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Influence of Clandestine Connections on Energy Loss Evaluation in Electrical Distribution Networks

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Abstract: In the literature, there are several methodologies to estimate technical losses in electrical distribution networks. The range of techniques is broad, ranging from basic techniques (based on loss factor, for example) to sophisticated ones (based on artificial intelligence). These methodologies are important, because the costs of technical losses represent a huge part of the total operation costs of distribution network operators (DNOs). However, the presence of clandestine connections, common in developing countries, was not considered in the methodologies encountered in the literature. Clandestine connections occur when a consumer has made his/her connection without DNO permission. In these cases, the amount of energy consumed by a clandestine "consumer" is a nontechnical loss (and, therefore, should be correctly computed as nonbilled energy). Therefore, a new methodology is proposed to consider the presence of clandestine connections in energy loss estimation in distribution systems.

Keywords: energy conservation; energy efficiency; power distribution; power system planning; technical losses.

1. INTRODUCTION

The costs of losses (technical and nontechnical) in electrical distribution networks represent an important part of the total operation costs of distribution network operators - DNOs (Fu et al. 2016, Ahmadimanesh and Kalantar 2017, Ahmad and Ul Hasan 2016). For this reason, the regulatory agencies are establishing challenging targets for loss levels. In general, nontechnical losses are obtained through subtraction of technical losses from the total losses, and detection depends on knowledge of local socioeconomic aspects (Aranha Neto and Coelho 2013, Faria et al. 2016). Total losses are easily obtained from a border meter (belonging to DNOs). However, technical losses cannot be easily measured, and new methods for their correct estimation are necessary to determine how good the operational performance of the electrical distribution networks is (Leal et al. 2009, Dashtaki and Haghifam 2013).

In the literature, there are several methodologies to perform technical loss estimation. Methods strongly based on statistical analysis typically need few data about the network and loads. However, they tend to show results with low accuracy. Methods that are deterministic or weakly based on statistical analysis, typically based on power flow tools, provide results with high accuracy. The choice between both types of method depends on the data available in the DNOs' data centers and the target proposed by the DNOs' planners. In both cases, the methods can include all electrical segments (service connections, secondary and primary networks, distribution transformers, high-voltage/medium-voltage transformers, energy meters, capacitor banks, and voltage regulators) or only some segments. In the latter case, several methodologies should be applied together to obtain a complete power loss estimation.

The range of techniques is broad. Artificial neural networks (ANNs) have been used (Leal et al. 2009, Hong-Rui et al. 2007, Ni and Yu 2009, Lee et al. 2011) to estimate technical losses in a distribution system. In other research (Lasso et al. 2006), a technique named “stratified sampling” was used to estimate technical losses in the secondary energy distribution network. In another study (Poursharif et al. 2018), domestic smart meter readings were used to estimate the actual losses in low-voltage networks. The relationship between the demand data time resolution and errors in the estimated losses on secondary networks has been investigated (Urquhart and Thomson 2015). In other research (Huilan et al. 2007), a genetic algorithm was used in line loss calculation for a distribution network. In other studies (Aranha Neto and Coelho 2013, Shulgin et al. 2012), a stochastic approach was used to calculate energy losses. A finite-element technique was used in loss calculation of distribution transformers (Yazdani-Asrami et al. 2013). In other work (Delfanti et al. 2013, Ayres et al. 2014), the impact of dispersed generation on distribution network losses was evaluated. Regression analysis was used to estimate technical losses in distribution systems or in some parts of them (Queiroz et al. 2009, Rao and Deekshit 2006, Madrigal et al. 2015). Clustering approaches were applied (Grigoras et al. 2010, Dashtaki and Haghifam 2013) to perform loss calculation. In another study (Yang et al. 2014), adjustment factors were used to estimate line loss in secondary networks. A new parameter named the “loss coefficient” was created to improve loss estimation (Queiroz et al. 2012).

Despite several methodologies using sophisticated techniques, one of the oldest and most widely used method is the utilization of a loss factor, which represents the ratio of average power loss to the peak load power loss over a given period of time (Nickel and Braunstein 1981, de Oliveira et al. 2008). For example, in previous research (Oliveira and Padilha-Feltrin 2009, Poryan 2009, Grigoras et al. 2012), technical losses in distribution systems were estimated through loss-factor-based techniques. The deficiencies of methods based on the loss factor have been presented and discussed (Onen et al. 2014). Two formulas were proposed for calculation of the loss factor to improve the classical method, based on the minimum load factor and the load factor (Fu et al. 2016).

