Evaluation of Machine Learning Methods in a Rain Detection System for Partial Discharge Data Analysis

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***Abstract* — Partial discharges (PD) on high voltage insulator surfaces are directly related with the deposition of pollution over the insulators. A complete partial discharge sensor network was previously developed and has been in operation for approximately three years. This system records the PD activity classifying it into four levels. As the PD activity is influenced by the weather conditions the sensor network measures the one hour average temperature and relative humidity. Also a fuzzy inference system was developed to extract the flashover occurrence risk level based on the partial discharge activity recorded. However, a strong rain event can wash the insulators strings almost instantaneously decreasing the risk level. To a correct result interpretation it is important to properly analyze the weather data to detect the rain occurrence. This paper presents a comparison among three approaches for rain detection from humidity and temperature data. The three approaches, Naïve Bayes Classifier, Support Vector Machines and Multilayer Perceptron Neural Network are trained on data gathered by meteorological stations located nearby the PD sensors and used in conjunction with the data obtained by those. Promising preliminary results are presented.**

Keywords; Partial discharges; rain detection; pattern recognition; leakage current; insulators.

I. INTRODUCTION

The high voltage transmission lines are affected by many problems. One of them is the pollution accumulated over the insulators strings. When combined with high relative humidity the pollution layer becomes a conductive layer. A leakage current flows by this conductive layer causing irregular heating and then humidity evaporation, creating thin dry bands. The increase of electric charges in dry bands borders combined with the high electric field causes partial discharges near these dry bands [1]. The partial discharges phenomenon increases its rate and intensity until a complete discharge, known as flashover, bypassing all insulators causes a failure on the transmission line [2].

One way to avoid the flashover is by removing the pollution layer deposited over the insulator string by washing. However, this is a high cost operation and failures may occur during the procedure.

Aiming to assist the decision regarding the need for maintenance of the insulator string, a sensor network was previously developed to detect and classify partial discharges according to their frequency of occurrence and intensity [3]. This system comprises an optical sensor coupled to an optical fiber, which transmits the leakage current [4] signal to an electronic processing module, which has also a temperature and a humidity sensor [5]. The collected data are transmitted via satellite and stored in a database.

A fuzzy inference system has been developed in order to extract the flashover risk occurrence. The risk level is incremented and decremented according to the level of partial discharge activity considering its intrinsic relation with relative humidity [6]. The use of a fuzzy system has the advantage of being able to represent uncertainties of natural language, such as, for example, “the insulator string is slightly polluted”.

However, on strong rain events the insulator string is washed ceasing the flashover risk after it. This almost instantaneous risk variation is not reflected on the fuzzy sequential decrement risk level. This work aims to develop a system capable of detecting the instantaneous cleaning of the insulator by strong rains, based on the available humidity and temperature data. The rain detection will make the fuzzy risk classification system more precise and turn the maintenance schedule more robust, reducing costs due to unnecessary washes.

Common electronic rain sensors are only capable of detecting rain in a small surface and are not capable of quantifying the event [7]. Electromechanical rain sensors are capable of easily detecting and quantifying rain. Nevertheless, when installed in outdoor environments this kind of sensor accumulates water, in turn attracting infestation by wasps or bees. The presence of these insects increases the risk for operators of the power transmission company and increases the failure rate of the rain sensor itself once the hives might block the mechanical parts of the sensor.

Temperature and humidity data gathered by the sensor network exhibits a daily regular pattern. This pattern is changed by rain events and a new rain pattern starts to occur. So, a pattern recognition system can be applied to detect the insulator washing by rain. A pattern recognition prototype system was developed based on the reliable data obtained from the Brazilian Institute of Meteorology, INMET, database. This database has humidity and temperature information as also the amount of rain precipitation per hour.

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This paper compares three approaches for the rain detection system proposed: Naïve Bayes Classifier, Support Vector Machine (SVM) and Multilayer Perceptron Neural Network (MLP). After this analysis, the MLP was applied in a data set gathered by the partial discharge sensor network and visual inspections were realized to ensure empirically the rain detection success.

The following sections are organized as: Section 2 describes the satellite sensor system network; Section 3 describes the used data sets and the rain pattern; Section 4 discuss the concepts of each approach for rain detection; Section 5 describes the methodology used in this work; Section 6 presents the results and finally, the conclusions and final considerations are in Section 7.

