7
Referências bibliográficas

1 AGÊNCIA NACIONAL DE ENERGIA ELÉTRICA. **Aprimoramento da metodologia utilizada pela ANEEL para o cálculo das perdas de energia elétrica na distribuição constante do Módulo 7 – Cálculo de Perdas na Distribuição do PRODIST.** Disponível em: <http://www.aneel.gov.br/aplicacoes/audiencia/arquivo/2011/025/documento/nota_tecnica_0014_dir.pdf>. Acessado em 7 abril 2011.

2 M. E. OLIVEIRA, A. PADILHA-FELTRIN. A Top-Down Approach for Distribution Loss Evaluation. **IEEE Transactions on Power delivery**, vol. 24, NO. 4, pp. 2117-2124, Outubro 2009.

3 AGÊNCIA NACIONAL DE ENERGIA ELÉTRICA. **Procedimentos de Distribuição de Energia Elétrica no Sistema Elétrico Nacional – PRODIST – Modulo 7 – Cálculo de Perdas na Distribuição.** Disponível em: <http://www.aneel.gov.br/arquivos/PDF/Modulo7_Revisao_3-Final.pdf>. Acessado em 5 abril 2013.

4 G. GRIGORAS, G. CARTINA, E. C. BOBRIC. An Improved Fuzzy Method for Energy Losses Evaluation in Distribution Networks. in Proc. 2010 **MELECON 2010 - 2010 15th IEEE Mediterranean Electrotechnical Conf**., pp. 131-135.

5 P. S. NAGENDRA RAO, RAVISHANKAR DEEKSHIT. Energy Loss Estimation in Distribution Feeders. **IEEE Transactions on Power delivery**, vol. 21, NO. 3, pp. 1092-1100, Julho 2006.

6 J. DICKERT, M. HABLE, P. SCHEGNER. Energy Loss Estimation in Distribution Networks for Planning Purposes. **IEEE Bucharest Power Tech Conference**, June 2009.

7 I. FERREIRA VISCONTI. **Modelos de cargas baseados em medições para simulações dinâmicas em sistemas elétricos de potência**. Pontifícia Universidade Católica do Rio de Janeiro - PUC-RIO. Outubro de 2010.

8 M. DE ESCOBAR DE OLIVEIRA. **Avaliação de Metodologias de Cálculo de Perdas Técnicas em Sistemas de Distribuição de Energia Elétrica**. Universidade Estadual Paulista "Júlio de Mesquita Filho". Agosto de 2009.

9 AGÊNCIA NACIONAL DE ENERGIA ELÉTRICA. **Anexo IV – Cálculo do Condutor Tronco e Ramal para os alimentadores do SDMT.** Disponível em: <http://www.aneel.gov.br/aplicacoes/audiencia/arquivo/2011/025/documento/nota_tecnica_0014_anexo_iv_.pdf >. Acessado em 2011.

10 KERSTING, WILLIAM H. **Distribution System Modeling and Analysis**. Las Cruces - New Mexico: CRC Press, 2002.

11 C. S. CHENG AND D. SHIRMOHAMMADI. A three-phase power flow method for real-time distribution system analysis. **IEEE Transactions on Power System**, vol. 10, NO. 2, pp. 671-679, Maio 1995.

12 L. ROKACH, O. MAIMON. **Data Mining and Knowledge Discovery Handbook**. US: Springer, 2005.

13 DIOGO C. LUCAS. **Algoritmos Genéticos: uma Introdução,** Universidade Estadual do Rio Grande do Sul. Março de 2012.

14 PERES SERRADA, A. **Una introducción a la computación evolutiva**. Disponível em: < http://www.geocities.com/igoryepes/spanish.zip>. Acesso em setembro de 2000.

15 MICHALEWICZ, Z. **Genetic algorithms + data structures = evolution programs**. Berlin: Springer-Verlag, 1999.

16 GEYER-SCHULTZ, A. **Fuzzy rule-based expert systems and genetic machine learning**. Heidelberg: Physica-Verlag, 1997.

17 GOLDBERG, D. E. **Genetic algorithms in search, optimization & machine learning**. [S.l.]: Addison-Wesley, 1989.

18 BARBOSA, H. J. C. **Algoritmos genéticos para otimização em engenharia: uma introdução.** In: **IV Seminários sobre Elementos Finitos e Métodos Numéricos em Engenharia**, Juiz de Fora, MG, Brasil, 1996.

Apêndice A
Sistema IEEE 34 Barras

Neste Apêndice é apresentado o diagrama, características e parâmetros do sistema IEEE 34 barras (Figura A.1).

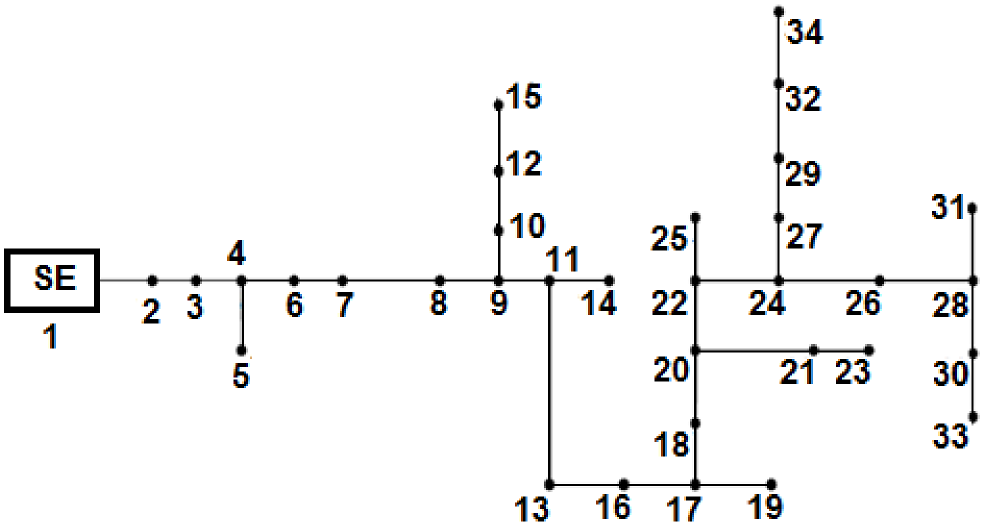


Figura A.1 - Sistema IEEE 34 barras

Na Tabela A.1 são apresentadas todas as características das linhas da rede em média tensão do sistema de distribuição utilizadas para a realização dos estudos de fluxo de potência nas simulações apresentadas neste trabalho.

