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# DC series arc fault detection algorithm using Convolution Neural Network

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**Abstract**— The detection of electrical failures and more specifically electric arcs faults detection becomes absolutely necessary because of their dangerousness. Unlike the main methods in the literature based on frequency analysis, we propose in this paper a method of detection based on CNN models (LeNet5 – 28\*28 and 64\*64 images). Series arc faults are produced in a circuit composed of a 270 Volt DC supply voltage and mainly resistive loads. The line current is recorded (dataset composed of about 11000 signatures with and without arc faults). We also consider the case of load variation without arc faults. The selected sections of the current signals are then transformed into 2D matrixes (images). Then, the network is trained, validated and tested using the dataset. The performance of this method is also studied and discussed. More precisely, the detection results are presented using a confusion matrix. Experimental results show that the method we propose can effectively detect arcing faults.

**Keywords**— Series arcing fault, DC grid, fault detection, LeNet5 model

## I. INTRODUCTION

New electric avionics systems migrate from alternative to continuous voltage 270V<sub>DC</sub> topology in order to meet energy needs and weight. In air safety traffic, detecting electrical arcing is critically important, particularly in serial arc faults. The detection of electrical failures and more specifically electric arcs faults detection becomes absolutely necessary because of their dangerousness. A lot of methods of detection are presented in the literature. Most of them concern the detection of arc faults in solar photovoltaic panels [1]. Temporal analysis of the electrical characteristics of the current or in some cases the voltage delivered by the power supply can be done (analysis of the variance, ...). But, most of the proposed methods are based on the frequency analysis of the line current.

In [2], the authors have proposed a detection method for DC SSPC (28V-supply voltage) and have retained the bandwidth frequency [10Hz, 10kHz] in

the case of inductive loads. In [3], the authors analyzed the source of an arc-voltage noise and observed the variations that occurred within the three bandwidths [1-10kHz, 10-40kHz, 40-400kHz]. The frequency band proposed for PV-DC arc detection was limited to [0.1- 4kHz] for [4], [40kHz – 100kHz] for [5] but multiple frequencies [6-8]. For several years, new studies have been based on machine learning methods to try to improve detection performances. Authors [9] compared for example the performances of detection for various machine learning models showing that the algorithm performances varies largely with the operating conditions. In our work, we have voluntarily chosen to use a CNN network (LeNet5 type) that can be easily implemented in an electronic embedded system. The sampled serial data will be decomposed into segments and then transformed into an image (2D matrix) [10]. Authors [11] proposed as for them a method based on lightweight transfer convolution network with adversarial data augmentation. Each windowed sample is transform in a 2D matrix (32\*33). It is also possible to combine a time frequency analysis to CNN approaches (Discrete Wavelet Transform or STFT). Authors in [12] proposed as for them an improved LeNet5 CNN model after a DWT transform

This paper is organized as follows. Section II presents the experimental setup used to record all current signatures analyzed in this paper. Section III explains the dataset construction. Section IV gives a background of the designed algorithm for detecting series arcing faults (CNN and CNN+STFT). In the last section, the results obtained are presented.

## II. EXPERIMENTAL MEASUREMENTS

### A. Test bench

The proposed series arc fault detection algorithm based on current line analysis is validated using a database of current signatures measured in normal operation (without arcing fault) and then under the presence of series arc faults in an experimental electrical circuit. The experimental setup is shown in Figure 1.

For each load, the recorded current signature is composed of one part under healthy operating

conditions then in the presence of an arc fault. The experimental test bench makes it possible to reproduce series arcs defects by opening contacts on a DC power line obtained in this work with copper electrodes (6.3 mm) according to the standard UL 1699B. The arc voltage measurement validates the presence of the fault.

