# CLASSIFICATION TECHNIQUES APPLIED TO ELECTRICAL ENERGY DISTRIBUTION SYSTEMS

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## *INTRODUCTION*

*The degree of complexity and the large volume of information normally associated with electrical distribution networks pose the most significant challenges for the engineers and/or operators dealing with such networks. Yet, despite the complexity of these systems, similar patterns of behavior can be identified among the same type of equipment, thus allowing a significant reduction in the number of individuals to be analyzed. Such reduction is made possible by the use of classification techniques aimed at classifying or grouping similar individuals in a single group (category or family).*

*This paper presents and discusses the application of classification techniques to solve specific problems in distribution systems. Their common feature is the need to represent large groups of individuals, in a reduced way identifying their typical patterns or elements.*

*The first one is to set patterns for low voltage circuits based on a sample obtained from field data collection. Each LV circuit was represented by a set of attributes, considering that some of them, as circuit configuration, length and conductors were known only for the selected sample. The other circuits, about 50000 of them, were then classified, according to the previously established patterns. Two classification techniques were used: artificial neural networks and hierarchical classification, as part of an R&D project for RGE[1], to assess technical energy losses*

*The second problem was to identify, among a large group of distribution transformers, those groups or categories sharing similar features regarding both the physical aspects and the load characteristics. A statistical classification technique – cluster analysis – was used with data obtained from the set of 35000 transformers as well as from the load curve measurements of a sample of 140 transformers. The results of this classification process were used in a study made for AES Su1[1]. This research aimed at establishing the optimal transformer load and loss of life.*

*The third problem was to characterize the load in a utility's concession area. The data obtained from load curve measurements, taken from samples representing each type of consumer, stratified by level of consumption or demand, per level of voltage, render the typical curves and their market percentage. The process is divided in steps utilizing the techniques of hierarchical classification and cluster analysis. The methodology was used in the tariff review process of COPEL[1] and CELESC[1].*

1 These are large utilities operating in southern Brazil.

## THE CLASSIFICATION TECHNIQUES

Presently, some classification techniques are widely accepted, while others are not so well known. As a rule, the classification techniques are developed in the areas of statistics and Artificial Neural Networks (ANN).

Among the statistical techniques, one of the best known is that of Cluster Analysis, normally using the *k-Means* Method. The techniques in the area of Artificial Neural Networks include the ANN model with unsupervised training, also known as *SOM – Self Organizing Map*.

Regardless of the technique being utilized, the individuals must be identified according to their attributes. As an example, in the case of distribution transformers (individuals), their attributes may be their rated power, primary and secondary voltage and maximum loading. Once classified, these individuals are grouped into families, also identified by their attributes.

Attributes such as loading represent a continuous variable, i.e. they may have any value within a given range. Other attributes, as primary voltage represent a discrete variable, meaning they may only have certain specific values. For instance, in the example mentioned above, the primary voltage of the transformer can only be 13.8 kV or 23.1 kV.

This characteristic of the attribute needs to be taken into consideration for selecting the classification technique. It is also important to emphasize that neither classification technique is better than the other, but one of them is the best for a specific type of application.

## LOSS ESTIMATION IN LV CIRCUITS

Calculating the energy losses in an LV circuit may seem an easy task, simply involving the calculation of the load flow. However, when a detailed database is not available for this type of circuit, as is often the case at some Brazilian utilities, modeling techniques for LV circuits need to be considered [1].

Thus, the aim of the classification techniques for this application is that of setting LV circuit patterns that adequately represent the actual networks.

In the case of RGE, the database offers the following information regarding the company's LV circuits: (1) rated power of the distribution transformer [kVA]; (2) type of distribution transformer (1-bushing single-phase transformer, 2- bushing single-phase transformer or three-phase transformer); (3) primary voltage of the distribution transformer [kV] and (4) type of area in which the transformer is located (urban or rural).

A set of 310 LV circuits was then selected from RGE's entire LV system (this set will be referred to as the Basic Set from now on). Geographical and electrical diversity aspects were taken into account for including LV circuits in the Basic Set. In addition to the four basic attributes available for any LV circuit, LV circuits in the Basic Set were assigned, through extensive field measurements, two more attributes: loss coefficient [1] and circuit length.

