Electrical faults detection for the intelligent diagnosis of a photovoltaic generator

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Abstract — the work presented in this paper is dedicated to improving the methods of detection and diagnosis of faults affecting production systems, particularly photovoltaic systems. We proposed a new intelligent algorithm for the detection and diagnosis of PV installations, capable of detecting and resonate to define the type of defects that can affect this type of system. This new algorithm is based on the notion of pattern recognition, for that it is able to prepare the representation space and the decision space on the one hand, and on the other hand, the classification of all new observations collected during the functioning of the system. This algorithm mainly based on the method of k-nearest neighbor and two tools of artificial intelligence to improve this method and increasing the rate of its classification, which are fuzzy logic to optimize the location of the centers of gravity of classes and also the new observations, and the neural network that can classify the case of discharges ambiguity and releases distance which presents the limitations of the method of the k-nearest neighbor. We tested the performance of our algorithm on a database of a photovoltaic system at the research unit of GHARDAIA Algeria.

Keywords — Photovoltaic field, electrical defaults, pattern recognition, fuzzy logic, neural network, k-nearest neighbor.

1. Introduction

In many industries, dependability is a key issue to ensure optimum competitiveness of the production tool. Productivity gains are a daily concern for business leaders. Competitiveness of the sector through the controls necessary the availability of the means of production, improving its operation, the safety of its users and reducing maintenance costs.

The fault diagnosis of industrial systems, when done effectively and if it allows early detection of degradation, is a means to help achieve better productivity gain. Its primary purpose is to detect and locate a possible failure of the equipment. Increasingly, it becomes an integral part of the maintenance function. Become a major discipline, supported on the ground by modern technology (in other artificial intelligence), the diagnosis has become a disciplined industrial player in the field of dependability.

All technological systems subject to a diagnosis are likely to change in various modes of operation. These modes are not necessarily all known, some may not have ever been observed on the system. On the other hand, if some of these modes correspond to a normal operation, another has the feature to appear in case of failures.

In the literature, they are a lot of work on the modeling [6,10] and the diagnosis of photovoltaic installations the generator which is particularly the main unit, analysis and treatment of these documents is the exit that the applied diagnosis is to different types and tools, depending on type, because there are two types of diagnosis: the first is the diagnosis in real time when the fault is present [23] and the second is based on the prediction, because the control system detects a degradation not a failure at the hardware level as the work done by [24], this depending on the type. By cons the classification of tools is broader because it depends on methods and how reasoning to find a solution to the problem.

They are works that are based on the diagnostic tools of artificial intelligence [13]; to develop and implement the concept of intelligent diagnosis among these tools artificial neural networks [2, 3], fuzzy logic [4, 15, 16], SVM [5], Bayesian network hers [1] and kernel methods [7], also other works are based on diagnostic methods such as case-based reasoning [8], signal processing and vibration [9,17], accumulation of higher order [12], the analysis of parameters [11] or based on the analysis of the IV characteristic, power and energy losses [14].Then some work is based his diagnostic on the development of algorithms based on models like the model PMC (Perfect Minicomputer Corporation) [19], and the model rational approximation of the square root [20], or on software such as LabVIEW [18], CEP technology in a smart grid [21], and to identify satellite snow [22].

Our objective is to develop an intelligent algorithm replaces the Diagnosis classic and should be able to associate with any new observation collected on the system's its failure mode.

So this article will be organized as follows:

- The first part is to objectively present the photovoltaic system with its main components and also some of its shortcomings.
- The second part is devoted to the presentation of the new proposed algorithm which is based on the method of k-nearest neighbor and the two tools used to improve which are fuzzy logic and neural networks.

2. Photovoltaic system

Chain type of energy conversion of such a system is shown in Fig.1 consists of three main parts: a PV generator that produces continuous power by converting solar radiation, a group of converters and the grid [4] [6] [23].

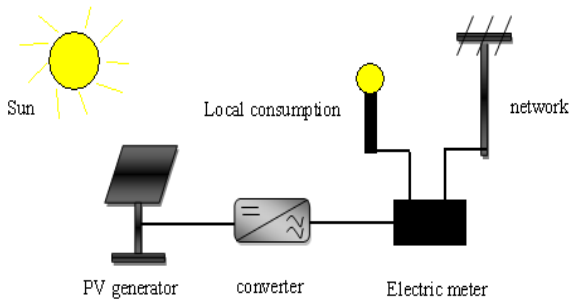

Fig.1 Chain energy conversion of a grid-connected PV system proposed

The electrical block diagram of a PV system connected to the network is composed of the following component parts:

-*PV generator:* production unit of electrical energy in the form of DC. The basic component of this unit that converts solar energy into electrical energy is the photovoltaic cell.