To avoid the use of loss factors, methodologies were proposed (Meffe and de Oliveira 2009, Donadel et al. 2009) to estimate technical losses per segment of a power distribution system. Such methodologies are based on typical daily load profiles for each kind of customer (divided in 24 steps), using a load flow tool. Adjusting the differences between the energy from the estimated load profile and the energy from the measured load profile (such a difference is named "nonbilled energy") was proposed, based on measurements performed in the peak load time, considering a uniform distribution of nonbilled energy (Meffe and de Oliveira 2009) and a nonuniform distribution of nonbilled energy (Donadel et al. 2009). The latter one was based on estimations of illegal consumers — consumers who are recorded in the DNO's database and have a meter system provided by their DNO, but who tamper with it. In the same way, a method that considers that DNOs have hourly flow measurements at each of their feeders and make these measurements available to their engineers was presented (Onen et al. 2014). In this case, the shape of load curves can be adjusted too, to achieve more accuracy.

However, the presence of clandestine connections, common in developing countries, was not considered in methodologies encountered in the literature. Clandestine connections occur when a consumer has made his/her connection without DNO permission. In these cases, the amount of energy consumed by a clandestine "consumer" is a nontechnical loss (and, therefore, should be correctly computed as nonbilled energy). Therefore, an improved methodology is proposed to consider the presence of clandestine connections in energy loss estimation of a power distribution system.

The remainder of this work is organized as follows. In Section 2, the proposed methodology is presented, including the mathematical formulation. In Section 3, numerical results are presented, and the results obtained by the application of the proposed methodology are deeply discussed. The conclusions are presented in Section 4.

2. ENERGY LOSS ESTIMATION METHODOLOGY

Consideration of the presence of clandestine connections in the energy loss estimation of a power distribution system is proposed. To do this, it is necessary to know (or estimate) where clandestine connections are located and how big their electrical energy consumption is (clandestine consumer connection point and consumption can strongly affect the results of load flow studies). In an ideal scenario, in which data on clandestine-connection locations/consumptions are known, load flow studies result in a correct value of energy losses. Because of practical reasons (e.g., financial aspects), these data are not completely available. Therefore, available data about clandestine connections should be used to estimate their condition in the entire distribution system and, therefore, their impact on distribution system energy losses. Thus, good estimates of clandestine-connection locations/consumption lead to good estimates of energy losses.

Brazilian DNOs used to perform inspections of their electrical distribution networks to detect clandestine connections and generate a database from the data obtained from these inspections. In a long term, performed inspections help DNO to reduce clandestine connections. However, in a short/medium term, data from performed inspections can be used as a good estimator of clandestine connections. Commonly, the data available are: area identifier (area ID), date of inspection, and number of clandestine connections detected in each inspection. Area represents the region where clandestine connections were detected; it commonly coincides with a neighborhood's limits, and it is represented by a polygon in the DNO's geographic information system (GIS).

The proposed methodology is based on typical daily load profiles for each kind of customer (divided into 24 steps), using a load flow tool, as in previous research (Meffe and de Oliveira 2009, Donadel et al. 2009). It proposes adjusting the nonbilled energy based on measurements performed in the peak load time, considering a nonuniform distribution of nonbilled energy from estimations of clandestine connections. The methodology strategy is shown in Fig. 1. The methodology's steps are presented below.

Step 1. Load data from the DNO's GIS: electric power substations' boundaries, areas' boundaries, historical data of performed inspections, electrical networks' topologies, and historical data of consumers.

Step 2. Define E_{PS} — the set of electric power substations of interest. The proposed methodology should be applied to each electric power substation i, $i \in E_{PS}$, individually (from Step 3 to Step 8).

Step 3. Electrical distribution networks are not restricted to a specific area, i.e., one electric power substation can supply consumers in distinct areas. In this step, the set of areas (A_R) which are partially or totally supplied by each electric power substation i is determined from geographical data.

Step 4. For practical reasons, clandestine-connection estimations obtained from historical data cannot be compared to field data for validation purposes. Therefore, in this step, it is verified whether the number of inspections performed in each area k ($k \in A_R$) is statistically representative, leading to a reliable average value for the number of clandestine connections. This step guarantees the accuracy of estimated data. From the central limit theorem, the minimal number of inspections is given by (1) (Sprent and Smeeton 2007, Fleiss et al. 2003).