Once the loss coefficient and the length are known for a circuit not belonging to the Basic Set, the estimation of its losses is easily achieved from the transformer loading at any time *t* (given by the transformer daily load curve) and equation (1).

$$p_t = LC \cdot \left( \frac{D_t}{l} \right)^2 \qquad (1)$$

where:

$p_t$ : loss of demand at time $t$ [kWh];

$LC$ : loss coefficient of circuit [kW m$^2$ / kVA$^2$];

$D_t$ : demand at time $t$ [kVA];

$l$ : total length of circuit [m].

The problem at this point is how to assign the two extra attributes (loss coefficient and circuit length) to every circuit not belonging to the Basic Set, so that the losses can eventually be estimated.

The classification process was conducted in two steps. In the first step, the classification techniques were applied to the Basic Set. Each resulting category was assigned an average loss coefficient and an average length (the average values were computed considering all circuits in each category).

In the second step, each circuit not belonging to the Basic Set (i.e., a circuit for which the loss needs to be estimated) was marked as being member of one of the categories found in the first step. After that, it was assigned the average loss coefficient and the average length for its category, from which its losses were then estimated.

In this work, two different techniques were used to classify the circuits: Hierarchical Classification and Self-Organizing Maps, which will be presented in the next section.

## Hierarchical Classification

The Hierarchical Classification technique first requires an order of importance to be specified for the attributes. Then, for the first attribute, a number of categories are created; this number is equal to the number of possible values of the first attribute. For every first-attribute category, a number of subcategories are created according to the number of possible values of the second attribute.

The Hierarchical Classification is well adapted when the attributes are described by discrete values (for instance, 13.8 kV and 23.1 kV for primary rated voltage). When an attribute is described by continuous values (for instance, transformer loading as a percentage of its rated power), it has to be discretized in an adequate number of ranges (0-30%, 30%-70%, and so on). Once the categories have been established, the classification process is very simple: each LV circuit is assigned to the correct category just by inspecting its attributes.

Depending on the problem at hand, the Hierarchical Classification technique often produces categories with too few elements, a situation which can be inconvenient in some situations. In this case, a regrouping procedure may be executed, whereby elements in small categories are reassigned to other categories.

## Self Organizing Map

The Self Organizing Map (SOM) model was developed in the area of Artificial Neural Networks [2], [3]. It consists of a network of interconnected processing units.

A SOM network consists of *m* processing units. This means that the network is able to automatically define up to *m* categories for a given classification set.

A SOM network can operate in two different modes: training and classification. In the training mode, weights are initialized to arbitrary values and a training set (containing an adequate number and type of training vectors) is presented to the network. Weights are then adjusted according to the training algorithm [3]. The weight adjustment means that boundaries between categories are automatically established from the information contained in the training set. Once the training is completed, a category ID is manually assigned to each unit. SOM training is of unsupervised type because the category ID is assigned only upon training completion.

In the classification mode, input vectors are sequentially applied to a previously trained network. For a given input vector, the unit with the lowest Euclidean distance is called the winner unit and its category is assigned to the input vector (no weight corrections are made in the classification mode).

## Results

Using the classification techniques described above, a large number of categories was obtained in the process of category identification. This result was expected since the field measurements of the circuits in the sample indicated a lack of standardization and great diversity in the topological features of the LV circuits.

Thus, when these techniques were used to classify any given circuit in one of the preset categories, the results were not always positive. The Hierarchical Classification, on the other hand, rendered better results. Table 1 presents two of the categories formed through Hierarchical Classification and Table 2 shows two LV circuits to be classified. Symbols in the table's header are as follows. **TRP**: Transformer Rated Power [kVA], **PRV**: Primary Rated Voltage [kV], **TL**: Type of Location (Urban or Rural), **ALC**: Average Loss Coefficient of the category [$kWm^2/kVA^2$], **AL**: Average Length of the category [m], **LC**: Loss Coefficient of the circuit [$kWm^2/kVA^2$] and **L**: Length of the circuit [m].

