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A Smart Algorithm for the Diagnosis of Short-Circuit Faults in a Photovoltaic Generator

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Abstract—This paper deals with a smart algorithm allowing short-circuit faults detection and diagnosis of PV generators. The proposed algorithm is based on the hybridization of a support vector machines (SVM) technique optimized by a k-NN tool for the classification of observations on the classifier itself or located in its margin.

To test the proposed algorithm performance, a PV generator database containing observations distributed over classes is used for simulation purposes.

Keywords—Photovoltaic generator, SVM, k-NN, short-circuit fault, smart classification, linear programming.

NOMENCLATURE

PV	=	Photovoltaic;
SVM	=	Support Vector Machines;
k-NN	=	k-Nearest Neighbor;
CO	=	Class of Observation;
X	=	SVM input vector,
Y	=	SVM output vector,
f	=	Linear function;
Φ	=	Kernel function;
w	=	Weight vector;
x	=	Problem variable;
x^*	=	New problem variable;
C	=	Class addition;
α	=	Lagrange multipliers;
c_i	=	Class number i ;
D	=	Y diagonal.

I. INTRODUCTION

The performance of a photovoltaic generator is the ratio between the amount of energy supplied by the generator - which is in the form of continuous electrical energy converted by a PV converter to an alternative electrical energy used by consumers - and the solar energy - which is in the form of solar radiation received by the solar panels in the principle of the photovoltaic effect [1].

Unfortunately, this performance is unstable, thanks to a series of factors among them: the cell material, the cell average temperature, the tilt of the solar panel to the sun, and the presence of defects which may cause significant power losses, especially short-circuit faults [2-3]. The PV generator faults diagnosis [4-7] and prognosis [8-12] can stabilize its

performance and ensure its availability and reliability. In this context, the paper objective is the development of an algorithm for the fault detection and diagnosis for a photovoltaic generator. Indeed, the paper contributions are twofold: 1) Development of a fault detection and localization algorithm; in particular short-circuits in a cell, bypass, and blocking diodes. 2) Development of a smart classifier based on observation collected from the control system. It is based on the support vector machines (SVM) and k-NN tools [13-22].

II. CLASSICAL DIAGNOSIS ALGORITHM

The proposed diagnosis algorithm is designed for the detection and the localization of short-circuits in a PV generator cells, bypass, and blocking diodes. This is a critical fault as it creates hot spots in addition to the voltage degradation.

The diagnosis algorithm consists of four main hierarchical steps.

A. Step I

If a PV generator voltage is less than the one provided by a healthy generator, and its current is equal or greater than the current supplied by a healthy generator; this therefore means that there exist some short-circuited components. A zoom must be carried-out on the generator components characterization to check string states.

B. Step II

This step consists in the characterization of a string state (short-circuit). In this context, there is numerous condition dealing for a short-circuit detection. The main one is to consider a string short-circuited when its voltage is zero. Another specific fault is the blocking diode short-circuit that will deteriorate the PV generation. This fault is particularly difficult to detect.

C. Step III

This step consists in the characterization of a module state. A module is considered as short-circuited if its voltage is zero and its current is maximal. This situation means that all its

groups are short-circuited. Otherwise, it is an indication that the module contains at least one short-circuited group.

D. Step IV

This step consists in the characterization of a group state. A group is considered as short-circuited if its voltage is zero and its current is equal to the short-circuit value. In this case, all the components are considered as short-circuited. Otherwise, if the group voltage is strictly greater than zero and strictly less than its normal operation value, and its current is equal to the sum of its cells currents, then this group contains at least one good cell and the others are short-circuited. Moreover, when the group voltage is zero and its current is equal to the sum of the cells short-circuit current and the bypass current, this situation means that all the group cells are defectives. Finally, if the group voltage is zero and its current is equal to the sum of the healthy cells currents and the current through the bypass diode, this last situation means that this group is connected by a short-circuited bypass diode.

