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REAL-TIME DIAGNOSIS OF BATTERY CELLS FOR STAND-ALONE PHOTOVOLTAIC SYSTEM USING MACHINE LEARNING TECHNIQUES

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Key words: Stand-alone photovoltaic system, Battery, Anomaly detection, Support vector machine, Diagnosis, Accuracy.

Battery as a critical element in the stand-alone photovoltaic system remains without an appropriate protection fuse for short-circuit failure inside it. Therefore the safety is threatened and the lifetime of the battery is reduced. To address this problem, supervision of battery internal short-circuit is proposed using a machine learning anomaly detection and support vector machine (SVM) as fault detection and diagnosis respectively. Simulation of Stand-alone photovoltaic system with battery is carried-out to obtain data learning. In addition, a real profile of irradiance and temperature captured from Centre de Development des Energies Renouvelables (CDER), Algeria, during nine days is used as input of the system simulation. The developed anomaly detection and SVM diagnosis model show their ability to detect and diagnose the faults with high accuracy in test real-time data.

1. INTRODUCTION

The deployment of stand-alone photovoltaic (SAPV) systems over the world is still late compared to the grid-connected system [1]. The main reason is the lack of incentives governmental on the one side; on the other side, the high price of these systems. The battery as a storage element has been used for many renewable energy sources [2]. In addition, this component is the most sensitive and expensive part that needs to be permanently maintained. The battery is characterized to degrade faster if it operates in an unfavorable way, including Deep discharge, overcharge and internal short-circuit. The presence of these failures led to an early defect of the battery, and causes, performance degradation, loss of storing energy capability, and catastrophic damage like an explosion, fire, and acid contamination [3].

The battery protection against internal short-circuit is a pretty complicated task because of the lack of selecting the right sizing fuse as well as the problem of the location of this fuse [3]. International Energy Agency (IEA) has given in [4] an evaluation of battery in PV-diesel hybrid system based on the analysis of the battery voltage graph in short- and long-term evaluation. However, the exact state of the battery cannot be guaranteed as well as many days are needed to detect a possible failure. Monitoring of battery internal resistance is proposed in [5] to supervise the changes related to the battery like aging. The author in [6] uses an estimation of solar irradiance to predict the battery overcharge and the increasing of internal resistance. In [7–10], a performance assessment of the whole SAPV system including battery is performed from the point of view energy losses.

Even though there has been a performance analysis of the battery or the whole system, no studies efficiently examine the battery faults. Furthermore, the realization of the battery's internal short-circuits under real working conditions is crucial for experimental validation. To overcome this issue, real-time surveillance of battery internal short-circuit is proposed using two machine learning technics: 1) anomaly detection and 2) support vector machine (SVM). The proposed algorithms work as fault detection and classification respectively, in which the main advantage of adopting such method consists basically of the amount of fault data used for training, and the high classification accuracy. The simulation tool is used to validate the proposed approach.

The adopted methods are largely used in the field of fault detection and classification. Anomaly detection has been used for fault detection in rotating machinery [11] and in PV arrays grid-connected systems [12,13]. SVM knows a wide application area [14–17] due to its excellent characteristics which consist of the high generalization ability (better than artificial neural network and hidden Markov model). Moreover, it requires a small number of training data [18]. The training and test data are obtained from the simulation model under Matlab/SimPowerSystem, where the system takes as input the meteorological measurements (irradiance and temperature) captured from CDER, Algeria. The battery of 12 V is divided into six sub-batteries of 2 V connected in series to model the full cells and allowing the realization of internal short-circuit fault. Only two features are chosen as input variables to train, validate and test the proposed approach, where these features are the current and voltage of the battery.

In this paper, a development of fault detection and diagnosis model is performed. Their performance is verified in test real-time, the results show a high accuracy achieved (about 98 %) for both anomaly detection and SVM to detect and classify these internal short-circuits. Furthermore, the time response is reduced as long as the number of short-circuited cells increases. This paper is organized as follows: the first part describes the SAPV system with their mathematical model, then the theory behind anomaly detection and SVM is given. Then a test and validation of the proposed approach is realized and finally, the conclusion is given.