Table 1 - Categories formed through Hierarchical Classification

| Cat. | TRP | PRV | TL | ALC | AL |
|---|---|---|---|---|---|
| 45 | 45 | 13.8 | U | 6.8 | 157.0 |
| 75 | 75 | 23.1 | U | 207.9 | 501.0 |

Table 2 – LV Circuits to be classified

| Circuit | TRP | PRV | TL | LC | L |
|---|---|---|---|---|---|
| 3315.4-246 | 45 | 13.8 | U | 9.7 | 173.4 |
| 1615.2-83 | 75 | 23.1 | U | 101.5 | 506.9 |

Circuit 3315.4-246 was classified in category 45 and circuit 1615.2-83 in category 75. It can be noticed that both circuits were classified in categories that represent them well.

## OPTIMAL TRANSFORMER LOADING

Developing a procedure to establish the optimal loading of distribution transformers is of vital importance to assess the situation of the group of transformers. It offers guidelines for the relocation of the units in the points and service areas that are more appropriate to their characteristics, thus increasing the number of transformers within the right loading ranges, taking into account their present load and future growth [4].

Yet, the number of distribution transformers in a distribution network is quite high, which makes it unfeasible to analyze each transformer separately.

Applying classification techniques to the entire population of a utility's transformers, and having them appropriately represented by their attributes, the population is grouped into families, which allows several analyses to be made.

In the case of AES Sul, the transformers were represented by the following attributes: (1) rated power of the transformer [kVA], (2) type of market being supplied (typically residential or typically non-residential) and (3) transformer loading [%]. This last attribute is obtained from the database of AES Sul, as a result of a kVAs function, relating the transformer consumption in kWh with its maximum demand in kVA.

Using the Hierarchical Classification, families were formed from the population of transformers, belonging to AES Sul, and represented by these three attributes. For each family that was formed, a sample of transformers was selected to measure the load curves on the field. .

During the measurement period, the average demand was registered for each 15-minute-interval. Once the field measurements were obtained, it was possible to determine the typical load curve (average and standard deviation), for the 15-minute-intervals for each family. The maximum demand for the period was also established, which determined the kVAs curve for that particular family.

Once the typical load curve of a specific family is known, it is possible to calculate the loss of life and the economical loading of a transformer. In order to calculate the loss of life, the thermal equations of the transformer are calculated and a curve is obtained, which determines the transformer's life cycle, based on the load curve that is typical for that family. The calculation of the economical loading takes into account the transformer's annual amortization cost, the annual cost of the losses and the increase in load.

As all the transformers in a family share similar building and load features, the results that are obtained can be extended to all the transformers in that particular family. Thus, is it possible to identify which groups or families of transformers present beyond optimal loading and which groups need to be relocated to achieve their optimal loading.

## LOAD CHARACTERIZATION

Load characterization means obtaining typical load curves that adequately represent the customers on a specific distribution system. The characterization of the load is probably one of the most important challenges of this sector due to its random features. Furthermore, it is an extremely vital analysis which can be used in very basic applications, as for example for the calculation of load flow and losses, as well as in more complex ones as for the calculation of loss of life in distribution transformers and the tariff structure process. The latter is the application that will be presented in this section.

As per Brazilian legislation, all utilities shall periodically perform a **tariff review process**. Basically, this entails setting the percentage of responsibility at peak time for each type of consumer, be it residential, commercial, industrial, rural or other. Notably, load characterization is a very significant input as it is the basis for the tariff structure, i.e. which consumer groups will pay more and which will pay less for the electricity.

In the process of load characterization, obtaining the typical load curves is associated with an extensive measurement job, in which a sample representing the population of consumers will be defined in order to measure the load curve.

For the consumers that are part of the sample, the load is measured for a period of 10 days, with readings of the active power at 15-minute-intervals. The readings are made at hundreds of consumers so that at the end of the process the utility can count on approximately 10,000 daily load curves.

This amount of data collected from the readings, allows the process of calculating the typical load curves to be initiated. A classification technique will then be used for this purpose. In the case of the tariff review, the measured load curves are selected manually. For each measured consumer, one curve is selected to represent the day of the week, another one for Saturdays and still a third to represent Sundays and holidays. This selection process greatly reduces the number of curves to be classified, although it is slow and subjective in nature.

For the case presented in this article, all the measured load curves are considered in the classification process. The method used here is known as the *Dynamic Cloud Method*. It was applied for each consumer group for which typical load curves were to be obtained.

### The Dynamic Cloud Method

The *Dynamic Cloud Method* is made up of three steps: (1) cluster analysis (through the *k-Means* Method); (2) setting of strong profiles and (3) reduction of strong profiles (using *Ward's Method*). These three steps are explained in detail, below.