III. INTELLIGENT DIAGNOSIS ALGORITHM

A. SVM Algorithm

Support vector machines are supervised learning techniques, for solving classification problems in many fields such as pattern recognition, text categorization, or medical diagnosis [23-26].

The SVM technique highlight compared to traditional learning ones is that it does not depend on the data representation space dimension. However, the choice of the kernel function adapted to the problem, or calculation time based on the data number to be treated, can make the use of this tool more complicated. The analysis and study of this method brings out two major drawbacks for its use which are: 1) Binary classification, which means that it cannot handle more than two classes at the same time; 2) Support vectors classification. In other words, observations located at the margin and especially those located on the separator itself are not well-determined.

In this particular restrictive context, our objective is to find a solution to the problem of multi-class SVM classifier. For that purpose, we propose to treat the problem by solving a set of equations, each presenting a classifier between a class and its complement. If the observation does not belong to this class, we repeat the separation. The following SVM algorithm summarizes our proposal.

1) **Step 1:** *Construct the SVM classifier.* Our objective is to construct a function f which, for each input value x in a set \mathbb{R}^d , will match an output value $y \in \{-1, 1\}$. The goal is to try to learn f from a set of pairs (x_i, y_i) . In the linear case, a discriminate function is obtained by a linear combination of the input vector x , allowing a quick access to our objective. In a nonlinear case, a change in the data space becomes mandatory with a linear separation in a new space of a larger

dimension. In this case, the use of an implicit function Φ becomes necessary.

2) **Step 2:** *Determining the hyper-plane.* There are many separating hyper-planes; the best is the one that maximizes the margin. This one is defined as the distance between a hyper-plane and the closest sample points that are called support vectors. The maximum margin hyper-plane, which is intended to classify any new observation, is given by a shape resulting from linear programming.

SVM classifier second drawback is observations classification: for support vectors and data situated in the margin, side classification error, especially if the margin is not wide which is based on the distribution of data space, and also side classification of observations located on the classifier himself. This paper proposes then a solution for the above-described SVM disadvantage. Indeed, it is proposed the use of the well-known tool in classification; the so-called k-NN.

B. k-NN Method

k-NN is one of the unsupervised learning algorithms that solve the problem of classifications used in many areas such as diagnostic. This algorithm consists in three main steps. In this work, it is proposed mathematical modeling by matrices for flexibility and ease to use purposes [27-29].

1) **Step 1.** This first step aims to determine a representative for each observation $X = \{x_1, x_2, \dots, x_N\}$ in the learning space $X: n \times m$. There is a lot of works concerning this step. In particular, calculating the gravity centers for each observation and therefore deriving the resulting vector center (x) is the most used approach.

2) **Step 2.** This step concerns the observation classification. It also needs a representative by calculating its gravity center, to obtain a vector center (x^*) .

3) **Step 3.** This last step concerns the determination of the minimum value index class of the Manhattan type Euclidean distance between (x^*) and (x) as given by (1).

Even if the above described method has several advantages as robustness and efficiency, it has, as traditional classification methods, some disadvantages. Among them, two main problems: remotely and ambiguity discharges. This work is not concerned by the first problem as it is already classified by the SVM. However, in the second situation, there are several minimum distances. In other words, there are more than one distance between the new observation and the old ones. In this case, we have to check if the old and new observations belong to the same class; otherwise, the new observation belongs to the class of ambiguity discharges.

C. The Proposed Smart Algorithm

In this paper, it is particularly proposed a smart algorithm allowing smart classification of observations retrieved from the studied PV generator operation.