-*The converter*: the converter group's role is to extract the maximum power from the PV generator and convert it to AC power before being injected into the network.

-*Wiring and junction box:* The implementation of several modules in series to form a string is provided by cables. To minimize the risk of ground fault or short-circuit after installation, the use of single conductor cables with double insulation is highly recommended.

-*Protection system:* As with other power plants, there are several kinds of protection for photovoltaic system: protection stakeholders, protection against lightning, protection of the PV generator.

During its functioning, a PV system can be optionally subjected to various faults and abnormal operating conditions. Defects and anomalies appeared to vary from one installation to another depending on its design, installation, operation and maintenance. In this work, we select only the major faults listed in Table I.

Table I. Faults of a PV system

Default	faulty element
umbrage	Module
Warming cells	Cell
fissure	Cell
Penetration of moisture	module

The different elements of the system was simulated, are presented in this following table II:

TABLE II
Characteristics of the PV field

Element	Number
PV field	1
String PV	5 in each field
PV module	5 in each string
PV group	2 in each module
PV cell	18 in each group

3. Diagnosis by pattern recognition

The objective of the diagnostic function is to investigate the causes and locate the organs which led to a particular observation. The diagnostic function consists of two basic functions: locating and identifying causes. Location to determine the subset faulty functional while the identification of the cause is to determine the causes that led to an abnormal situation.

Methods of diagnosis by PR with are applied in this work have some advantages in the context of complex systems. Indeed, on problems such as nuclear, automotive, steel, chemical ... where the modeling of processes used is often laborious, the preferred approach PR.

The development of a diagnostic system by PR takes place in two phases. The analysis phase includes the analysis of data (pre-processing ...), the definition of a space of representation, and the establishment of a decision space in which define the different functioning modes, the exploitation phase where its objective is to associate for each new observation its modes of functioning.

The process leading to the development of a diagnostic system by PR is illustrated by Fig. 2.

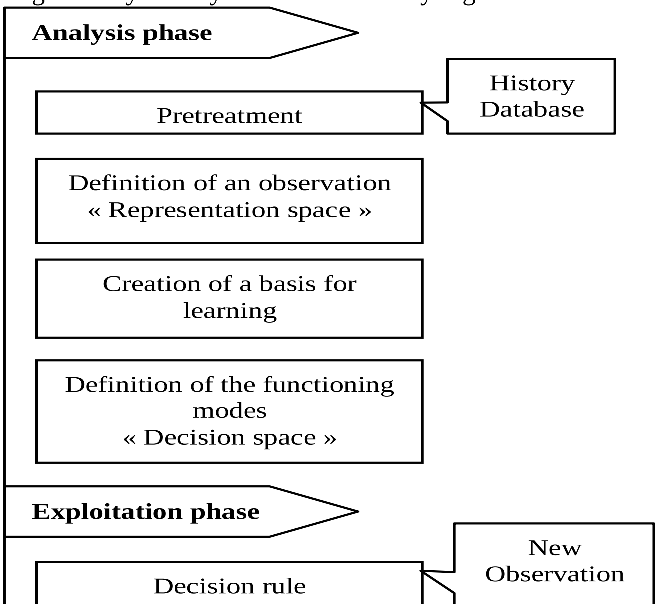

Fig. 2 Phases of development of a diagnostic system Pattern Recognition

1. Classical diagnosis algorithm proposed

This figure shows an algorithm for the classical detection and diagnosis of a photovoltaic system, which based on the comparison of the four main parameters: the characteristic IV cells, photo-current, series resistance of the cells and its temperature in good / malfunction. Numerical change in the IV characteristic of a PV system indicates the presence of a fault, and then the numeric change in the other parameters indicates the type of fault, as the algorithm in the following figure shows.