Na Tabela A.2 são apresentadas as demandas nominais das cargas conectadas nas barras do sistema e os parâmetros ideais que definem o comportamento e o tipo de carga que elas são.

Tabela A.1 - Dados das linhas do sistema IEEE 34 barras

Linha	Barra inicial	Barra final	R [ohm]	X [ohm]	Comprimento [km]
1	1	2	1.2586	0.5549	0.7869
2	2	3	0.8432	0.3720	0.52765
3	3	4	15.7483	6.9441	9.83015
4	4	5	2.8520	1.2586	1.77022
5	4	6	18.2903	8.0601	11.4375
6	6	7	14.5082	6.3861	9.06765
7	7	8	0.4879	0.2151	0.00305
8	8	9	0.1513	0.0670	0.09455
9	9	10	0.8370	0.3677	0.52155
10	9	11	4.9849	2.1948	3.11405
11	10	12	23.4984	10.3542	14.68575
12	11	13	0.4098	0.1804	0.2562
13	11	14	1.4818	0.6510	0.92415
14	12	15	6.6961	2.9574	4.1907
15	13	16	9.9822	4.3959	6.2342
16	16	17	0.2536	0.1116	0.1586
17	17	18	17.9803	7.9361	11.23315
18	17	19	11.4082	5.0221	7.11565
19	18	20	0.4879	0.2151	0.00305
20	20	21	1.8972	4.0797	0
21	20	22	2.4056	1.0540	1.4945
22	21	23	5.1523	2.2692	3.2208
23	22	24	2.8458	1.2524	1.77815
24	22	25	0.7936	0.3484	0.4941
25	24	26	0.9858	0.4346	0.6161
26	24	27	0.1364	0.0603	0.0854
27	26	28	1.3082	0.5766	0.8174
28	27	29	0.6572	0.2902	0.41175
29	28	30	0.1364	0.0603	0.0854
30	28	31	0.4197	0.1848	0.2623
31	29	32	1.7794	0.7812	1.1102
32	30	33	1.5872	1.0416	1.4823
33	32	34	0.2585	0.1141	0.16165

Tabela A.2 - Dados das cargas do sistema IEEE 34 barras

			Parâmetros da potência ativa			**Parâmetros da potência reativa**		
Barra	$S^{nominal}$ (kVA)	**cos(φ)**	α_P	β_P	γ_P	α_Q	β_Q	γ_Q
2	0.00	0.00	1	0	0	1	0	0
3	21.50	0.89	0	1	0	0	1	0
4	0.00	0.00	0	0	1	0	0	1
5	5.96	0.89	0,3	0,3	0,4	0,3	0,3	0,4
6	0.00	0.00	1	0	0	1	0	0
7	0.00	0.00	0	1	0	0	1	0
8	0.00	0.00	0	0	1	0	0	1
9	0.00	0.00	0,3	0,3	0,4	0,3	0,3	0,4
10	0.15	0.88	1	0	0	1	0	0
11	12.72	0.89	0	1	0	0	1	0
12	16.78	0.89	0	0	1	0	0	1
13	26.19	0.45	0,3	0,3	0,4	0,3	0,3	0,4
14	2.32	0.89	1	0	0	1	0	0
15	0.00	0.00	0	1	0	0	1	0
16	0.00	0.00	0	0	1	0	0	1
17	0.00	0.00	0,3	0,3	0,4	0,3	0,3	0,4
18	1.40	0.89	1	0	0	1	0	0
19	0.00	0.00	0	1	0	0	1	0
20	0.00	0.00	0	0	1	0	0	1
21	4.92	0.89	0,3	0,3	0,4	0,3	0,3	0,4
22	0.00	0.00	1	0	0	1	0	0
23	11.26	0.89	0	1	0	0	1	0
24	34.59	0.78	0	0	1	0	0	1
25	25.00	0.00	0,3	0,3	0,4	0,3	0,3	0,4
26	0.00	0.00	1	0	0	1	0	0
27	55.25	0.84	0	1	0	0	1	0
28	3.42	0.89	0	0	1	0	0	1
29	14.75	0.89	0,3	0,3	0,4	0,3	0,3	0,4
30	188.20	0.79	1	0	0	1	0	0
31	10.36	0.89	0	1	0	0	1	0
32	11.35	0.78	0	0	1	0	0	1
33	8.49	0.89	0,3	0,3	0,4	0,3	0,3	0,4
34	0.00	0.00	1	0	0	1	0	0

Apêndice B
Algoritmos Genéticos (AG)

Os algoritmos genéticos utilizam conceitos provenientes do princípio de seleção natural para abordar uma série ampla de problemas, em especial de otimização ou minimização de funções. Robustos, genéricos e facilmente adaptáveis, consistem de uma técnica amplamente estudada e utilizada em diversas áreas [13].

O funcionamento dos AG é inspirado na maneira como o darwinismo explica o processo de evolução das espécies. Holland decompôs o funcionamento dos AG nas etapas de inicialização, avaliação, seleção, cruzamento, mutação, atualização e finalização como amostrado no fluxograma da Figura B.1.