II. SATELLITE SENSOR SYSTEM NETWORK

The satellite network is composed by six nodes operating and it has been in operation for three years in the Northeast region of Brazil. Each node is composed by an optical sensor, an electronic processing module and a satellite transmission modem [3], as illustrated in Fig. 1.

Each hour the sensor node transmits the partial discharges activities, average temperature and average humidity. The partial discharge activity is classified into four current ranges named N1 to N4, which are related to current pulses larger than 5, 10, 20 and 40 mA, respectively [3].

The information gathered by each sensor is organized into two 64-bit packets and transmitted via satellite each half hour. After reception the data are stored in a database. The access to this database is provided by the ADECI (from their initials in Portuguese – Electric Performance Evaluation on Insulator Strings) system. Only identified employees of CHESF (the generation and distribution company in the Northeast region of Brazil) can access the information.

III. DATA SETS AND RAIN PATTERN

The temperature and humidity have an almost regular daily behavior. During the day, the temperature is high and the humidity is low; at night the temperature falls down and the humidity goes up. During rain events this behavior is modified because the rain causes an immediate increase in humidity and decrease in temperature. This behavior can be seen in Fig. 2 – at rain events the temperature falls down and the humidity goes up. This behavior is better observed in heavy rain events than in light rains.

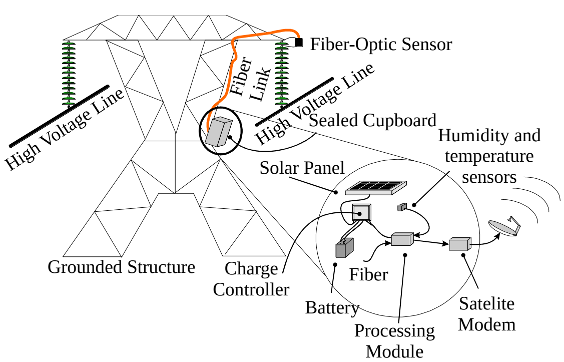

Figure 1. Sensor node for partial discharge monitoring.

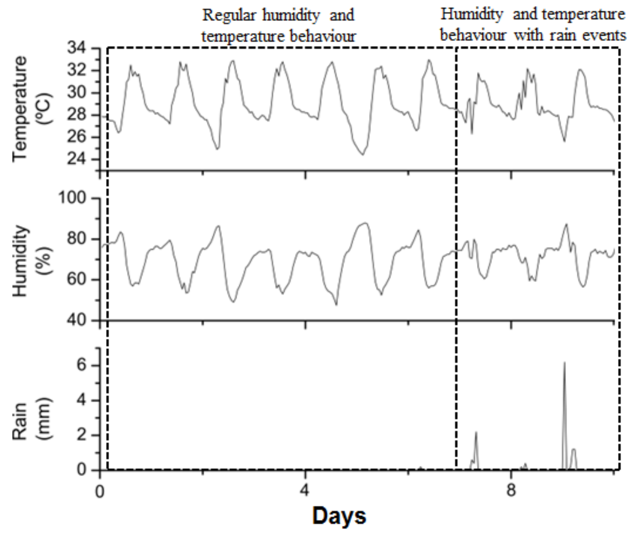

Figure 2. Plots of temperature and humidity patterns.

The INMET meteorological stations data contain average temperature and humidity as also the amount of rain precipitation in millimeters per hour. Linear interpolations were used to complete the series on every data missing less than 5 hours. When the time period of the missing data was larger than 5 hours, data for the full day were excluded from the database.

The INMET database was used to train each detection rain model for further use on ADECI bases. Fig. 3 shows the sensor network topology and each node of the nearest INMET meteorological station. Although each sensor node has a near INMET station, the distance between them is about tens of kilometers and a rain in the INMET station does not imply a rain in the nearest ADECI sensor location.

The data set was organized on day-long vectors as show in Table I. T0 to T23 represents the temperatures for the 24 hours as well as U0 to U23 represent humidity values. If the day has a total rain precipitation larger than 1 mm, the day is classified as rainy. Otherwise it is classified as no rain.

