Fault Detection based on neuro-fuzzy and mathematical models applied to a solar inverter

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Abstract: This paper presents an implementation of a fault detection scheme based on the identification of neuro-fuzzy models of a photovoltaic system in the AC conversion circuit. Fast fault detection implies the ability to perform preventive rather than corrective maintenance, which represents a benefit in the economical, material and environmental fields. Therefore, a method based on fuzzy logic with fuzzy residuals is proposed for the correct and fast detection of different types of faults. A residual evaluation is performed and a decision is made to what kind of threshold for robust fault detection is better. The results obtained show the good performance of the proposed scheme, where the detection system demonstrates its robustness to different faults. The proposed method is compared with traditional methods like mathematical model based on state-space equations and detection methods like Unknown Input Observers (UIO). The methods were applied into a real solar inverter and the results obtained were similar and as good as in simulations.

Keywords: Fault detection, neuro-fuzzy models, fuzzy thresholds, Artificial Intelligence, state-space equations, state observers, photovoltaic systems

1. INTRODUCTION

The faults diagnosis acquired great importance in industrial processes, due to the potential benefits that can be obtained by reducing maintenance and repair costs, increasing productivity, safety and environmental protection Zhang (2014). An early faults detection can help to make correct decisions and reduce the damage that they can cause to the plant, therefore static diagnostic techniques allow to improve not only the efficiency of the process, but also the reliability of the systems Patan (2008).

Robust fault detection under model uncertainty is the main requirement for modern fault detection systems. Robustness, in this case, is considered as the insensitivity to model uncertainty of the fault detection system. The idea behind the adaptive threshold technique is to accept the imperfection of the model and examine the influence of this fact on the residual signal. To avoid false alarms generated by the model disturbances or uncertainties, thresholds are defined for the residual signal. The interval defined by these thresholds defines the values of the residuals that correspond to the faultless mode Frank (1997).

Inside the detection methods there are different approaches, such as pattern recognition, statistics, artificial intelligence, among others. The tools contained in these approaches are associated with fault detection methods but in an independently way. The most convenient would be a tool that relates the specialist's knowledge and the historical data of the faults for diagnosis purposes. One of the most important and discuss method of this class are methods based on neuro-fuzzy hybrid models Isermann (2006). The concept of incorporating fuzzy logic into a neural network has grown and became popular in research topics due to its good performance and wide range of applicability Ensari (2010) and Souza (2010).

Currently, photovoltaic systems have been the subject of many studies due to their importance for the use of renewable energy. Photovoltaic solar energy directly transforms sunlight into electricity, using a technology based on the photoelectric effect. The electrical energy generated by photovoltaic solar panels is inexhaustible and non-polluting, so it contributes to sustainable development.

For faults detection purposes in photovoltaic systems, methods based on power voltage (P-V) and intensity voltage (I-V) characteristic curves analyzing degradation indicators have been developed. These methods perform well but are not accurate for large scale PV plants; are easily affected by installation circumstances and are limited by the number of faults to be identified. Other detection methods applied to this type of system and with better results are those based on artificial intelligence such as neural networks, techniques based on statistics and fuzzy systems where these are used to model the system and based on residual methods to apply fault detection Triki-Lahiani (2017).

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In this work, a fault detection scheme for a solar inverter is proposed. The AC converter circuit was identified and modeled using a neuro-fuzzy algorithm. A comparison between the proposed method and traditional one such as Unknown Input Observers (UIO) is discussed.

2. THEORETICAL BASIS

One of the main application area of the neuro-fuzzy systems are in control applications. In control, the focus of neuro-fuzzy research is on the approximation of non-linear functions, specifically in the modeling and identification of systems. Otherwise, in the context of fault detection, the ability to build decision-making systems is more important Abdelkrim (2019) and Kumbhar (2020).

One of the most used scheme is based on an Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines the concepts of fuzzy logic and neural networks to form an intelligent hybrid model of the system. It also combines the advantages of fuzzy theory and its ability to establish a reliable model that describes the behavior of the system and translates human experience in the form of linguistic variables and fuzzy rules with artificial neural networks Kaid (2018).

