ESTIMATION OF ENERGY CONSUMPTION FOR DSO'S REVENUE RECOVERY DUE TO CONSUMERS WITH PROVEN IRREGULAR PROCEDURE

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ABSTRACT

This article presents new methods towards non-technical losses estimation in power utilities of Energisa Group. In accordance with Brazilian regulation, these approaches permit the utilities to make the appropriate retroactive charging of illegal electricity consumption which was not billed. It is proposed different models to estimate the non-technical losses for two groups of activities (residential and other classes) using typical load and demand factors, as well as the results from surveys carried out among consumers supplied by Energisa.

INTRODUCTION

The occurrences of technical and non-technical losses in Brazil are extremely high. According to the Brazilian regulatory agency (ANEEL), the non-technical losses correspond to approximately 7.3% of the total energy injected into the distribution systems, and costs around US$ 1.76 billion annually. Non-technical losses also causes negative impacts to society as they reflect higher rates to regular consumers, since the amount diverted by fraudulent agents composes the DSO tariffs. Furthermore, it also demands efforts and costs from DSO to regularize the supply and reduce the abstractions of electricity.
The Brazilian regulator establishes that, once an energy theft is verified, the utility may estimate the monthly consumption and make the retroactive charging for, at least, the period of 6 months. For residential class, the energy consumption can be calculated by using the powers and time of use of the appliances listed during the inspection of the fraudulent consumer. For other classes, such as commercial, industrial and rural, it is necessary to perform the estimation from typical load and demand factors based on the metering readings and equipment. Once these typical factors are unavailable, it should be used typical factors of an economic activity with greater similarity.
Article 130, item IV of the Brazilian normative resolution n° 414/2010 states [1]:
"*IV - determine the power consumption and the demands of active and reactive power surplus, through the diverted load, when identified, or through the installed load, verified at the time of the irregularity detection, applying for residential class, average time and the frequency of use of each load; and, for the other classes, load and demand factors, obtained from other consumer units with similar activities.*"
In this context, the proposed methodologies use data already available by utilities, such as load curves and results from a survey of appliance possession and consumption habits.

METHODOLOGY FOR RESIDENTIAL CONSUMERS

In absence of metering reading, the load curve of a household consumer can be estimated by identifying their principal home appliances, respective powers, quantities, usage frequencies and time of use. Through the optimum combination of these variables, it is possible to compose a theoretical load curve close to the real one. It should be pointed out the applicability of this method when it is detected irregular consumption, as it permits to infer with good accuracy the amount of energy consumed in a period and consequently the revenue recovery to the utility.
Nonetheless, in practice the application of such detailed surveys for all irregular consumers would require high effort and costs, considering utilities attend a broad market. In accordance with ANEEL, this study proposes the use of typical factors obtained from metering readings of a sample of low voltage consumers supplied by Energisa, as well as the results of a survey carried out among them.

Theoretical Load Curve

The survey was carried out in order to identify the main household appliances found in the different concession areas of Energisa Group and their respective daily usage.
Based on the results, it is possible to compose the monthly load curve from a sample of N residential individuals and M types of appliances, according to equation (1):

$$D_h = \sum_{j=1}^{N} \sum_{i=1}^{M} P_i \cdot q_{i,j} \cdot \left(\frac{\alpha_i}{60}\right) \cdot \left(\frac{\beta_i}{30}\right) \cdot \delta_{h,i,j} \qquad (1)$$

Where:
D_h = hourly aggregate demand in hour h (W/month);
P_i = typical power of equipment i (W);
$q_{i,j}$ = quantity of equipment i of consumer j;
αi = time of use of equipment i in a hourly interval (min/h);
βi = frequency of use of i equipment (days/month);
$\delta_{h,i,j}$ = use of the equipment i of customer j during hour h (0 or 1).

The variables α and β are strictly necessary for appliances that present high power and/or short time of use, such as electric showers, hair driers and microwave ovens. These variables minimize distortions in the load curve as well as reduce the risk of overestimated energy [2].
In this context, once confirmed an irregular consumption, the amount of energy that should be charged might be estimated by multiplying these factors for their respective quantities. It is important to emphasize that the typical powers should be applied only in cases which is not possible to determine the real power of the equipment.

