Auto-diagnosis of faults in photovoltaic pumping systems

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Abstract

This article presents the synthesis of the work carried out with a view to proposing an auto-diagnosis tool for faults in a photovoltaic pumping installation. During operation, all modules of the pumping system are likely to experience faults that can lead to the progressive degradation of performance or the total shutdown of the system. The photovoltaic system studied here consists of modules such as the photovoltaic field, the boost converter, the inverter, the motor, the pump and the filtration unit. Matlab/Simulink was used for the modeling of the entire system. The auto-diagnosis tool based on the artificial neural network allows the collection and processing of data at the end of which a response is returned to the user on the nature of the faults listed in easily interpretable signatures and codes. The diagnosis method used is that of estimating the parameters knowing their values when the modules are in good working order. The residual curves are plotted for each of the modules of the system. Analysis of these curves shows that the algorithm reacts effectively when faults appear; this demonstrates the robustness of the auto-diagnosis tools developed as part of this work.

Keywords: auto-diagnosis, solar pumping, defaults, artificial neural networks

Introduction

Abrupt production shutdowns due to faults in production systems are costly and very detrimental to performance and service quality. The situation can be more critical when there is no efficient maintenance policy in place (Kiata and al., 2024). The operation of photovoltaic pumping installations is also affected by the risks of cessation of activities due to possible breakdowns that may occur at various links in the pumping chain (Boussaibo and al. 2023). During operation, faults are inevitable on a photovoltaic installation. Examples include open circuit faults, short circuit faults, connection faults, and total or partial shading faults of the photovoltaic panels (Triki-Lahiani and al., 2018; Madeti and al., 2017). At the level of static converters, we can note the short circuit of the transistor and the fault of the output capacitor. At the pump level, we can cite the power supply fault, the obstruction of the pipes, damage to the blades, the short circuit of the windings, etc. (Kiata and al., 2024). In the absence of a system for monitoring the operation of the installations, undetected faults are likely to worsen and/or lead to other faults on the other modules of the installation (Boussaibo and al., 2023). It is therefore wise to develop monitoring, detection and alert tools in the event of the occurrence of faults on photovoltaic pumping installations in order to facilitate decision-making that can protect the various equipment of the installation. Several approaches for fault detection in PV systems, based on models, have been reported in the literature.

Regarding the diagnosis in photovoltaic panels, some methods are also proposed in the literature. Among them, several model-based fault diagnosis methods have been proposed and include the converter. The best of them focus on the converter part of the PV system, on open circuit faults (Malik et al., 2022) or on short circuit faults on insulated gate bipolar transistors (Madeti et al., 2017). Some works also address an approach for sensor faults by focusing only on the converter output (Abuelnaga et al., 2021). Todizara et al., (2017) propose the use of the least squares method for the detection of shading and mismatch faults. Ayang (2020) developed diagnosis tools for the PV/chopper/load subsystem, using analytical diagnosis methods such as parametric estimation and active disturbance rejection controls. The results of testing these controls on the subsystem show that the states and disturbances are well estimated; this proves the robustness of the estimators used. Assuming a 5% tolerance, defects are detectable, localizable, and identifiable by state estimation and structural analysis of the residuals against threshold values. There are other non-electrical methods that allow crack detection on PV panels. These include mechanical bending tests, photoluminescence and electroluminescence imaging, and thermography tests (Ahn et al., 2017; Quan et al., 2017). Bandou et al., (2011) proposed a diagnosis and repair support tool that uses case-based reasoning methodology, with the aim of ensuring proper operation and facilitating maintenance strategies for photovoltaic pumping installations. Bonsignore et al., (2014) developed a neuro-fuzzy fault detection method that is a combination of neural networks and fuzzy logic for photovoltaic systems. This method is based on calculating sets of parameters of a PV module under different operating conditions, using a Neuro-fuzzy approach. The results show that the diagnosis system is able to distinguish between normal and faulty operating conditions and with the same faulty existence of noise and disturbances. Grichting et al., (2015) presented a cost-effective algorithm based on fuzzy logic to detect arc fault in a photovoltaic system. According to the authors, good results can be expected when the detector works with DC-AC and not as a standalone device. Ducange et al., (2011) used fuzzy logic to compare the measured power of a PV system and the estimated power. The results showed that the system is able to recognize more than 90% of fault conditions, even in the presence of noisy data. The faults sought are: broken cells, progressive shading and short circuit.

Regarding the electrical part of pumps, Khodja (2007) developed an intelligent system for real-time monitoring and automatic diagnosis of induction motor faults. Chakroune et al., (2020) conducted a study to demonstrate the effectiveness of fuzzy logic for fault diagnosis of induction machines. The simulation results demonstrated the importance of fuzzy logic, based on signal classification, for fault detection. Bessam (2016) developed a tool for analyzing and detecting faults in asynchronous machines based on intelligent techniques such as neural networks and NANFIS. The system aims to detect, locate and identify internal faults in the stator and rotor of the asynchronous machine. Chouidira et al., (2019) proposes the detection and localization of faults in induction machines using neural networks. The results of their work demonstrated that the application of artificial neural networks based on effective values plays an important role in detecting and localizing faults with high accuracy.

In view of all the work in the literature presented in this section, it can be noted that diagnosis apply in most cases to faults that can be identified through the behavior of directly measurable physical quantities. This article aims to extend self-diagnosis to other modules of the photovoltaic pumping system and to other faults that are not necessarily diagnosed through measurable physical graders.