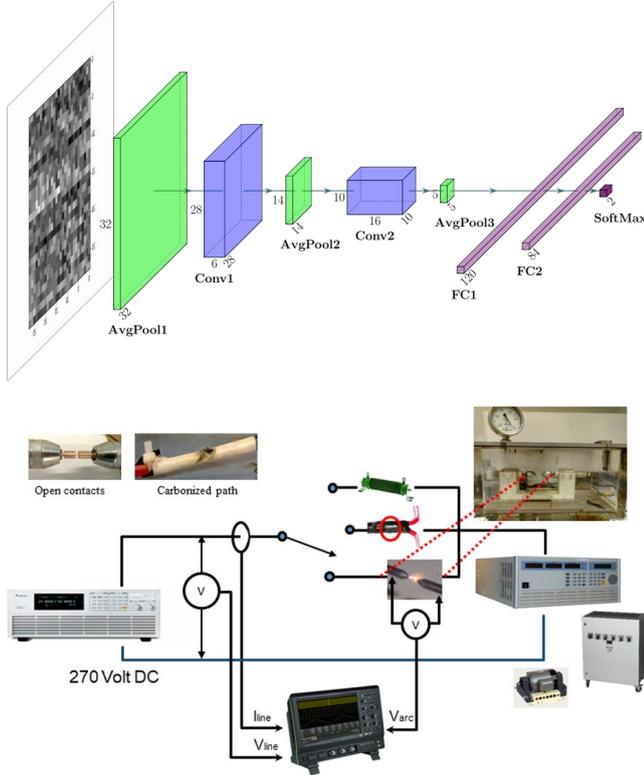


Figure 1: Experimental set-up.

Two different continuous stabilized power supplies (270 VDC) are used (CHROMA 62000H - ETSystem 3kW) in this experiment. The electric loads that make up the circuit are linear : Variable resistance (from 12 to 240Ω) with an inductance (between 30μH and 100μH)

The electric arc fault ignition in the line results in a current drop similar to that obtained for load change. So for each appliances, a first test is performed by placing a series arc in the power line as shown in Figure 1, then replacing the electric arc with a resistance (called lure) of impedance close to that of the electric arc and thus causing the same current drop. The algorithm must detect the presence of an arc fault in the circuit while being insensitive to load variations.

A LECROY HDO4096 oscilloscope at a sampling frequency of 1 MHz performs the measurements over a duration of 3 seconds.

Measurements of line and arc voltages are made using an active differential probe Testec TTSI9010. The current probe AP015 (Lecroy) has a 75 MHz (cal 0.1A) bandwidth.

The current signature database used to evaluate the performance of the detection algorithm contains a total of about sixty current signatures.

### III. DATASET CONSTRUCTION

#### IV. CNN NEURAL NETWORK FOR DETECTION

Convolution neural network is a feed-forward artificial neural network largely used in many domains and is especially adapted to image recognition and classification. In this work, we have chosen the classical LeNet5 architecture composed of two significant types of layers (Convolution and sub-sampling layers, as shown in fig 4). Moreover, this model has naturally imposed itself because of its easy implementation in an embedded electronic system.

The size of the input images of the model that we choose to test will be 28\*28 and 64\*64 which corresponds to a limited time frame of 784μs for the first case or 4.096ms for the second one.

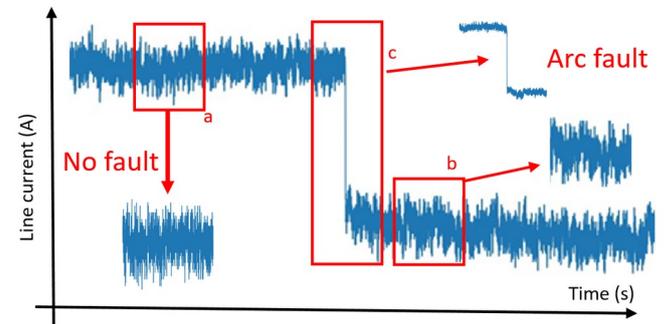


Figure 2: Dataset construction

From the set of recorded current signatures, we extract, as represented in figure 2 :

- segments in the area without arc defect (a)
- segments in the area with arc fault (b)
- segments in the area in the transition zone between No fault and arc fault (c).

Each segment of time series data is then transformed into a 2D matrix according to the process described in figure 3.