2. MODELISATION AND DESCRIPTION OF SAPV SYSTEM

2.1 MATHEMATICAL MODEL OF SAPV SYSTEM

A basic SAPV system constituted of PV panels, battery, and load connected in parallel and can be modeled by the following:

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2.1.1 PV PANEL MODEL

A single diode model used to develop the relation *I-V* of PV panel [19, 20] by using the following equations:

$$I = I_{ph} - I_0\left[\exp\left(\frac{V + R_s I}{\eta V_t}\right) - 1\right] + \frac{V + R_s I}{R_{sh}}, \qquad (1)$$

where I_{ph} is the generated photo-current, I_0 is the saturation current of diode, R_s and R_{sh} are respectively the series and shunt resistance of panel, n is the ideality factor of the diode, and V_t is the thermal voltage.

The diode saturation current changes according to the temperature by the equation (2):

$$I_0 = I_{0,ref}\left(\frac{T}{T_{ref}}\right)^3 \exp\left[\frac{qE_g}{\eta k}\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)\right], \qquad (2)$$

where T_{ref} and $I_{0,ref}$ are respectively the reference temperature and diode saturation current, k is the Boltzmann constant, q is the charge of the electron, and E_g is the bandgap energy.

2.1.2 LEAD-ACID BATTERY MODEL

The model of the battery included in SimPowerSystems/Matlab has been used [21], which has the expression (3) and (4) indicating the charge and discharge respectively.

$$V_{batt} = E_0 - R \cdot i - k\frac{Q}{it - 0.1Q} \cdot i^* - k\frac{Q}{Q - it} \cdot it + \exp(t) \qquad (3)$$

$$V_{batt} = E_0 - R \cdot i - k\frac{Q}{Q - it} \cdot (it + i^*) + \exp(t)\ , \qquad (4)$$

V_{batt} is the voltage of the battery, E_0 is the constant voltage of the battery, Q is the battery capacity, it is the actual capacity, k is the polarization resistance , i is the current of the battery, i^* is the filtered current and $\exp(t)$ is the exponential zone voltage.

2.1.2 LEAD-ACID BATTERY MODEL

A resistive load is considered in this work which takes a fixed value during the simulation.

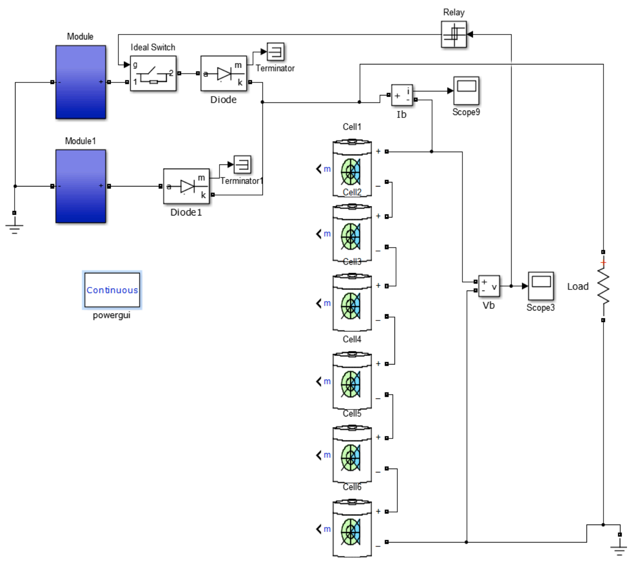


Fig. 1 – SimPowerSystem implementation of SAPV system.

2.2 PHYSICAL PROGRAMMING OF SAPV SYSTEM

The PV panel used is Isophoton 12 V/106 W where the five parameters are found in [22]. The type of lead-acid battery used is 12V contains 6 cells, where each cell voltage is 2 V. In order to create faults inter-cells, the battery is considered as sub-batteries connected in series to represent cells of the battery as illustrated in Fig. 1. This configuration allows the study of faulty battery by assuming the battery cells has identical electrical characteristics as given in Table 1. The table gives also the electrical characteristics of the PV panel and load.