2. Materials and methods

2.1. Simulink model of the pumping and auto-diagnosis system

Figure 1 shows the Simulink model of the photovoltaic pumping system to which the self-diagnosis module is associated. The system consists of modules such as the PV generator, the chopper, the inverter, the asynchronous motor, the centrifugal pump and a filtration unit. In order to simulate faults and instantly obtain responses in the different modules, we duplicated each module of the system. The first module constitutes the normal operation (without failure) and the second module is considered as faulty. In practice, the different modules operating without faults are replaced by a database of the system in normal operation provided by the manufacturer. For reasons of presentation of Figure 1, we connected the auto-diagnosis module only at the level of the PV generator.

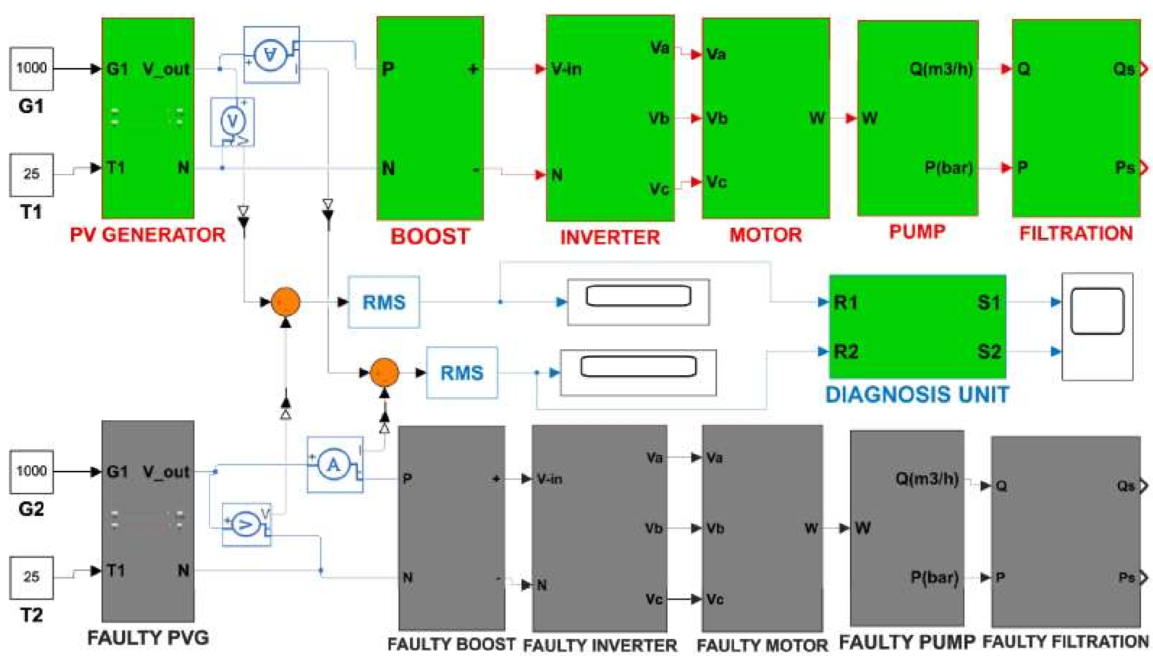

Fig.1: Simulink model of global system

2.2. Flowchart of the auto-diagnosis algorithm

Figure 2 represents the architecture of the neural network-based fault self-diagnosis algorithm. The implementation of the fault auto-diagnosis algorithm requires first obtaining the various parameters relating to the normal operation of the system to be auto-diagnosed.