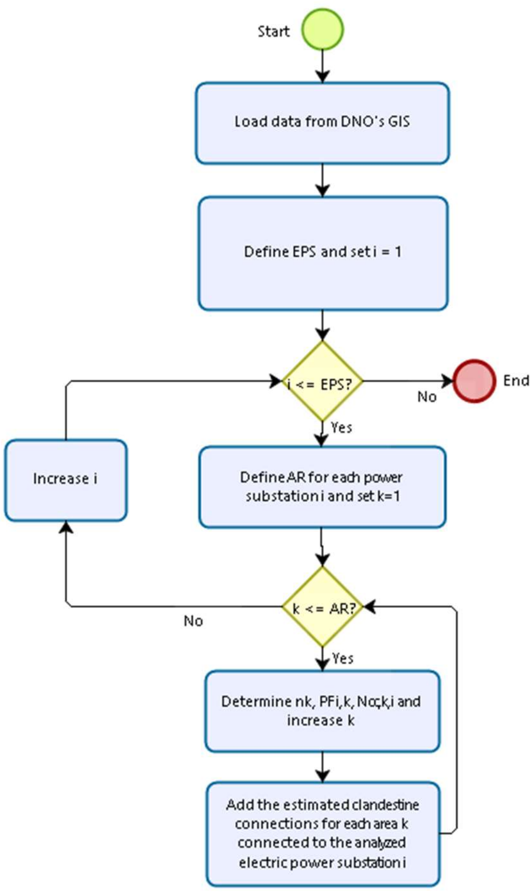

Fig. 1 Methodology proposed in this study

$$n_k \geq \frac{N_{c,k}\sigma_k^2 z_{\gamma/2}^2}{(N_{c,k}-1)E^2+\sigma_k^2 z_{\gamma/2}^2} \tag{1}$$

Where:

n_k Minimal number of inspections for area k
$N_{c,k}$ Number of consumers of area k
$z_{\gamma/2}$ z-value, corresponding to the desired confidence level (γ)
σ_k Population standard deviation (approximated by sample standard deviation) of area k
E Margin of error

If the minimum number of inspections for area k is not achieved, area k is joined with another area/areas to create a bigger area with a sufficient number of inspections.

Step 5. Each area k can be supplied from distinct electric power substations. This step aims to calculate the participation factor of the analyzed electric power substation i in each covered area k determined in Step 3. The participation factor is given by (2).

$$PF_{i,k} = \frac{C_{k,i}}{C_{k,total}} \tag{2}$$

Where:

$PF_{i,k}$ Participation factor of electric power substation i in area k
$C_{k,i}$ Number of consumers in area k, connected to the analyzed electric power substation i
$C_{k,total}$ Number of consumers in area k

Step 6. Estimate the number of clandestine connections for each covered area k, connected to the analyzed electric power substation i, given by (3). If $n_{insp,k} < n_k$, data from similar areas are used, since they have $n_{insp,k} \geq n_k$.

$$N_{cc,k,i} = PF_{i,k}\frac{\sum_{j=1}^{n_{insp,k}} N_{cc,k,j}}{n_{insp,k}} \tag{3}$$

Where:

$N_{cc,k,i}$ Number of clandestine connections estimated for area k connected to the analyzed electric power substation i
$N_{cc,k,j}$ Number of clandestine connections detected in each inspection j for area k
$n_{insp,k}$ Number of inspections performed in area k

Step 7. Add the estimated clandestine connections for each area k connected to the analyzed electric power substation i. Clandestine connections are uniformly distributed. Clandestine-connection consumption was estimated by the DNO in previous studies (performed in field) in the range 150-200 kWh and they are typically connected in a secondary network. Therefore, in this study, for simplification purposes, clandestine-connection consumption has a uniform probability density function varying between 150 and 200 kWh. All clandestine connections were connected to a secondary network.

Step 8. Estimate energy losses according to the methodology described in a previous study (Meffe and de Oliveira 2009), using a load flow tool. However, energy losses values in kWh (or MWh) cannot be presented (they are considered classified information). Therefore, results will be presented in terms of the percentage variation of energy losses between the methodology used as reference by local DNO, and the methodology presented in this study.

All processed data were available in Comma Separated Values (CSV) files. Microsoft Access was used to manipulate these files and a commercial load flow tool (Pertec) was used to calculate power and energy losses.

3. NUMERICAL RESULTS AND DISCUSSION

The methodology presented in Section 2 was applied at 16 electric power substations with unbalanced load (Donadel et al. 2009) over 12 months. The feeders supply an urban/rural region, having different characteristics. This region was chosen because it has a broad database of historical data of performed inspections. These data have been kept unchanged in the analyzed period.