Table 1

Electrical characteristics of SAPV system component

PV panels	Battery	Load
Pmpp =212 Wp (106×2) *Vmpp*=17.40 V, *Impp*=12.20 A *Isc*=13.08 A, *Voc*=21.60 V	*C* =200 Ah (200 Ah for cell) *Vs* = 12 V (2V for cell) SOC0=90 % (90 % for cell)	*P* =50 W *V* =12 V

The manufacturer parameters of PV panel, battery, and load are described below:

Under stc (*i.e.* 1000 W/m^2 and 25C$^\circ$), *Pmpp*, *Impp*, and *Vmpp* refer respectively to the PV power, current, and voltage at the maximum power point. *Isc* and *Voc* is the current and voltage at short and open circuit PV panels.
C is the battery rated capacity, *Vs* is the nominal voltage of the battery, and SOC0 is the initial state of charge.
P and *V* are the power and voltage of the load.

3. BATTERY FAULT DETECTION AND DIAGNOSIS METHODOLOGY

The main objective is the detection and identification of faults that occurred in cells of battery for SAPV system application (Fig. 2), where the fault detection algorithm proposed is anomaly detection in which it is based on the historical data of normal operating state, this method is suitable for the case of the battery where it is hard to obtain a database that covers all faults coming in the battery, in addition, the complex behavior of the battery makes the modelization of this system uncertain. To identify the type of fault a classification process may give a good solution, however, it needs a huge database in the stage of learning, for this reason, the SVM is proposed as faults classification since it needs a small number of data for training. In Fig. 3 the strategy for fault diagnosis is given by the flowchart, it's shown that the fault classification is activated only when the fault is occurring.

Anomaly detection is a machine learning technique mostly used in fault detection [23] where the faulty data are not available or cannot be modeled, the anomaly detection aim to recognize any abnormal from normal data by making

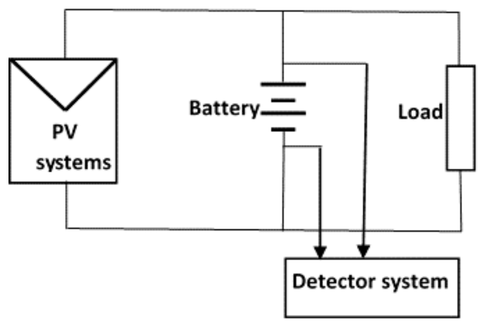


Fig. 2 – Schematic block of detector system used in Battery for SAPV system.

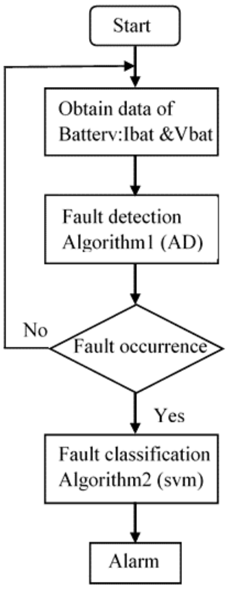


Fig. 3 – Flowchart of the proposed fault diagnosis process.

an assumption that the data are distributed under Gaussian distribution and calculating the Gaussian probability density, the fault can be determined. SVM is a successful classification method used in many research areas, which gives high accuracy in a small number of data learning and has the ability of generalization better than other classifiers such as artificial neural network [18]. As shown in Fig. 4 SVM aims to find the optimal hyperplane that maximize the margin distance separating both classes, where the data that lies on the margin are the support vectors that create a limit boundary. SVM is intended for binary classification, however, it can be extended to multi-class machine learning using several ways, in which the ''one *vs.* one'' is used in this work to construct $C(C-1)/2$ binary SVM, where C is the number of class. In fault classification method, each class represents one type of fault or the healthy state.