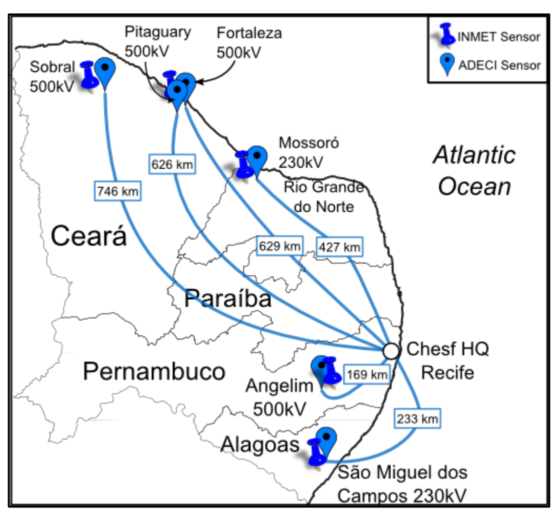

Figure 3. Sensor node and INMET station location.

TABLE I. DATA SET ATTRIBUTES AND CLASS.

Attributes						Class
T0	...	T23	U0	...	U23	[rain / no rain]

IV. APPLIED TECHNIQUES

A. Naïve Bayes Classifier

A Naïve Bayes Classifier [8] is a supervised-learning statistical technique. A vector x represents m features $(x_1, x_2, \dots, x_m)$, in this work, each dimension of vector x comprehends an attribute of the database. The a posteriori probability of having rained in a specified day can be calculated using Bayes theorem as

$$P(rain|x) = \frac{P(rain)P(x|rain)}{P(x)}. \qquad (1)$$

In (1), $P(x)$ is the probability of x occurring in the data set and $P(x|rain)$ is the likelihood probability of x occurring in the "rain" class.

By using the naïve assumption, i.e. the attributes are conditionally independent, the likelihood probably of $P(x|rain)$ is

$$P(x|rain) = \prod_{i=1}^{m} P(x_i|rain). \qquad (2)$$

It means that under the naïve assumption, the conditional distribution over the "rain" class can be expressed as

$$P(rain|x) = \frac{1}{Z} P(rain) \prod_{i=1}^{m} P(x_i|rain), \qquad (3)$$

where Z, the evidence, is a scaling factor dependent only on the features of the x vector.

All the Naïve Bayes Classifier parameters (the class prior and feature probability distributions) can be approximated with relative frequencies from the training set. In this work the continuous values associated with each class were considered to have a Gaussian distribution.

B. Multilayer Perceptron Neural Network

The MLP [9] is an artificial neural network whose architecture is based on multiple layers of neurons: an input layer, one or more hidden layers and an output layer. The number of hidden layers can be changed depending on the application.

Each neuron can be seen as an element with inputs, weights, one activation function and the output signal. The output signal of each neuron is given by

$$y_j = f\left(\sum_{i=1}^{n} x_{ji} w_{ji}\right), \qquad (4)$$

where, y_j is the output signal of the j neuron, x_{ji} is the *ith* entry of the j neuron, w_{ji} is the *ith* weight of the j neuron and f is the activation function. In this work the sigmoid function was used as activation function [9]. The signal is propagated from the input layer to the output layer – where the classifier result is available.

The training of a MLP consists on the weights adjusts. The objective is to train the MLP network to achieve a balance between the ability to respond correctly to the input patterns used for training and the ability to provide good results for other similar inputs, i.e. train the network to be capable of performing generalization. For this task, the classic backpropagation algorithm was used to realize the training of the neural network [9].

C. Support Vector Machine

The SVM [10] is a statistically robust learning method in which the training process consists into finding an optimal hyperplane which maximizes the margin between two classes of data in the kernel induced feature space.

Given an input data of n samples x_i $(i = 1, \dots, n)$ classified into two classes. Each one of the classes associated with labels are $y_i = +1$ for the positive class (rain) and $y_i = -1$ for the negative class (no rain), respectively. For linear data, it is possible to determine the hyperplane

$$f(x) = xw + b = 0, \qquad (5)$$

where w an M-dimensional vector and b is a scalar. This separating hyperplane should satisfy the constraints

$$\begin{aligned} x_i w + b \geq 1, if\ y_i = +1 \\ x_i w + b \leq -1, if\ y_i = -1 \end{aligned} \qquad (6)$$

Furthermore, as the SVM searches for an optimal hyperplane, the margin width between the support vectors and the optimum hyperplane must be maximized, as showed in Fig. 5. The margin is calculated as

$$2.\mathrm{d} = \frac{2}{||\mathrm{w}||}, \qquad (7)$$

so ||w|| must be minimized.