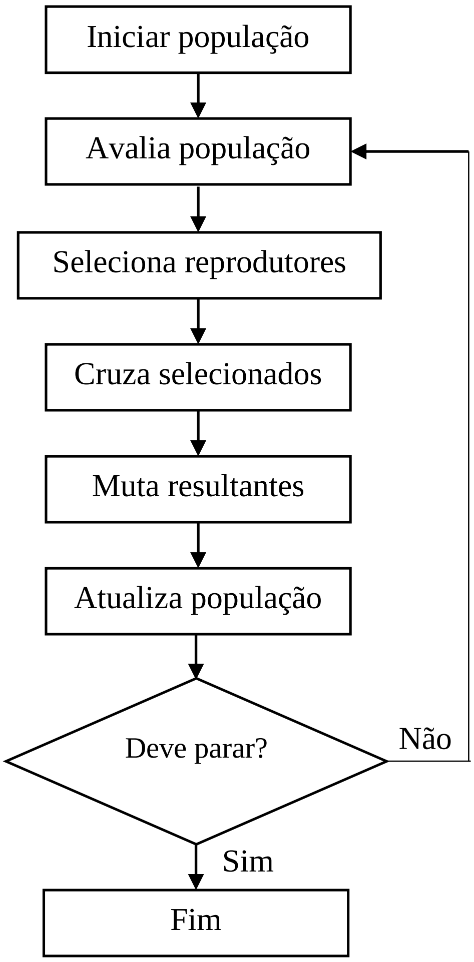


Figura B.1 - Fluxograma do funcionamento dos Algoritmos Genéticos

Basicamente, o que um algoritmo genético faz é criar uma população de possíveis respostas para o problema a ser tratado (inicialização) para depois submetê-la ao processo de evolução, constituído pelas seguintes etapas:

1. Avaliação: Avalia-se a aptidão das soluções (indivíduos da população). É feita uma análise para que se estabeleça quão bem elas respondem ao problema proposto.
2. Seleção: Indivíduos são selecionados para a reprodução. A probabilidade de uma dada solução de ser selecionada é proporcional à sua aptidão.
3. Cruzamento: Novos indivíduos são gerados baseados na recombinação das características das soluções escolhidas.
4. Mutação: Características dos indivíduos resultantes do processo de reprodução são alteradas, acrescentando assim variedade à população.
5. Atualização: Os indivíduos criados nesta geração são inseridos na população.
6. Finalização: Verifica se as condições de encerramento da evolução foram atingidas, retornando para a etapa de avaliação em caso negativo e encerrando a execução em caso positivo.

Por causa de maneira particular como os AG operam, neles se destacam as seguintes características:

- Busca codificada: Segundo o autor Pérez Serrada [14], "os AG não trabalham sobre o domínio do problema, mas sim sobre representações de seus elementos". Tal fator impõe ao seu uso uma restrição: para resolver um problema é necessário que o conjunto de soluções viáveis para este possa ser de alguma forma codificado em uma população de indivíduos.
- Generalidade: Os AG simulam a natureza em um de seus mais fortes atributos: a adaptabilidade. Visto que a representação e a avaliação das possíveis soluções são as únicas partes (de um considerável conjunto de operações utilizadas em seu funcionamento) que obrigatoriamente requisitam conhecimento dependente do domínio

do problema abordado, basta a alteração destas para portá-los para outros casos. A preocupação de um programador de AG não é então de que forma chegar a uma solução, mas sim com o que ela deveria se parecer.

- Paralelismo explícito: O alto grau de paralelismo intrínseco aos AG pode ser facilmente verificado se considerarmos o fato de que cada indivíduo da população existe como um ente isolado e é avaliado de forma independente. Se na natureza todo processo de seleção ocorre de forma concorrente, nos AG essa característica se repete.
- Busca estocástica: Ao contrário de outros métodos de busca de valores ótimos, os algoritmos genéticos não apresentam um comportamento determinístico [1115]. Não seria correto, no entanto, afirmar que tal busca se dá de forma completamente aleatória — as probabilidades de aplicação dos operadores genéticos fazem com que estes operem de forma previsível estatisticamente, apesar de não permitirem que se determine com exatidão absoluta o comportamento do sistema.
- Busca cega: De acordo com [16], um algoritmo genético tradicional opera ignorando o significado das estruturas que manipula e qual a melhor maneira de trabalhar sobre estas. Tal característica lhe confere o atributo de não se valer de conhecimento específico ao domínio do problema, o que lhe traz generalidade por um lado, mas uma tendência a uma menor eficiência por outro.
- Eficiência mediana: Por constituir um método de busca cega, um algoritmo genético tradicional tende a apresentar um desempenho menos adequado que alguns tipos de busca heurística orientadas ao problema. Para resolver tal desvantagem, a tática mais utilizada é a hibridização [16], onde heurísticas provenientes de outras técnicas são incorporadas.
- Paralelismo implícito: A partir do teorema dos esquemas de Holland, tem-se que ao fazer uma busca por populações, a evolução de um algoritmo genético tende a favorecer indivíduos que compartilhem determinadas características, sendo assim capaz de avaliar

implicitamente determinadas combinações ou esquemas como mais ou menos desejáveis, efetuando o que chamamos uma busca por hiperplanos, de natureza paralela [17].

- Facilidade no uso de restrições: Ao contrário de muitos outros métodos de busca, os AG facilitam a codificação de problemas com diversos tipos de restrição, mesmo que elas apresentem graus diferentes de importância [18]. Neste caso, se dois indivíduos violam restrições, é considerado mais apto aquele que viola as mais flexíveis (*soft constraints*) em detrimento do que viola as mais graves (*hard constraints*).

Apêndice C
Artigo 1

No anexo desta dissertação é apresentado o artigo referente ao trabalho desenvolvido. O artigo foi apresentado na 23ra Conferência e Exposição Internacional em Sistemas de Distribuição (CIRED 2015 – Lyon, França).

