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Study of Proposed Identification of Non-Technical Losses of Electricity in Brazil

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Abstract

The electric utilities have large revenue losses annually due to commercial losses, which are caused mainly by fraud on the part of consumers and faulty meters. Automatic detection of such losses where there is a complex problem, given the large number of consumers and the high cost of each inspection, not to mention the wear of the relationship between company and consumer. Given the above, this paper aims to briefly present some methodologies applied by utilities to identify consumer frauds.

Keywords: Non-technical losses, identification and classification, electrical energy consumer

1. Introduction

In the last years, the Brazilian system had many changes, passed the period of the privatization of the generation companies, transmission and distribution of electric energy, this results in the creation of a competitive market in the national scenario. The investments made by the private companies have with main aim a great improvement of theirs technical and financial performance, through more productivity, efficiency and profitability [1].

Commercial losses or non-techniques are those associated with marketing of the energy supplied to the user and refer to the energy delivered but not billed, generating a loss in the revenue. Are also defined as the difference between total losses and technical losses, and are mainly related to illegal connections in distribution system [2].

Although advances in this area have been observed in recent years, particularly with regard to the different measurement techniques of electrical energy, it becomes increasingly necessary to research alternative methods with great flexibility and easy to adaptation to the context of the problem, as computational techniques models with intelligent algorithms [3].

Among the computational intelligence techniques commonly used for the detection of commercial losses are Artificial Neural Networks, Support Vector Machines, Nearest neighbors, Fuzzy Logic, among many others. The applications of these intelligent algorithms enable the development of computational tools used for the estimation and identification of fraud (commercial losses) in several companies, analyzing the data of a particular customer and their transactions, and you can check if there is any suspicious transaction occurrence of irregularity.

The intelligent techniques help to identify the potential fraudsters by analyzing data of each consumer, but the company still needs to invest in other procedures to assist in the correct identification of delinquency, as well as consumer awareness of the problem. With the aim to reduce the value of the non-technical losses, the electric energy companies usually work in:

- Inspection programs: consists in verifying the integrity of the measurement system, detecting equipment failures, fraud and theft of energy, connection errors and other problems that may compromise electrical energy measurement [4];
- Replacement of meters: the assessment consisting of lots of meters through field sampling, laboratory testing and analysis of the meters removed in the field. In addition, the replacement of meters with service life expired or possible technical failures;
- Regularization of sites with high probability of illegal connections, such as slums, through a program of regulatory nature, consequently reducing commercial losses;
- Implementation of trade policies: consists of visits to the community about explanations, talks and trainings on the consumption of electricity;
- Shares of energy efficiency with a focus on reducing electric bills and effective use of energy, serving as an incentive for consumers to not defrauding.

One of the most traditional types of detect and reduce the commercial losses is conducting inspections on consumers. The selection of which consumers should be inspected is an arduous task for the experts, and then the need for the use of intelligent computational systems to help in the treatment of thousands data from millions of consumers registered.

Many actions have been taken in the search for technological solutions and methodological effective to solve the problem of trading losses. However, the experience has demonstrated the impossibility of applying unique solutions for their economic agents, even within the concession area of the business, which is due not only physical factors but mainly to the enormous cultural, social and economic Brazilian society. This scenario suggests the need to construct creative solutions differentiated by the distributors.

In this context, this paper presents a survey of some actions taken by the Brazilian utilities to detect and reduce non-technical losses. These actions are used to improve the database of knowledge of each consumer profile, which assists in the development of computational tools for identifying and classification of consumers.

2. Shares Applied for Distributors to Detect and Reduce Commercial Losses

The high damage caused by fraud energy, made the distributors takes some actions that help to detect and reduce commercial losses, such as:

- Identification of critical areas: a clear identification of areas with the highest concentration of commercial losses inside the concession area of distribution is essential to solve the problem;
- Energy balance: the difference between the amount of energy measured in distribution transformers and the sum of individual consumption of customers served in that region can be a good indicator of commercial losses;
- Billing systems: important action to detect and reduce non-technical losses is the insertion in their billing systems, of tools that allow obtaining and maintaining accurate information pertaining to sharp variations in energy consumption units, for example, may be carried out using neural networks or data mining;
- Development and/or use of new technologies: several innovative technologies have been developed and/or implemented in the search for more effective solutions to detect and reduce commercial losses, with emphasis, among others, the use of external measurement and electronic meters, shielding cables and the development of new types of meters and software that employ artificial intelligence to increase the effectiveness of inspections;
- Actions of institutional marketing: distributors have used institutional marketing, usually with the development of educational campaigns with the underserved communities, in order to provide information on the proper and efficient use of electricity;
- Motivating employees: for an effective fight against non-technical losses, it is essential to engage all employees in the company;
- Establishment of specialized teams: it is necessary to set up specialized teams to detect and reduce commercial losses, which receive constant training and remuneration consistent.