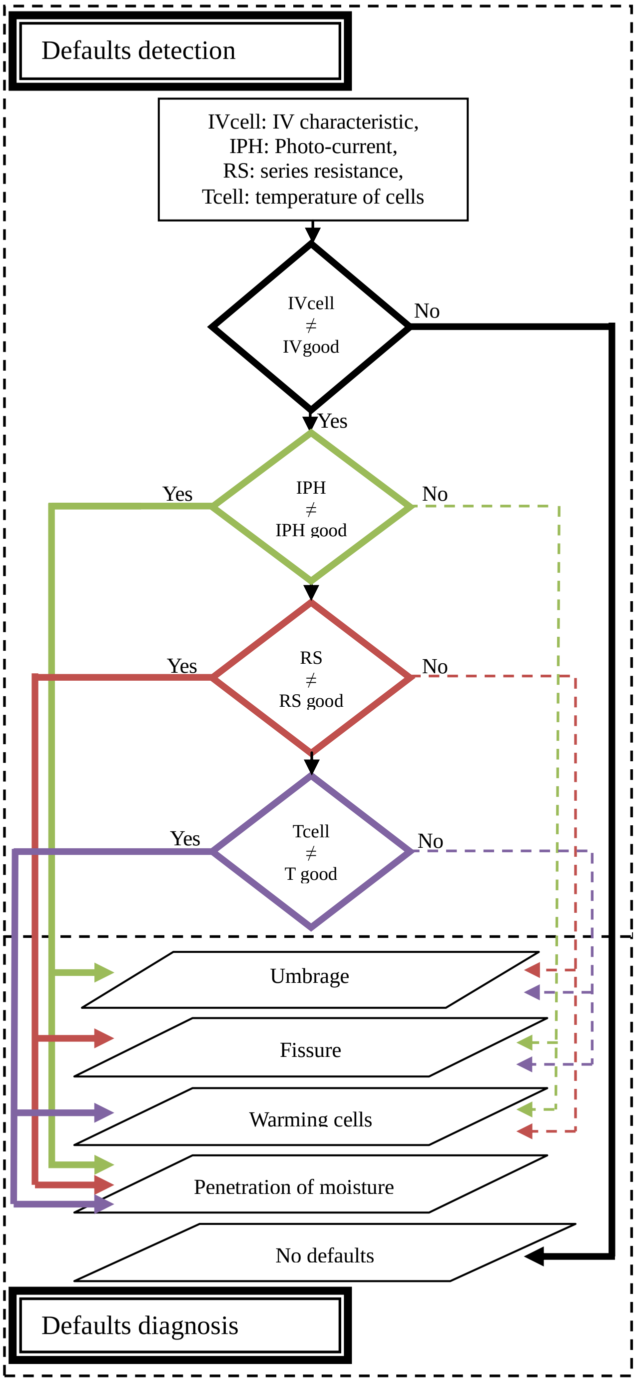

Fig.3 Proposed algorithm for the classical detection and diagnosis of a photovoltaic system

The industry practically photovoltaic system is one of the important areas for improving quality and productivity. To do this, its maintenance and diagnostic have been equipped with artificial intelligence through the use of modern techniques, these computational intelligence techniques that account. They are able to make these autonomous systems to enable them to analyze information and then take appropriate decisions in place of the man, and act accordingly to ensure that one or more desired actions.

2. Intelligent diagnoses

1) intelligent diagnosis algorithm proposed

This figure shows an algorithm for the intelligent detection and diagnosis of a photovoltaic system, which based also on the comparison of the four main parameters: the characteristic IV cells, photo-current, series resistance of the cells and its temperature in good / malfunction.

