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Neuro-Fuzzy fault detection method for photovoltaic systems

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Abstract

In this work we present a faults detection method for photovoltaic systems (PVS). This method is based on the calculation of sets of parameters of a PV module in different operating conditions, by means of a Neuro-Fuzzy approach. The PV system status is determined by evaluation and comparison of norms based on the aforementioned parameters, with threshold values. This intelligent system developed in Matlab&Simulink environment, consists on the study of the crucial information that the six parameters in normal and faulty condition contain. They are calculated using the I-V curves and synthesized by "hybrid" models. Results show that the diagnosis system is able to discern between normal and faulty operation conditions and with the same defective existence of noise and disturbances.

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Keywords: Photovoltaic system; Fault diagnosis ; Neuro-Fuzzy model; I-V characteristic analysis; Norm-test

1. Introduction

With the growth of world energy consumption and the concerns about environmental effects of fossil fuels, human society is in desperate need of renewable energy sources (e.g., solar, wind, geothermal). They are clean and eco-friendly. Among this renewable energy sources, photovoltaic (PV) energy draws a significant attention since solar energy is accessible and abundant [1].

The problem is that, differently from traditional power sources, the photovoltaic (PV) energy may have undetectable and unlearned faults in current and in voltage during the utilization in conventional overcurrent (OCPD) and in overvoltage (OVPD) protection devices.

The faults in PV plants do not only affect the performances and services of the plant but may also lead to critical and detrimental situations. In fact, without proper fault detection, the presence of faults in PV arrays not only causes power losses, but also can cause a probable fire hazard for the whole system [2]. Having considered these problems, it is of paramount importance to check the PV system status (normal

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or off-normal condition).

Accordingly, numerous PV monitoring and fault detection methods related to a definite PV model have been studied in the literature. Firstly, the traditional modeling approaches based on long-term energy yield and power losses (V-I measurement and Flash test) have been proposed [3, 4].

An extension of method using correlation function and the matter-element model was suggested to identify specific the fault types of a PV system (PVS) [5]. Furthermore, a decision tree model has been proposed for the detection and classification of defects in PV systems [6]. Additionally, the capacitance measurement (ECM) and the time domain reflectometry (TDR) for fault detection in PV array were introduced [7].

Finally, intelligent system (based on neural network, Fuzzy systems or Neuro-Fuzzy network) for automatic detection of faults in PV fields were proposed [8-10]. Interpreting I-V curve characteristic by applying flash test to determined fault type [11, 12] and using signal processing to detect online fault in PV system [13, 14]. However, none of the previous works have presented a complete algorithm and methodology for faults detection and classification that is able to represent the real system effectively.

After reviewing relevant works in PV systems diagnosis area, this paper presents an intelligent faults diagnosis system, based on "Norm-test"of the six attributes of I-V curves.

The detection system initially uses an I-V curves estimation by the ANFIS PV model simulator. Secondly it uses a Norm-test to generate the difference among sets of parameters calculated in different conditions at operating conditions. The diagnostic method can detect the fault and classify the specific fault type and it deals with noises and disturbances. The models of the PV system and the whole diagnostic procedure has been developed on Matlab&Simulink environment.

This intelligent procedure of fault detection has been tested for a a-Si:H triple layer amorphous module (Uni-Solar ES-62T), that is installed at the MIS laboratory renewable energy platform at the University of Picardie Jules Verne, Amiens (France).

2. Photovoltaic module modeling in ANFIS

For modelling the PV systems for real time applications, two main approaches can be followed: the "classic" one based on equivalent electric circuits [15÷19] and the "innovative" one based on meta-heuristic algorithms (Neural network, Fuzzy logic and Neuro-Fuzzy systems) [20, 21]. In this work we have chosen an Adaptive Neuro-Fuzzy Inference System (ANFIS), using the most common Fuzzy system architecture that is Sugeno model, because it is less time consuming and more transparent than other Fuzzy models.

The advantage of the proposed representation is that Neuro-Fuzzy model of a PVS includes both the ability of neural networks to learn from the experience (training/testing phase) and, then, to provide a quite precise output when real-time input are used, and the potentiality of Fuzzy systems to establish relationships between input and output variables. On other hand this type of modelling works well if there are a large number of data to be used for training. To obtain these data, we have employed a hybrid simulator PV model, implemented in Matlab Simulink/ Simscape / SimElectronics / Pspice library [13, 14,22].