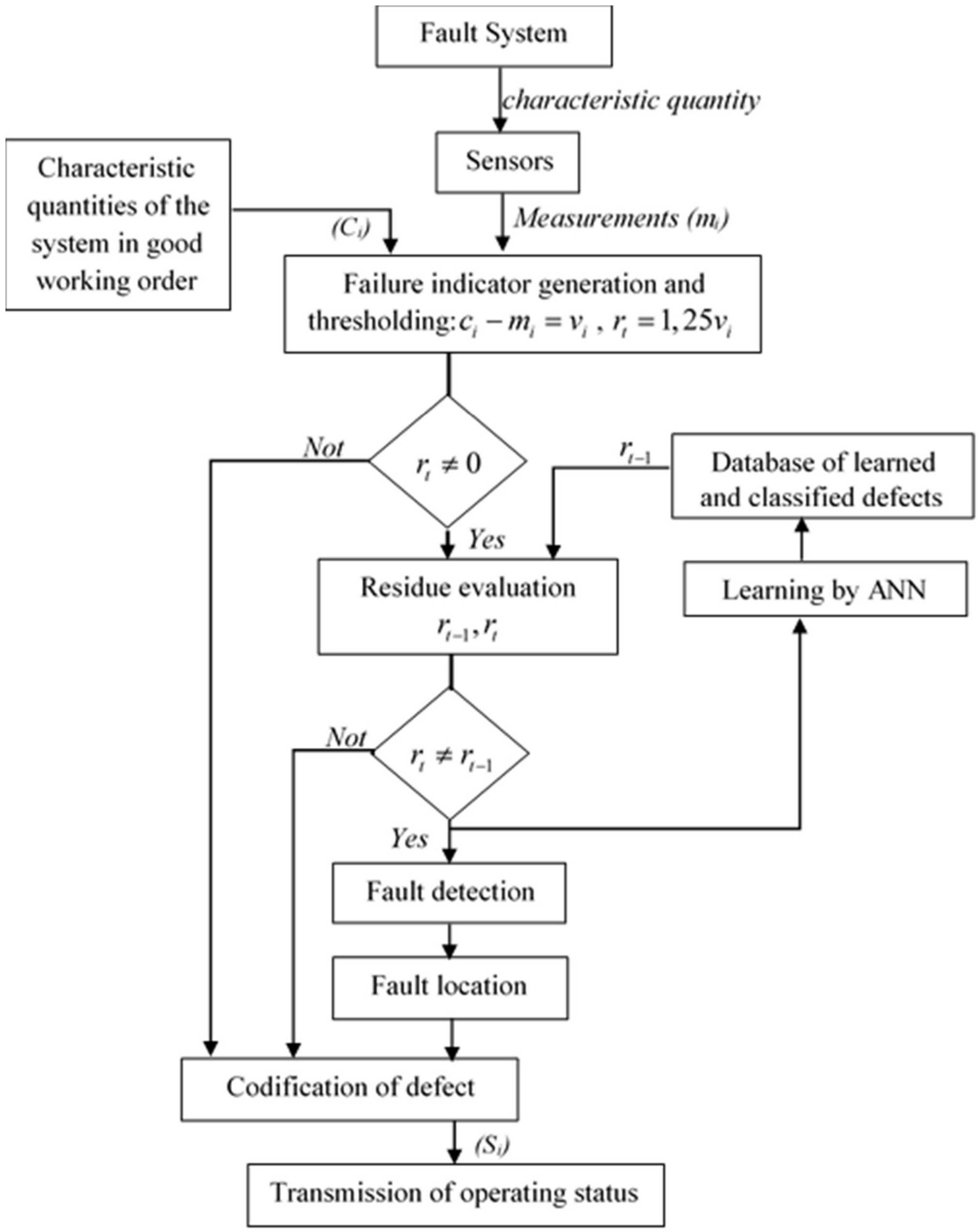

Fig. 2: Auto-diagnosis flowchart.

These values are classified in the matrix $c_i = [c_1, c_2, \cdots c_n]$. At the beginning, the algorithm receives the operating parameters from the system to be self-diagnosed instantly (m_i) through the relevant sensors. These measurements are successively compared with those contained in the system database in normal operating state $(c_i - m_i = v_i)$. The value v_i obtained following this comparison allows us to conclude on the operating state; but in order to avoid making erroneous decisions, this value is in turn compared to a threshold for the generation of residues (r_t) or symptoms of the system. The thresholding depends on the parameter being evaluated. For example, for the internal temperature of a PV cell, $T = 22°C$, the threshold is set to $27,5°C$, i.e. a heating of 25% of its value in the normal operating state. Subsequently, depending on the value of the residual, the algorithm can perform the following tasks as desired:

- Provide user with information that the system is in good working order, if the residual is zero $(r_t = 0)$;
- Evaluate the residue in the case where it is non-zero $(r_t \neq 0)$.

The case where the residual is different from zero corresponds to the detection of a failure in the system. This residual is directly coded for transmission if it already appears in the database of learned and classified defects $(r_t = r_{t-i})$. Otherwise, the residue does not exist in this database $(r_t \neq r_{t-i})$, the algorithm must therefore learn it. The new fault thus detected is learned, classified, coded and transmitted to the user.

The auto-diagnosis algorithm uses artificial neural networks (ANN) to learn the newly detected defects through the gradient backpropagation algorithm, presented in the figure 3 follow.