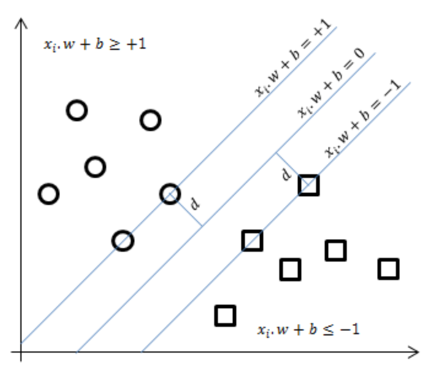

Figure 4. Support Vectors and separating hyperplane.

There is also the introduction of positive slack variables ξ_i, to measure the distance between the margin and the vectors x_i , which means that some mistakes can be tolerated. The optimal hyperplane separating the data can be obtained by solving the optimization problem

$$min\frac{1}{2}||w||^2 + C\sum_{i=1}^{M} \xi_i, \tag{8}$$

subject to

$$y_i(x_i.w + b) - 1 + \xi_i \geq 0 \tag{9}$$

The constraints aim to put the instances with positive label at one side of the margin of the hyperplane, and the ones with negative labels at the other side. C is the cost parameter, with is a positive constant specified by the user.

The optimization problem of the SVM is usually solved by introducing the Lagrangian multipliers α_i, transforming the problem on the dual quadratic optimization.

SVM can also be used to classify nonlinear problems. By using a nonlinear mapping function, called Kernel function, the original data are mapped into a high-dimensional feature space, where the linear classification is possible. There are different Kernel functions used in SVMs, such as linear, polynomial, sigmoidal and Gaussian RBF. The selection of the better Kernel function is very important, since this function will define the feature space in which the training set examples will be classified [10].

V. METHODOLOGY

A. *Experiments to setup parameters*

At first, some experimental arrangements were made in order to evaluate the best set up parameter for the ANN MLP and for the SVM.

For the used ANN MLP the numbers of hidden layers were limited in two. The tested topologies are showed in the Table II. There are two MLP output neurons, one indicates the "rain" class and the other indicates the "no rain" class. The validation set, necessary to avoid overfit was generated by selecting randomly 30% of the normalized complete data set.

TABLE II. EXPERIMENTAL ARANGEMENT FOR MLP.

Neuron quantity	
First hidden layer	**Second hidden layer**
10	0
20	0
30	0
40	0
5	5
10	10
20	20
30	30

For the SVM, four kernel functions were tested: radial basis, linear, sigmoid and polynomial. For each kernel function the C parameter assumed respectively 1, 5, 10 and 30. The ε parameter was fixed in 0.001. And for the Naïve Bayes Classifier a gaussian distribution function was assumed.

The test method for all experiments was the stratified cross-validation 5-fold. For the MLP the experiment was repeated twenty times. One INMET database (near São Miguel dos Campos) was used to evaluate the best setup parameter for the techniques.

The metrics used to compare the three techniques are the TP (True Positive) rate and the F-Measure. The F-Measure is an accuracy evaluation which considers the precision generating an overall score about the classifier. For this application, the TP of no-rain class is a very important measure, and this rate must be maximized. A false positive for the rain class will cause a decrease of the risk level of a flashover and the prediction system can miss the flashover event because of this false positive rain detection.

B. *Experiments to evaluate the trainig applied in other data bases*

With the best setup parameters, all three techniques were trained with the data from São Miguel dos Campos INMET station and the trained models were applied in all others INMET stations.

The main objective was to evaluate if a training realized on one station could be applied to another one. The geographic limits of the training and the influence of the climate were also investigated.

C. *Results on ADECI data*

The trained models were applied on ADECI databases aiming to verify if the rain detection was satisfactorily.

The analysis of these experiments could not be measured in mathematical ways because the ADECI data does not include the rain information. Instead careful visual inspections were made to identify the temperature and humidity behavior changes in order to qualitatively verify the results obtained.

VI. RESULTS

A. *Evaluation of setup parameters*

Table III presents the results for the Naïve Bayes Classifier. There are no parameters to adjust on this classifier.