By the hybrid model a set of I-V curves of a PV module are calculated in different operating conditions, defined by means of PV module temperature (T_{PV}) and global irradiation on the plane of the array (G_{PoA}). For each I-V curve, four parameters (I_{mpp},V_{mpp}, I_{sc}, V_{oc}) are extracted. Knowing the first four parameters, we can define and calculate other two parameters named S_1 and S_2, where:
- S_1 is the incremental derivative ratio calculated considering the following relevant points in the I-V curve: short current point (0; I_{sc}) and maximum power point (V_{mpp} ; I_{mpp});
- S_2, is the incremental derivative ratio considering the two points (V_{mpp} ; I_{mpp}) and open circuit (V_{oc} ; 0). S_1 and S_2 have the following expressions:

$$S_1 = \frac{I_{mpp} - I_{sc}}{V_{mpp} - V_{oc}} \qquad S_2 = \frac{0 - I_{mpp}}{V_{oc} - V_{mpp}} \tag{1}$$

Our target is to apply ANFIS techniques to model PV module starting from the data calculated by means of hybrid model. The following steps are performed : 1) loading input(T_{PV}, G_{PoA}) and output (I_{mpp},V_{mpp}, I_{sc}, V_{oc}, S_1, S_2); 2) generation of ANFIS system; 3) training and test ANFIS system. In this way, instead of saving the whole I-V curves, just six values (I_{mpp},V_{mpp}, I_{sc}, V_{oc}, S_1, S_2) are considered and used as output target of the general ANFIS model in normal and faulty conditions. Fig.1 shows qualitativelly how the faults can affect the shape of an I-V curve in normal operation conditions (red line) where three distict zones can be identified : 1) a slightly sloped region above short circuit point; 2) a bend or "knee" in the curve in the region of the maximum power point; 3) a steeply sloped region below open circuit point;.

Six characteristics (named Cx) are shown in fig.1(see the dashed red lines) that differ from the I-V curve in normal operating condition for some symptoms due to the presence of faults.

Each fault generates a set of symptoms which can be identified by means of the variations of one or more parameters. In Table 1 the six charateristics are listed, for each Cx the corrispondent following information are provided: 1) the zone of I-V curve affected by the fault, 2) the involved parameters (i.e. the parameters that have changed their values compared to the ones calculated starting from the I-V curve on the same operating conditions but without faults), 3) the related symptoms.

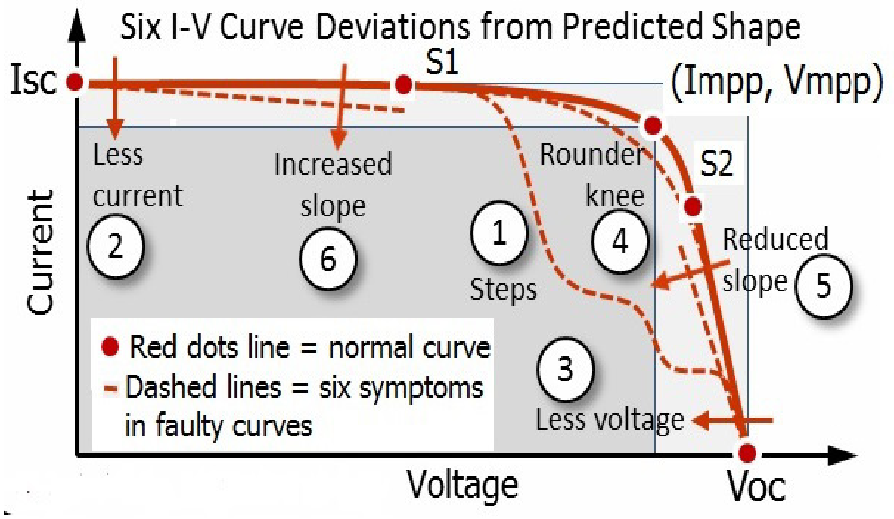

Fig.1. Pattern of six points along the I-V curve

Table 1. Presents of different symptoms identified

Characteristic	Zone	Involved parameters	Name of symptoms
C1	2	I_{mpp},V_{mpp}	Change maximum power point, (rounder knee)
C2	1	V_{oc}	Smaller V_{oc}
C3	3	I_{sc}	Smaller I_{sc}
C4	2	-	Step(s) in the I-V curve
C5	3	S_2	Reduced slop near V_{oc}
C6	1	S_1	Increased slop near I_{sc}