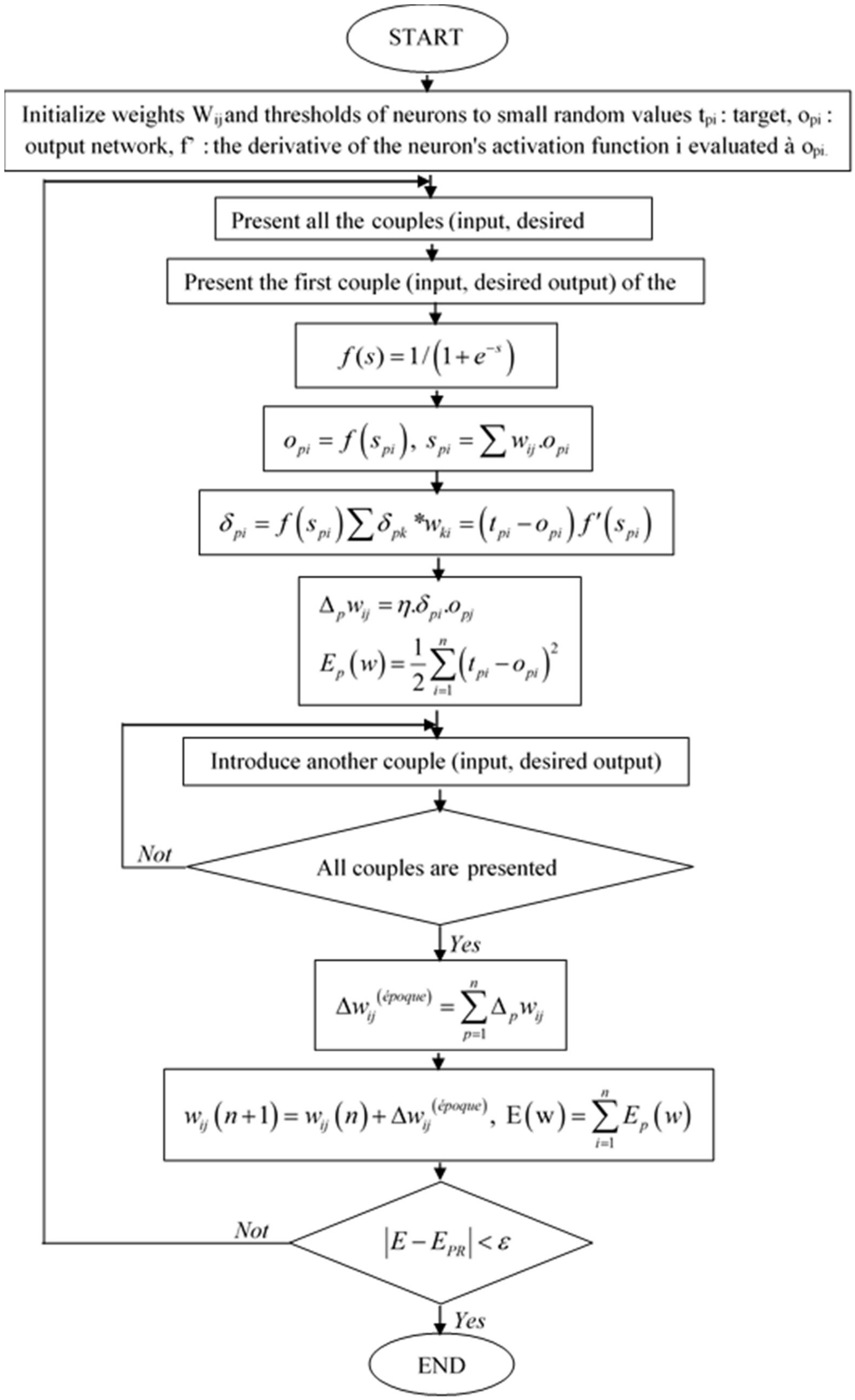

Fig.3: Backpropagation algorithm

2.3. Development of defect signatures

Table 1 below shows the classification of some faults recorded in the auto-diagnosis module with their signatures.

Table.1: Classification of some defects and signatures

Module	Défaut	Signature
PV Generator	Normal operating state	0010
	Shading of a photovoltaic panel at 50%	0011
	Shading of a photovoltaic panel at 100 %	0012
	Increase in series resistance	0013
Boost	Normal operating state	0020
	Switch short circuit (IGBT)	0021
	Open circuit of the switch (IGBT)	0022
	Defective output capacitor	0023
Inverter	Normal operating state	0030
	1^{st} arm switch short circuit	0031
	1^{st} arm switch open circuit	0032
	Faulty control circuit	0033
Motor	Normal operating state	0040
	Single-phase cut-off 1	0041
	Single-phase cut-off 2	0042
	Two-phase cut-off 1	0043
Centrifugal Pump	Normal operating state	0050
	Partial increase in load torque	0051
	25% pressure loss	0052
	Pump blocked	0053

3. Results

3.1. Training parameters of artificial neural networks

Before implementing the backpropagation algorithm that allows the auto-diagnosis strategy to learn from the fault-related residuals, it first underwent automatic training using Matlab/Simulink software until the smallest possible squared error was obtained. For the first neural network, the smallest mean squared error was obtained after 22 iterations, for the second after 64 iterations and after 56 iterations for the third ANN as shown in Table 2 below which summarizes the different results obtained for the three neural networks used.

Table 2 : Training parameters of artificial neural networks

NEURAL	*Input layer*	*Hidden layers*	*Output layer*	*Number of iterations*	*Root mean square error*
ANN N°1	*2*	*4-5*	*2*	*22*	*3,547e-23*
ANN N°2	*6*	*8-6*	*2*	*64*	*9,176e-20*
ANN N°3	*2*	*3-4*	*2*	*56*	*5,242e-21*

3.2. Implementation of the auto-diagnosis algorithm for faults

Each fault is applied after the transient state has elapsed (after start-up) and then eliminated after a sufficient time for its appearance. The duration of each sampling is a few seconds. Furthermore, the characteristic curves of these faults are stored in digital form (matrix). In this section, we will present the different results obtained by applying the proposed auto-diagnosis strategy. These are the characteristic curves of the residues (symptoms) in each faulty module.

3.2.1. Auto-diagnosis of PV generator

Figure 4 shows the behavior of the residual voltage and current from the photovoltaic generator during fault-free operation.

