Classification of disturbances in electrical systems

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Abstract: This paper presents an application of a classification approach based on Learning Algorithm for Multivariable Data Analysis –LAMDA-, to the electrical power quality problem.
The basic methodology applied in this research has the following basic steps: Data abstraction processing, learning process, class recognition and electrical disturbance classification based on expert analysis. The performance of this algorithm, in the recognition process, has been evaluated as a tool for power quality analysis.

Keywords: Abstraction, classification, time series, power quality.

1. Introduction

Electrical energy is supplied in form of a three-phase voltages of sinusoidal nature. There are four parameters that characterize the voltage wave, allowing to measure its degree of quality. This parameter are: frequency, amplitude, shape and symmetry. Electrical power stations produce a sine wave of 50 or 60 practically perfect cycles per second.

However, during the energy transport and distribution from the generation stations to the final customer, these parameters can suffer alterations which affect the wave quality. These alterations could have their origin in the electrical facility (as a result of breaker switching, failures, and so on), in natural phenomena (lightning) or during the normal operation some special loads (rectifying bridges, arc furnaces, and so on). This alteration of the sinusoidal wave is usually transmitted to the whole electrical system [1].

Among various power quality assessment methods, one of the important methodologies is disturbance classification. This is because if we classify disturbance types, we can define the major effects of the disturbances at the load and analyse the source of the disturbances. Large number of disturbances occur in electricity distribution lines. Then, automatic classification on them is highly desirable. However, relatively little work has been done on automatic classification, and correct classification rates for the actual events are not as high as classification methods used in areas such as pattern recognition, speech recognition, and so on [2]-[7].

The aim of this approach is to improve the supervision of electrical power service by using expert diagnosers of the wave quality. To achieve this goal, first of all the quality of the electrical wave in the electrical system and its loads is monitored. Then, the quality of the wave will be assessed using the expert knowledge available. Finally, a Situation Evaluator will be developed in order to detect the faults and propose solutions taking into account the wave quality measured.

In section 2, the problem definition is presented, followed by a short description of the LAMDA methodology used for perform the classification in the section 3. The general methodology used to conduct this approach is presented in section 4. Finally results of a real power system disturbance classification is presented in section 5.

2. Problem definition

One alteration frequently found in power systems is known as voltage sag. Sag of voltage is defined as reduction of the magnitude followed by the recovery after a short period of time (0,5-30 cycles). Short circuits and large motors starting are frequent causes of voltage sag.

The following are some of the main sag's characteristics [1]

Sag Magnitude. Is the existing effective voltage during the significant reduction of voltage, respect to the pre-fault voltage (U_H). (In case of nonrectangular sags, this magnitude is function of the time).

Voltage Drop. It is the difference between the pre-sag effective voltage and the effective voltage during the sag (ΔU). (In case of nonrectangular sags, also it is function of time).

Duration of the voltage sag. Time during the effective voltage is inferior to the 0.9 p.u. and superior to 0.1 p.u. of the nominal voltage (Δt).

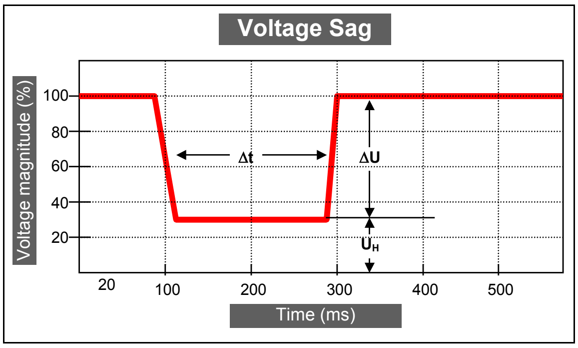

Figure 1. Voltage sag

Until now the methods proposed in most of documents has been used to classify the voltage sags using its magnitude and duration values [1].

Using these two descriptors (duration "Δt" and depth "ΔU"), it is tried to make a new classification that allows to associate causes and severity of voltage sags.

In order to make this work a tool of artificial intelligence called LAMDA will be used as classification system. This algorithm is settled in order to identify the possible cause associated wit the severity of this power disturbance.