The Naïve Bayes Classifier achieve TP rate over 0.5 for both classes. However, the FP (false positive) rate of the "no-rain" class is still high for the application (the FP for the "no rain" class is 0.227). The high result of FP "no rain" is a bad issue as it can lead to unnecessary maintenance action for insulators wash.

Table IV presents the results for all ANN MLP topologies experimented.

TABLE III. EXPERIMENTAL ARANGEMENT FOR NAÏVE BAYES CLASSIFIER.

TP rate "rain"	TP rate "no-rain"	F-Measure "rain" class
0.807	0.798	0.746

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TABLE IV. RESULTS FOR ANN MLP.

Topology (as in Table II)	TP rate "rain" class	TP rate "no-rain" class	F-Measure "rain" class
10, 0	0.802 (0.047)	0.873 (0.020)	0.790 (0.016)
20, 0	0.793 (0.049)	0.877 (0.022)	0.788 (0.016)
30, 0	0.784 (0.049)	0.878 (0.021)	0.783 (0.016)
40, 0	0.784 (0.049)	0.878 (0.021)	0.783 (0.016)
5, 5	0.810 (0.050)	0.866 (0.025)	0.791 (0.016)
10, 10	0.810 (0.051)	0.869 (0.024)	0.792 (0.017)
20, 20	0.814 (0.049)	0.867 (0.022)	0.793 (0.016)
30,30	0.812 (0.051)	0.867 (0.022)	0.793 (0.018)

In order to choose the best topology for the ANN MLP, statistical tests were made. With the Shapiro Wilk test, all samples follow the normal distribution, and with the F test, all samples have the same variance. So, the T-Student test was applied to evaluate the best topology with statistical significance. The result of the T-Student test proves that there is no statistical difference between the topologies. So, the topology with fewer neurons in one layer was chosen. As shown in the highlighted cells in Table IV the results of the ANN MLP were better than those of the Naïve Bayes Classifier.

Table V presents the results for the SVM. In this table, only the best results for each kernel function are presented.

As the SVM classifier presents a unique solution, the set of parameters that resulted on the highest F-Measure was chosen (Radial Basis kernel function and C equals 10.0).

The results obtained with training and execution of the classifiers within the same database shows that the rain pattern recognition is possible.

TABLE V. RESULTS FOR SVM.

Kernel Function	C	TP rate "rain"	TP rate "no-rain"	F-Measure "rain"
Linear	1	0.758	0.896	0.781
	5	0.754	0.880	0.767
	10	0.754	0.880	0.767
Polynomial (3 degree)	1	0.256	0.973	0.393
	5	0.575	0.929	0.676
	10	0.643	0.916	0.717
Radial Basis	1	0.720	0.910	0.766
	5	0.749	0.889	0.777
	10	0.758	0.902	0.785
Sigmoidal	1	0.671	0.921	0.741
	5	0.744	0.905	0.778
	10	0.754	0.905	0.784

B. *Evaluation of trainig applied in other databases*

Each classifier was trained with the data from the São Miguel dos Campos INMET station and applied in all others INMET stations. The parameter set used for the ANN MLP and for the SVM were the ones chosen in the previous section. The results for the Naïve Bayes Classifier, ANN MLP and SVM methods are presented on Tables VI, VII and VIII, respectively.

TABLE VI. NAÏVE BAYES CLASSIFIER TRAINED WITH *SÃO MIGUEL DOS CAMPOS* INMET STATION.

Data Base used for Evaluation (INMET station)	Naive Bayes Classifier		
	TP rate "rain" class	TP rate "no-rain" class	F-Measure "rain" class
Sobral	0.585	0.720	0.385
Fortaleza	0.033	1.00	0.065
Mossoró	0.203	0.989	0.316
Angelim	0.995	0.060	0.522

TABLE VII. ANN MLP TRAINED WITH *SÃO MIGUEL DOS CAMPOS* INMET STATION.