Computational Optimization

The composition of a theoretical load curve with both demand and energy (area) as close as possible to the real one is not a trivial task, as it should be considered the individual consumption habits of all consumers of the sample. As result, the high number of variables involved makes the problem difficult to be solved by usual algebraic methods [3].
Given this scenario, it was developed a computational optimization algorithm based on evolutionary technique, using the Solver tool of Microsoft Office®. Due to its high capacity to solve multivariable problems through repetitive genetic operators, the evolutionary algorithm provided the most satisfactory results among the techniques analyzed. The algorithm developed in this study has the following characteristics:
(I) Input data: correspond to the dataset, such as the metering readings of the sample, time of use and quantities of the appliances.
(II) Variables: correspond the parameters to be defined by computer simulation for each equipment, such as typical power, monthly frequency of use (days/month) and minutes of usage per hour (min/hour).
(III) Restrictions: the use of evolutionary optimization Solver tool requires the lower and upper limits of the problem variables, i.e., it is necessary to establish the intervals which the factors may vary.
(IV) Objective function: involves determining the optimal combination of variables that result in a load curve, estimated by the equation (1), as close as possible to the aggregate metering readings of the individuals who responded to the survey. An alternative to measure the difference between these curves consists in calculate the sum of squared error for the 24 hours:

$$Square\ error_{curve} = \sum_{h=1}^{24} \left(D_h^{est} - D_h^{med}\right)^2 \qquad (2)$$

Where:
D_h^{est} = estimated demand in hour h (W/month);
D_h^{med} = measured demand in hour h (W/month).

However, variables in the simulation had a tendency to concentrate on the boundaries of the intervals, contrary to expectations. In this context, it was added a component to penalize the variables that were far from the average of their respective intervals, according to equation (3).

$$Square\ error_{variable} = \sum_{i=1}^{M} (p_i - \bar{p}_i)^2 \qquad (3)$$

Where:
p_i = estimated value of the variable p on the equipment i;
$\dot{p}_i$ = the variable interval average p on the equipment i;
M = number of equipment types.

It should be noted that equations (2) and (3) must be normalized, as they involve variables with different orders of magnitude. Normalizing these equations:

$$N.Sqr.Error._{curve} = \sum_{h=1}^{24} \left(\frac{D_h^{est} - D_h^{med}}{D_{máx}^{med}}\right)^2 \qquad (4)$$

$$N.Sqr.Error._{variable} = \sum_{i=1}^{M} \left(\frac{p_i - \bar{p}_i}{p_i^{sup}}\right)^2 \qquad (5)$$

D_{max}^{med} = maximum demand of the aggregate measured curve (W/month);
p_i^{sup} = upper limit of the interval for variable i.

It was defined additional components in order to provide a better fit between the estimated and measured curves. The insertion of the standard deviation of square errors aims to minimize the difference between both curves, while the second component seeks to ensure that they have the same energy.

$$\varphi \cdot std.dev_{curve} + \omega \cdot \left|\frac{E_{est} - E_{med}}{E_{med}}\right| \qquad (6)$$

Where:
E_{est} = energy of the estimated curve (kWh/month);
E_{med} = energy of the measurement curve (kWh/month);
{φ, ω} = adjustments variables, if necessary adjust the order of magnitude of the errors.

Finally, objective function can be solved by minimizing the sum of the equations (4), (5) and (6):

$$F.O. = min\{\sigma \cdot N.Sqr.Error._{curve} + \sum N.Sqr.Error._{variable} + \varphi \cdot std.dev_{curve} + \omega \cdot \left|\frac{E_{est} - E_{med}}{E_{med}}\right|\} \quad (7)$$

Like the variables φ and ω described in equation (6), the variable σ aims to adjust the magnitude of the quadratic error, if necessary.
(V) Setting parameters: correspond to the parameters of the evolutionary algorithm, such as mutation rate, population size, random propagation, convergence of the method and maximum time for improvement.