ENERGY LOSS MINIMIZATION BY LOAD ALLOCATION ON DISTRIBUTION SYSTEMS

Victor Armaulía
PUC RJ - BRASIL
vdas86@hotmail.com

Delberis Lima
PUC RJ - BRASIL
delberis@ele.puc-rio.br

ABSTRACT

In this paper, a new load model is proposed for electric power distribution systems under varying voltage conditions in order to estimate the energy losses and, consequently, optimize the energy losses in the system. The proposed methodology is based on the adjustment of the polynomial ZIP load parameters related to active and reactive power as a function of the static voltage variations measured at the substation. The ZIP parameters are determined using the Genetic Algorithm in order to minimize the error between the measured and estimated active and reactive power at the substation. The estimation of the energy losses during a period of analysis is determined by the computation of the power flow using the ZIP model of each load in the system and the substation voltages measured. The procedure requires information of the feeder topology, distribution lines, rated power of the transformers, and a database containing voltage and power measurements at the substation during the period of analysis. If additional information from meters installed along the feeder is available, the proposed approach can use this information to improve the estimation. Finally, with the model allocated for each load, a tap change at the substation can be used to minimize the energy losses. To illustrate the approach, a real Brazilian feeder was used. Results are compared with a database generated in order to test the effectiveness of the methodology with ideal losses on the system.

NOMENCLATURE

Measurements

$P_1^{SE}(t)$ Active power at the substation at the time t.
$Q_1^{SE}(t)$ Reactive power at the substation at the time t.
$V_1^{SE}(t)$ Voltage at the substation at the time t.
$P_i^{msr}(t)$ Active power at the node i at the time t.
$Q_i^{msr}(t)$ Reactive power at the node i at the time t.
$V_i^{msr}(t)$ Voltage at the node i at the time t.
V_1^{ref} Reference voltage at the substation (nominal voltage of the system).

Parameters

x_i Fraction of the active power at the substation allocated to the load i.
y_i Fraction of the reactive power at the substation allocated to the load i.
$\alpha_p,\beta_p,\gamma_p$ Vector of load ZIP parameters for the active power. Each element of the vector is related to each load of the system.
$\alpha_q,\beta_q,\gamma_q$ Vector of load ZIP parameters for the reactive power. Each element of the vector is related to each load of the system.
u_i Parameter of correlation between the voltage substation and voltage at bus i.

Variables

$P_i(t)$ Active power allocated to the load i in each time interval t.
$Q_i(t)$ Reactive power allocated to the load i in each time interval t.
$L_P(t)$ Active power loss of the system in each time interval t.
$L_Q(t)$ Reactive power loss of the system in each time interval t.

Sets

Ω_L	Set of loads at the system.
Ω_{NM}	Set of nodes without meters.
Ω_M	Set of nodes with meters.

I. INTRODUCTION

Modern power system is an integrated complex system and due to its scale and complexity, the power system operation and control heavily rely on numerical simulations based on power system models including load models [1]. It is a consensus that load model plays an important role in power system analysis. The model validity directly affects simulations results accuracy [2]. Naturally, the model validity of various components in the power system directly affects the security and the economy of power system operations. Many efforts have been dedicated to explore model structures and parameters identification techniques because of the difficult task to model the power system loads.

Load model structures can be classified into two major categories: the physical models and the non-physical models. The physical models have clear physical inference to the model. The widely applied load model combining the constant impedance, the constant current and the constant power, denoted often as ZIP model is a typical physical one. The non-physical load models include the exponential load model, the difference equations, and the neuro-net model, etc. Mathematically, the physical and non-physical models are equivalent in the matter of input and output data; however, due to the clear physical inferences of the ZIP model, it has gained more popularity [3].

In electrical distribution systems, one of the greatest challenges for utilities is the estimation of the technical energy losses on the feeders. Specifically in Brazil, the correct evaluation of the energy losses provides valuable information for the regulator to establish the energy distribution tariffs.

There are different ways for estimating energy losses, but due to the difficulty of modelling precisely the equipment of the system, as well as the energy consumed by each load, the energy losses estimation can lead to huge errors. In addition, the difficulty to split technical energy losses and non-technical energy losses, which is usually caused by metering errors, unmetered company or customer use and billing cycle errors [4], aggravates the problem.

In this paper a new methodology based on a statistical model and a Top-Down approach for energy loss estimation is presented. To be more specific, the methodology attempts to estimate technical energy losses along a period by allocating parameters of the load model applied, taking into account the measurements of voltages and power at the substation and, when available, the measurements of voltages and power demanded by loads with meters installed at the transformers. The main contribution of the proposed method is the application of a statistical model for energy losses estimation using network information and the correlation between the power consumed and the voltage, which is usually neglected for other methods. After that, the model can be used to minimize energy losses changing the tap of the transformer at the substation.

To describe the proposed method in detail and its features, this paper is organized as follows: Section II describes the proposed load model; Section III describes the proposed methodology for energy loss estimation; Section IV presents a case of study using a real feeder from Brazil, and Section V presents the conclusions of this work.

II. PROPOSED LOAD MODEL

The polynomial or ZIP load model represents the variation (with voltage) of a load as a composition of constant impedance, constant current and constant power type of load [6] as shown in (1) and (2) for the active and reactive power demanded by each load i:

$$P_i\,(t)=P_i^{ref}(t)\left\{\alpha_{p_i}\left(\frac{V_i(t)}{V_i^{ref}}\right)^2+\beta_{p_i}\left(\frac{V_i(t)}{V_i^{ref}}\right)+\gamma_{p_i}\right\},\ \forall i\in\Omega_L \quad (1)$$

$$Q_i\,(t)=Q_i^{ref}(t)\left\{\alpha_{Q_i}\left(\frac{V_i(t)}{V_i^{ref}}\right)^2+\beta_{Q_i}\left(\frac{V_i(t)}{V_i^{ref}}\right)+\gamma_{Q_i}\right\},\ \forall i\in\Omega_L \quad (2)$$

Considering that the power supplied by the substation is distributed to every load on the feeder, the power reference of the ZIP model for each load may be expressed as a percentage of the power at the substation. In addition, considering that the voltages at the nodes may not be available, they are substituted by an approach given by a percentage of the voltage at the substation. With the previous considerations applied to (1) and (2), the proposed models are shown as follows:

$$P_i\,(t)=x_iP_1^{SE}\,(t)\left\{\alpha_{p_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)^2+\beta_{p_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)+\gamma_{p_i}\right\} \quad (3)$$
$$\forall i\in\Omega_L$$

$$Q_i\,(t)=y_iQ_1^{SE}\,(t)\left\{\alpha_{Q_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)^2+\beta_{Q_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)+\gamma_{Q_i}\right\} \quad (4)$$
$$\forall i\in\Omega_L$$

The expressions (3) and (4) will be used in the methodology for the estimation of losses.