This algorithm is considered smart as it results from the hybridization of the SVM technique (artificial intelligence family) optimized by the k-NN tool.

$$f(x^*) = \left[\begin{array}{l} \text{If the problem is linear separable} \\ \left[\begin{array}{l} \text{sign} \left(\alpha_{c_1, \delta(c_1)}^T X x^* - \frac{1}{2} \left(\max_{y_i=-1} (\langle w_{c_1, \delta(c_1)}, x_i \rangle) + \min_{y_i=1} (\langle w_{c_1, \delta(c_1)}, x_i \rangle) \right) \right) \\ \vdots \\ \text{sign} \left(\alpha_{c_{m-1}, c_m}^T X x^* - \frac{1}{2} \left(\max_{y_i=-1} (\langle w_{c_{m-1}, c_m}, x_i \rangle) + \min_{y_i=1} (\langle w_{c_{m-1}, c_m}, x_i \rangle) \right) \right) \end{array} \right] \\ (1-\xi) \text{ Else} \\ \left[\begin{array}{l} \text{sign} \left(K(x^*, X^T) D \alpha_{c_1, \delta(c_1)} - \frac{1}{2} \left(\max_{y_i=-1} (\langle w_{c_1, \delta(c_1)}, \phi(x_i) \rangle) + \min_{y_i=1} (\langle w_{c_1, \delta(c_1)}, \phi(x_i) \rangle) \right) \right) \\ \vdots \\ \text{sign} \left(K(x^*, X^T) D \alpha_{c_{m-1}, c_m} - \frac{1}{2} \left(\max_{y_i=-1} (\langle w_{c_{m-1}, c_m}, \phi(x_i) \rangle) + \min_{y_i=1} (\langle w_{c_{m-1}, c_m}, \phi(x_i) \rangle) \right) \right) \end{array} \right] \\ \text{End} \end{array} \right] + \xi * CO \left(\text{index} \min \left[\begin{array}{l} \frac{1}{N} \sum_{j=1}^N |x_{j1} - x_j^*| \\ \frac{1}{N} \sum_{j=1}^N |x_{j2} - x_j^*| \\ \vdots \\ \frac{1}{N} \sum_{j=1}^N |x_{jM} - x_j^*| \end{array} \right] \right) \quad (1)$$

Where $\xi = 1$ if x is in the margin of the SVM classifier, else $\xi = 0$.

This tool is particularly used to increase the classification rate against observations on the classifier itself or located in the margin which is not wide.

IV. SIMULATIONS RESULTS

To illustrate the performance of the proposed fault detection and diagnosis algorithms several simulations have been carried-out on a typical PV generator.

A. Faulted PV Generator Characterization

The main simulation results are shown by Fig. 1 to 3. Figure 1 clearly illustrates the PV generator power performance under short-circuited cells. In particular, this figure shows that the power decreases proportionally to the number of short-circuited cells (the current is independent of the number of defective cells).

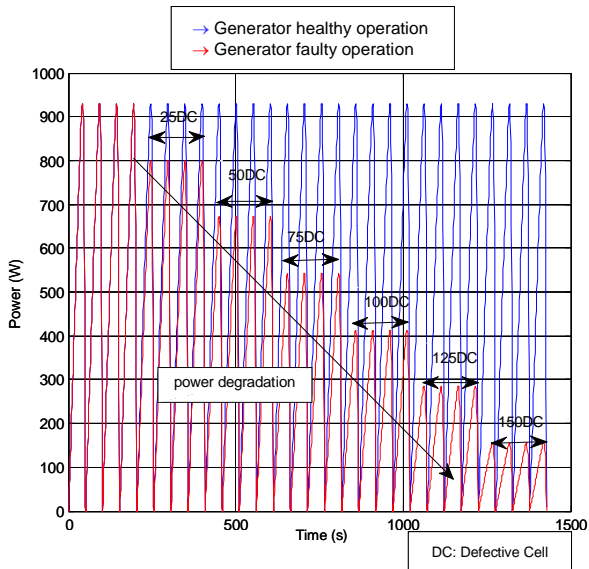


Fig. 1. Short-circuited cells influence on the PV generator operation.

Figure 2 shows the influence of the bypass diodes short-circuits on the generated power. These diode short-circuits have a greater impact on the PV generator performance. Indeed, bypass diodes short-circuits affect a group voltage. Again, the current remains independent of fault type unless all string groups are failed.