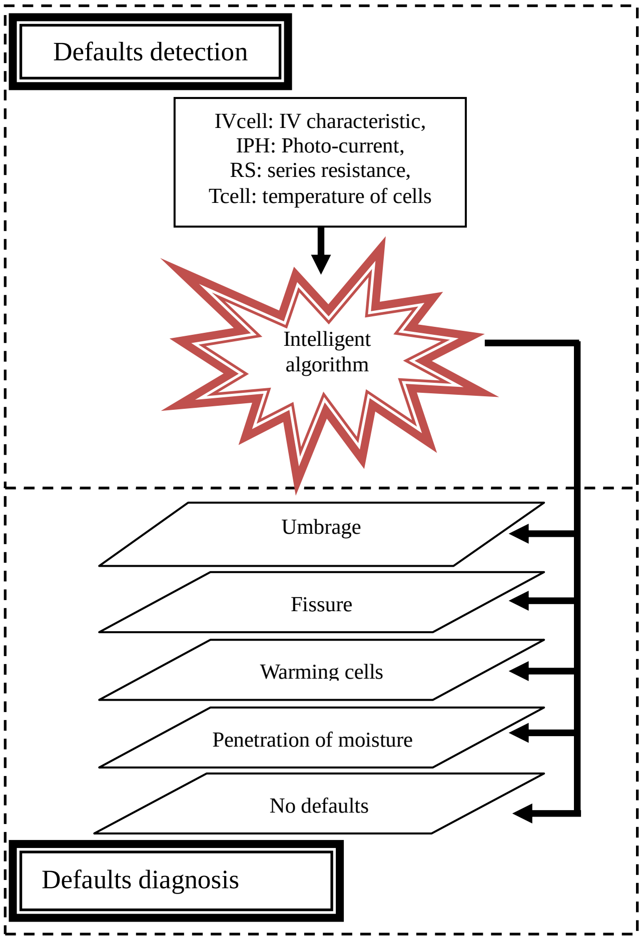

Fig.4 Proposed algorithm for the intelligent detection and diagnosis of a photovoltaic system

2) tools

The proposed algorithm is composed of three main portions which are:

- FL

Fuzzy logic is a method of treatment for problems specified setting by decision-making established in 1965 by Professor Lotfi A ZADEH. The algorithm Fig.5 of a fuzzy logic system firstly treats the input variables to transform its variables are numeric to the variables linguistic, this step calls fizzification, and he treats these variables by inference engine and to do this it uses its database and its fuzzy rules, and in the end it turns its variables for a second time but in the opposite direction to make its variables in a numerical format, this step calls defizzification [4] [15] [16].

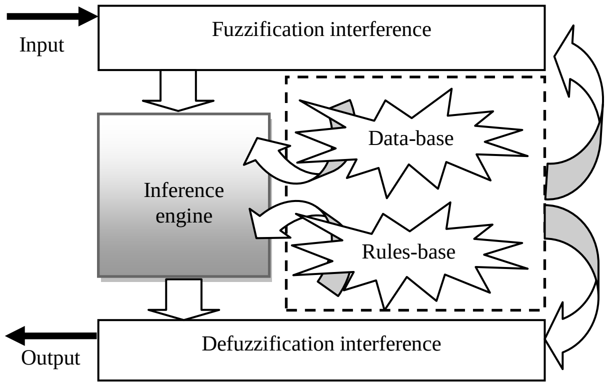

Fig.5 Algorithm for the FL method

- NN

The artificial neuron is a computational model whose conception is inspired by the true functioning of natural neurons. This formal neuron can be considered as an operator receiving a variable number of inputs from the external environment, each of these inputs is weighted by a synaptic weight, and providing an output only when the sum exceeds a certain threshold internally. Its mathematical model is as follows [2] [3]:

$$O = f\left(\sum_{a=1}^{X}(w_a \times i_a) + (w_0 \times i_0)\right) \quad (1)$$

Where:

i_a: Input vector,w_a: Synaptic weight vector,
O: output vector
$(w_0 \times i_0)$: internal threshold, f: Activation function

The capacity of a single neuron is limited. The implementation of complex functions requires the integration of several neurons, operating in parallel, in the form of a specific network topology. The inputs of a neuron are either global network entries or the outputs of other neurons. Connections between neurons that make up the network describe the model topology. It can be anything, but in most cases it is possible to distinguish some regularity. Consider the multilayer neural network of Z layers, n inputs and m outputs and its mathematical model is as follows:

$$O(N_{nn\,l_z}^{l_z}) = f\left(\sum_{nU\,(l_z)=0}^{nn\,l_{z-1}} w_{nU\,(l_{z-1})}^{nU\,(l_z)} \times O\left(N_{nn\,l_{z-1}}^{l_{z-1}}\right)\right) \quad (2)$$

Where:

$N_{nn\,(l_z)}^{l_z}$ Neuron number nn of the layer l_z
$O\left(N_{nn\,l_z}^{l_z}\right)$: The output of the Neuron number nn of the layer l_z
$O(N_{nn\,l_{z-1}}^{l_{z-1}})$): The input of the Neuron number nn of the previous layer.
$w_{nU\,(l_{z-1})}^{nU\,(l_z)}$ The weight between one upstream unit $(z-1)$ and a downstream unit (z), this unit has an input or neuron.

The algorithm Fig.6 of any multilayer neural network consists of three main steps and one test that determine its stopping criterion. His first step is to initialize all the weights of the different connections existing in the network the connections between the input vector and the first layer or between the inner layer itself, however, this step is performed by default i.e. the weights are chosen at random.