3. Techniques and Methodologies Used to Identify Fraud

Many techniques are used to detect and reduce commercial losses such as neural networks, support vector machines, k-nearest neighbors, genetic algorithms, fuzzy logic, among others. Each technique has its advantages and disadvantages, and sometimes is more or less efficient for a particular profile of customer than to another, according to the focus of the search, the region of operation, etc., making it very difficult to establish a technique like the best for all possible scenarios.

In this paper we will detail three different techniques that have been widely used in the literature in recent years, which are neural networks, the support vector machines and technique of near neighbors.

1.1. Artificial Neural Networks

The Artificial Neural Networks (ANN) consist of a method of solving problems related to engineering and science through simple circuits that mimic the human brain, including their behavior, learning, making mistakes and making discoveries. In a technical view, it is a computational model that use inherently parallel processing techniques and adaptive through a large number of processing simple units [5].

An ANN is formed by small modules which simulate the operation of a neuron, working like the elements that were inspired, receiving and transmitting information. A simple artificial neuron model has the main features of a biological neural network, parallelism and high connectivity, a neuron is composed of a linear combination and a transfer function.

The transfer function is responsible for processing the information received and is also responsible for the output of the neuron and it can assume values of type Binary (0 or 1), Bipolar (-1 or 1) or Real [6]. Fig. 1 presents the model of an artificial neuron.

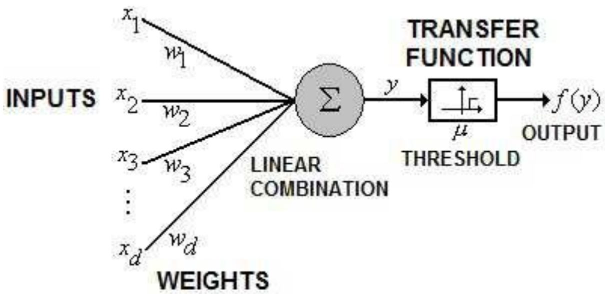

Fig. 1. Simple artificial neuron

In the training phase the weights of the network are adjusted to make the ANN able to identify a pattern input and process a correct answer with respect to this pattern. The training time is influenced by several factors, but one should always use a stopping criterion, such as error rate, maximum number of cycles or periods of training. The most common training is the algorithm "*Backpropagation*".

The idea of the "*Backpropagation*" is use pairs of inputs and outputs, previously known, to adjust the synaptic weights of the network through an error correction mechanism and during the training process, the output value is generated and compared with the known value. The error obtained is used to adjust the synaptic weights in order to gradually reduce this error. This error is propagated from the output layer to the input layer. Therefore, the synaptic weights of the inner layers will be corrected according to the error when it is done the *"backpropagation"*.

When the training wad finished, occurs the testing phase, when the patterns which have not yet been presented to the network are tested and the answers of the network will be evaluate. If the number of write answers was satisfactory, the network is ready to be implemented otherwise, one can repeat the training choosing a new topology for the network, like the number of layers or the number of neurons per layer.

1.2. Support Vector Machines:

The Support Vector Machines (SVMs) is an application of statistical learning theory. This is a research area that offers many options to work, most of them being more conceptual than merely technical, and his its scope has increased significantly in terms of new algorithms and a further theoretical understanding with great speed [7], [8].

In recent years, many successful applications of SVMs have shown that this technique not only has a more solid substantiation as ANN but are also able to replace them with similar or better performance [8].