The mathematical theory behind both anomaly detection and classification is given, where a detailed SVM classification algorithm is found in [24]. These two methods are summarized below:

3.1. ALGORITHM 1 (ANOMALY DETECTION)

For each $x \in R^n$ the Gaussian probability density is defined as:

$$P(x)=\frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) \tag{5}$$

where the parameters μ and σ^2 are respectively the mean and the variance defined below:

$$\mu=\frac{1}{m}\sum_{i=1}^{m}x^{(i)}\,, \tag{6}$$

$$\sigma^2=\frac{1}{m}\sum_{i=1}^{m}\left(x^{(i)}-\mu\right)^2 . \tag{7}$$

The value of Gaussian probability density decide if we have a fault or not, this threshold (th) can be calculated using $F1$ score as evaluation metric expressed by the following :

$$F1=\frac{2.prec.rec}{prec+rec}\,, \tag{8}$$

where *prec* is the precision and *rec* is the recall given by these equations:

$$prec=\frac{tp}{tp+fp};\quad rec=\frac{tp}{tp+fn}\,, \tag{9}$$

tp and *fp* are the true and false positive respectively, where *fn* is the false negative.

3.2. ALGORITHM 2 (BINARY SVM)

Let the input data x_n (n = 1,…,N), where N is the number of sample data and the corresponding output $y_n \in \{1,-1\}$ which indicate the first and second class. To find the optimal hyperplane separating data, the following minimization problem must be solved.

$$\min J(\theta)=\frac{1}{2}\sum_{n,m=1}^{N}\theta_n\theta_m y_n y_m k(x_n,x_m)-\sum_{n=1}^{N}\theta_n \tag{10}$$

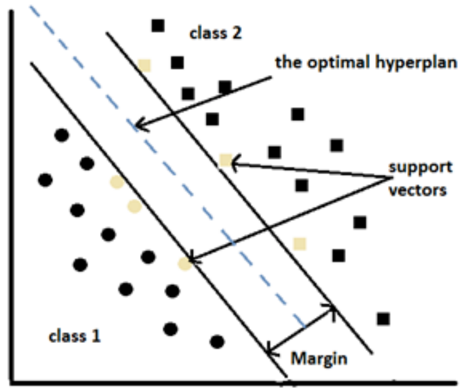


Fig. 4 – Schematic of separating binary class by SVM.

subject to

$$\sum_{n=1}^{N}\theta_n y_n=0 \quad 0\le\theta\le D \quad \text{for } n=1,\dots,N .$$

where the Gaussian kernel function is defined as: $k(x_n,x_m)=\exp\left(-\frac{\|x_n-x_m\|^2}{2\sigma^2}\right)$, and $\theta=\begin{bmatrix}\theta_1\\ \vdots\\ \theta_N\end{bmatrix}$ is the Lagrange multipliers.

The optimization problem in (10) is solved in which the support vectors $x_1, x_2,\dots, x_s$ and the corresponding y_n, θ_n are saved, where s is the number of support vectors.
For given a new example x:

$$k(x)=\begin{cases}1 & \text{if } \operatorname{sign}\left(\sum_{n=1}^{S}\theta_n y_n k(x_n,x)+b\right)\ge 0\\ -1 & \text{otherwise}\end{cases}\,, \tag{11}$$

where b is the bias value.

4. TEST AND VALIDATION THE FAULT DETECTION AND DIAGNOSIS

4.1. DATA COLLECTION OF BATTERY

A simulation of SAPV system as described above is carried out using the weather condition profile (irradiance and temperature) as input. These meteorological