His second step is for objective to determine for each neuron - the input to the output of the network - its output to make that we used for the activation function in this application the sigmoid function.

And the last step is to calculate the error between the calculated output vector and the output vector desired. Following these three steps and because the algorithm based on the value of the error which should not pass certain threshold can decide its judgment if the error is acceptable or continues to loop until the error should be acceptable.

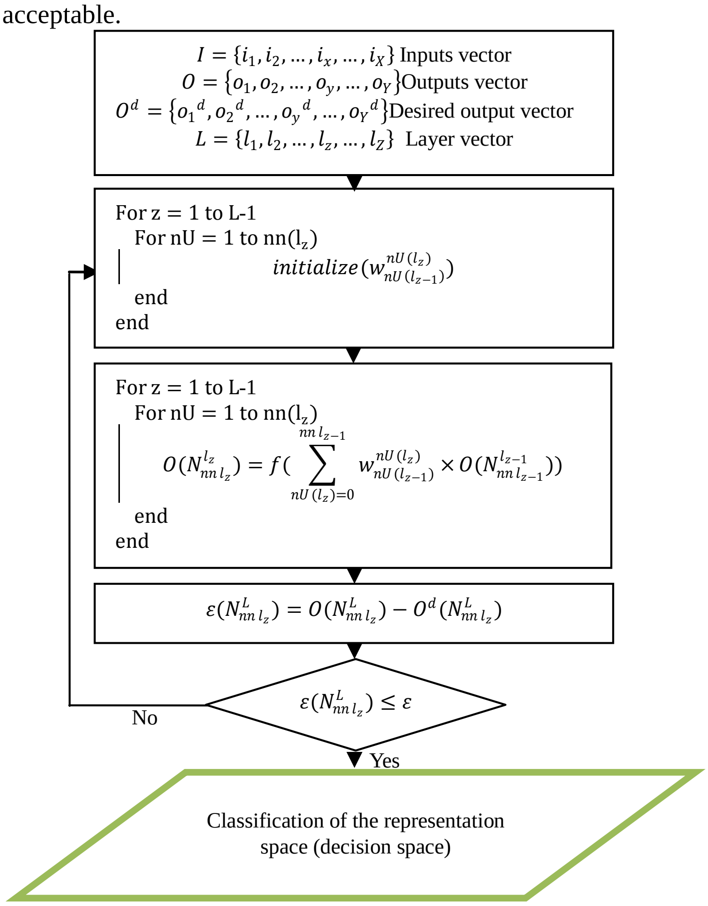

Fig.6 Proposed algorithm for the NN method

- k-NN

In pattern recognition, the classifier algorithm Fig.7 "k - nearest neighbors" is an automatically supervised learning method tries to bring out rules from a training set containing examples already treated and validated. This method of supervised classification providing performance very interesting in finding new forms to diagnose systems, The general principle of the K-NN is relatively easy, to predict the class of a new observation, the algorithm searches for the K nearest neighbors of this new observation and predicts its class at the end to know the class of K nearest . The method therefore uses two parameters: the number K and the similarity function to compare the new observation with the old observations already classified.

So, the algorithm of k-nearest neighbor used in this work is based on his presentation of its forms on the calculated of its centers of gravity, so that firstly calculates for each observation (of the database) its center of gravity, and it also calculates the center of gravity of the new observation, and then it calculates the distance between the center of gravity of this letter and the centers of gravity of all the old observations calculated above, there are in the literature several types of distance among them and it is used in this application MAHALANOBIS distance. Then the algorithm search to find the minimum distance from the distances the previously calculated and on the basis of this distance can classier this new observation.

And finally, the algorithm makes a test on this distance if its value exceeds a certain threshold which is set by an expert, then this observation may be rejected or it belongs to the class of distance rejections.

But if this distance is less than this threshold then it passes through another test that can calculate the number of minimum distances, if there is only one minimum distance then this new observation belongs to the class of the observation of the center of gravity nearest, otherwise i.e. there are several minimum distances then this new observation belongs to the class of discharges ambiguity because the existence of several minimum presents the case of the existence of this observation within two or more classes. So this method as we have seen can classify all new observations but only that they submit to the conditions above, for this our contribution in this work is to improve and optimize the k-NN classifier to find a solution to the classes of the distance discharges and ambiguity discharges because the conventional solution is to create new classes to these types of observations, but the practice shows that this solution is not always valid because they are certain cases where this type of observation and especially the release of this ambiguity may some form of one of the classes already exist but they have some characteristics of other classes. So to find a solution to this problem we propose a neural network to classify these types of observations ambiguity discharges and distance discharges on the one hand and on the other by the fuzzy logic to calculate and determine the wellness centers of gravity of all observations (new and old).