III. PROPOSED METHODOLOGY

The application of the proposed methodology requires information about the feeder: topology, line impedance, nominal power of the transformers, a database containing voltages and power measured at the substation and, if it is available, scenarios of voltage and power measured at nodes along the feeder.

The database must be organized according to time intervals *"w"* during a day or scenario *"s"*, so each value of voltage and power measured would be identified by a unique coordinate pair *"(s,w)"*. In order to improve the model, the data can be organized by clusters, according to its level of load (light, medium and peak). The clusters are desired for the statistical models because it uses the similarities of the load pattern scenarios.

The proposed methodology uses an optimization model to adjust the parameters of the load model, minimizing, in an iterative process, the square difference between power measured at the substation and the power allocated for each load plus the power losses for each time interval of the period. The convergence is achieved when no significant change is observed between the power losses calculated in the current and in the previous interaction for each time interval. As a result, the energy losses are a by-product of the proposed method for the corresponding period. Fig. 1 shows the flowchart of the proposed methodology:

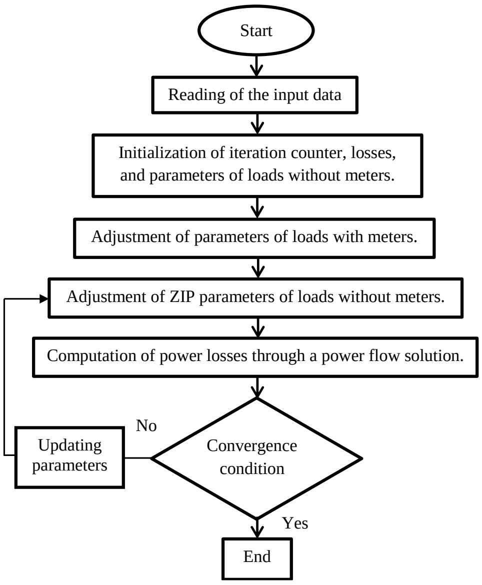


Figure 1. Flowchart of the methodology proposed for the estimation of power losses.

Each stage of the process is explained as follows:

A. Initialization of parameters

Consider an iteration counter *"k"* set to zero. The active and reactive power losses at iteration *"k"* must be set to zero for each time interval of the period of analysis, and the parameter *"u"* for the loads without meters must be set to one.

B. Initialization of parameters

Before the adjustment process, some constraints for the load parameters, with or without meters, are described:

1) Constraints for "x" and "y": For each load, these parameters must be bound considering the relationship between the nominal power of the loads and the power at the substation at nominal conditions.

2) Constraints for the ZIP parameters: For each load, the sum of the parameters *"α"*, *"β"* and *"γ"* equals to one for the active and reactive component.

Before the adjustment of the parameters in the proposed model, an estimation of "u" for loads with meter installed take place. This adjustment is done by using the Least Square method, in which "u" is calculated based on the relation between the voltage measured at load "i" and the voltage at the substation as shown in the expression (5).

$$\min_{u} \left\{ \frac{1}{n_s \cdot n_{CL}} \cdot \sum_{s=1}^{n_s} \sum_{w=1}^{n_{CL}} \left[\frac{V_i^{msr}(s,w) - u_i \cdot V_1(s,w)}{V_i^{msr}(s,w)} \right]^2 \right\} \quad (5)$$

Where "n_s" is the number of scenarios considered in the analysis, and "n_{CL}" is the number of time intervals from the period or cluster in analysis.

In addition, the parameters of the loads with meters must be adjusted by using the Least Square method to minimize the error between the power measured of the loads with meters and the their allocated power given by the modified load model as shown in the expression (6).

$$\min_{\substack{x,\alpha_P,\beta_P,\gamma_P,\\ y,\alpha_Q,\beta_Q,\gamma_Q}} \left\{ \frac{1}{n_s \cdot n_{CL}} \sum_{s=1}^{n_s} \sum_{w=1}^{n_{CL}} \left(\left[\frac{P_j^{msr}(s,w) - P_j(s,w)}{P_j^{msr}(s,w)} \right]^2 + \left[\frac{Q_j^{msr}(s,w) - Q_j(s,w)}{Q_j^{msr}(s,w)} \right]^2 \right) \right\} \quad (6)$$

C. Adjustment of the loads parameters without meters

The Least Squares method is applied to minimize the error between the power measured at the substation and the sum of power of the loads with and without meters installed, and the power losses in the current iteration "k" for each time interval as shown in the expression (7) and (8) for the active and reactive components.

$$\min_{x,\alpha_P,\beta_P,\gamma_P} \left\{ \frac{1}{n_s \cdot n_{CL}} \sum_{s=1}^{n_s} \sum_{w=1}^{n_{CL}} \left[\frac{P_1^{SE}(s,w) - P_1^{cal}(s,w)}{P_1^{SE}(s,w)} \right]^2 \right\} \quad (7)$$

$$\min_{y,\alpha_Q,\beta_Q,\gamma_Q} \left\{ \frac{1}{n_s \cdot n_{CL}} \sum_{s=1}^{n_s} \sum_{w=1}^{n_{CL}} \left[\frac{Q_1^{SE}(s,w) - Q_1^{cal}(s,w)}{Q_1^{SE}(s,w)} \right]^2 \right\} \quad (8)$$

$$P_1^{cal}(s,w) = \sum_{i \in \Omega_{NM}} P_i\ (s,w) + \sum_{j \in \Omega_M} P_j\ (s,w) + L_{P(k)}(s,w)$$

$$Q_1^{cal}(s,w) = \sum_{i \in \Omega_{NM}} Q_i\ (s,w) + \sum_{j \in \Omega_M} Q_j\ (s,w) + L_{Q(k)}(s,w)$$

D. Computation of power losses

The iteration counter increases ($k=k+1$) and the power losses are calculated using the power allocated to the loads in step C and the voltage at the substation.