3. LAMDA Method (Learning Algorithm for Multivariate Data Analysis).

Classification methods based on hybrid connectives combine both the pure numeric and the pure symbolic classification algorithms, taking profit from the generalizing power of fuzzy logic and the interpolation capability of hybrid connectives [8] [9]. A classification technique called LAMDA (Learning Algorithm for Multivariate Data Analysis) is based on implementation of this possibilities as a fuzzy method of conceptual clustering. It uses data mining techniques under the supervision of the expert to obtain a model of the process [10]. Classification is performed using LAMDA under a supervised learning approach whereas the unsupervised one allows clustering

One object (X_i) has a number of characteristics called "descriptors". This descriptors are used to describe the object. Every object is assigned to a "class" in the classification process. Class (c_i) is defined as the universe of descriptors which characterize one set objects.

In Figure 2 the classification process is presented. The MAD (Marginal Adequacy Degree) concept is a term related to how similar is one object descriptor to the same descriptor of a given class, and GAD (Global Adequacy Degree) is defined as the pertinence grade of one object to a given class [11] [12].

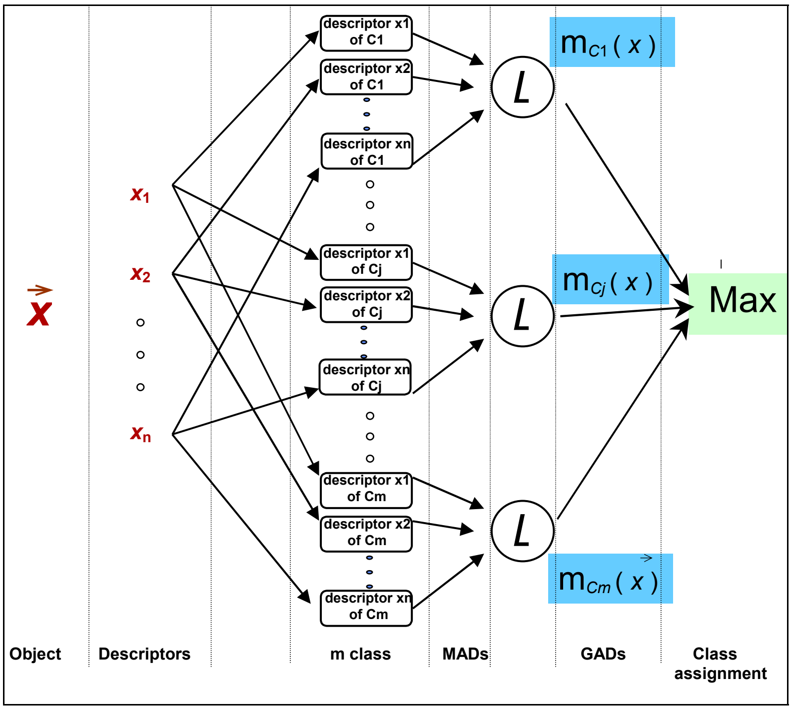

Figure 2. Basic LAMDA methodology

Classification, in LAMDA, is performed according to a similarity criteria computed in two stages. First MAD to each existing class is computed for each descriptor of an object. Second these partial results will be aggregated in order to get a GAD of an individual to a class.

The former implementation of LAMDA included only a possibility function to estimate the numeric descriptors distribution[9]. It was a "fuzzification" of the binomial probability function computed as :

$$MAD_{c,d} = \rho_{c,d}^{X_{i,d}} \quad (1-\rho_{c,d})^{(1-X_{i,d})} \tag{1}$$

Where

$\rho_{c,d} =$ Learning parameter (Ro) for class ***c*** and descriptor ***d***

$X_{i,d} =$ Descriptor ***d*** of individual ***i***

This is implemented in Ro-Algorithm as presented un Appendix A

Other implementation, when the volume of the observed data is important, they is very likely to follow a Gaussian or semi-Gaussian distribution [9]. The marginal adequacy will be computed as:

$$MAD_{c,d} = e^{-\frac{1}{2}\left(\frac{X_{i,d}-\rho_{c,d}}{0.15}\right)^2} \tag{2}$$

This is implemented in Gauss-Algorithm as presented un Appendix A

GAD computation is performed as an interpolation between a t-norm and a t-conorm by means of the β parameter such that β = 1 represents the intersection and β = 0 means the union.

$$\beta\, T(MAD) + (1-\beta)\, S(MAD) \tag{3}$$

4. General Methodology

The general methodology developed is composed by four steps: waveform gathering, abstraction processing data, learning and sag classification. The proposed model is showing in the figure 3.