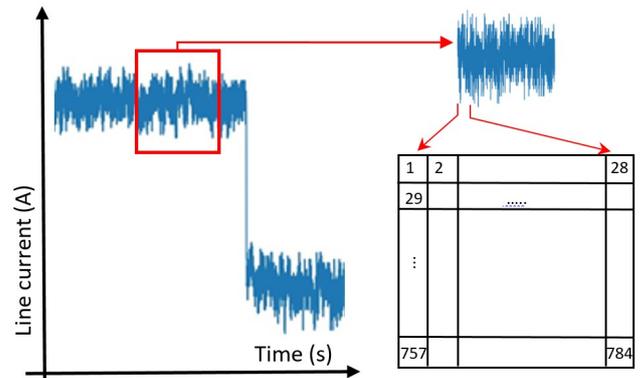


Figure 3: Construction of an image

The composition of the database is given in the following table I.

TABLE I. DATABASE

	Normal signals	Arcing	Normal signals	Arcing
Training set	5879	5427	7584	10827
Test set	148	169	440	511
Image size	28 * 28		64 * 64	

The adapted architecture is summarized in figure 2 for the particular case of an input compose of a 64\*64 image.

In the configuration of the model developed for this work, we have inserted a dropout layer between two convolution/pooling layers to weaken the influence of overfitting. Then, the features of the image are fully flattened (Flatten) and transmitted to the Fully connected block composed of a dropout layer and two ReLu type activation layers. The output of the model allows to classify the image between an arcing fault or a normal situation.

## V. RESULTS

### 4.1 Detection from the segments

The results of detection are presented in a matrix of confusion. A set of experimental test situations (True Class) combining operating modes both with arcing faults (Fault) and in normal operation (No Fault) are reproduced. From the detection of algorithm, both an arc fault can be detected (Fault) or a healthy situation (No Fault). The confusion matrix described in figure 4 is including 4 categories.

		Predicted Class	
		Fault	No Fault
True Class	Fault	TP	FN
	No Fault	FP	TN

Figure 4: Matrix of confusion

TP and TN represent the correctly classified cases either positive or negative. FN and FP represent the number of negative and positives cases misclassified.

Performances are estimated as :

- Sensitivity (true positive rate)  $TPR = \frac{TP}{TP+FN}$

- Specificity (True negative rate]

$$TNR = \frac{TN}{FP+TN}$$

$$- \text{Detection Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

The accuracy value represents the proportion of true positive results (both true positive and true negative). False positive rate (also called false alarm rate) isn expressed by the following relation :  $FPR = \frac{FP}{FP+TN}$

An optimal detection is obtained when the value of the specificity is low and the sensitivity value high.

The detection results are given in the two following tables.

Images 28\*28 = 784 points :

The model is tested using a dataset of 317 images. The performances of detection are presented in table II.

TABLE II. CONFUSION MATRIX (IMAGES 28\*28)

		Predicted class	
		No Arc	Arc
True class	No Arc	148	0
	Arc	23	146

Images 64\*64 = 4096 points :

TABLE III. CONFUSION MATRIX (IMAGES 64\*64)

		Predicted class	
		No Arc	Arc
True class	No Arc	440	0
	Arc	35	486

The model is tested using a dataset of 951 images. The performances of detection are presented in table III.

The value of the precision obtained is the same order of magnitude (92.74 % for 28\*28 images and 96.3 % for 64\*64 images).

### 4.2 Cases of false detection

In both cases, the signals causing false detection are the current signatures comprising a part without faults and a second part with an electric arc fault (figure 5). It would have been desirable to create a third label (start of electric arc) regrouping all these cases.

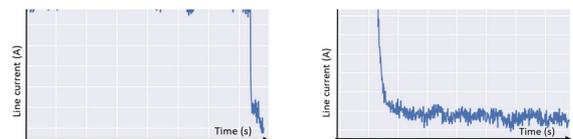


Figure 5 : Current signatures (false detection) (a)

### 4.3 Detection from the spectrogram

In this paragraph, the calculation of the spectrogram on the current segment is calculated first (time frequency feature extraction). The analysis then focuses on the image obtained (28\*28 or 64\*64).

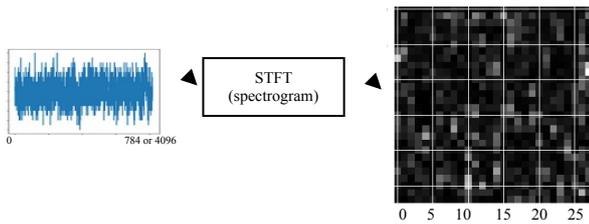


Figure 6 : Spectrogram for detection

Each segment of time serial data is then transform into a 2D matrix according to the process described in figure 3.