E. Verification of the convergence condition

If no significant difference is observed between the power losses calculated in the current iteration compared to the power losses calculated in the previous iteration, the convergence was reached. Otherwise, the process continues.

F. Updating the parameters "u"

The parameter *"u"* of each load without meter must be updated to the average of the set of relation values between the computed voltages of the load and the voltages at the substation for the corresponding time intervals as shown in the expression (9).

$$u_i = \frac{1}{n_s \cdot n_{CL}} \cdot \sum_{s=1}^{n_s} \sum_{w=1}^{n_{CL}} \frac{V_i^{cal}(s,w)}{V_1(s,w)} \qquad (9)$$

Where V_i^{cal} is the voltage computed at node "i".

Finally, the iterative process continues to step C using the updated parameters and power losses computed in step D.

IV. CASE STUDY

To evaluate the performance of the proposed methodology, a real feeder from a utility company of State of Sao Paulo, Brazil, was used. The nominal voltage of this system is 13.8kV and the nominal power is 4500kVA. The information of the feeder can be found in [5]. Fig. 2 shows the 23 nodes feeder with a substation at the first node and loads at the remaining nodes.

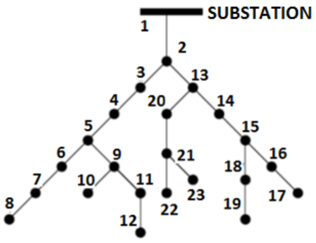


Figure 2. 23 nodes feeder of the case study.

For this case study, a database was generated by the power flow computation for 50 days (scenarios) with a 15-minute time interval and considering different types of load models for each load on the feeder. The load factor profile during a day was assumed according to a database with typical load factors values given in [6]. To highlight the features of the proposed method, three different profiles of voltage at the substation have been used. The first profile, type *A*, is similar to the load profile, with a maximum variation of ±2.5% around the nominal voltage. The second profile, type *B*, is a constant value equals to the nominal voltage. Finally, the third profile, type *C*, is a normally distributed profile per day with ±2.5% around the nominal voltage. The types of profiles are shown in Fig. 3 for the first scenario.

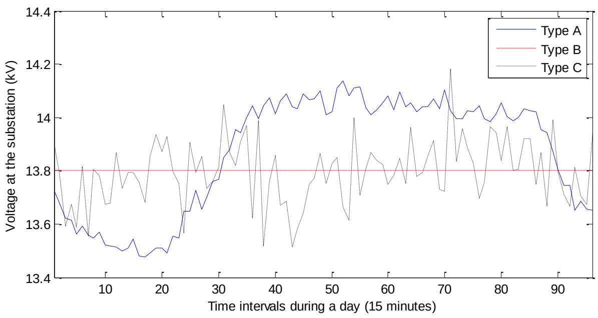


Figure 3. Types of voltage profiles for the case study.

With all information available, this section is divided in two parts:

A. Estimation of losses

The ideal or real power losses can be calculated in the period of analysis. Fig. 4 shows the 5, 50 and 95% quantiles of the daily apparent power and voltages at the substation along the 50 days.

In order to improve the approach by working with data more similar, the database was clustered into three groups based on the apparent power at the substation according to the period of the day. Note that for each cluster, every load on the feeder has one load model for active and reactive power. Using the clusters, six tests were performed to estimate the energy losses. The first three tests consider that the input data only has values of voltage and power at the substation. The second three tests consider meters at nodes 2 and 18.

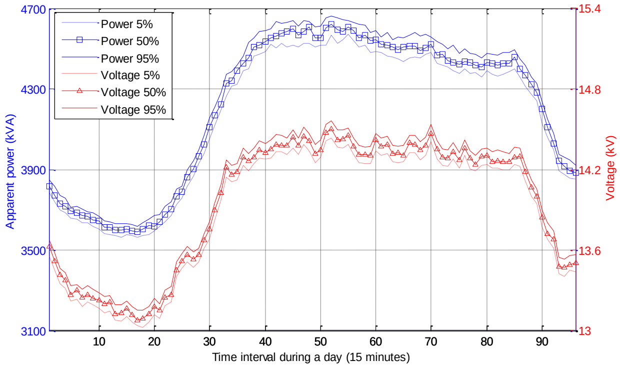


Figure 4. Quantiles for the apparent power and voltage at the substation.

The results obtained with the proposed methodology are compared with the actual values for each type of profile. The Table I shows the results considering no meters on the nodes with loads and the Table II shows the Absolute Percentage Errors of the estimations for the different tests performed previously.

TABLE I. ESTIMATION OF ENERGY LOSSES FOR THE SYSTEM WITHOUT METERS

Energy losses during 50 days (MWh)					
Type A (Test 1)		***Type B (Test 2)***		***Type C (Test 3)***	
Actual	***Estimated***	***Actual***	***Estimated***	***Actual***	***Estimated***
95.96	93.64	96.25	93.44	96.25	90.28

TABLE II. ABSOLUTE PERCENTAGE ERROR

Absolute percentage errors (%)		
Type A	***Type B***	***Type C***
2.41	2.91	6.20

The Table III shows the results considering meters on the nodes with loads 2 and 18, and the Table IV shows the Absolute Percentage Errors of the estimations for the different tests performed previously.