**Cluster Analysis.** The first step in the Dynamic Cloud Method is the analysis of clusters using the method of *k-Means*. The main problem of this method is the dependence of the results on the initial sorting of seeds. In order to reduce such dependence, the *k-Means* are performed $N$ times ($N$ experiments). At the beginning of each experiment the seeds are sorted. At the end, the resulting groups are stored to be used in the following step.

**Setting of strong profiles.** Assuming that each experiment in the previous step was run so as to obtain a maximum of $M$ groups, it is easy to conclude that at the start of this second step there will be a maximum of $M \cdot N$ groups. Each individual was grouped $N$ times, thus appearing in $N$ groups. Setting the strong profiles requires checking whether the individuals that were part of a specific group in experiment 1 are together in all other experiments. Should this be true, the group in question is a strong profiles. Otherwise, the group shall be divided so that all its subgroups are strong profiles. This process will be repeated for the rest of the groups in experiment 1. The strong profiles thus obtained at the end of this step are the individuals that will remain together in the same group for the entire process.

**Ward's Method.** Setting the strong profiles may significantly increase the number of groups. For this reason, once these groups have been determined, the strong profiles need to be reduced to an adequate number. Ward's Method is used for this purpose, as it merges the strong profiles in a succession until it reaches a preset figure. In order to select which groups need to be merged, the method calculates all the distances between the nuclei of the strong profiles and merges the two such profiles whose distance between nuclei is the smallest of all those calculated. At each of the mergers, the variance of each new group that was formed is then calculated, in order to control its homogeneous nature, i.e. the quality of the group. At the end of Ward's Method, the typical load curves are obtained for each type of consumption that has been analyzed.

### Results

The Dynamic Cloud Method was implemented in a friendly computational system, allowing the display of the groups that were obtained and the individuals in each group. As an example, Figure 1 shows some of the groups obtained for the commercial consumers in the range between 300 and 500 kWh of monthly consumption. Figure 2 presents some of the individuals in group 4. It is easy to observe that the Dynamic Cloud Method has clustered individuals with similar load profiles.

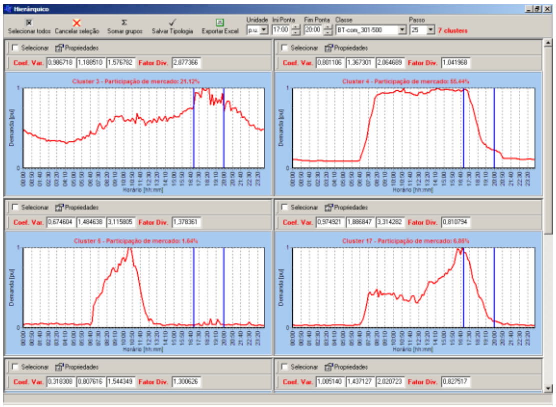

Figure 1 – Groups in the commercial category

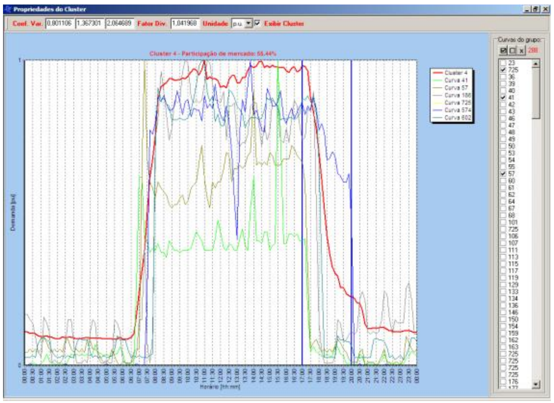


Figure 2 – Some individuals in group 4

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## CONCLUSIONS

This work shows the ways in which the classification techniques can be applied to the electric energy distribution systems, as well as the great relevance of such techniques to carry out different types of research.

Several techniques are discussed, each one considered as the most adequate for a certain type of application. Yet, all these techniques share one goal, i.e. to reduce the volume of information normally associated with distribution systems, so as to make the different analyses feasible.

For the purpose of the present article, the classification techniques have been used to calculate losses in LV circuits, to set the optimal loading for distribution transformers and to determine the load characterization in order obtain one of the main inputs for the tariff review process in Brazil.

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