LOSS ESTIMATION IN LV CIRCUITS USING INTELLIGENT TECHNIQUES - THE RGE EXPERIENCE

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ABSTRACT - *This paper presents a methodology for estimating technical losses in low voltage (LV) distribution circuits. It includes the models used for load representation and loss evaluation, and represents an attempt to overcome the lack of sufficient data that is normally associated with LV systems. A significant number of field measurements were carried out so as to form a reduced set of circuits that properly represent the whole population of LV circuits. Advanced classification techniques were then applied so as to group similar circuits in categories. An invariant value called "loss coefficient" (which is of paramount importance in this work) was computed for every circuit in the reduced set using the loss evaluation model. A given LV circuit not belonging to the reduced set is classified into one of the various categories previously found, and its loss coefficient is quickly assigned without any direct electrical calculation. This approach is currently being applied to Rio Grande Energia's distribution system. The paper also presents and discusses results obtained so far.*

INTRODUCTION

Rio Grande Energia (RGE) is an electricity distribution utility operating in Brazil's southern region. It supplies electricity to over 900,000 customers through approximately 400 medium voltage (MV) primary feeders and 50,000 LV circuits.

RGE's corporate database includes the whole of the MV subsystem, but it lacks a detailed description of the LV subsystem. Therefore, the planning and operational areas of the company normally encounter serious difficulties when dealing with the LV subsystem. Regarding LV circuits, the corporate database contains the following data: transformer rating, MV rated voltage, transformer loading, transformer type (1-phase or 3-phase), type of location (urban or rural), number of customers per type (residential, industrial, commercial, rural and others), and total monthly energy per type. In particular, it does not contain data on circuit topology, cable sizes nor section lengths.

The paper is organized as follows. First, the main aspects regarding load representation and loss evaluation are presented in detail. Next, the classification models adopted in this work (Hierarchical Classification and Self Organizing Map) are described. The application of the full methodology to RGE's LV distribution system and the corresponding results are presented and discussed in the following section. Finally, the conclusions of the paper are discussed and some interesting topics for further development are outlined.

METHODOLOGY

Load Representation

In this work, the load of every consumer is represented by a daily load curve that gives the actual demand (active and reactive) at 15-minute intervals. The starting point was the computation of typical daily load curves, which were established from a comprehensive set of field measurements. A typical curve consists of an average curve and a standard deviation curve, and it was established for each type of consumer (residential, commercial, industrial and rural) and also for different monthly energy consumption ranges within each type of consumer (e.g. 0-100 kWh per month, 101-300 kWh per month, etc.). These curves are given in pu of the monthly average active demand, so that knowing a particular consumer's monthly energy and its typical load curve, the computation of its daily load curve is straightforward. Figures 1 and 2 show the typical active and reactive curves for residential consumers with monthly energy above 500 kWh.

Loss Evaluation Model

This work represents a particular and important extension of a previous work on the subject of loss evaluation in distribution systems [1]. In that work, a methodology for evaluating technical losses in the various segments of a distribution system (distribution substation, MV circuits, distribution transformers, LV circuits, customer connections and energy meters) was developed.

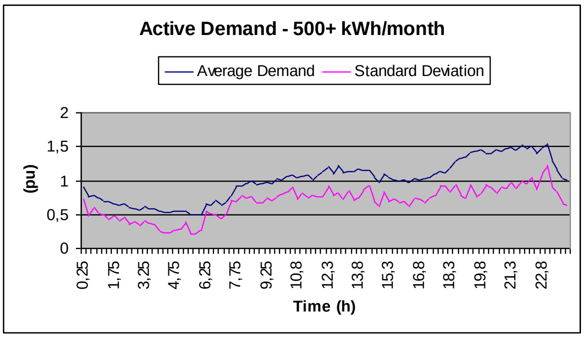

Figure 1 - Typical load curve - active demand

However, the methodology developed in the former work required a detailed description of the distribution system, especially with respect to the network topology, cable sections and consumer location. All this information is not readily available from current RGE's technical databases, so the focus was then placed on establishing average LV circuits that properly represent the actual circuits on the field.

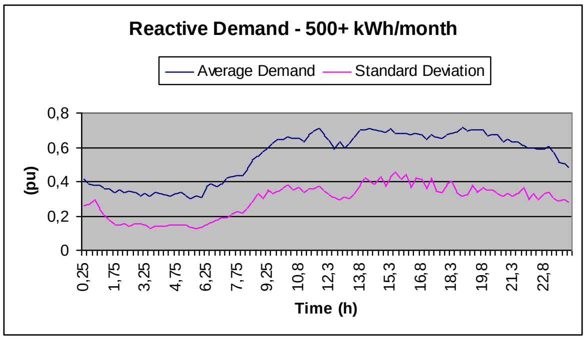

Figure 2 - Typical load curve - reactive demand

Data available for any LV circuit from technical databases include the following basic attributes: (1) distribution transformer rated power (kVA), (2) distribution transformer type (1-phase/1 bushing, 1-phase/2 bushings, or 3-phase), (3) distribution transformer primary rated voltage (kV), (4) type of circuit location (urban or rural), and (5) transformer loading (% of rated power).