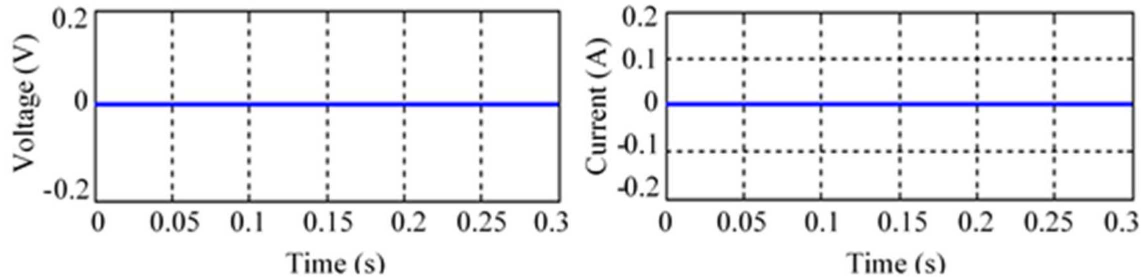

Fig.4: Characteristics of the residual voltage and current of the PV generator during normal operation

The characteristic curves of the residual voltage and current during this type of operation are straight lines with zero ordinate. This proves that the system is operating normally, and (r=0). The auto-diagnosis algorithm transmits the signature “0010” to the user. The curves in figures 5 and 6 below are those of the residual voltage and current at the output of the PV generator for 50% and 100% shading respectively.

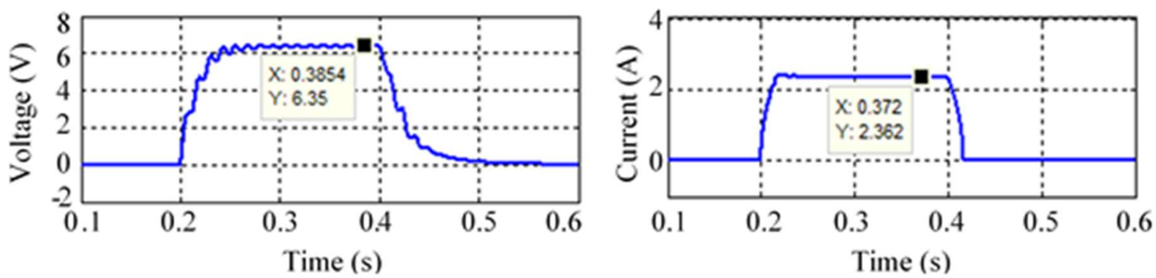

Fig. 5: Characteristics of PV generator residues at 50% shading

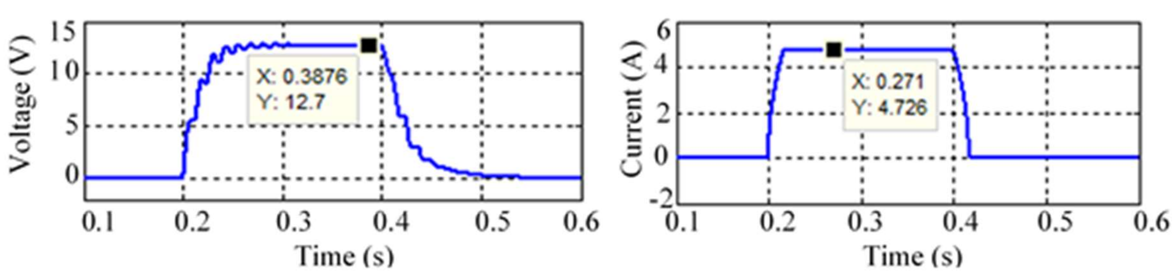

Fig. 61 : Residual characteristics of a PV generator at 100% shading

Unlike the residual characteristic during normal operation, the residuals generated by the algorithm for partial or total obstruction of the PV generator cells do not have zero ordinates during operation. This proves that the auto-diagnosis algorithm has detected a fault in the PV generator. The signatures transmitted to the user in the case of 50% shading are "0011" and "0012" for 100% shading. 100% shading of the PV generator cells can be likened to the absence of sunlight (totally overcast sky or nighttime operation).

Figure 7 below shows the residual characteristic obtained when the series resistance RS of the PV generator cells increases. The signature transmitted during such a fault is "0013".

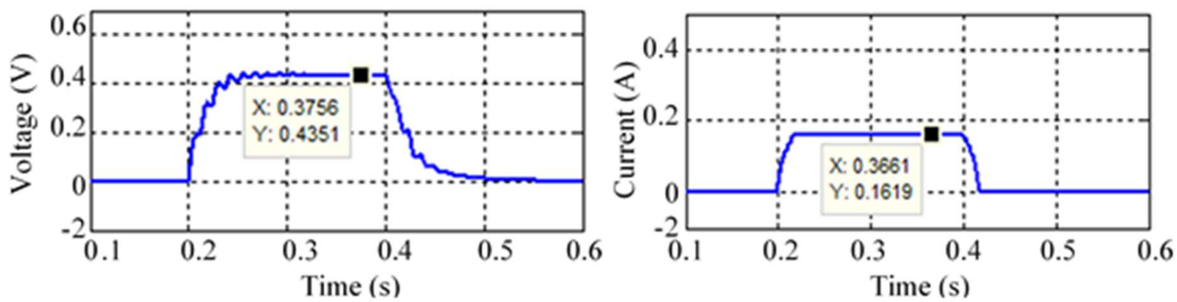

Fig. 7: Residual characteristic of a PV generator for Rs=1,55 Ohm.

3.2.2. Auto-diagnosis of boost

In the boost converter, we test the operation of the auto-diagnosis algorithm for a short circuit of the control switch. This type of fault greatly affects the behavior of the converted voltage but also the current. Figure 8 below illustrates the characteristic of the residual voltage and current as a function of the operating time, for a short circuit of the IGBT switch. The information transmitted in this fault case is “0021”.