2.1 Traditional methods

The most frequently used fault detection approaches, including observers, parity relations, Kalman filters and parameter estimation are outlined. The most important class of models that have been heavily investigated in fault diagnosis studies are the input-output or state-space models and hence the focus is on these types of models Venkatasubramanian (2003).

During the past decades, a large number of techniques have been investigated for robust fault detection. Different types of observers (e.g.,Luenberger's observer, UIO or Kalman filter etc.) have been used to achieve different fault detection performances. Among these techniques, the UIO has been proven as a useful tool for robust fault detection Feng (2019).

The performance of UIO is affected negatively by the modeling errors, parameter variations or other uncertain factors. Due to presence of uncertainty in the model of a physical system for designing a UIO, it is necessary that the design will be robust against the uncertain factors and disturbance Iman (2019).

2.2 Proposed methodology

The model-based fault detection idea assumes a comparison of the model's output with actual values measured from the process, generating residues. Residues are usually generated as the difference between model and systems outputs. This means that the residual signal must be close to zero in the faultless mode, otherwise it is significantly different from zero. Ideally, the residual signal should contain only information about faults, but in practice, it also contains disturbances, which are due to the model's uncertainties. In this case, it is necessary to establish residual limits to avoid false alarms. If the residual signal exceeds the range defined by the thresholds, the alarm will be activated, otherwise, the system will be working in faultless mode Korbicz (2007) and Razavi (2009).

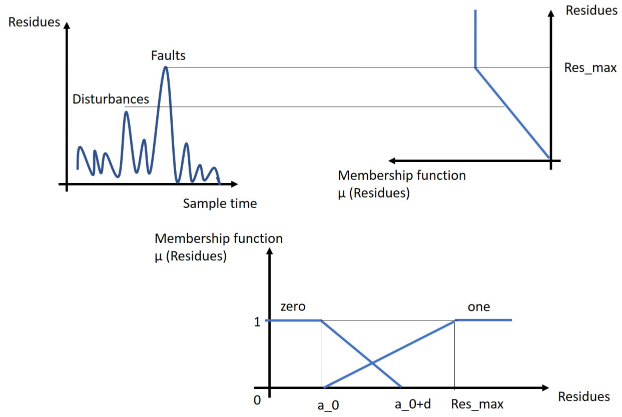

Figure 1. Membership function fuzzy sets.

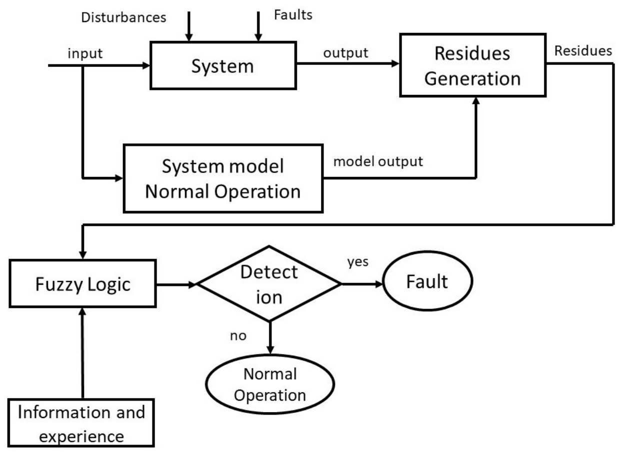

Figure 2. Fault detection scheme proposed.

Residues associated with a fixed threshold imply the danger of false alarms due to the fact that the thresholds have been chosen as small as possible, since any increase in the threshold is associated with a loss of sensitivity to faults. As a solution, can be replace the sharp threshold with a fuzzy threshold. The sets are replaced by fuzzy sets ***"zero"*** and ***"one"*** (see Figure 1), characterized by a membership function Frank (1997).

As we can see, there is an overlap of the fuzzy set membership functions, which is typical for the application of fuzzy logic. Therefore, it is necessary to define and evaluate rules as a basis for making the final decision on the occurrence of a faults in a specific situation.

The proposed diagnosis scheme (see Figure 2) consists of 2 stages: modeling and identification of systems; and the detection of operational states (normal or fault).