The ANFIS PV model is trained also in faulty conditions by using as output the previous six parameters, but it has a further input, that is the fault that has determined the variations of the parameter values. So, the PV model will be represented in the subsequent theoretical diagnostic procedure as a "black box", in which all data of the PV system are intrinsically contained in a more compact and effective manner.

Finally, taking in consideration the STC (Standard Test Condition, G_{PoA} = 1000 W/m^2 and T_{PV}=25 °C), the I-V curves of a PV module in normal and faulty operating conditions are calculated and they are shown in fig.2. The numerical values of the six parameters for each I-V curve are calculated and reported in Table 2. Based on these figures it is possible to achieve a quantitative comparison related to the fault impact on each I-V curve. This manner of proceeding consists in exploiting numerical information from the faulty I-V curve of a PV module. These pieces of information will be used in the next phase of diagnostic procedure in order to perform the fault detection and classification using the Norm-test.

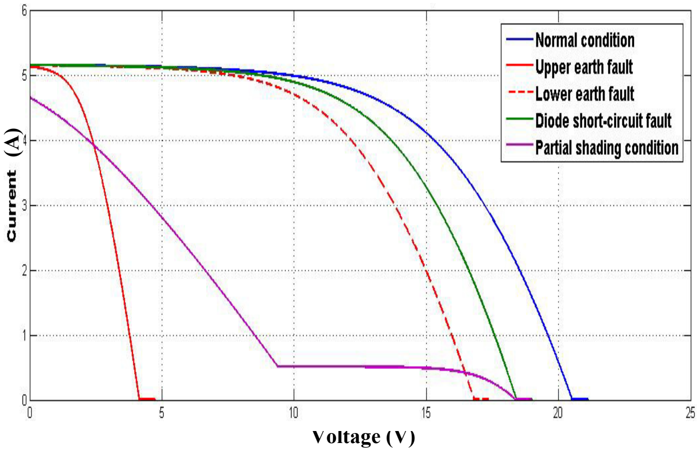

Fig.2. I-V curve in normal and faulty conditions

Table 2. Six parameters values in normal and faulty conditions

	Normal operation conditions	**Upper earth Fault**	**Lower earth Fault**	**Diode short-circuit fault**	**Partial shading condition**
Parameter					
I_{mpp} (A)	4.314	3.857	4.276	4.305	2.618
V_{mpp} (V)	14.370	2.463	11.478	12.858	5.380
I_{sc} (A)	5.155	5.127	5.153	5.154	4.666
V_{oc} (V)	21.123	4.743	17.419	19.019	18.975
S_1 (A/V)	-0.058	-0.514	-0.076	-0.066	-0.380
S_2 (A/V)	-0.638	-1.692	-0.719	-0.698	-0.192

3 “Norm-test“ of the six attributes of an intelligent system of faults diagnosis

We have found that the Neuro-Fuzzy PV model performs well and fast in both normal and faulty conditions and we have identified it with six attributes that allow us a nearly complete knowledge of the I-V characteristic.

The problem is that we used hybrid model, develop in Matlab / Simscape Environment, to simulate the behavior of the PV system (module), in this way we have neglected the impact of disturbances, that are always present in real PV systems, on the calculations of the six parameters. In fact, for example, irradiance is measured by pyrometer and cell temperatures are measured according to IEC61724 standard with a thermocouple and these signals have some noises due to both the variations of the measured variables and to measurements error. There also to consider effect of the presence of current and voltage transducers.

Finally we have to considered the noise and errors introduced by the acquisition systems that are used to handle real data. It is worth highlighting that it is be more precise and simpler characterize and model the PV system by means of synthesized data by means of numerical models (e.g. hybrid model); however for an effective diagnostic procedure. this type of characterization it is not enough because a real system behavior is not adequately modelled for all the considerations made previously about noise and disturbances.