According to the issues highlighted to control the effectiveness of learning algorithms, it is necessary that the capacity of the class of functions can be calculated. In the early days of his study, Vapnik [7] considered a class of *hyperplanes* in the space H dot product,

$$\langle w, x \rangle + b = 0 \tag{1}$$

where $w \in H, b \in \mathbb{R}$ correspond to decision functions

$$f(x) = sgn(\langle w, x \rangle + b) \tag{2}$$

Then he proposed the learning algorithm called Portrait Generalized for *hyperplane* separable problems. His idea is based in that among all *hyperplanes* separating the data, there is only one optimal *hyperplane* distinguished by the maximum margin of separation between any training point and this *hyperplane*. This *hyperplane* is calculated like the solution of

$$\max_{w \in \mathrm{H}, \mathrm{b} \in \mathbb{R}} \min \{\|x - x_i\| x \in H, \langle w, x \rangle + b = 0\} \tag{3}$$

Other important point is that the over fitting of the separating *hyperplanes* decreases with increasing margin. To construct the optimal hyperplane, it is necessary to solve

$$max_{w \in H, b \in \mathbb{R}}\, \tau(w) = {}^{1}\!/_{2}\, \|w\|^2 \tag{4}$$

subject to

$$y_i(\langle w, x_i \rangle + b) \geq 1 \qquad i = 1, \ldots, m \tag{5}$$

with the constraint (5) ensuring that $f(x_i)$ will be +1 for $y_i = -1\ e - 1$ for $y_i = -1$ and also fixing the scale of *w*. The function τ in (4) is called the objective function, while (5) are the inequality constraints.

1.3. k-Nearest Neighbor

The k-Nearest Neighbor (k-NN) classifier is based on analogy to the distances between the neighbors. It is very used in applications that involve classification tasks, and is easy to understand and implement. [9].

The k-NN has no processing during the training phase, it only make for each test sample a simple measurement of the distance between him and all samples of the training set. After this measurement, the class of the most part of the neighborhood will be the class of the tested sample [9].

If the parameter k was equal 1, the class of the tested sample will be the class of the most near neighbor, if k was greater than 1, for example 3, is checked the three nearest neighbors considering all the samples of the training set. In the Fig. 2 is showed a *k-NN* parameterized with $k=3$, when the green sample is be testing to discovery if it is from the red class or the blue class. We can see in the picture that two neighbors are from the red class and only one from blue class, so in this case the tested sample will be classified like a red sample.

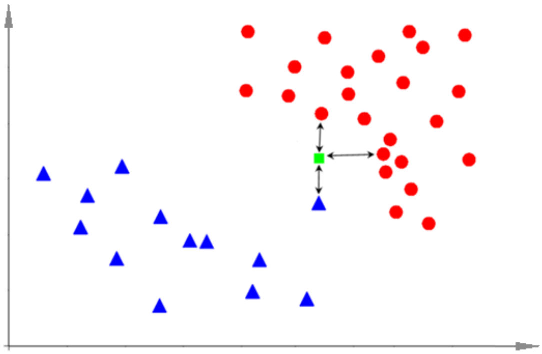

Fig. 2. A parameterized example for a *k-NN*

The only restriction is that must be careful in choosing the parameter k to be an odd number, because an even number could cause a conflict when a point has the same number of neighbors of each class, for example in the case of the Fig. 2, if the parameter k was set like 2, the *k-NN* will can't choose a class to the green sample, because the two most near neighbors was one red and one blue.

The classification rule of *k-NN* is based normally in Euclidean distance, but in specific problems may be necessary use other types of distances such as Manhattan and Minkowski [10].

If $p=(p_1,p_2,\dots,p_n)$ and $q=(q_1, q_2,\dots,q_n)$ was two points in $\Re^n$:

- Euclidian's distance between p and qis calculated by:

$$d(p,q) = \sqrt[2]{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \tag{6}$$

- Manhattan's distance between p and q is calculated by:

$$d(p,q) = |p_1 - q_1| + |p_2 - q_2| + \cdots + |p_n - q_n| \tag{7}$$

- Minkowski's distance between p and q is calculated by:

$$d(p,q) = (|p_1 - q_1|^j + |p_2 - q_2|^j + \cdots + |p_n - q_n|^j)^{\left(1/j\right)} \tag{7}$$

where $j \in \aleph$.

The Minkowski distance is a generalization of the two previous distances. It becomes the Manhattan distance when $j=1$ and it becomes the Euclidean distance when $j=2$.

4. Conclusion

Commercial losses are a big problem in Brazil, generating high annual losses of power distribution companies. To detect and reduce fraud are used several techniques such as neural networks, the support vector machines and k-nearest neighbors. Each technique has its advantages and disadvantages, and sometimes is more or less efficient for a particular profile of customer than to another, according to the focus of the search, the region of operation, etc., making it very difficult to establish a technique like the best for all possible scenarios.

This work presented a review of the main techniques to detect and reduce fraud in Brazil as well as an introduction to some of the most widely used techniques for the detection of fraud.

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