Fig. 2 shows the energy loss variations between the methodology described in a previous study (Meffe and de Oliveira 2009), used as a reference method by the local DNO, and the methodology presented in this work. The energy loss variations presented in Fig. 2 refers to all electric power substations, stratified by month.

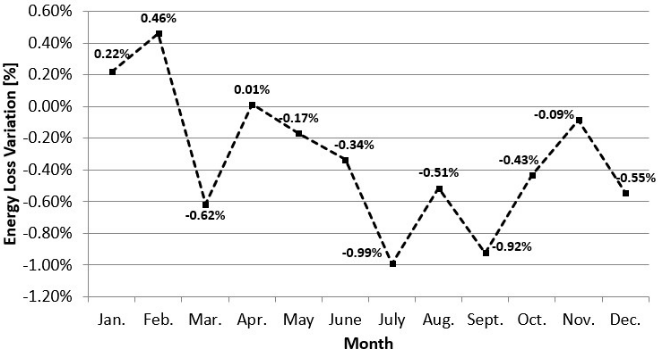

Fig. 2 Energy loss variations between a methodology described elsewhere (Meffe and de Oliveira 2009), used as reference method by local DNO, and the methodology presented in this study

In general, energy loss variations between the methodology described previously (Meffe and de Oliveira 2009) and the methodology proposed in this work (Fig. 2) are small, varying in the range between -0.99% and +0.46%. Therefore, the difference between the energy losses obtained from a uniform distribution of nonbilled energy and energy losses obtained from a nonuniform distribution of nonbilled energy (this methodology) varies in the range between -0.99% and +0.46%. Although the energy loss variations are small, there is a smooth trend of reduction of energy loss values. The energy loss variations' average value is -0.31%, when the values obtained with the previous method (Meffe and de Oliveira 2009) are compared to the values obtained with the proposed methodology, being negative in 83% of the analyzed months. In a global way, small values of energy loss variations between methods were expected, because the methodology proposed in the present study promotes a spatial redistribution of nonbilled energy (and, consequently, a spatial redistribution of energy losses associated with it) in the analyzed region, but the amount of nonbilled energy remains the same. However, an increase in these differences is expected when the analysis is performed in subregions (e.g., analyzed by feeder or neighborhood).

Energy losses can be evaluated by segment. For comparison purposes, the segments adopted in this study were the same segments adopted in the previous one (Meffe and de Oliveira 2009). They are meters, service connections, secondary network, distribution transformers, primary network, capacitor banks, and voltage regulators. Fig. 3 shows energy loss variations accumulated over one year, stratified by segment, between the methodology described previously (Meffe and de Oliveira 2009) and the methodology presented here.

Historically, the majority of illegal consumers and clandestine connections are in low-voltage networks (or secondary networks). Therefore, the methodology presented in this work tends to increase the amount of energy to be allocated in low-voltage networks. This redistribution process leads to an energy loss increase in low-voltage segments (service connections, secondary network, and distribution transformers). Service connections had their energy losses increased by 5.38%, secondary networks had their energy losses increased by 3.51%, and distribution transformers had their energy losses increased by 1.27%. Distribution transformers had the lower increasing rate because part of their energy losses is not variable with load. However, energy losses in medium-voltage segments (primary network) tend to decrease (-5.21% in Fig. 3). Although the entire amount of redistributed energy is still flowing through primary network, it is spread on the feeder, because the low-voltage consumers are spread on the feeder. Energy losses in meters, capacitor banks, and voltage regulators do not depend on the power flow through them. In these segments, energy losses are modeled as a constant value. Therefore, the total energy loss value depends only on the number of devices connected to the network. The number of capacitor banks and voltage regulators does not change (the network topology was kept unchanged). The methodology presented here includes new consumers without meters, an inherent characteristic of clandestine connections. Therefore, the total number of meters does not change.