Data Base used for Evaluation (INMET station)	ANN MLP		
	TP rate "rain" class	TP rate "no-rain" class	F-Measure "rain" class
Sobral	0.830 (0.041)	0.895 (0.020)	0.823 (0.024)
Fortaleza	0.856 (0.058)	0.887 (0.027)	0.832 (0.025)
Mossoró	0.842 (0.045)	0.883 (0.023)	0.821 (0.014)
Angelim	0.835 (0.043)	0.887 (0.020)	0.820 (0.016)

TABLE VIII. SVM TRAINED WITH *SÃO MIGUEL DOS CAMPOS* INMET STATION.

Data Base used for Evaluation (INMET station)	SVM		
	TP rate "rain" class	TP rate "no-rain" class	F-Measure "rain" class
Sobral	0.585	0.880	0.523
Fortaleza	0.366	0.981	0.506
Mossoró	0.270	1.000	0.423
Angelim	0.967	0.599	0.705

The Naïve Bayes Classifier presented unstable results. In the Fortaleza INMET station, only 3.3% of the examples of the "rain" class were correctly classified. But in the Angelim INMET station, the result was the opposite: only 6.0% of the "no-rain" class was classified correctly. A possible reason for this is the climate difference between these stations. Fortaleza has a tropical climate, with average temperature over 25ºC and there is almost no rain in the second semester of the year. Angelim is a mountain region with a mesothermal climate and average temperature of 20ºC. This is a strong clue that this classifier is sensible to climate differences.

The SVM presented a result similar to the Naïve Bayes Classifier; however, the result of SVM was better than the previous one. But the result analysis for the SVM indicates that this classifier is also sensible to climate differences. In fact, these results mean that the used kernel function is

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sensitive to the climate difference, i.e, the kernel was not able to provide a linear separation between the 'rain' and 'no-rain' class with the gathered data in all stations.

The ANN MLP was able to identify more assertively the pattern of rainfall in all other databases. This means that the power of generalization of this classifier acted more efficiently.

Comparing the three classifiers, the ANN MLP presented better results. The selected INMET stations are located in different climates. It implies differences on the mean values of temperature and humidity between the databases. This difference affects the Naïve Bayes Classifier, since the means and standard deviations (parameters of the Gaussian distribution) in the training can be very different in test dataset. This same influence affects the SVM, since this technique finds a unique hyperplane solution which separate booth classes, and the power of generalization depends on the parameter. Some variation experiments need to be done in order to evaluate the SVM. The ANN MLP also finds a hyperplane solution which separates booth classes. The solution might not be the optimum, but in this case it presented the higher generalization power.

C. Evaluation on ADECI data

The ADECI data does not include the information about the amount of rain, so, a visual analysis was made in order to verify results. Once the MLP presents better results only this strategy was applied on ADECI databases.

Fig. 5 shows the result of the ANN MLP trained with the data from São Miguel dos Campos INMET station and applied in the São Miguel dos Campos ADECI station. The result of the ANN MLP is a binary neuron indicating class "rain" (one) and "no rain" (zero). As can be seen in Fig. 5, the rain pattern was successfully recognized in some data subsets. The visual analysis of the rain pattern matches with the previous patterns in Fig. 2.

There are some possible rain events not successfully recognized. These events are marked in Fig. 5. But, for every rain detected the visual analysis of temperature and humidity suggests a rain event.

If a rain is not properly detected, as showed on highlighted areas of Fig. 5, the risk level will not be reset. If the risk level before the rain event was high enough to require a schedule maintenance, this maintenance will happen, even with the insulator rain wash, causing an unnecessary spending by the electric company. But some rain events were detected, and in these cases the maintenance schedule could be reprogrammed with this new information. It is not possible to quantify the rain detection efficiency but visually it is possible to verify that approximately 66% of rain events n Fig. 5 were properly detected.

Furthermore, during a rain event, naturally there is an increase in the activity rate, mainly N1 as can be seen in the last rain detection, marked in Fig. 5. This activity increase causes an increment in the risk level leading to wrong interpretations. With the proper rain detection, the activity increase can be related to the rain event and the risk level is not increased.

Fig. 6 shows the result of the same ANN MLP applied in the Mossoró ADECI station.