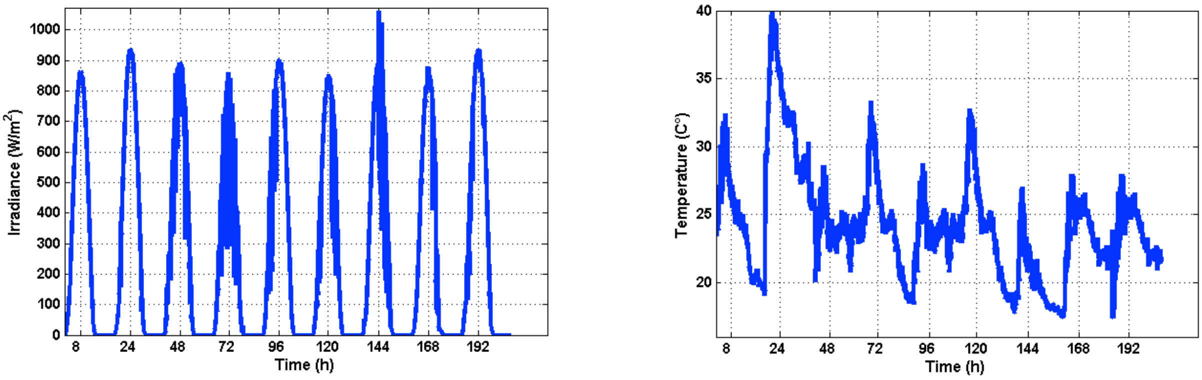


Fig. 5 – Irradiance and temperature profile.

measurements as shown in Fig. 5 are taking during Nine days with a sampling of 1 min from CDER, Bouzereah, Algeria. The Normal and faulty data of battery issued from the simulation of SAPV system are used for training, validation and testing the proposed approach. The first algorithm is trained with four days of Normal data which correspond to 5754 samples and validated with one day of faulty data which is equivalent to 1439 samples. The second algorithm is trained and validated with only one day (1439 samples), the rest of the days are used for testing both detection and classification algorithm.

4.2. TRAINING AND VALIDATION STAGE

The learning of detection and diagnosis system has been done by creating six faults between cells of the battery, these faults are ranged from short-circuit of one cell to six cells with *Rfault* = 0.1 ohm. Table 2 shows these faults as well as the symbol used. To avoid the false alarm happening with fault detection, the fault diagnosis is also trained by the Normal state to confirm the result of a fault. The validation set is used for choosing the best parameters: for anomaly detection (th = 0.0051) and for SVM (D = 1 and σ = 10). The general accuracy in training and validation data are given in Table 3, where it can be seen that high accuracy is obtained for both anomaly detection and SVM classification. This means that the proposed approach is well trained and good parameters are chosen.

4.3. ONLINE TEST

Four days out of nine are intended for the test, where these data are not included in the stage of training or validation. The test is performed for all faults in real-time, in which the battery work in a healthy state for the first four days, then a fault is occurring for the rest of the days. The overall number of data corresponds to nine days is 12947 data, in which the rate of good classification data, as well as the accuracy in test real-time for both anomaly detection and SVM classification, is given in Table 4. The results show that the Normal case is accurately detected and classified, and this is about 98 %. For the fault F1 to F6, the

Table 2

Different faults in battery for SAPV system

State of battery	**Symbol**
Normal	N
Short-circuit one cell	F1
Short-circuit two cells	F2
Short-circuit four cells	F4
Short-circuit five cells	F5
Short-circuit six cells	F6

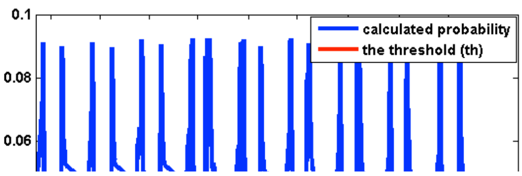


Table 3

General accuracy in training and validation data

	Anomaly detection	SVM
Training data	98.61%	97.77 %
Validation data	97.83%	98.14 %

Table 4

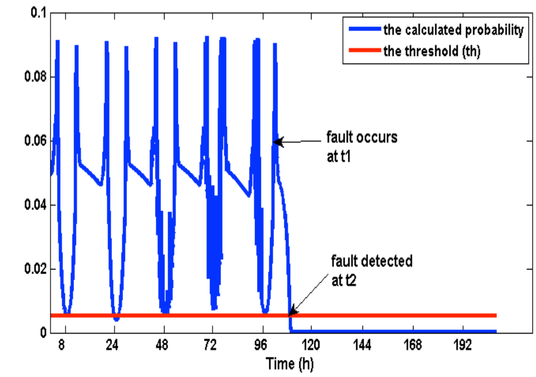
Accuracy and number of correct data predicted for AD and SVM