3. THEORY/CALCULATION

The ANFIS system configuration consists of five layers (see Figure 3): the first and fourth layers are the adaptive nodes, while the second, third and fifth layers are fixed nodes. Adaptive nodes are associated with their respective parameters, which are updated in each iteration, while

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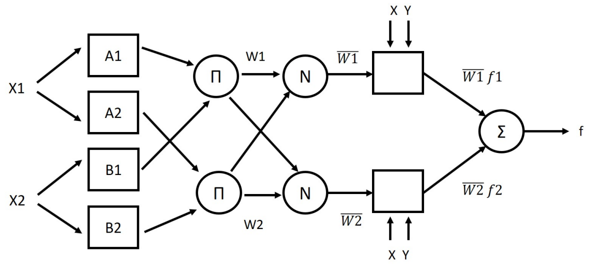


Figure 3. Adaptive neuro-fuzzy inference system architecture.

the fixed nodes are free of any parameters. Adaptive parameters are modified during the neural network learning process.

Rule 1: If x_1 is A_1 and x_2 is B_1 then $y_1 = f(x, y) = p_1 * x + q_1 * y + r_1$
Rule 2: If x_1 is A_2 and x_2 is B_2 then $y_2 = f(x, y) = p_2 * x + q_2 * y + r_2$

Where A, B are the fuzzy positions in the antecedent p, q and r are the design parameters that are determined during the learning process.

In the models obtained by the structure of the ANFIS adaptive neuro-fuzzy model, the inference rules are expressed in the form of functions, allowing to automatically generate these models based on the fuzzy rules using Takagi Sugeno inference models. The adaptive neuro-fuzzy model applies the learning mechanism for fuzzy inferences to the neural network, whose association function parameters are adjusted using the descending gradient learning algorithm in combination with the least squares algorithm corresponding to the experience in the system to be modeled Kaid (2018) and Ohja (2019).

Solar inverters are compounded by two main parts, a DC/DC and a DC/AC circuit, respectively. DC/DC converters are circuits that control the charge and discharge of energy in their passive energy storage elements (capacitors and inductors), achieving a change in the level of a direct voltage. The inverters, or DC/AC converters, are responsible for the conversion of continuous levels of voltage or current in alternating levels in smooth output, showing symmetry in amplitude Kabalci (2020) and Dogga (2019). These last converters are the ones used to applied the mentioned methods.

The system modeling and identification stage consists of obtaining a model that best represents the dynamic characteristics and the behavior of the real system under study in its normal operating state.

For systems identification purposes, a dataset of 19900 inputs and outputs voltages and currents samples were used. In both cases, 36 ANFIS models were trained using different I/O data that characterize different system behaviors. It was selected the model which shown the best performance. This analysis was based on the lowest average square error between the system output and the neuro-fuzzy model output obtained in the training and testing phases, respectively.

Within the stages of modeling and systems identification, is the stage of validation one of the most important, for the reason, which indicates whether the model obtained is suitable or not for the purposes for which it was obtained.

Two of the best known methods in the literature Mostefa (2020) were applied to evaluated the performance of the algorithm. They are: Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y_n})} \qquad (1)$$

and Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{n=1}^{N}\frac{|y_n - \hat{y_n}|}{|y_n|} \times 100\% \qquad (2)$$

where N represents the total number of samples, y_n represents the output of the system and $haty_n$ the output of the model.

For detection purposes the faults in the actuator described in Negash (2016) were simulated. The actuator faults that are considered include 1. Lock in Place (LIP) where the actuator states freeze at a particular value and will not respond to the subsequent commands, 2. Hard Over Failure (HOF) that is characterized by the actuator moving to its upper or lower saturation limits regardless of the commanded signal, 3. Loss of Effectiveness (LOE) is represented by lowering the actuator gain with respect to its nominal value, 4. Float fault occurs when the actuator floats with zero output and does not contribute to the control authority.

4. RESULTS

The results presented in this section are divided into the results obtained in the simulation where the system is identified and the simulated faults are detected. In addition, the results obtained using a circuit of a single-phase inverter and real data for the identification and detection of different behaviors and operating modes are presented.

4.1 Simulation results

In the training and testing stages the responses from the neuro-fuzzy system showed in Olazabal (2021) were obtained.