Finally, Fig. 3 illustrates the influence of blocking diode short-circuits on the PV generator operation. It is clearly shown that when this type of fault occurs, the generated power clearly exhibits a big drop. Indeed, the faulty strings will consume the power generated by the other healthy strings.

B. Smart Algorithm Tests

The proposed smart fault detection and diagnosis algorithm is tested using a PV generator database containing observations distributed over classes.

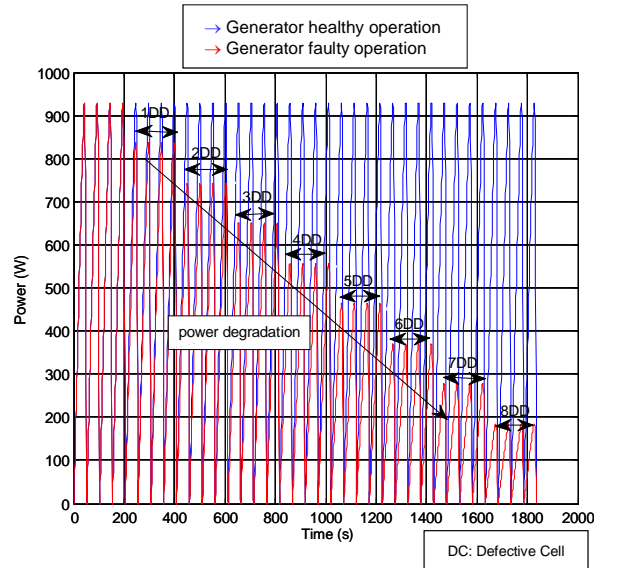


Fig. 2. Short-circuited bypass diode influence on the PV generator operation.

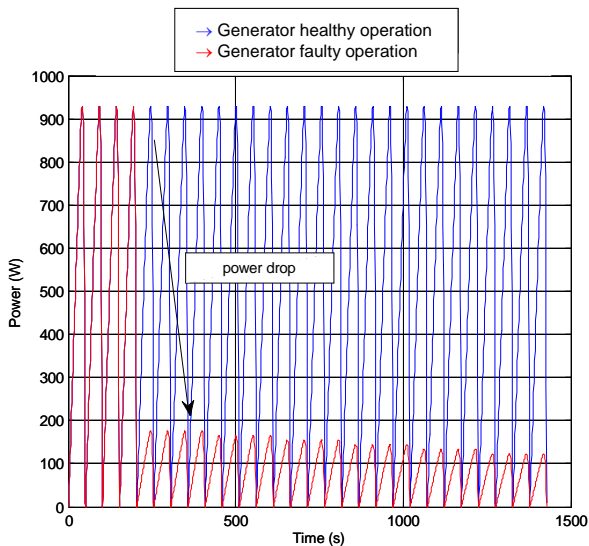


Fig. 3. Short-circuited blocking diode influence on the PV generator operation.

For that purposes, three indicators are used: the rate of good classified observations (Fig. 4), the classification error rate (Fig. 5), and the computation time to classify any new observation (Fig. 6). In this context, 60 samples are selected, each containing 1632 observations. For the classification of each observation of each sample, three classifiers are used for comparison purposes: SVM, k-NN, and the proposed SVM optimized by k-NN.

With the SVM classifier, the achieved results show that the rate of good classified observations is between 60 to 69.9% (Fig. 4), with a classification error rate between 0.8 to 0.9% (Fig. 5), and its computation time is between 5.5 to 7 time units (Fig. 6).

With k-NN classifier, the achieved results show that the rate of good classified observations is between 50 to 53.5% (Fig. 4), with a classification error rate between 1.5 to 2% (Fig. 5), and its computation time is between 2 to 3 time units (Fig. 6).

With the proposed classifier (hybrid SVM_k-NN), the achieved results show that the rate of good classified observations is between 68 to 75.8% (Fig. 4), with a classification error rate between 0.36 to 0.55% (Fig. 5), and its computation time is between 5 to 10 time units (Fig. 6).