TABLE III. ESTIMATION OF ENERGY LOSSES FOR THE SYSTEM WITH METERS

Energy losses during 50 days (MWh)					
Type A (Test 4)		***Type B (Test 5)***		***Type C (Test 6)***	
Actual	***Estimated***	***Actual***	***Estimated***	***Actual***	***Estimated***
95.96	96.35	96.25	96.81	96.25	98.19

TABLE IV. ABSOLUTE PERCENTAGE ERROR

Absolute percentage errors (%)		
Type A	*Type B*	*Type C*
0.40	0.58	2.01

B. Energy loss minimization

Beside of the estimation of losses in the period of analysis, with the load models is possible to predict the best way to vary the voltage at the substation for a predicted scenario or day (load forecast) in order to minimize the energy losses during that scenario. For this case study, using the database of the 50 days is applied the Neural Networks tool [7] to generate a load forecast at the substation for the next day (scenario 51). Fig. 5 shows the active and reactive power predicted for the scenario 51.

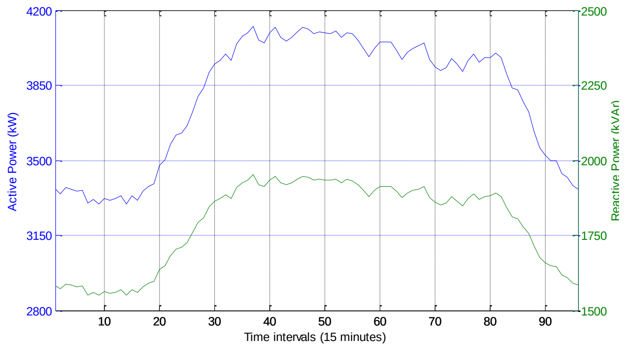


Figure 5. Active and reactive power at the substation for the predicted scenario.

The voltages at the substation must be selected considering the voltage at every node must be within a specified range, in this case the range is ±2.5% around the nominal voltage of the system. Using some values of voltage at the substation and the predicted active and reactive power at the substation, the loads are allocated using the load models obtained in the Test 1 (no meters at the system and voltage profile type *A*). Through a power flow method, the power losses are computed and the set of voltages are selected in order to minimize the losses during the predicted scenario. Fig. 6 shows the profile of the voltages the substation must have along the predicted scenario in order to minimize the losses in the system.

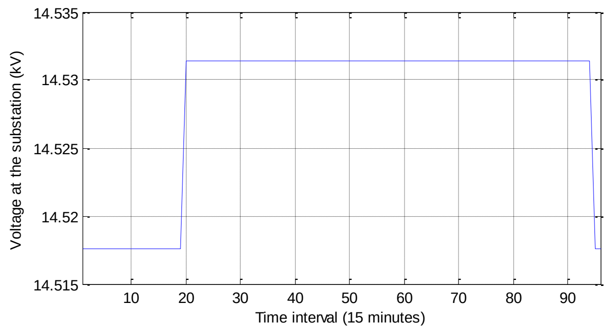


Figure 6. Voltage at the substation for minimum losses in the system for the predicted scenario.

As seen in the Fig. 6, for this particular case study, the voltage at the substation during the predicted scenario must be slightly higher than the nominal voltage of the system to minimize the power losses.

In order to highlight the benefits of this energy losses optimization, Table V shows the comparison between the energy losses obtained with the optimization performed and the energy losses for nominal conditions (constant voltage of 13.8kV at the substation) along the scenario 51.

TABLE V. ENERGY LOSSES COMPARISON

Optimized	*Not optimized*
1708.6kWh	1904.4kWh

V. CONCLUSIONS

This paper presented a model to estimate energy losses by a load allocation method. The results confirmed the efficiency of the model. As a result, the model can be used to optimize the operation of the system by changing the tap of the transformer at the substation. For this case, the results indicated that is possible to reduce the energy losses for 10.2% comparing the optimization of the voltage and no optimization of the voltage.

REFERENCES

[1] Kosterev D. N., Taylor C. W., Mittelstadt W. A., “Model validation for the August 10, 1996 WSCC system outage”, IEEE Transactions on Power Systems, vol. 14, NO. 3, pp. 967-979, August 1999.

[2] Jia Hou, Zhao Xu, Zhao Yang Dong, “Measurement-based load modeling at distribution level with complete model structure”, in *Proc. Power and Energy Society General Meeting, 2012 IEEE*, pp. 1-6.

[3] Jin Ma, Dong Han, He Ren-mu, Zhao-yang Dong, Hill D.J., “Measurement-based Load Modeling using Genetic Algorithms”, in *Proc. 2007 Evolutionary Computation, 2007. IEEE CEC 2007*, pp. 2909-2916.

[4] G. Grigoras, F. Scharlatache, “Energy Losses Estimation in Electrical Distribution Networks with Decision Trees-based Algorithm”, in *Proc. 2013 The 8th International Symposium on advanced topics in Electrical Engineering Conf.*, pp. 1-4.

[5] G. Sergio, "Cálculo de fluxo de carga em sistemas de transmissão com alimentadores primários de distribuição", MSc. dissertation, Dept. Electric. Eng., Univ. Estadual de Campinas, Brazil, 2005.

[6] C. Grigg, “The IEEE reliability test system: 1996”, IEEE Transactions on power delivery, vol. 14, NO. 3, pp. 1010-1020, August 1999.

[7] M. H. Beale, M. T. Hagan, H. B. Demuth. (2014). *Neural Network Toolbox: User’s guide*. [Online]. Available: https://www.mathworks.com

Apêndice D
Artigo 2

No anexo desta dissertação é apresentado o artigo referente ao trabalho desenvolvido. O artigo foi apresentado na Conferência PowerTech Eindhoven 2015 – Eindhoven, Holanda.