Faults detection results Once the model is obtained under normal operating conditions, the residuals are obtained from the difference between the outputs of the nominal system and the identified model. These residues are characteristic of the normal operational state. To analyze the faults detection stage, the faults described in the previous section were simulated.

Incorporating these faults into the systems, their behavior change and, therefore, the residues also change (see Figure 4). In the graph representing voltage, the behavior of all the residues are overlapped.

With the information of the residues, it is already possible to apply the fuzzy threshold technique to detect the presence of a fault or not. Using the fuzzy logic technique, the use of the membership functions and the proposed

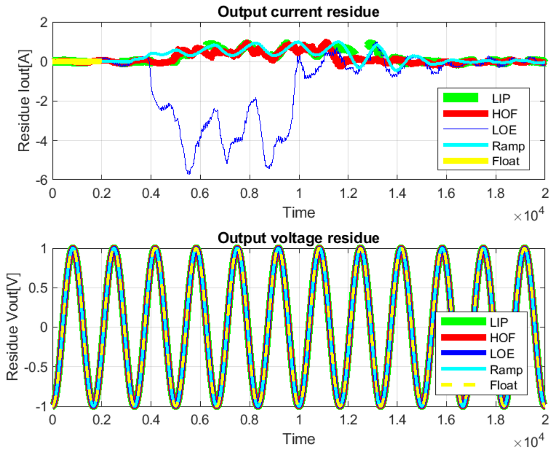


Figure 4. Residues used to fault detection

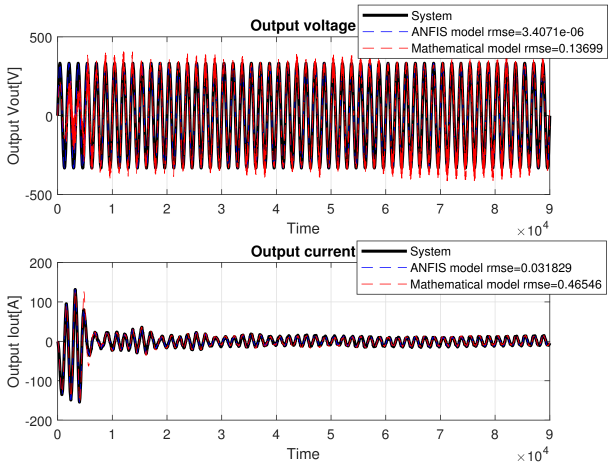


Figure 5. Comparison between neuro-fuzzy and state-space models

method, all faults were satisfactorily detected and the residual adaptive threshold method achieved 0% false alarms, which demonstrates the robustness of the method.

Comparison with traditional methods The following responses from the neuro-fuzzy system were obtained where it is shown that the model is quite close to the system. It is compared with the mathematical model based on state-space equations (see Figure 5). The validation metrics indicate the good performance obtained from both models.

In the fault detection stage using the UIO method, the actuator faults were detected as reflected in the current variable. These results are shown in Figure 6. In the graph representing voltage, the behavior of all the residues are overlapped.

4.2 Application in a real system results

In the training and testing stages (see Figure 7) the following responses from the neuro-fuzzy system were obtained.

Faults detection results To analyze the faults detection stage, the following operating and different behaviours were simulated, considering some of the most common