4.1. Sag measurement

In this step, the sag waveform is gathered whereas supplementary information related to causes is recorded. Both will be used to perform the final matching between classes generated and possible causes associated to severity, in the expert analysis step (see section 5).

4.2. Data processing

At this step, the obtained data from measurement will be processed in order to extract the significant information (descriptors) used to perform the classification in the following step. Different extractors are proposed in order to take only the useful and meaningful information for the classification purpose. On the abstraction process time series will be taken into account, using information as magnitude, duration, shape, change rate, etc

4.3. Learning

At this stage, the information obtained in the past step will be available. It is used to perform the first phase of LAMDA Methodology, learning. This phase is offline and is accomplished using sags data resulting from the abstraction process, and severity degree associated to every sag record. In this stage the algorithm generate classes and assign functional meaning to these classes by a dialogue with an expert.

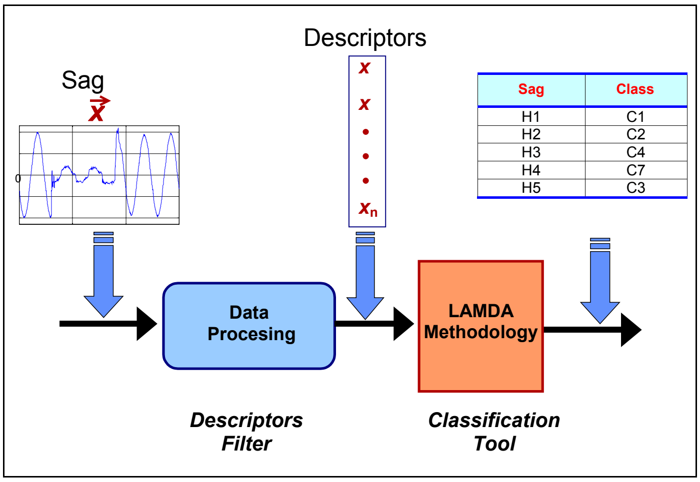

Figure 3. Functional steps for the identification process

4.4. Recognition

The second phase of LAMDA methodology, recognition phase, only use measurement data of the event whose causes associated to severity concept are desirable to be identified. Is possible that this stage will be accomplished online

In order to complete and validate the classification performed using LAMDA method, one expert will perform an analysis with purpose of correlating the classes generated by LAMDA and the causes associated to severity, collected as additional information for every sag event. This expert analysis only will be performing while the tool is setting up. When the tool is settled the correlation between sag and possible cause will be made automatically.

5. Results

5.1. Data sets

The data collected is measured from electrical facilities when a disturbance event is presented. The recorder device takes measurements of three phase voltages when one of these magnitudes drops below to 90 % of its rated value. The sag magnitude and time duration corresponds to the maximum value for a three phase electrical system.

For test purpose, the selected data are electrical registers taken by ENDESA in several electric facilities. The data correspond to sags measurements (object) and two descriptors were used for classification purpose: Three phase sag magnitude and the duration of them.

According to the selected object descriptors, a classification based on the *severity* was proposed: Three main zones were determined and named as high, medium and low severity, according to the possible effect in the electrical system. This topic is closed related to cause of voltage sag under study. A analytical distribution of severity is sowed in figure 4.

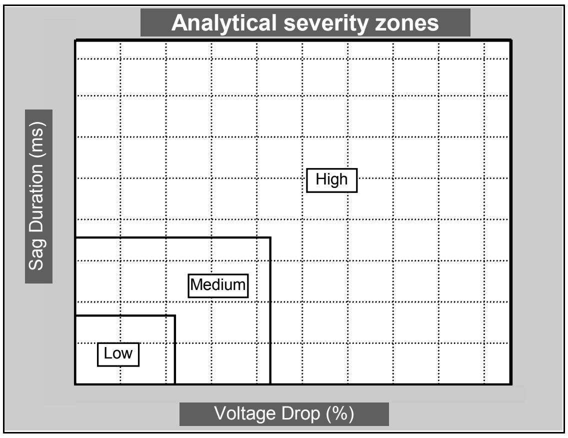

Figure 4. Analytical severity zones

The classification proposed for an expert after a detailed analysis founded in his experience is presented in the figure 5. The total amount of data were classified for the expert in three group of severity: high, medium and low. The edges in the referenced figure were normalized to values between zero and one.