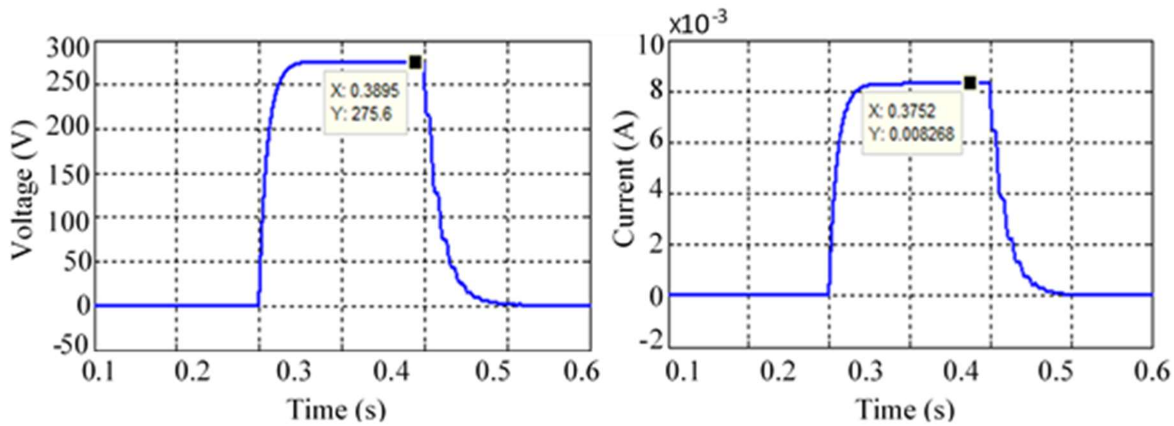

Fig. 8: Residual characteristic for a short circuit of the boost converter control switch

3.2.2. Auto-diagnosis of inverter

The motor that drives the submersible pump is of two types depending on the needs: three-phase motor or single-phase motor. For industrial applications, the three-phase motor is generally used. This type of motor necessarily requires a three-phase voltage inverter. Figures 9, 10 and 11 below present the residuals provided by the auto-diagnosis algorithm for an open circuit and a short circuit of the second switch of the first arm of the inverter and for a faulty control circuit respectively. The information transmitted to the user for these different faults are respectively “0031”, “0032” and “0033”.

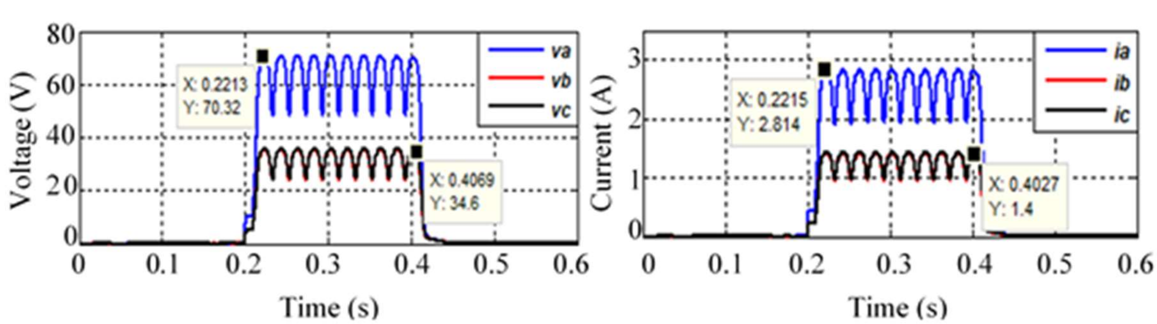

Fig. 9: Characteristic of the residues during an open circuit of the second switch of the first arm of the inverter.

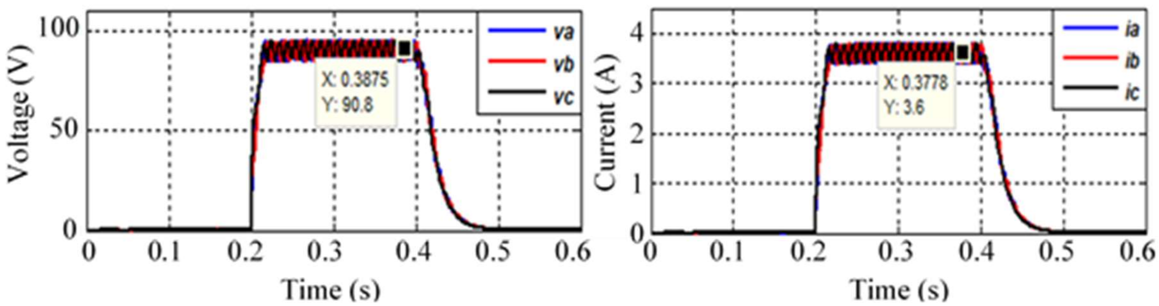

Fig. 10 : Characteristic of the residues during an open circuit of the second switch of the first arm of the inverter