In this context we consider in our model the losses linked to the measurements. The values that we attribute to the measurement noise and errors can be seen as a sort of systematic error that occurs in the same entity every time that measurements are performed (offset or bias). In this context, we assume an accurate knowledge of the measurement apparatus. Therefore the considerations made in paragraph 2 needs to be revised modifying the “Neuro-Fuzzy PV model” from ideal conditions (that is: two inputs and six outputs), to a new one where it has been added a new inputs that stands for the contributions of disturbances and noises to the Neuro-Fuzzy PV model. As matter of fact we have: in normal condition, three inputs and six outputs, whereas in faulty condition, four inputs (the fourth is the faulty type) and six outputs. ”Fig.6 (step 1) shows the “Neuro-Fuzzy PV system” in ideal, normal and faulty condition.

3.1 Fault diagnostic system

The proposed theoretical diagnostic procedure is carried out in four consecutive steps:

1. **Identification of the object of fault diagnosis;**
2. **Generation of the residual signals;**
3. **Calculation of norms;**
4. **Evaluation of test norms and classification of system status.**

First of all, we want to define the objects of our procedure for detection of faults; so we define three Neuro-Fuzzy PV blocks, that model the PV module in three conditions, such as: “ideal”, “normal” and “faulty”.

To fulfill our analysis of fault diagnosis these blocks are compared in pairs:

-“ideal” and “normal”;

-“ideal” and “faulty”.

These are the two cases that we want to analyze and they can be used in reality for on-line diagnosis system. Given the operation condition (irradiance and PV cell temperature), the Neuro-Fuzzy block model of an “ideal” PVS is the reference. It presents all the desired features in terms of values of input and output variables, that we suppose are perfectly constants and not affected by noises and disturbances, on the basis of which we evaluate the other two blocks. On the contrary, the “normal” and “faulty” Neuro-Fuzzy PV models recreate the monitored mode of operation of the PV module that reflects the real behavior that can be expected in practice or not. As already mentioned, to show the real behavior of the PV module we chose to add the effect of real losses measurements (noises and disturbances), assuming that their values are constant and they arise in the same entity every time that the measurement campaign is repeated. After identification of the blocks, we can start the effective diagnosis procedure, that is developed for each value of T_{PV} and G_{PoA}, and which is based on residuals calculation and Norm-test.

Specifically residuals calculation procedure consists on the generation of twelve residual signals through the comparison of a target signal output (generated always from the ideal system) and estimated output (generated as the first from the normal system and then, as second from the fault system).

We denote the set of input variables (T_{PV}, G_{PoA}) by I_1, the set of noises and disturbances that can occur in a PV system by I_2 and, the set of possible faults (diode short-circuit, lower earth fault, upper earth fault, partial shading condition) by I_3. Then we denote by X the set of the output variables(six parameters), that assume different values in ideal (X_{id}), normal (X_{nm}) and faults (X_{ft}) conditions. Then the residuals (RX) have to be evaluated, specifically the generic i-th component $RX_{id,nm}$ and $RX_{id,ft.}$ are expressed in this way :

$$RX_{id,nm.} = X_{id} - X_{nm} \qquad RX_{id,ft.} = X_{id} - X_{ft} \tag{2}$$

After the generation of residue, for each value of PV temperature and irradiation, the norm test includes the evaluation of all the values of norms N_n in normal condition and N_f for each type of fault.

So we can define two Euclidean real norms:

$$\left|N_n\right| = \sqrt{\sum_{i=1}^{6}\left(\mathrm{RX}_{\mathrm{id,nm}}\right)^2} \qquad \left|N_f\right| = \sqrt{\sum_{i=1}^{6}\left(\mathrm{RX}_{\mathrm{id,ft}}\right)^2} \tag{3}$$

- N_n, that is the numerical value of norm calculated by a comparison between the Neuro-Fuzzy PV model in ideal condition and the Neuro-Fuzzy PV model in normal condition;
- N_f, that is the numerical value calculated by a comparison of the Neuro-Fuzzy PV model in ideal condition and the Neuro-Fuzzy PV model in faulty condition.