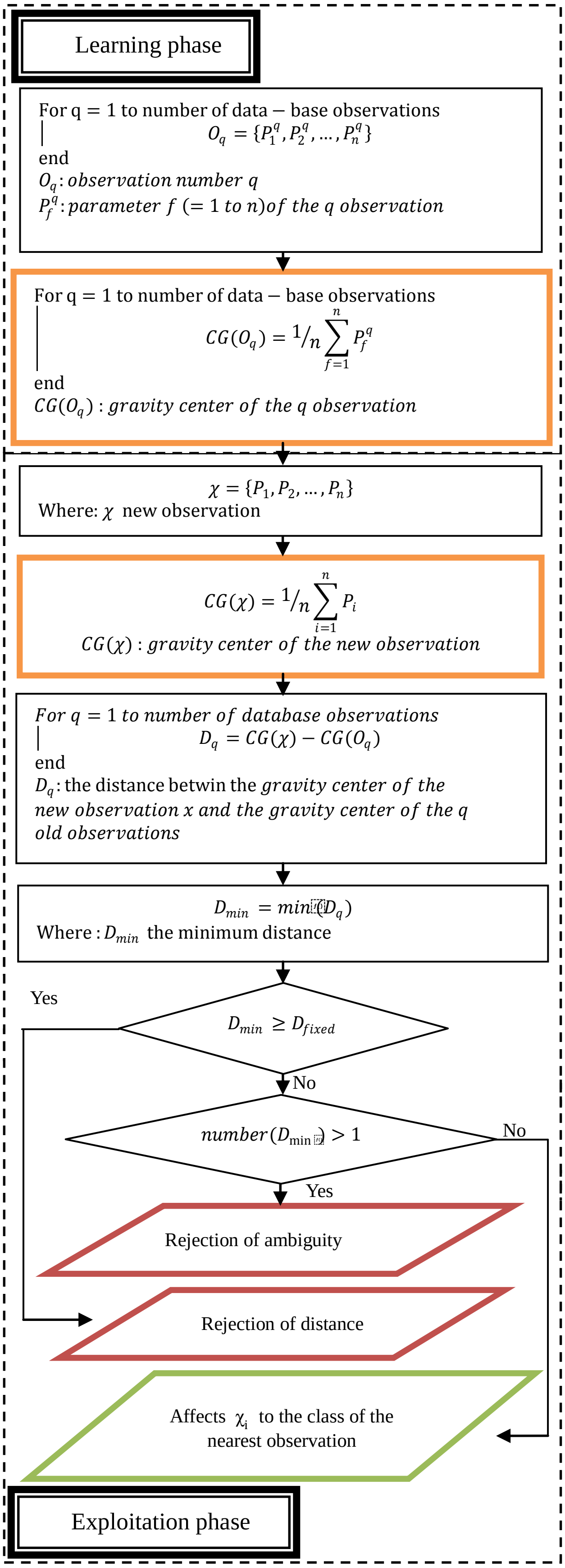

Fig.7 Proposed algorithm for the K-NN method

3) fault detection intelligent algorithm proposed

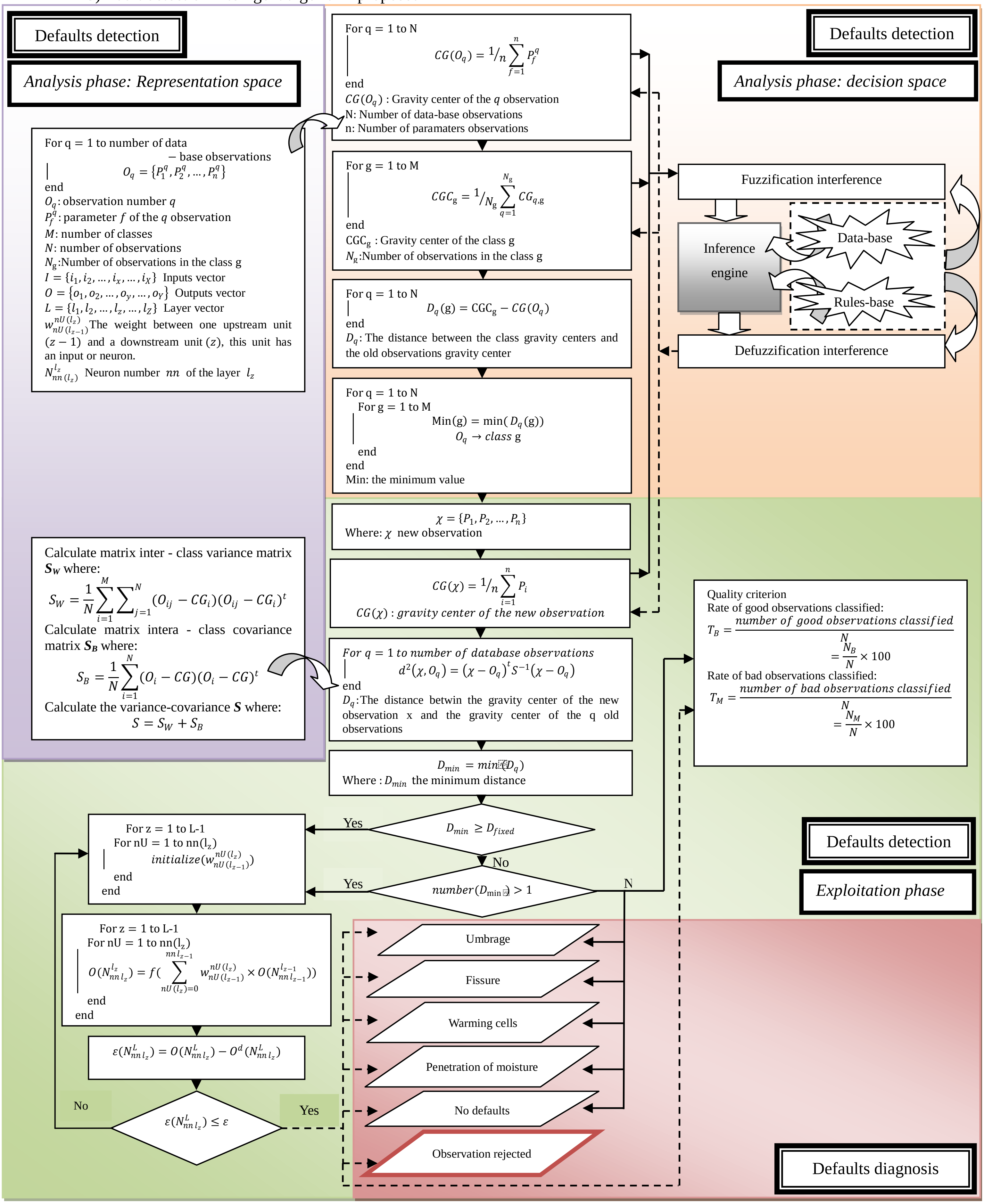

Fig.8 Proposed algorithm for the intelligent detection and diagnosis of a photovoltaic system

The proposed algorithm and as indicated in fig.8 consists of two main parts, the first is reserved for fault detection, and at this part our contribution exists, because we used to improve the detection and make smarter the concept of pattern recognition, which is itself composed of two parts, the first is called the analysis phase, which consists of two steps: the first is to prepare the space of representation who contain different observations as a data base, and the second is dedicated to the preparation of the decision space for this we used fuzzy logic to definite centers of gravity of each observation database. And the second part of pattern recognition called exploitation phase consists of two steps: the first is to calculate the center of gravity of the new observation by fuzzy logic, and the second is to classify on the one hand the new observations by the method of K-NN, and secondly to classify the ambiguity discharges and the distance discharges by neural networks. The second part of the proposed algorithm is intended to diagnosis of the photovoltaic system studied.

4) Simulation results

For testing the performance of the algorithm, we simulated the algorithm in the environment of MTLAB by a database of a photovoltaic generator at the research unit of GHARDAIA Algeria.