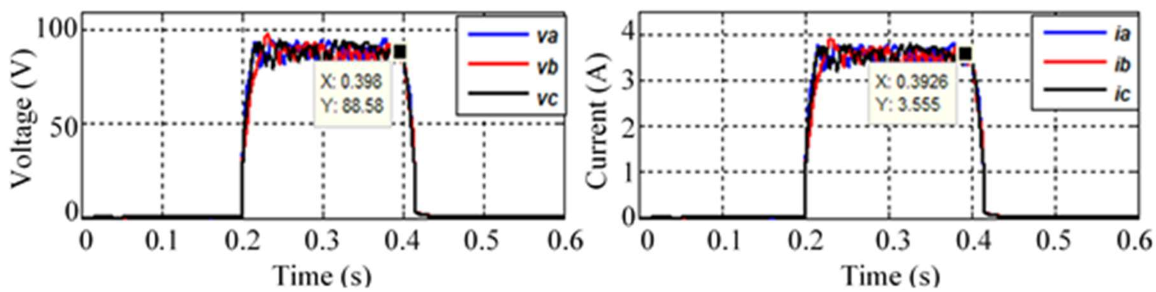

Fig. 11: Residual characteristic for a faulty control capacitor

3.2.3. Auto-diagnosis of motor

In the asynchronous motor, we also test the operation of the auto-diagnosis algorithm for three types of faults, namely a single-phase 1 break (V_a), a two-phase 1 break (V_{ds}) and a two-phase 2 break (V_{qs}). The characteristics of the residuals of the speed and the electromagnetic torque provided by the auto-diagnosis algorithm are illustrated in the following figures 12, 13 and 14. The operating parameters monitored in the motor are the rotation speed and the electromagnetic torque. The signatures transmitted to the user in these malfunction cases are respectively “0041”, “0042” and “0043”.

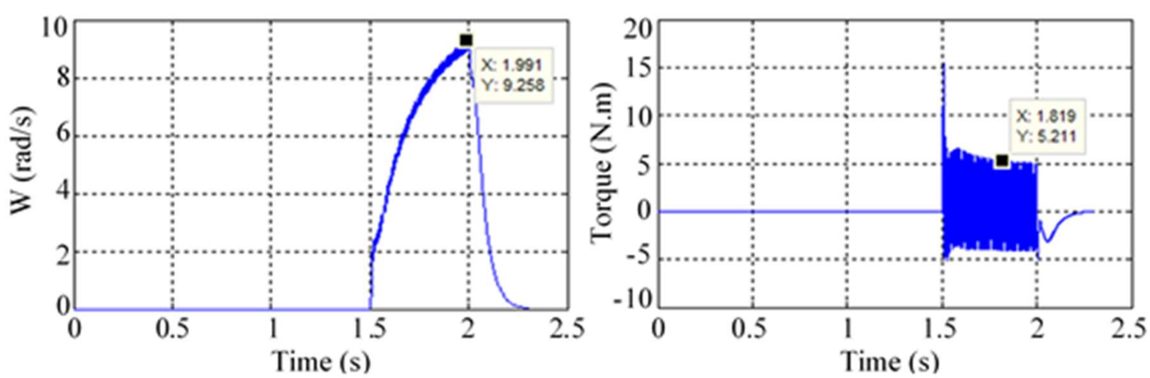

Fig.22 : Characteristics of the residues of single-phase cut-off 1

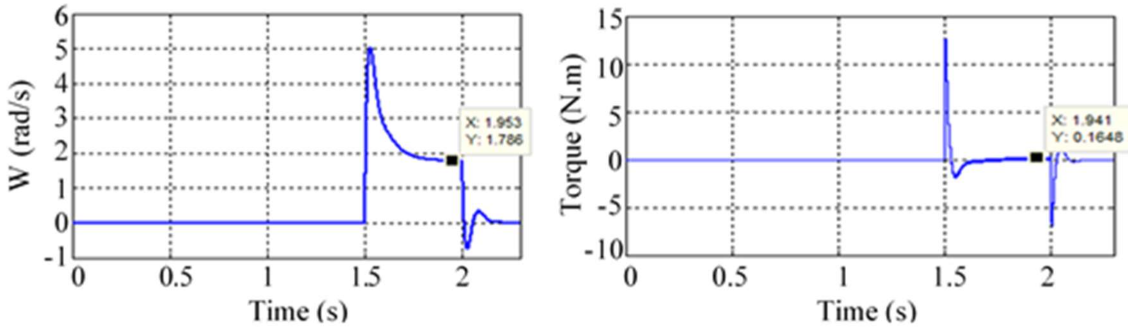

Fig.13 : Characteristics of the two-phase cut-off residues

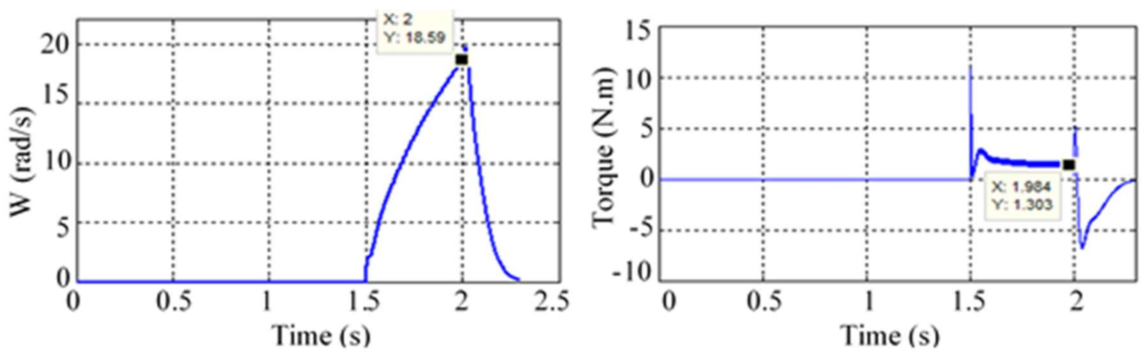

Fig.14 : Characteristic of the residues of the two-phase cut 2

3.2.4. Auto-diagnosis of centrifugal pump

In the pump, we test the behavior of the auto-diagnosis algorithm by first simulating an increase in the load torque, which can correspond in practice to the presence of sand in the impeller or the presence of a viscous fluid (presence of sludge). In the second case, we simulate the blocking of the pump. The parameters controlled in the pump are the flow rate and the pumped pressure. Figures 15 and 16 below represent the characteristics of the residuals provided by the auto-diagnosis algorithm in the two fault cases. The information transmitted to the user in this fault case are respectively the signatures “0051” and “0053”.