Figs.3 a) and b) show graphically what has been explained mathematically, pointing out the passage between the generation of residues in the normal and faulty case and the calculation of norms N_n and N_f. The norms N_n and N_f have to be compared with suitable reference values in such a way not only to identify if there is just a normal disturbance in the PV system but also to detect the correct fault that is eventually present in the system.

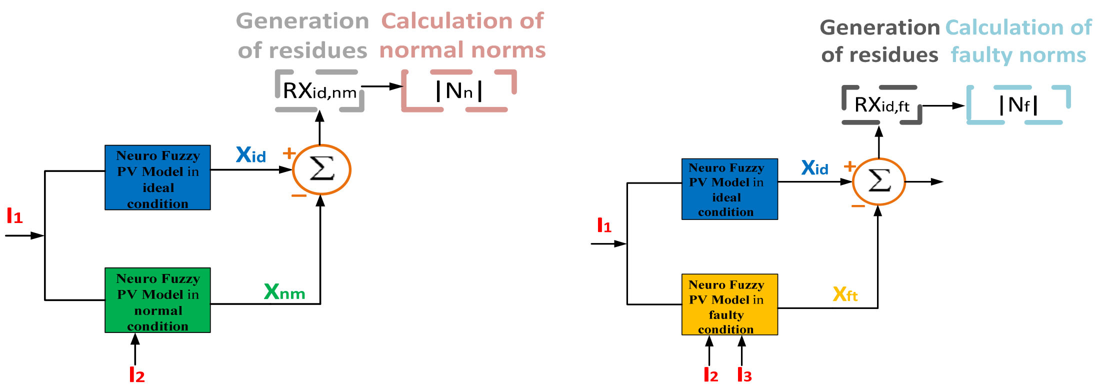

Fig.3. (a) Block diagram from the residual generation in the normal case to the calculation of norm N_n
(b) Block diagram from the residual generation in the faulty case to the calculation of norm N_f

The reference value that allows to understand if there is or not a fault in the system is called "threshold", S, and we have fixed it equal to 0.9. This value has been calculated by means of random simulations, where in each simulation the values of the measured variables (G_{PoA}, T_{PV}, current and voltage) are generated with a given error (determined by the type of sensors). A threshold value equal to 0.9 is an optimal value that represents a compromise between an high probability of fault detection and a low probability of a false alarm. In practice, interpreting the threshold as a constant boundary, we can define these two rules valid for the PV diagnosis system based on norms evaluation :
- if the value of norm is under the boundary it means that the PV system is in normal condition;
- if the value of norm is over the boundary it means that the PV system is considered in faulty condition.

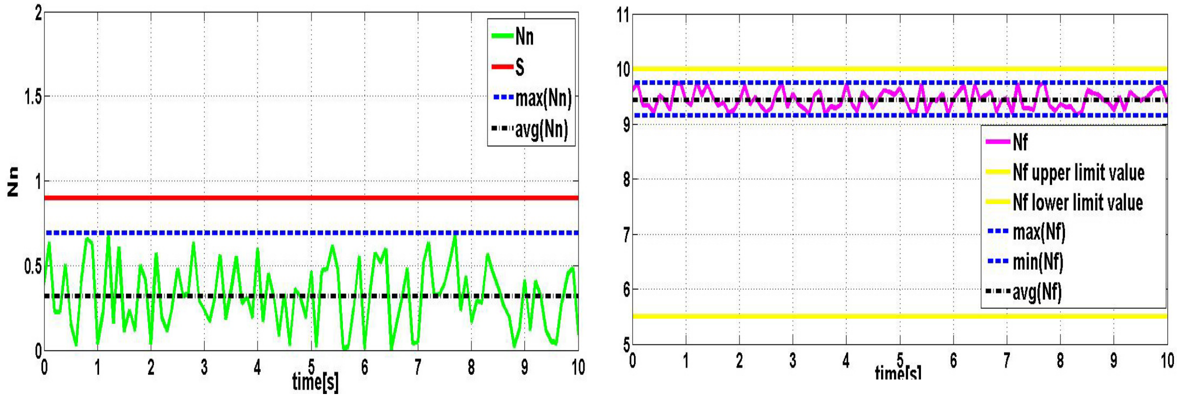

Fig.4.(a) Trend of normal norm for a PV module (b) Trend of faulty norm for a PV module in partial shading

Finally the main results of the diagnosis and fault detection procedure are summarized in figs.4 a) and b), where the trends of the calculated norms in both normal and partial shading condition are plotted.