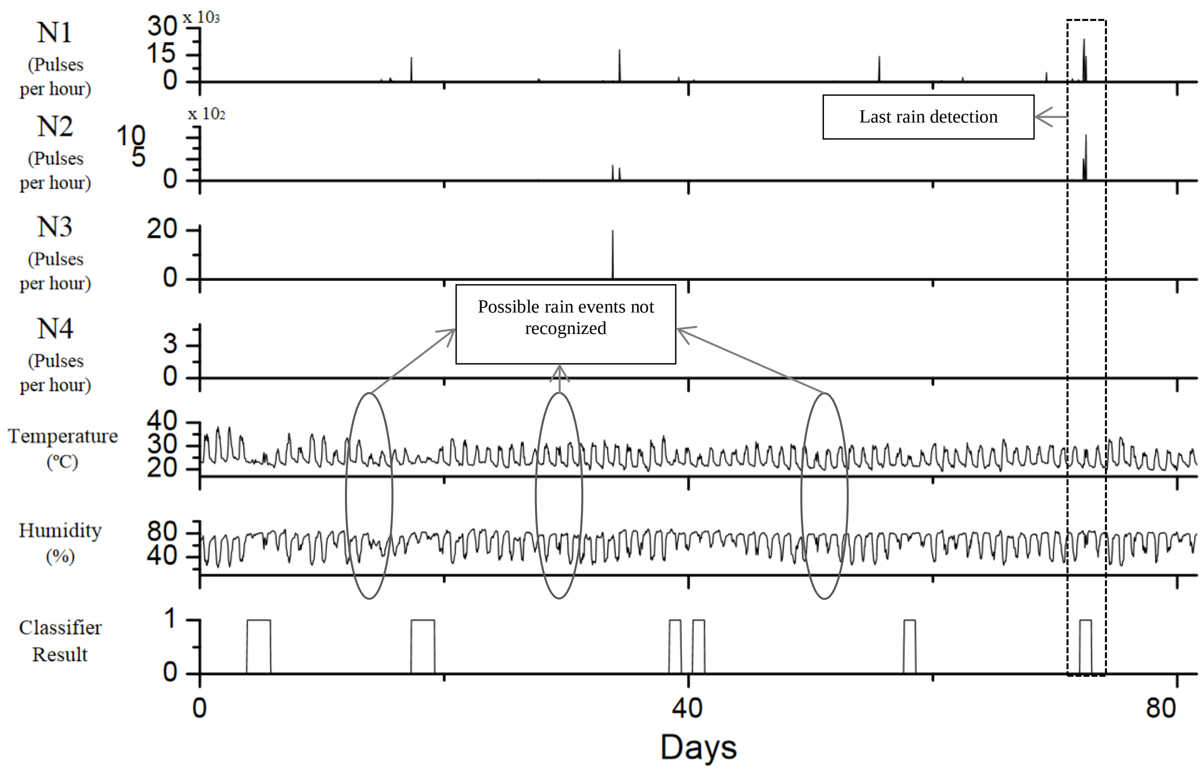

Figure 5. Application of ANN MLP in *São Miguel dos Campos* ADECI station.