METHODOLOGY FOR OTHERS CLASSES OF CONSUMERS

Regarding to Brazilian regulation, the energy estimation to other classes should be carried out by using load and demand factors obtained from other consumers units with similar activities.

Similar Activities

This paper proposes the use of CNAE Table (National Classification of Economic Activities) from IBGE (Brazilian Institute of Geography and Statistics). This table lists all official economic activities in Brazil through a hierarchal classification, as the lower levels tend to group activities with higher levels of similarity. The hierarchal organization is depicted in Figure 1.

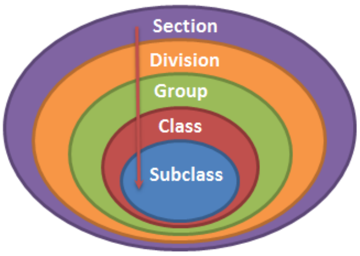

Figure 1: Hierarchal structure of CNAE Table.

It should be noted that this structure fulfills the regulatory requirement imposed by ANEEL by eliminating any subjectivity in the determination of similar activities [4].

Calculation of Typical Factors

For a sample of consumers supplied by Energisa, their load (LF) and demand factors (DF) are calculated using equations (7) e (8).

$$LF = \frac{D_{mean}}{D_{max}} \quad (7)$$

$$DF = \frac{D_{max}}{InsCap} \quad (8)$$

Where:
D_{med}: medium demand;
D_{max}: maximum demand;
InsCap: Installed Capacity.

For each consumer, the average and maximum demands were obtained from their respectively metering readings. Therefore, their economic activities were associated with the activities listed in CNAE Table.
This paper proposes three different methods to determine the load and demand factors for activities without valid measurement. In these cases, they should be related to a similar one that contains a valid measure, respecting the structure defined by the CNAE Table.
(I) Arithmetic Mean: economic activities that do not have their factors defined by actual measurements would be associated with an average value of economic activities which were classified as similar, according to CNAE Table. Figure 2 presents a hypothetical example in which is defined the load and demand factors of two activities that did not have related measurements.

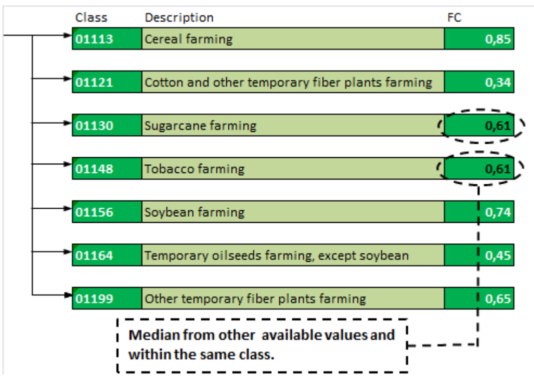

Figure 2: Arithmetic Mean Method.

(II) Median Method: similar to the average method, it is used the median to define valid values of all similar economic activities.

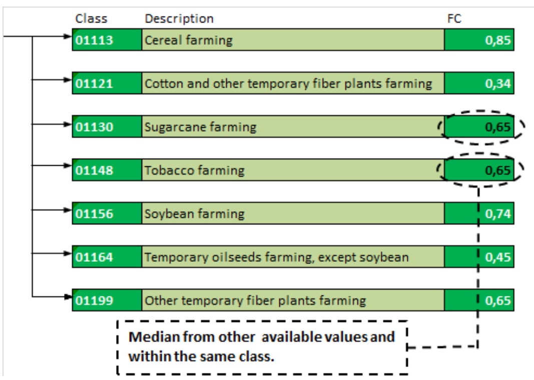

Figure 3: Median Method.

(II) Regression: seeks to estimate the consumption of fraudulent consumers using a statistical model of regression, which considers the load and demand factors obtained by the regression of equations (9) and (10).

$$DF_i = \alpha \cdot P_i^a \qquad (9)$$
$$LF_i = \beta \cdot P_i^b \qquad (10)$$

Where:
a, b, α e β : regression coefficients.
P_i = Installed Capacity of consumer i.

