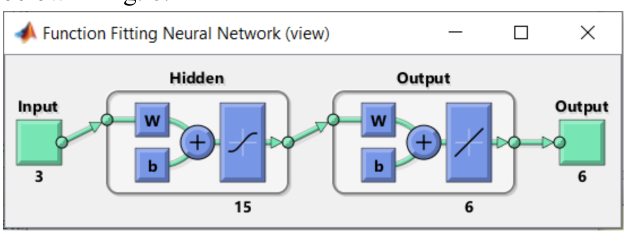

Fig. 7. The ANN used

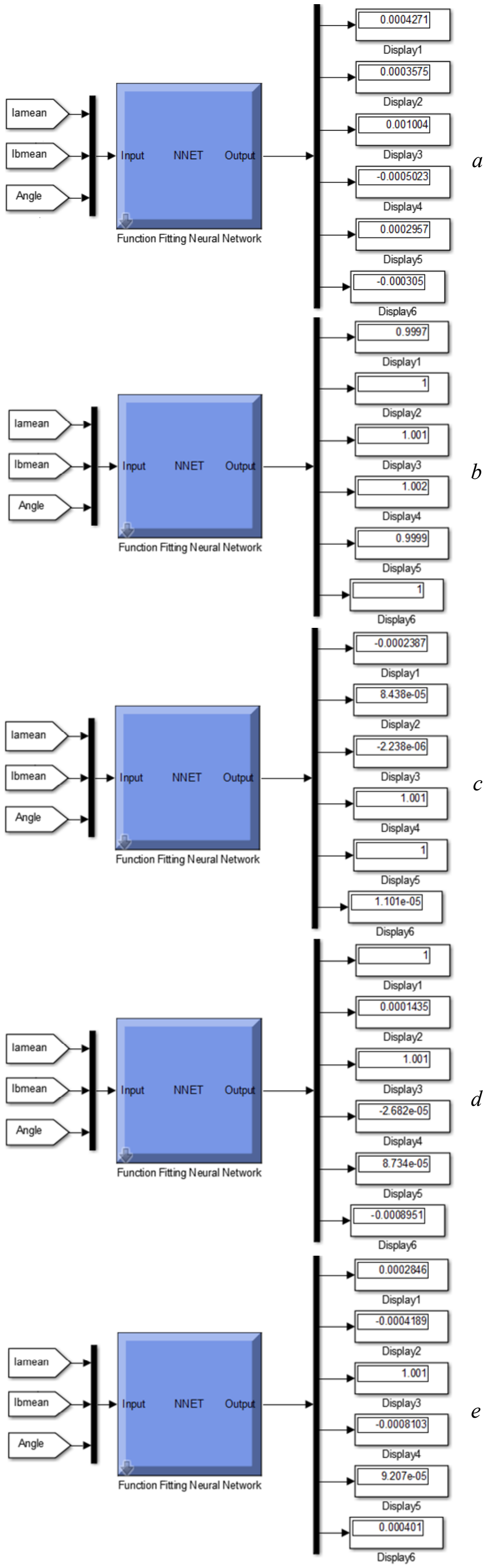

Fig. 8. Simulation results in state: (a) Healthy, (b) Fault in DC-DC Boost Converter, (c) Fault in T4 and T5, (d) Fault in T1 and T3, (e) Fault in T3

According to the results obtained during the test, it can be seen that the results of the ANN used evolve according to the desired results for the different types of operation.

Conclusion. This paper proposes the use of artificial neural networks to classify open circuit faults in IGBTs of power converters in photovoltaic systems. The resulting network has a simple design with an input layer, a decision output layer, and a hidden layer of 15 neurons, as well as graphical outputs that display the learning results. After multiple learning tests, it can be established that a good choice of artificial neural network structure results in greater learning performance. The simulation results, as shown above, demonstrate the reliability and performance of the fault detection and diagnosis system created for the photovoltaic system's power converters.

Conflict of interest. The authors declare that they have no conflicts of interest.

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