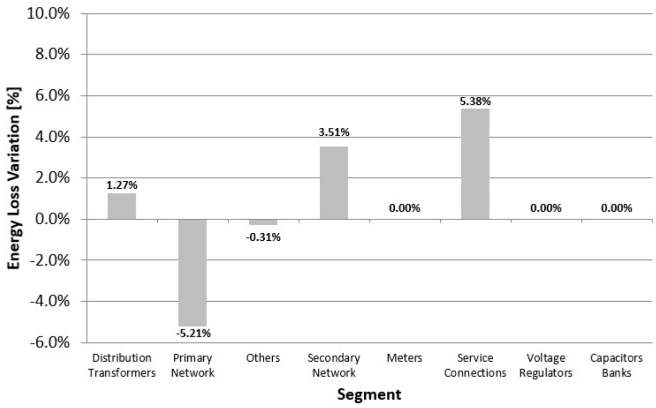

Fig. 3 Energy loss variations accumulated over one year, by segment, between a methodology described in previous research (Meffe and de Oliveira 2009) and the methodology presented in this study

When the analysis is performed for each single substation (numbered from #1 to #16), energy loss variations between the previous methodology (Meffe and de Oliveira 2009) and the methodology proposed in this study vary in the range between -4.06% and 2.82%, as shown in Table 1. For example, energy losses for Substation #1 were 0.06% higher with the proposed methodology; however, energy losses for Substation #10 were 0.86% lower with the proposed methodology.

As expected, higher variations can be observed when an analysis by feeder is performed (varying in the range between -8.50% and 12.61%, between the previous study (Meffe and de Oliveira 2009) and this one). Energy loss variations increase more when the analysis is made by area. Fig. 4 shows energy loss variations for 17 areas selected as an example (the entire analyzed region has more than 300 areas), varying in the range between -5.30% and 36.59% when the values obtained from the previous method (Meffe and de Oliveira 2009) are compared to the values obtained in this study. These results represent a powerful tool for DNOs' planners, because they can choose the priority areas to receive financial resources from DNOs to reduce energy losses.

Table 1. Energy Loss Variations for Each Electric Power Substation

Substation	Energy loss variations between Meffe and de Oliveira (2009) and this work
#1	-0.06%
#2	-0.57%
#3	0.52%
#4	-1.58%
#5	-0.91%
#6	-0.02%
#7	-2.29%
#8	-0.15%
#9	-3.70%
#10	0.86%
#11	2.49%
#12	-0.49%
#13	-0.94%
#14	-4.06%
#15	2.82%
#16	1.61%

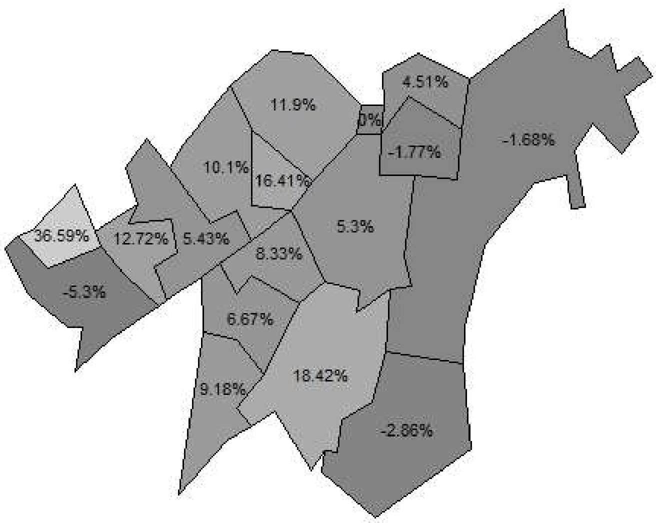

Fig. 4 Energy loss variations for 17 areas between the methodology described in previous research (Meffe and de Oliveira 2009) and the methodology presented in this study

4. CONCLUSIONS

Methodologies for energy loss estimation are important, because the costs of technical losses represent a huge part of the total operation costs of DNOs. The methodologies should have high accuracy to help DNOs' planners in their decisions. A new methodology for energy losses estimation was proposed. It can consider the presence of clandestine connections in the network, while keeping the advantages of previous methodologies proposed in the literature: the estimation of energy losses by segment and considering a nonuniform distribution of nonbilled energy. The main advantages of the proposed methodology are as follows.

- It presents a higher accuracy when compared to existing methods because it considers a more realistic perspective, in which losses are not evenly distributed along the distribution network.

- It promotes a nonuniform redistribution of the nonbilled energy, based on historical data of clandestine connections, bringing the methodology closer to the situations that occur in practice.

- It enables DNOs' planners to stratify the energy loss values by segment, feeder, substation, and area, improving DNOs' technical planning process.

- It enables DNOs' planners to choose the priority areas/feeders/substations to receive financial resources from DNOs to reduce energy losses.

Naturally, the proposed methodology can express the behavior of losses considering the confidence level desired in each case, as expected for statistical methods.

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