Once known the installed capacity of a particular consumer, it is possible to estimate the load and demand factor, regardless its economic activity. It is noteworthy that the regressions were divided into 6 bands of consumption to ensure greater statistical correlation in their estimation (adjusted R^2). Table 1 and 2 present the values obtained for EPB, one of the DSOs of Energisa Group.

Table 1: Demand Factor Coefficients –EPB.

Variables	*Bands of Consumption (kWh/month)*					
	0-200	200-500	500-1000	1000-2000	2000-5000	> 5000
a	-0,34	-0,09	-0,35	-0,46	-0,32	-0,15
α	5,27	0,78	8,14	25,44	9,27	2,40

Table 2: Load Factor Coefficients - EPB.

Variables	*Bands of Consumption (kWh/month)*					
	0-200	200-500	500-1000	1000-2000	2000-5000	> 5000
b	-0,58	-0,88	-0,63	-0,45	-0,52	-0,42
β	12,36	437,2	103,1	30,83	93,02	46,6

Nonetheless, the practical applicability of this method would require change in Brazilian regulation rules, as current rules state that load and demand factor must be obtained from consumers with similar activities. Hence, this approach had not the same priority as the previous ones in this paper.
To sum up, once calculated the load and demand factors for a particular economic activity in specific (either by any of the three proposed methodologies), the estimated monthly energy for a period of time Δt can be calculated using equation (11).

$$Consumption = InsCap \cdot LF \cdot DF \cdot \Delta t \qquad (11)$$

ANALYSIS OF RESULTS

Residential Consumers

For five utilities of Energisa Group (EPB, EBO, ESE, EMG and ENF), it was determined the powers and typical times of uses of the main residential appliances in order to best fit between the estimated and measured curves of the sampled low voltage consumers.
Figure 4 present the estimated and measured aggregate load curves for each utility as the quantities of sampled consumers for each distributor are depicted in Table 1. In all simulations, the parameters σ, φ and ω were empirically set to 50, 200 and 100, respectively.

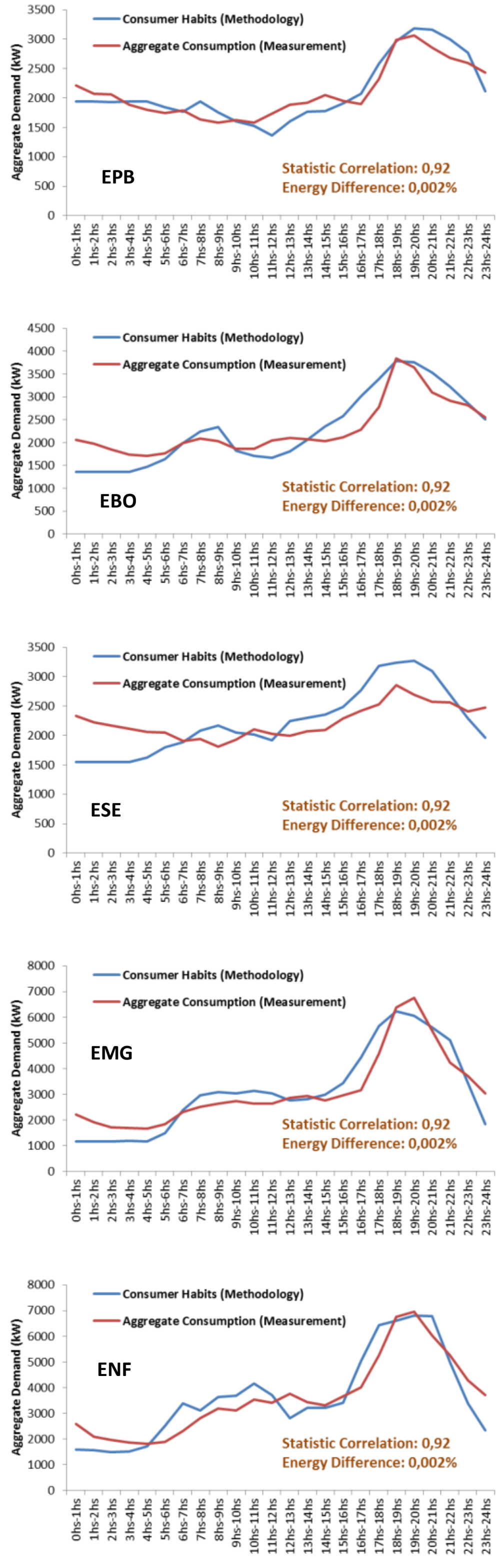

Figure 4: Load curves – results from simulation.