The performances of detection are presented in the following tables.

images 28\*28

		No Arc	Arc
True class	No Arc	148	0
	Arc	23	146

images 64\*64

		No Arc	Arc
True class	No Arc	440	0
	Arc	25	486

With this database, the detection performance with the spectrogram analysis has not strongly increased but remains quite acceptable. Also in this configuration, signals with one part without defect and a second part with an arc are the cause of false detections.

VI. CONCLUSION

In this paper a method for series arc fault detection in DC electrical network based machine learning techniques is presented. The transformation of the current signature (Segments) into a 2D matrix makes it possible to use a CNN. The algorithm gives good performances of detection although false detections are always obtained with the same type of signals.

In the future, priority improvements include:

- More complete Dataset of current signature
- Optimization of the sample frequency and the 2D matrix dimension
- Testing other models (LSTM, ...)
- Combining models (CNN/LSTM ....)
- Implantation of the algorithm in an electronic embedded system..

REFERENCES

- [1] S. R. Madeti, S.N. Singh. "A comprehensive study on different types of faults and detection techniques for solar photovoltaic system", in: Solar Energy, 158 (2017), pp 161
- [2] Meng Xie and al. "Arc fault detection for, DC solid state power controllers", in: IEEE Conference and Expo Transportation Electrification Asia-Pacific (ITEC AsiaPacific), (2014), pp. 1-6.
- [3] M. Wendl, M. Weiss, F. Berger. "HF characterization of Low Current DC Arcs at Alterable Conditions", in: The 27th International Conference on Electrical Contacts (ICEC), (2014), pp. 1-6.
- [4] Y. Gao, J. Zhang, Y. Lin, Y. Sun. "An innovative photovoltaic DC arc fault detection method through multiple criteria algorithm based on a new arc initiation method", in: IEEE 40th Photovoltaic Specialist Conference (PVSC), (2014), pp. 3188-3192
- [5] B. Novak. "Implementing arc detection in solar applications: achieving compliance with the new UL 1699B Standard". Texas Instruments, (2012).
- [6] J. Johnson, S. Kuszmaul, W. Bower, D. Schoenwald "Using PV module and line frequency response data to create 13 robust arc fault detectors", in: Proc. 26th European Photovoltaic Solar Energy Conference and Exhibition Hamburg, (2011), pp. 3745-50.
- [7] J. Johnson, C. Oberhauser, M. Montoya, A. Fresquez, S. Gonzalez and A. Patel, "Crosstalk nuisance trip testing of photovoltaic DC arc-fault detectors," in: 38th IEEE Photovoltaic Specialists Conference, Austin, TX, (2012), pp. 001383-001387
- [8] J. Johnson, J. Kang. "Arc-Fault Detector Algorithm Evaluation Method Utilizing Prerecorded Arcing Signatures", in: 38th IEEE Photovoltaic Specialists Conference (PVSC), (2012), pp. 001378-001382.
- [9] H. -L. Dang, J. Kim, S. Kwak and S. Choi, "Series DC Arc Fault Detection Using Machine Learning Algorithms," in IEEE Access, vol. 9, pp. 133346-133364, 2021, doi: 10.1109/ACCESS.2021.3115512.
- [10] Chu, R.; Schweitzer, P.; Zhang, R. Series AC Arc Fault Detection Method Based on High-Frequency Coupling Sensor and Convolution Neural Network. Sensors 2020, 20, 4910.
- [11] Wang, Y.; Bai, C.; Qian, X.; Liu, W.; Zhu, C.; Ge, L. A DC Series Arc Fault Detection Method Based on a Lightweight Convolutional Neural Network Used in Photovoltaic System. Energies 2022, 15, 2877.
- [12] Li, T.; Jiao, Z.; Wang, L.; Mu, Y. A Method of DC Arc Detection in All-Electric Aircraft. Energies 2020, 13, 4190. <https://doi.org/10.3390/en13164190>