Two important considerations can be made even in such a noisy and disturbing condition.

For the Neuro-Fuzzy PV model in normal condition (PV module in normal state), the norm signal value N_n is nearby zero and does not exceed the limitation of threshold S according to its maximum values max(N_n); instead, for the Neuro-Fuzzy PV model in faulty condition (PV module in partial shading condition), the norm signal value N_f is far from the zero value and exceed the threshold value S; besides N_f is in the range distinctive of the Partial shading condition, i.e. comprised between an upper and a lower limit constant values.

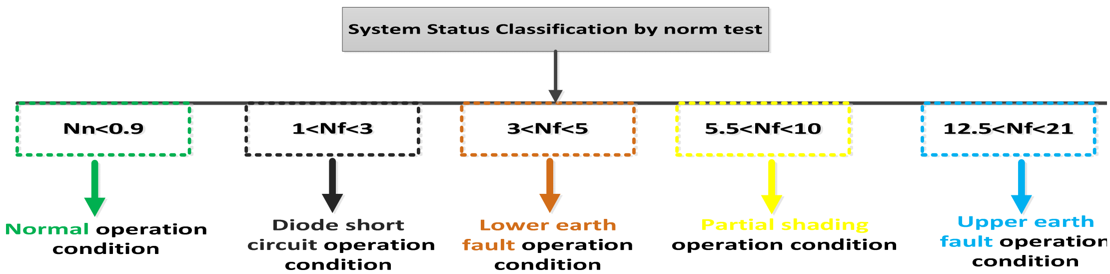

Fig.5. PV system status classification by Norm-test

After establishing and showing the rules of theoretical diagnostic in the normal and partial shading condition, we can extend and make the same considerations for the other type of faults.

Table 3. Minimum and Maximum norms numerical values in normal (at STC) and faulty conditions

	Normal operation conditions	Diode short-circuit fault	Lower earth fault	Partial shading condition	Upper earth fault
Norms values	0.318÷0.694	1.103÷2.962	3.006÷4.963	5.650÷9.758	12.720÷20.648

In this context we realize a classification by Norm-test , as shown fig.5, where the correspondence between ranges of N_n or N_f and normal or faulty operating condition is established. To prove this system status classification by Norm-test, Table 3 displays the maximum and minimum norms numerical values, for the Standard Test Condition (STC) in both operation cases of normal operation condition and of faulty condition of the PV system (diode short-circuit fault, lower earth fault, partial shading condition and upper earth fault).

Finally, Fig.6 shows the general flowchart of the proposed intelligent diagnostic system. It summarizes what has been developed about diagnostic in PV systems.