State of Battery	**Anomaly detection**		**SVM**	
	No. of good classification	Accuracy	No. of good classification	Accuracy
N	12813	98.97 %	12714	98.20 %
F1	12332	95.25 %	12411	95.86 %
F2	12585	97.21 %	12507	96.60 %
F3	12678	97.93 %	12592	97.26 %
F4	12725	98.29 %	12583	97.19 %
F5	12752	98.50 %	12667	97.84 %
F6	12777	98.69 %	12799	98.86 %

accuracy of fault detection and classification worth between 95 % and 98 % where the smallest value recorded in F1 to increase slowly to F6. The reason is that the battery is more vulnerable to the increasing of cells number short-circuited and this leads to more accurate results in detection and identification.

To display the passage from the Normal state to the fault in real time for fault detection and identification, the results of the test, realized above is shown in Fig. 6 to Fig. 13. The Gaussian probability is plotted with the threshold (th) for fault detection, and for classification a scatter plot of predicted class with the actual or desired class. The moment of appearance the fault is the same for all the tested faults.

Figures 6 and 7 show the test of the normal case, where it can be seen from Fig. 6 that the probability doesn't drop below the threshold (th) with exception of two false alarms marked. To confirm the result a classification is performed as shown in Fig. 7 where it indicates Class N with some misclassified data.



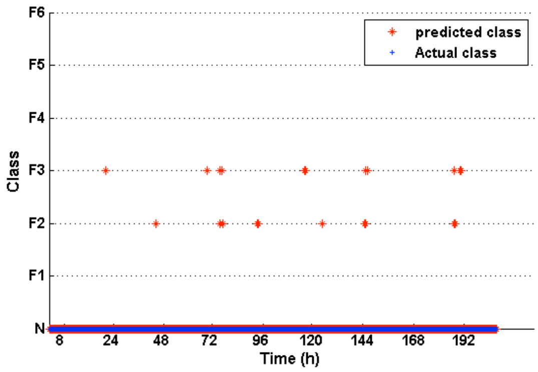


Fig. 7 – SVM diagnosis test result: normal case.

Fig. 8 – Anomaly detection test result: short-circuit one cell (F1).

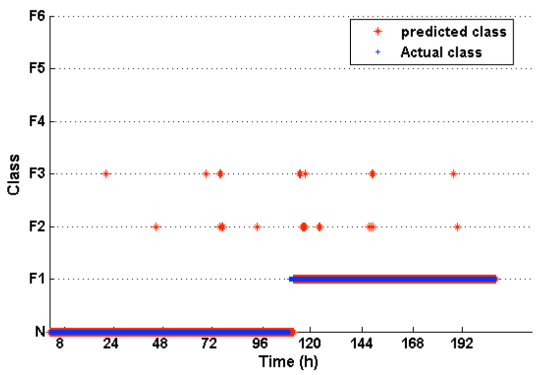


Fig. 9 – SVM diagnosis test result: short-circuit one cell (F1).

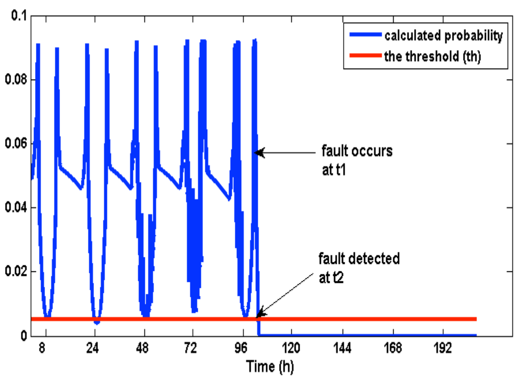


Fig. 10 – Anomaly detection test result: short-circuit three cells (F3).

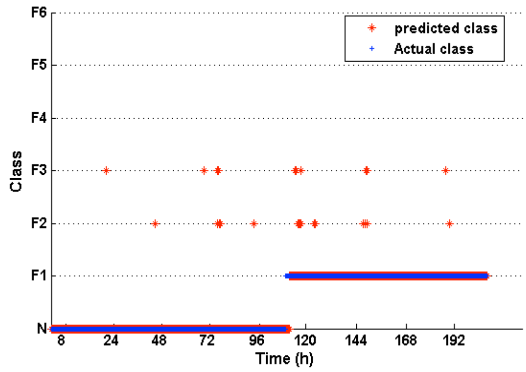


Fig. 11 – SVM diagnosis test result: short-circuit three cells (F3).