The total amount of classified registers correspond to 1000 voltage sags events taken from the electrical transmission system of Spain by Fecsa-Endesa

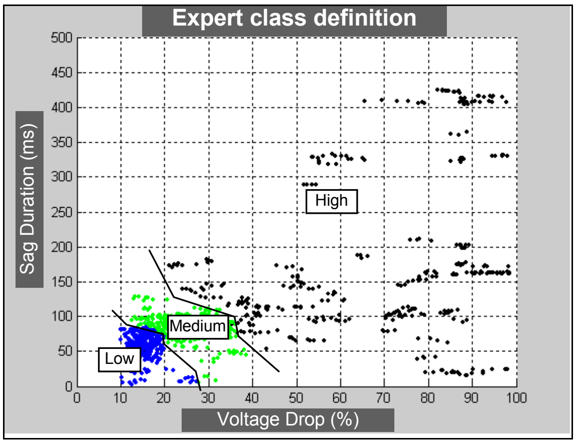

Figure 5. Sags severity according to expert classification

5.2. Learning and class recognition

Three different circumstances was consider in this part: The first one is related to the evolution of LAMDA learning process, taking into account that this process was supervised by an expert. Its mean imposed classes. The second one is related to error computation in recognition process, using different LAMDA based recognition algorithms. The last one was performed in order to estimate the performance of algorithm in class generation using de data registers gathered.
Due to selectivity desired in this approach, for LAMDA calculation, the parameter β was selected equal to 1.

Learning process evolution. In the figure 6, Ro parameter evolution is presented. This figure shows how is settled the main parameter of LAMDA learning module. It was computed, following a supervised learning process, in order to determine the number of elements to be used to train this algorithm. As a result is possible to see(figure 5), how from 350 elements by class is lower than 0.25 per 100 elements.

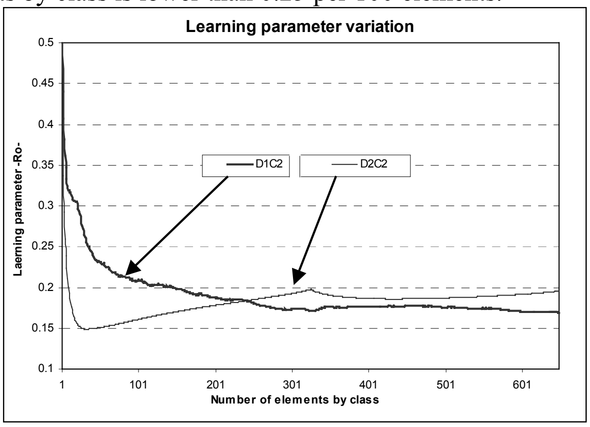

Figure 6. LAMDA Learning evolution process

Error computation on recognition process. Different results of data classification are presented according to different algorithms used in LAMDA methodology. The difference between this algorithm is due to the way of perform the MAD calculation. The equations of all MAD definitions are presented in the appendix A

The total error presented in the recognition stage is presented in the table 1. It corresponds to the comparison between the expert severity classification and the performed by the LAMDA methodology.

Total recognition error using LAMDA classification method				
Ro	*Ro-center*	*Ro distace*	*Gauss*	*Cubic*
12,4%	12,4%	23,7%	12,0%	9,7%

Table 1. Total error in the recognition process

Class generation. This stage is called Self learning process and it shows how the LAMDA method, has the capability of "create" classes following a determinate pattern. In Figure 7, the same set data classify by an expert and showed in section 5.1, are presented. The algorithm Ro_center was used.