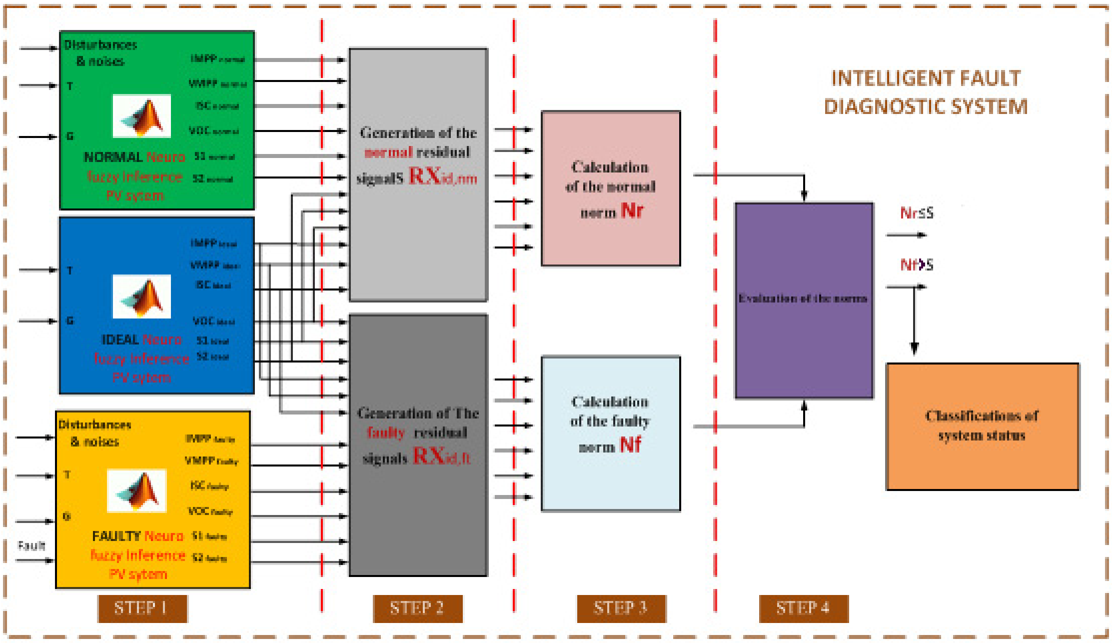

Fig.6. General flowchart of the intelligent fault diagnostic system

4. Conclusions

In this work, an intelligent fault diagnosis system, in the MATLAB&Simulink environment, has been developed. It includes: a Neuro-Fuzzy model of PV modules, I-V characteristic analysis of the six attributes, and the application of a Norm-test. The main idea of the proposed system of diagnosis and fault detection of a PV module is based on a periodical inspection of the I-V curve six parameters calculated by using an hybrid model.

Through this parameters extraction we can recreate, at first, the PV system as a "Neuro-Fuzzy PV system" and, secondly, we define the theoretical PV system status by the norms evaluation in normal and faulty condition, according to a certain threshold value. Finally cataloged these norms information, the intelligent fault diagnostic system effectiveness is ready to be checked in a PV system in a real time application.

The Neuro-Fuzzy model is very flexible, so it can be extended to PV module strings and PV array quite easily; in fact, using either data coming from numerical models or measurements, it is possible to have the I-V curves (for example of a string) and then to calculate the six attributes. Of course, when a

PV system is considered other faults have to be considered mainly due to the presence of cables that connect the PV modules.

Future research aims to verify experimentally the proposed method; besides the proposed intelligent diagnostic method has to be intended as a "general method;" so additional work has to be carried out in the following areas:

- considering other PV module technologies (silicon crystalline, thin film and organic cells);
- extension of the proposed methodology to a PV generator made by many modules and strings.
- continuing the diagnosis studies considering also the AC part of the PV system (converter).

Nomenclature

PVS	photovoltaic system
T_{PV}	temperature of PV cells/module (°C)
G_{PoA}	global irradiation on the plane of the array (W/m^2)
STC	standard test condition of the PV module ; T_{PV} = 25°C, G_{PoA} = 1000 W/m^2, AM=1
I_{mpp}	current of maximum power point (A)
V_{mpp}	voltage of maximum power point (V)
I_{sc}	short-circuit current (A)
V_{oc}	open-circuit voltage (V)
S_1	incremental derivative ratio between the point (0 ; I_{sc}) and the point (V_{mpp}; I_{mpp})
S_2	incremental derivative ratio between the point (V_{mpp}; I_{mpp}) and the point (V_{oc} ; 0)
I_1	set of input variables (T_{PV}, G_{PoA})
I_2	set of noises and disturbances that can occur in a PV system
I_3	set of possible faults (diode short circuit fault, lower and upper earth faults, partial shading)
X_{id}	set of the output variables(I_{mpp}, V_{mpp}, I_{sc}, V_{oc}, S_1, S_2) in ideal condition
X_{nm}	set of the output variables(I_{mpp}, V_{mpp}, I_{sc}, V_{oc}, S_1, S_2) in normal condition
X_{ft}	set of the output variables(I_{mpp}, V_{mpp}, I_{sc}, V_{oc}, S_1, S_2) in faulty condition
$RX_{id,nm}$	residual signals generated from the difference between X_{id} and X_{nm}
$RX_{id,ft}$	residual signals generated from the difference between X_{id} and X_{ft}
N_n	Norm, Euclidian distance between X_{id} and X_{nm}
N_f	Norm, Euclidian distance between X_{id} and X_{ft}

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