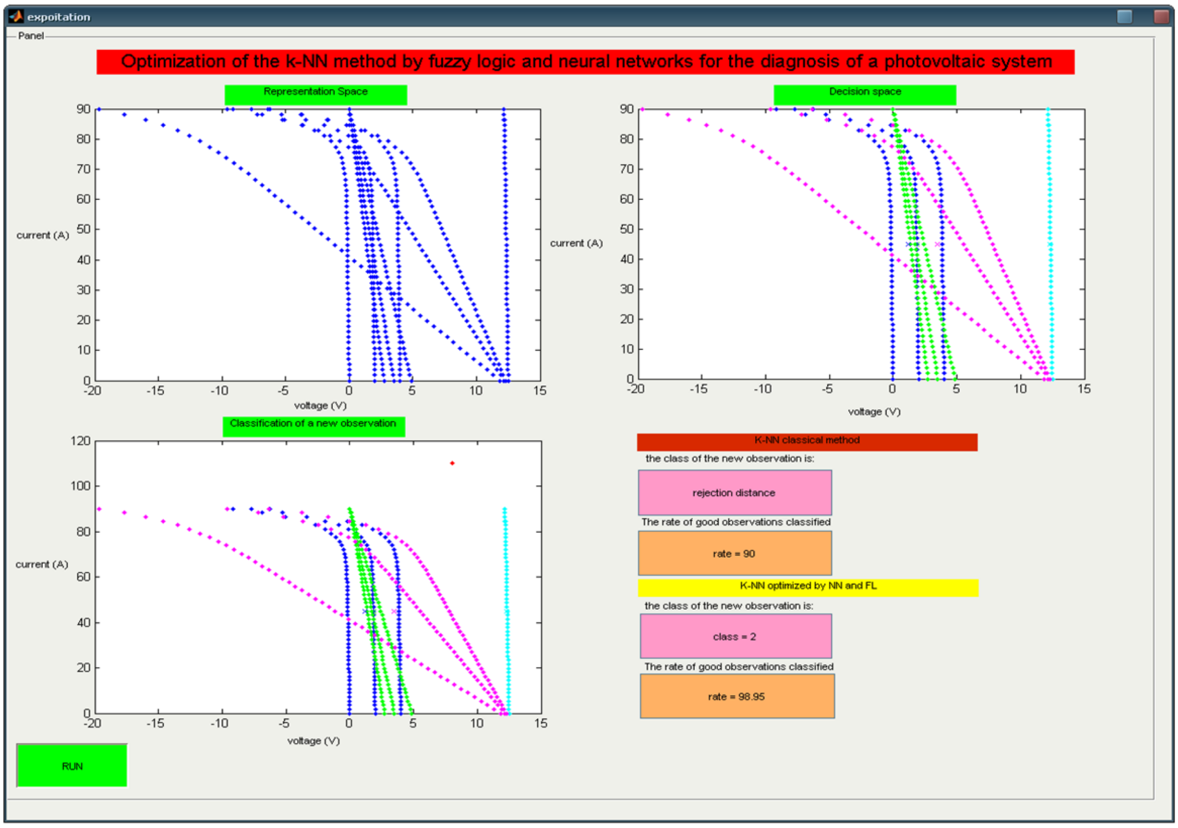

Fig.9 Simulation results

The simulation shows three figures, the first presents the representation space - figure on the top left- that shows the distribution of all the old observations of the database. The second shows the decision space - figure on the top right with each color present one of the class types- is a space that all its observations are classified and can even noticed the placement of centers of gravity of each class, and this space is ready to classify all new observations. And ultimately, the operating space - in the bottom left- is for objective to classify all the new observations - red point- collecting the system by the method of k-NN in the cases not conditioned, and neural networks for discharges of ambiguity, and rejections distance. The results are very effective and by this proposed algorithm we increased the classification rate from 90% which is by the K-NN method to 98.95% by the K-NN method optimized by fuzzy logic and neural network.

3. Conclusion

In this paper we propose a new intelligent algorithm based on the recognition of Forms capable of detecting and diagnosing of faults affecting the photovoltaic systems practically, but in the scientific research this algorithm is to improve and develop the method of k-nearest neighbor in the accuracy of displacement of the centers of gravity of observations by fuzzy logic and find a solution to the observations of discharges ambiguity and discharges distance by the neural networks.

We consider our algorithm as a diagnostic method without model since it uses the operating history of an industrial system. The proposed algorithm does not require additional effort for the user to do the interpretation of variables used. The results show that our algorithm can improve the speed and accuracy of a diagnostic system. Our algorithm requires some improvements to process uncertain and incomplete data that generally characterize industrial systems.

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