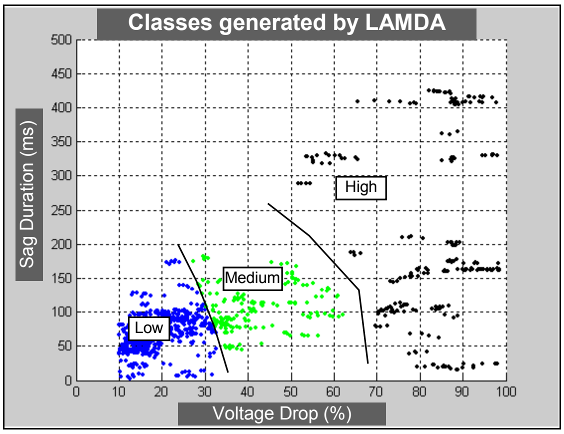

Figure 7. Classes generated by LAMDA

Is possible find a strong correlation between data classification defined in by an expert (figure 5) and recognized data presented in this section (figure 7)

6. Conclusions

This approach shows how to apply IA techniques to electric power quality assessment, using real data from electrical utilities, obtains a low value in the recognition error, using only two descriptors as significant information.

In other hand, using techniques which help the power system engineers to correlate the possible cause with the event measurement, made possible an evident improvement due the ability to determine the origin of this perturbation presented in this approach.

7. Future Work

Both, UdG an Fecsa-Endesa, are currently working in reduce the margin of total error by means of extract more information from the voltage sag measured.

In addition, the voltage sag identified will be analyzed according to the relaying system operation, in order to establish the relationship between the protection system and the classification performed.

8. Acknowledgments

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10. Appendix A. MAD computation

10.1. Conventions used

i = Individual, c = class, d = descriptor,
X = individual descriptor matrix (***i*** rows by ***d*** columns)

$MAD_{c,d}$ =	Marginal adecuation degree for descriptor ***d*** to class ***c***
$\rho_{c,d}$	Ro by class ***c*** and descriptor ***d***
$x_{i,d}$ =	Descriptor ***d*** of individual ***i***

10.2. Ro algorithm

$$MAD_{c,d} = \rho_{c,d}^{X_{i,d}}\left[(1-\rho_{c,d})^{(1-X_{i,d})}\right] \tag{A1}$$

10.3. Ro-center algorithm

$$MAD_{c,d} = \left(\rho_{c,d}^{X_{i,d}}\right)\left[\left(1-\rho_{c,d}\right)^{\left(1-X_{i,d}\right)}\right] \Big/ \left(X_{i,d}^{X_{i,d}}\right)\left[\left(1-X_{i,d}\right)^{\left(1-X_{i,d}\right)}\right] \tag{A2}$$

10.4. Ro_distance algorithm

$$\rho_{\max_{c,d}} = \max\left[\ \rho_{c,d}\ ,\ \left(1-\rho_{c,d}\right)\right] \qquad and \qquad X_{\rho-dist\ \ i,d} = 1-\left|X_{i,d}-\rho_{c,d}\right| \tag{A3}$$

$$MAD_{c,d} = \left(\rho_{\max_{c,d}}^{X_{\rho-dist\ \ i,d}}\right)\left[\ \left(1-\rho_{\max_{c,d}}\right)^{\left(1-X_{\rho-dist\ \ i,d}\right)}\right]$$

10.5. Gaussian algorithm

$$MAD_{c,d} = e^{-\frac{1}{2}\left(\frac{X_{i,d}-\rho_{c,d}}{0.15}\right)^2} \tag{A4}$$

10.6. Cubic algorithm

$$A_{c,d} = \left(1-2\rho_{c,d}\right) \Big/ \left(1-3\rho_{c,d}^2\right) \qquad B_{c,d} = 1 \Big/ \left[\ \rho_{c,d}^2\ \left(2A\rho_{c,d}-1\right)\right]$$

$$C_{c,d} = -A_{c,d} \times B_{c,d} \qquad D_{c,d} = -A_{c,d} - B_{c,d} \tag{A5}$$

$$MAD_{c,d} = \max\left\{\ \left[\left(C_{c,d} \times X_{i,d}^3\right) + \left(B_{c,d} \times X_{i,d}^2\right) + \left(d_{c,d} \times X_{i,d}\right)\right]\ ,\ \ 0\right\}$$