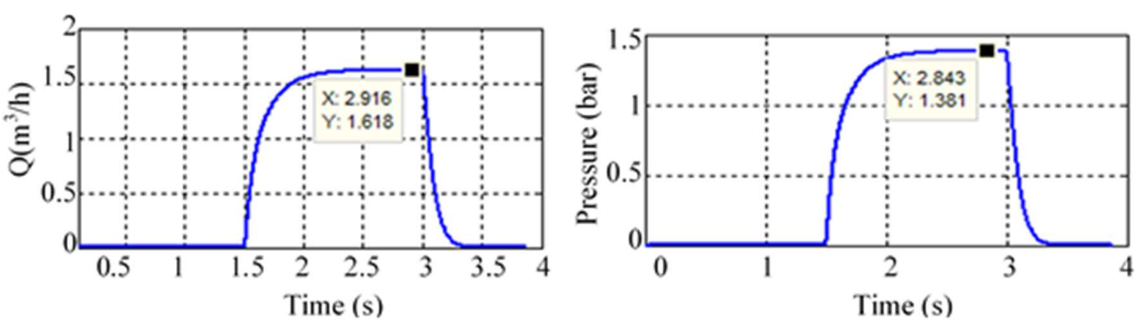

Fig.15: Residual characteristics for increased load torque

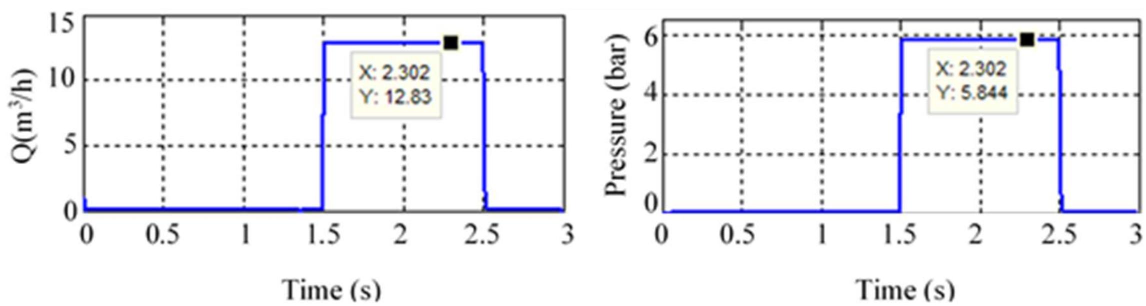

Fig.163 : Residue characteristics for pump blockage

For a pressure drop of 50%, we can conclude that the membrane of the ultrafiltration module is clogged and the algorithm transmits the information “0052” to the user, the characteristic of the residues provided can be observed in the following figure 17.

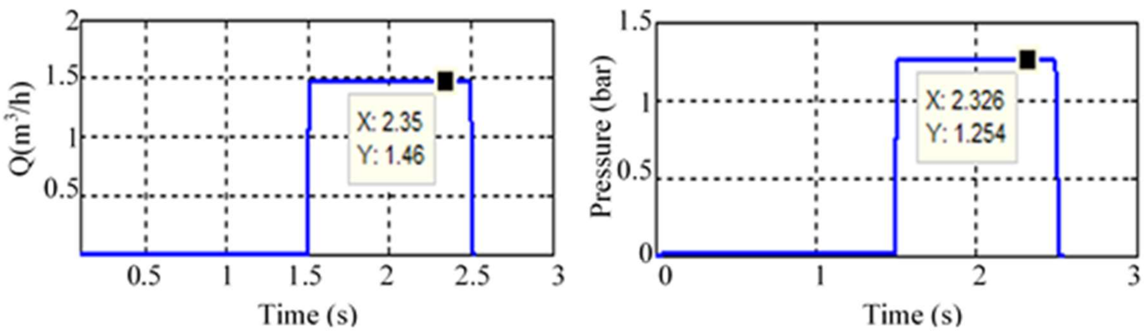

Fig.17: Residue characteristics for membrane clogging

It can be seen from the various residual curves provided by the auto-diagnosis algorithm that the residual values are zero when the fault has not yet been induced. But the moment the fault is induced, it is immediately detected and transmitted to the user.

CONCLUSION

The results obtained in this research work offer the possibility of ensuring the supervision of a photovoltaic pumping installation using the auto-diagnosis algorithm that is modeled and implemented. The different modules of the system are subjected to the auto-diagnosis algorithm which allows to inform the user about the operating state of the module and the nature of a possible fault thanks to the signatures which are assigned to each type of fault. In perspective, we planned to develop an interface allowing the user to receive and manage information relating to the operating state of the system in order to make decisions to anticipate total failures of the auto-diagnosed system.

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