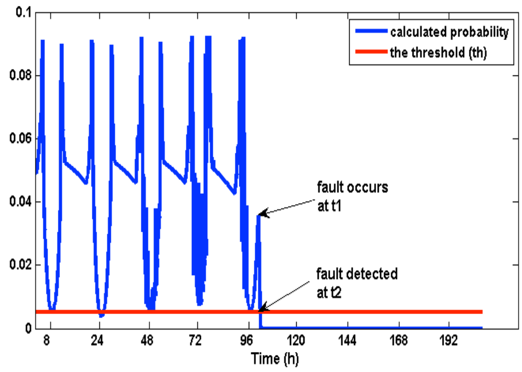


Fig. 12 – Anomaly detection test result: short-circuit six cells (F6).

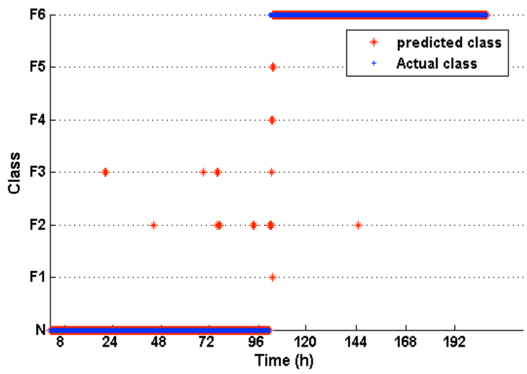


Fig. 13 – SVM diagnosis test result: short-circuit six cells (F6).

Figures 8 and 9 show the test of one cell short-circuited, and as indicated in Fig. 8, when the fault occurs the probability decrease under the threshold (*th*). The algorithm takes a certain time to detect the fault, and at this moment, SVM classification is launched to identify the fault F1 with certain delay and making some misclassification data.

Figures 10 and 11 show the test of three cells short-circuited, where in Fig. 10 the probability descend under the threshold more rapidly than in F1. As a consequence, the order is quickly given to SVM to recognize the fault F3 as illustrated in Fig. 11. Some delay in the recognition compared the actual class has been noted with some misclassification data.

Figures 12 and 13 show the test of six cells short-circuited, where in Fig. 12, the probability descend immediately under the threshold indicating the presence of fault. The SVM classification started more rapidly as shown in Fig. 13 to identify the fault F6 with some error.

From these figures, it can be seen that the time of fault detection reduced with the number of cells defected and by consequence, the time of classification is also reduced. The reason is that when the battery is strongly affected, the voltage drops immediately and this last accelerates the detection followed by the classification.

The achieved results from Fig. 6 to Fig. 13 show a significant improvement in terms of precision and the time spent to recognize the faults. Whereas previous studies [4, 10] provide only an evaluation of the battery or the SAPV system without determining the fault type, and the process is carried out at the end of the day.

5. **CONCLUSION**

In this paper, Anomaly detection and SVM machine learning classification are applied to detect and identify the internal short-circuit of battery for the SAPV system application. The battery current and voltage are used as features to train and test the detector system. Due to the difficulty of obtaining faulty data of battery, Anomaly detection and SVM algorithm offer a good solution in fault detection and diagnosis. By the reason that, Anomaly detection requires only healthy data and SVM needs a small number of data. This work is validated using simulation data of the whole SAPV system, in which the battery is considered as a series connection of sub-battery to represent cells. This way allows the realization of faults under different meteorological conditions of a real profile of irradiance and temperature taken during nine days from CDER (Algeria).

The proposed approach shows high accuracy in fault detection and classification for both training and test data. In addition, the result can be more accurate and rapidly signals the fault in real-time if the number of cells defected is increasing. The future work consists to implement these methods in battery charge regulator to work in real-time.

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