A set of 187 LV circuits was then selected from RGE's whole LV system (this set will be referred to as 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 five basic attributes available for any LV circuit, LV circuits in the Basic Set were assigned, through extensive field measurements, two more attributes: loss coefficient and circuit length.

The loss coefficient (LC) of a circuit is given by the circuit's demand loss at peak time (L_{peak}) divided by the square of its linear loading at peak time. Linear loading at any time t (δ_t) is simply the circuit's demand at time t (D_t) divided by its length (l):

$$LC = \frac{L_{peak}}{\delta_{peak}^2} \qquad \frac{kW}{\left(\frac{kVA}{m}\right)^2} , \qquad (1)$$

$$\delta_t = \frac{D_t}{l} \qquad \frac{kVA}{m} . \qquad (2)$$

The loss coefficient is constant for a given circuit, and it reflects the circuit's topology, cable resistance and voltage level in a convenient, compact way. For instance, for a 3-phase circuit with uniform loading, the demand loss at peak time is given by:

$$L_{peak3} = 3 \cdot r \cdot l \cdot I_{peak}^2 = \frac{r \cdot l^3}{3 \cdot V^2} \cdot \delta_{peak}^2 , \qquad (3)$$

where r is the resistance per unit length (Ω/m) and V is the line-to-line voltage of the circuit (V). From equations (1) and (3) above, it follows that the loss coefficient for the 3-phase circuit is given by:

$$LC_3 = \frac{L_{peak3}}{\delta_{peak}^2} = \frac{r \cdot l^3}{3 \cdot V^2} . \qquad (4)$$

The loss coefficient of each circuit in the Basic Set is obtained from a load-flow analysis of the circuit. Uniform loading is assumed in this analysis.

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 equations (1) and (2).

The problem now 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. To this end, circuits in the Basic Set were grouped into categories according to their similarity. Obviously, the criterion for deciding for the similarity among circuits is based upon the five basic attributes.

The classification process was conducted in two steps. In the first step, the classification tools 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 has 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 of 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.

LV CIRCUIT CLASSIFICATION

This section describes the classification problem and the models implemented for classifying LV circuits.

The classification problem can be broadly stated as grouping similar individuals from a population into categories. The individuals (LV circuits) are identified through a set of attributes, which in the present case are the five basic attributes established earlier. Also, a metric for quantifying the similarity between two different circuits must be specified in advance. In the next sub-sections, the two classification techniques used in this work will be presented in some detail.

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. This process is repeated for all classification attributes, as illustrated in Figure 3.

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 in percent 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.

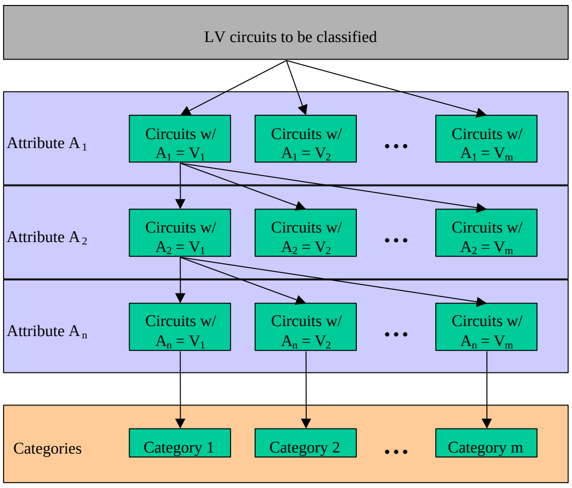

Figure 3 - Category setup in Hierarchical Classification

Depending on the problem at hand, the Hierarchical Classification technique often produces categories with too few elements, 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*. Figure 4 shows the structure of a processing unit.

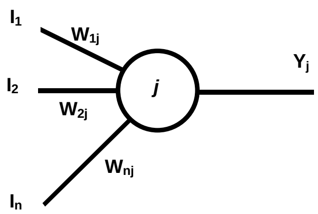

Figure 4 - SOM processing unit *j*

The generic unit *j* of Figure 4 possesses *n* inputs ($I_1, I_2, ..., I_n$), one output Y_j and a category identifier (ID). Also, a weight value W_{ij} is associated with the unit's i^{th} input. The number *n* represents the number of attributes. Individuals (LV circuits in this case) are represented by *input vectors* of the form:

$$I = [I_1 \quad I_2 \quad \dots \quad I_n] . \tag{5}$$

For a particular input vector, each entry I_i is the value of the i^{th} attribute of that vector.

Each processing unit represents a category. The category attributes are stored in the weight vector of the category:

$$W_j = [W_{1j} \quad W_{2j} \quad \dots \quad W_{nj}] . \tag{6}$$

Finally, the output of unit *j* for a given input vector is the euclidean distance between the input vector and the unit's weight vector:

$$Y_j = \sqrt{\sum_{i=1}^{n} (I_i - W_{ij})^2} . \tag{7}$$

A SOM network consists of *m* units similar to the one of Figure 4. 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 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 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 classification mode).