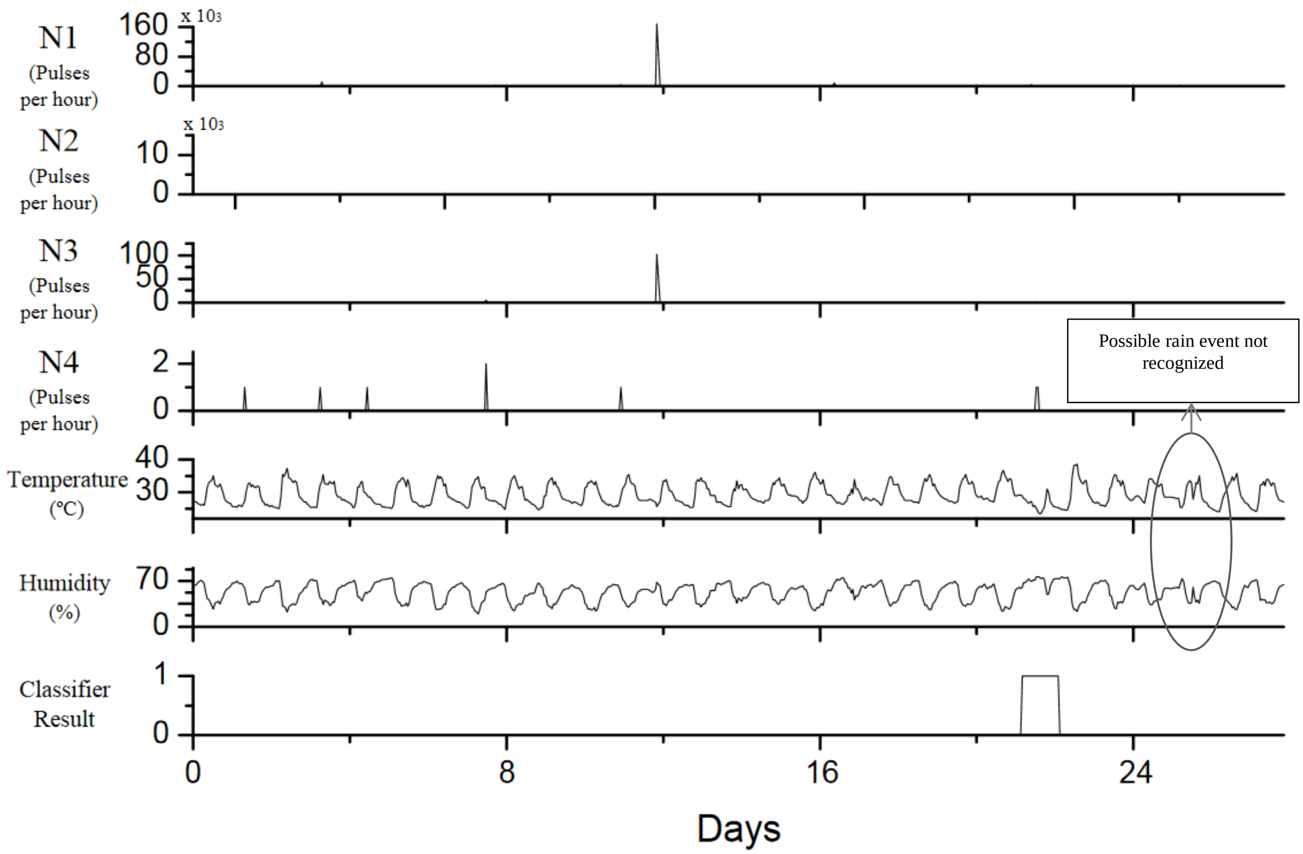

Figure 6. Application of ANN MLP in *Mossoró* ADECI station.

A clear rain pattern was successfully recognized, but the visual analysis also suggests that some rain events were not successfully recognized. The general visual analysis suggests that the false negative rain rate was higher in Mossoró ADECI station than in São Miguel dos Campos ADECI station. The efficiency decrease observed to Mossoró ADECI station suggests that it decreases with distance, indicating that one single model can not be used to analyze all network nodes.

VII. CONCLUSION AND FUTURE WORK

This work presented an initial attempt to detect rain with relative humidity and temperature obtained from the partial discharges satellite sensor network. Preliminary results show that it is possible to detect rain events and use them to improve the flashover risk classification.

The initial tests were performed on the reliable data from INMET meteorological stations in the Northeast Region of Brazil. Three techniques were applied: Naïve Bayes Classifier, ANN MLP and SVM.

All three techniques presented acceptable results when tested on data from the same base. However, when the three classifiers were trained with data from one station and applied in the others INMET stations, only the ANN MLP presented acceptable results. The main reason for this is the different climates between each station, so the generalization ability of the classifier is an important feature.

The ANN MLP trained with the São Miguel dos Campos INMET station was applied in data sets from ADECI database (obtained from the sensor network). Two ADECI stations were used to evaluate the ANN MLP. The rain pattern was successfully recognized in this database, however some false negatives were visually observed.

The result of this work will improve the maintenance schedule system. Without the rain detection attibute, when a rain event occurs, the initial humidity increase causes a PD activity increase rising the risk of a flashover in the prediction system. With the addition of the rain detection attribute, this effect will not be taken into account and after the rain event, the flashover risk can be reset because the insulator string was washed.

Future works aims to evaluate the threshold of rain precipitation, in millimeters, used to label the day as a rainy day and use larger data sets to evaluate the techniques. Data sets from different locations will also be used in order to test the climate characteristics influence on the proposed approach to rain detection and define the borders where the same model can be applied.

Another improvement on the system is to split the days in mornings and nights because rain events during mornings cause a greater change in the temperature/humidity behavior than on nights.

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