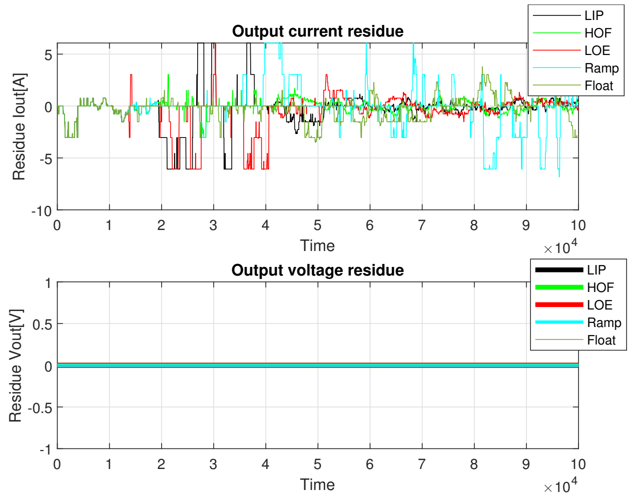
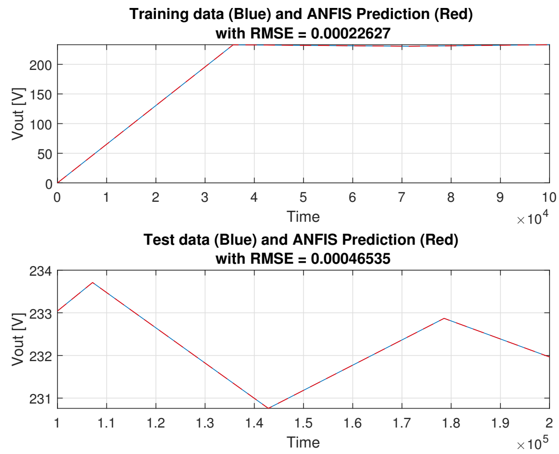
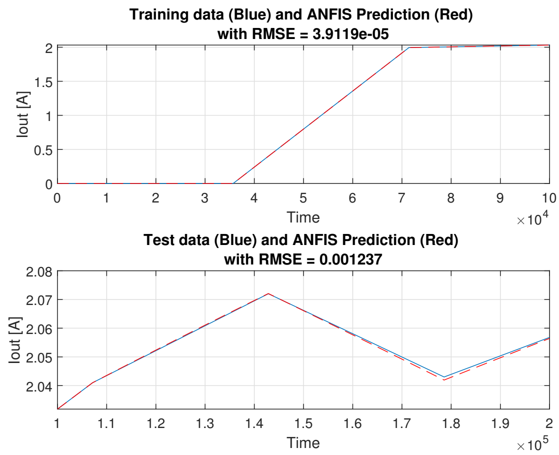


Figure 6. UIO faults detection



(a) Voltage



(b) Current

Figure 7. Neuro-fuzzy model output.

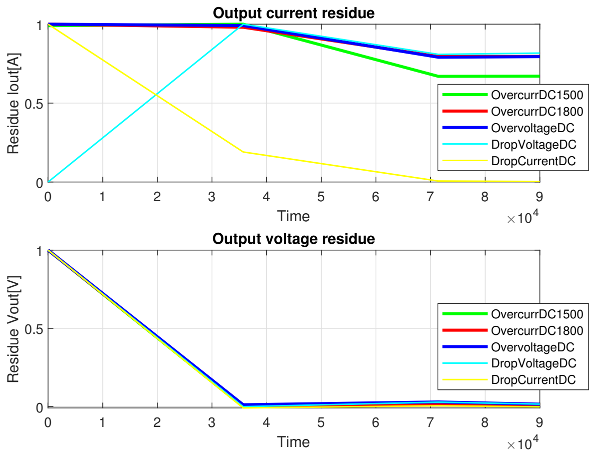


Figure 8. Residues used to fault detection

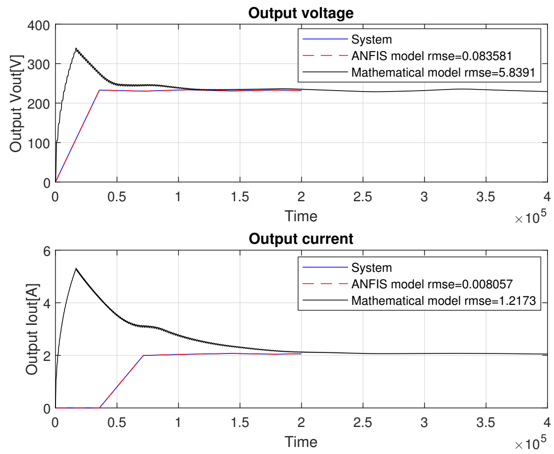


Figure 9. Comparison between neuro-fuzzy and state-space models

faults and operation modes seen in photovoltaic systems. 1. DC Over current 1500 and 1800 that represent a DC current surge in 2 steps resulting in rapid power increase, 2. DC Over voltage is a sudden increase of DC voltage, 3. DC Voltage Drop that may represent a rapid DC voltage drop, cut string cable or broken panel, and 4. DC Current Drop that is a rapid DC current drop, string failure or shadow by external object, its mean not cloud. A 2.5 kW single-phase inverter and a bidirectional source of 18 kW power, 1500 V DC, 40 A representing the solar panels were used for these simulations.