Table 3: Low voltage consumers quantities.

EPB	EBO	ESE	EMG	ENF
138	155	148	116	75

Other Classes

Regarding to other classes, this item presents comparative studies among the current methodology applied by Energisa, the three proposed models and the actual consumption. The results are illustrated in figures 5 to 8. Estimated consumptions become more accurated as the points get closer to the dotted line. Considering the current Brazilian regulation and the results obtained, it is understood as prudent to adopt the median method to estimate the load and demand factors, and then consequently, estimate the energy consumption.

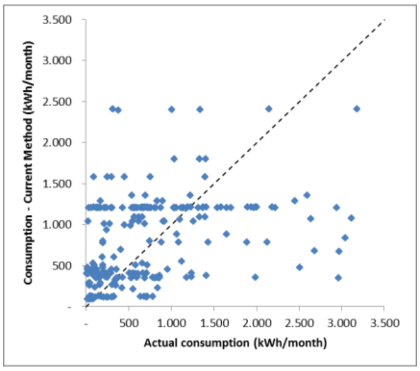

Figure 5: Actual Consumption X Current Methodology.

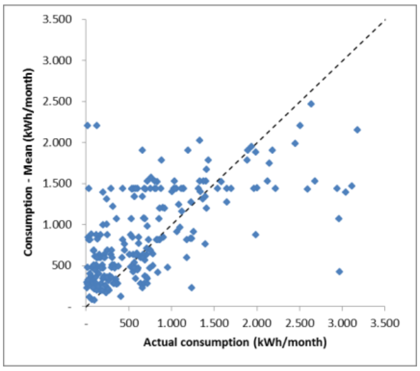

Figure 6: Actual Consumption X Arithmetic Mean Method.

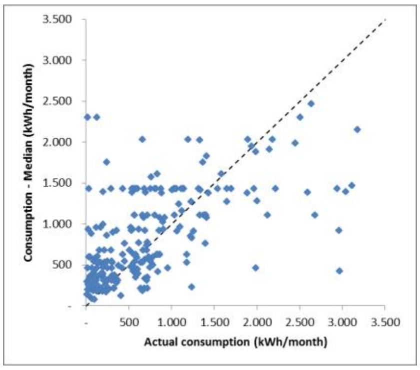

Figure 7: Actual Consumption X Median Method.

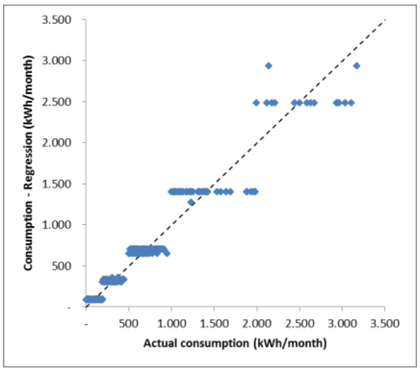

Figure 8: Actual Consumption X Regression Method.

Nevertheless, it is worth mentioning that any of the methods herein proposed are applicable to any worldwide power distributor company, besides being flexible to any adjustments that may be necessary due to the reality of each concession area to be studied.

CONCLUSION

This paper proposes methodologies to non-technical losses based on consumption habits and typical load factors. Since there is no proper reading metering in these cases, it was developed robust methods without any subjectivity in order to determine the consumption as close as possible to the real one.

The results obtained from five utilities of Energisa Group show relevant adherence to the residential class, as stated by high statistical correlation and low energy difference between the actual and estimated curve. Regarding to other classes, the proposed methods presented greater adherence to estimate the actual consumption of fraudulent consumers than the current method used by the DSO. Finally, although this study proposed a new methodology using statistical regression, it still depends on changes in Brazilian regulations, since it does not link the resulting factors to a particular economic activity.

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