RESULTS

This section presents and discuss some results from the application of the proposed methodology to RGE's LV distribution system.

Figure 5 shows measured and calculated daily curves for both active demand and standard deviation regarding circuit number 333.6-216, which was used for validating the load representation model. A good agreement can be observed between measured and calculated values, especially with respect to the demand curves.

Next, the SOM classifier is considered. The Basic Set was divided in two groups: the training set, containing 165 circuits, and the testing set, containing the remaining 22 circuits (total of 187 circuits in the Basic Set). During training, the 165 circuits in the training set were classified into 120 categories. This relatively high number of categories resulted from the circuits' high diversity. Table 1 shows data corresponding to categories 11 and 45, which will be used to discuss the classification results. 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 (kW/(kVA/m)^2), and **AL: Average Length** of the category (m).

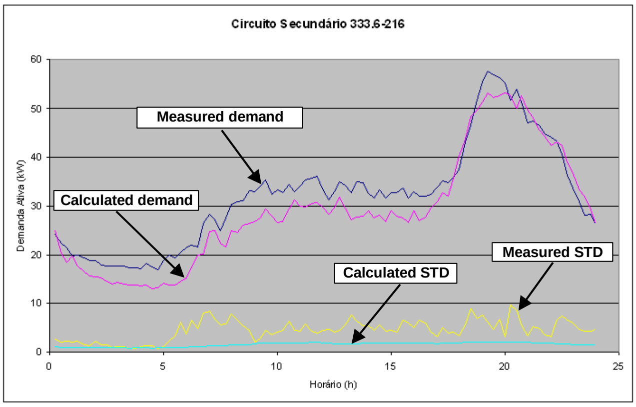

Figure 5 - Measured and calculated daily curves

Table 1 - Categories formed by the SOM network

Cat.	TRP	PRV	TL	ALC	AL
11	75	23.1	U	208.6	413.0
45	45	13.8	U	1357.3	810.9

Table 2 shows data and assigned category for circuits 3315.4-246 and 1615.2-83, both belonging to the testing set. New symbols in the table's header are as follows. **LC: Loss Coefficient** of the circuit (kW/(kVA/m)^2), and **L: Length** of the circuit (m).

Table 2 - Classification results - SOM network

Circuit	TRP	PRV	TL	LC	L	Categ.
3315.4-246	45	13.8	U	9.7	173.4	45
1615.2-83	75	23.1	U	101.5	506.9	11

From Tables 2 and 1, it can be seen that circuit 3315.4-246 was classified into a category that do not represent it properly, indicating that further refinement in SOM training is required. Circuit 1615.2-83, on the other hand, was classified into an adequate category. It should be pointed out that the loss coefficient varies in a rather wide range, from 1 to 60000 approximately, while the length varies between 30 an 3200 m.

As for the Hierarchical Classification, 180 circuits from the Basic Set were used to form the categories (95 categories were formed). The remaining 7 circuits were used for validation purposes. Table 3 shows data corresponding to categories 45 and 75, which will be used to discuss the classification results.

Table 3 - 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

In this case, circuit 3315.4-246 was assigned to category 45 and circuit 1615.2-83 was assigned to category 75. From this and from circuit data in Table 2, it can be seen that both circuits were assigned to categories that properly represent them.

Finally, circuit 3315.4-246 was further considered for validating the overall loss evaluation procedure. Demand and daily energy losses for this circuit were computed through the proposed methodology and also through a loadflow analysis. In this case, the loss coefficient and the length were taken as the actual circuit values, rather than the average values of category 45 which was assigned in the Hierarchical Classification. This was done in order to assess the contribution of the loss coefficient approach on the overall error (the contribution of the averaging procedure inherent to the classification process was thus eliminated). Results in this case are presented in Table 4.

Table 4 - Loss evaluation for circuit 3315.4-246

	Losses	
	Daily energy (kWh)	Demand (W)
Proposed Methodology	45.5	170.4
Loadflow	39.0	161.4

Although results in Table 4 show good agreement between the values estimated through the proposed approach and the reference (loadflow) values, the following facts also account for differences between them. First, in the computation of the loss coefficient for the circuits in the Basic Set (resulting from field measurements), it was assumed that all circuit sections possessed the same length, equal to the average length (total length divided by the number of sections). Second, the electrical model considers that the load is distributed uniformly along the circuit, which is also untrue. Finally, it should be noted that a thorough validation, involving an adequate number of reference circuits, is required in order to allow a consistent conclusion to be reached. This comprehensive validation is currently under development.

CONCLUSION

This paper has presented a new methodology for estimating demand and energy losses in LV circuits. The methodology represents an attempt to overcome the lack of information normally associated with such circuits. The methodology is based on a comprehensive study of a reduced set of circuits and the extrapolation of some parameters (loss coefficient and circuit length) to the whole LV circuit population.

Preliminary results show that the load representation model, which uses the concept of typical daily load curves, produces very good results as far as the daily load curve at the distribution transformer is concerned. The proposed methodology relies on the fact that a good circuit classification can be carried out using the available information; in this respect, the Hierarchical Classification technique has produced good results, while the application of the SOM classifier requires further refinement.

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