Using the proposed methods, all faults were satisfactorily detected and the residual adaptive threshold method achieved 0% false alarms, which demonstrates the robustness of the method.

The residues used are shown in Figure 8

Comparison with traditional methods The responses obtained from the neuro-fuzzy system (Figure 9) shown that the model is quite close to the system. It is compared with the mathematical model based on state-space equations. The validation metrics indicate the good performance obtained from both models, in this case there is a difference in the accuracy between the neuro-fuzzy and the state-space model.

In the fault detection stage using the UIO method, the faults were detected as reflected mostly in the current variable. These results are shown in Figure 10. In the graph representing voltage, the behavior of all the residues are overlapped.

5. DISCUSSION

The system was identified from which a multivariate model (voltage and current) was obtained that can represent the behavior of the system in more than 99%, which was demonstrated graphically and analytically through the validation indexes. The obtained model represents the normal operating state of the system.

Faults were simulated, which significantly affect the systems and the residues were obtained from the differences with the model. Making use of these residuals that were

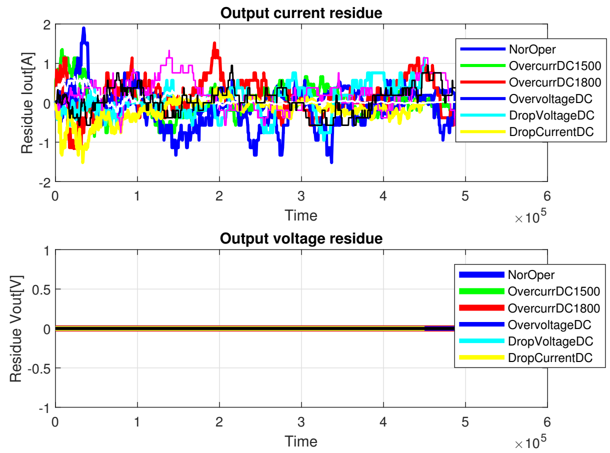


Figure 10. UIO faults detection

normalized in the range [-1,1] as part of the data treatment and to better work with them, and using the fuzzy threshold technique and the methods of fuzzy logic, the 100% of faults were satisfactorily detected, differentiating them from disturbances.

The developed methods were used in a real application using a photovoltaic inverter.

The obtained neuro-fuzzy models were compared with the state space based mathematical models, both models describe with great accuracy the behavior of the real system. The comparison did not show significant differences in the simulation results, however the results of the real application did show significant differences, with better performance of the neuro-fuzzy model.

According to the equations (1) and (2) the validation metrics obtained for both scenarios were (see Table 1):

Regarding the detection methods, a comparison was made between traditional methods based on UIO. The observer and the proposed fuzzy logic based method performed well in detecting the simulated faults.

Table 1. Validation metrics

Simulation	Voltage	Current
	ANFIS model	
RMSE	0.1382	0.0813
MAPE [%]	8.3496e-05	0.0017
	State-space model	
RMSE	0.13699	0.46546
MAPE [%]	0.0594	4.3209e-04

Real application	Voltage	Current
	ANFIS model	
RMSE	0.0836	0.0081
MAPE [%]	3.9222e-10	8.6086e-08
	State-space model	
RMSE	5.8391	1.2173
MAPE [%]	5.8191e-06	1.8059e-05

6. CONCLUSIONS

A fault detection scheme for a photovoltaic system composed of two stages was proposed: identification and modeling of the system and the detection of the operational states, that is, normal operating or fault.

A neuro-fuzzy model of the system was obtained, which represents the characteristics and behavior of the real system in an approximate manner, with only a minimal difference.

The proposed detection system, based on fuzzy logic, was able to detect 100% of the simulated faults. The fault detection time was considerably quick, which represents a benefit. False alarms caused by signal disturbances or noise were avoided.

The proposed fault detection scheme was applied to a real circuit of a single-phase inverter, having good and similar results to those of the simulation.

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