The analysis of the above achieved results shows that the proposed hybrid classifier has the following specific features: a high classification rate with a low error rate but it is a little bit time consuming due the mathematical computations.

V. CONCLUSION

This paper dealt with a smart algorithm allowing short-circuits detection and diagnosis in PV generators. The proposed algorithm is considered smart as it results from the hybridization of the SVM technique (artificial intelligence family) optimized by the k-NN tool that was used to increase the classification rate against observations on the classifier itself or located in the margin which is not wide.

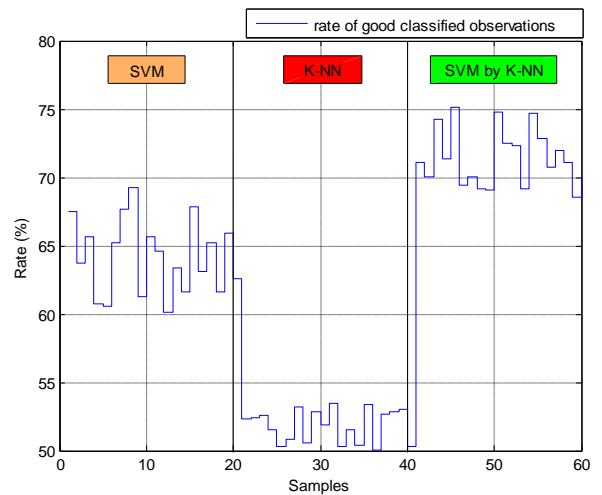


Fig. 4. Observation classification rate vs tools.

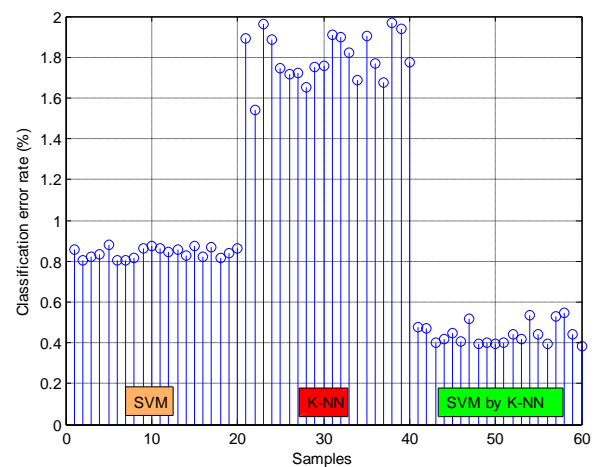


Fig. 5. Observation classification error rate vs tools.

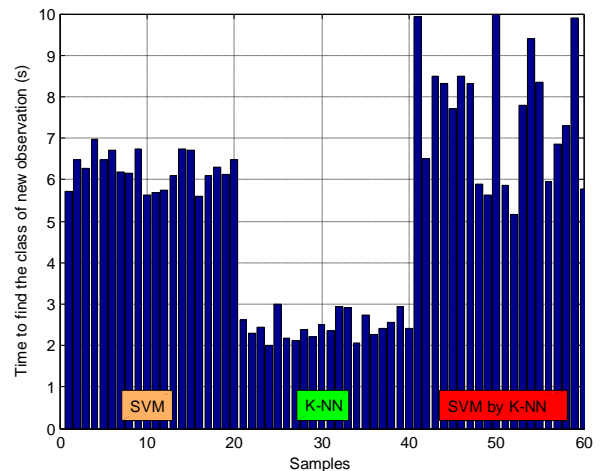


Fig. 6. New observation classification elapsed time vs tools.

The proposed smart fault detection and diagnosis algorithm was tested using a PV generator database containing observations distributed over classes.

The analysis of the achieved results shows that the proposed hybrid classifier has the following specific features: a high classification rate with a low error rate but it is a little bit time consuming due the mathematical computations.

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