Statistical Top-Down Approach for Energy Loss Estimation in Distribution Systems

V. Armaulia Sanchez
Delberis A. Lima
DEE
PUC-RJ
Rio de Janeiro, Brazil
delberis@ele.puc-rio.br

Luis F. Ochoa
School of Electrical and Electronic Engineering
The University of Manchester
Manchester, UK
luis_ochoa@ieee.org

M. E. Oliveira
Dept. of Academic Areas
Federal Institute of Goias – Campus Itumbiara
Goias, Brazil
marcelo.oliveira@ifg.edu.br

***Abstract*— This work proposes a statistical top-down methodology for energy loss estimation in medium voltage (MV) distribution systems. A statistical model is used to adjust the load parameters (i.e., ZIP coefficients) of the aggregated load allocated to each secondary transformer along the MV feeder. This adjustment process also results in the estimation of the corresponding energy losses. The information required by the proposed methodology is limited to the feeder topology, conductors, rated capacity of the transformers, and the voltage and power measurements at the primary substation during the period of analysis. If available, additional information from meters installed along the feeder can be used to improve the estimation. To illustrate the approach, a real Brazilian 13.8kV feeder is used. The results, compared with other methodologies available in the literature, demonstrate the benefits of the proposed methodology.**

***Index Terms*—Energy losses, load allocation, distribution system, ZIP coefficients.**

NOMENCLATURE

Measurements

$P_1^{SE}(t)$ Active power at the substation at the time t.

$Q_1^{SE}(t)$ Reactive power at the substation at the time t.

$V_1^{SE}(t)$ Voltage at the substation at the time t.

$P_j^{msr}(t)$ Active power consumed by the load j with meter.

$Q_j^{msr}(t)$ Reactive power consumed by the load j with meter.

$V_j^{msr}(t)$ Voltage at the bus j with meter.

$P_1^{SE\,(nom)}$ Active power at the substation for nominal conditions on the system.

$Q_1^{SE\,(nom)}$ Reactive power at the substation for nominal conditions on the system.

V_1^{ref} Reference voltage at the substation (nominal voltage of the system).

P_i^{nom} Rated active power of the load i.

Q_i^{nom} Rated reactive power of the load i

Parameters

x_i Fraction of the active power at the substation allocated to the load i.

y_i Fraction of the reactive power at the substation allocated to the load i.

$\boldsymbol{\alpha_P},\boldsymbol{\beta_P},\boldsymbol{\gamma_P}$ Vector of load parameters for the active power. Each element of the vector is related to each load of the system.

$\boldsymbol{\alpha_Q},\boldsymbol{\beta_Q},\boldsymbol{\gamma_Q}$ Vector of load parameters for the reactive power. Each element of the vector is related to each load of the system.

u_i Parameter of correlation between the voltage substation and voltage at bus i.

Variables

$P_i(t)$ Active power allocated to the load i in each time interval t.

$Q_i(t)$ Reactive power allocated to the load i in each time interval t.

$L_P^k(t)$ Active power loss of the system at iteration k in each time interval t.

$L_Q^k(t)$ Reactive power loss of the system at iteration k in each time interval t.

Sets

Ω_{L} Set of loads at the system.

Ω_{M} Set of loads with meters.

Ω_{NM} Set of loads without meters.

Ω_{T} Set of T time intervals of the period of analysis.

I. INTRODUCTION

In electrical distribution systems, one of the greatest challenges for utilities is the estimation of the technical energy losses on the feeders. In [1] the authors estimate that the energy losses throughout the world's electric distribution networks vary from country to country between 3.7% and 5.7% of the electricity use, which implies that there is a large potential for improvement. Specifically in Brazil, the correct evaluation of the energy losses provides valuable information for the regulator to establish the energy distribution tariffs.

There are different ways for estimating energy losses, but due to the difficulty for modeling precisely the equipment of the system, as well as the energy consumed of each load, the energy losses estimation can lead to huge errors. In addition, the difficulty to split technical energy losses and non-technical energy losses, which is usually caused by metering errors, unmetered company or customer use and billing cycle errors [2], aggravates the problem.

In the literature, several works can be found that face this issue. In [3], the average demand is used for estimating the energy losses. Artificial intelligence techniques, like fuzzy logic [4] and decision trees based algorithms 0 are also applied to solve the problem. In Brazil, the methodology established for the energy losses estimation on medium voltage for utilities is based on the average power loss during a period, computed by a multiple linear regression model provided by the National Agency of Electric Energy (ANEEL in Portuguese) [5]. None of those methods considers the voltage effect to estimate the energy losses, which can vary at the substation and along the feeder and, therefore, influence the energy losses estimation.

In this paper, it is proposed a new methodology based on a statistical model and a Top-Down approach for energy loss estimation. Hereinafter the proposed method is called Statistic Top-Down Approach (STDA). To be more specific, the methodology attempts to estimate technical energy losses along a period by allocating parameters of the load model applied, taking into account the measurements of voltages and power at the substation and, when available, the measurements of voltages and power demanded by loads with meters installed at the transformers. The main contribution of the proposed method is the application of a statistical model for energy losses estimation using network information and the correlation between the power consumed and the voltage, which is usually neglected by other methods.

To describe the proposed methodology in detail and its features, this paper is organized as follows: Section II describes the proposed methodology for energy loss estimation; Section III presents a case of study using a real feeder from Brazil. Additionally, in this section, a comparison with other methods takes place; finally, section IV presents the conclusions of the work.

II. PROPOSED METHODOLOGY

The application of the proposed methodology requires information about the feeder: topology, line impedances, nominal power of the transformers, a database containing voltages and power measured at the substation and, when it is available, the voltage and power measured at the transformers along the feeder. In order to improve the model, the data can be organized by clusters, according to its level of load. The clusters are desired for the statistical models because it uses the similarities of the load pattern during the period of time considered.

To estimate the energy losses, firstly, the load parameters should be adjusted to allocate loads properly. Then, in order to apply the proposed methodology, a modified ZIP model is established. Considering that the power supplied by the substation is distributed to every load on the feeder plus the power losses, the power reference of the modified ZIP model for each load may be expressed as a percentage of the power at the substation. In addition, since the voltages at the nodes are not available, in this proposed model, they are substituted by a percentage of the voltage at the substation. Thus, the modified ZIP model can be written for each load i, for active and reactive power, as follows:

$$P_i\ (t) = x_i P_1^{SE}\ (t) \left\{ \alpha_{p_i} \left(u_i \cdot \frac{V_1^{SE}(t)}{V_1^{ref}} \right)^2 + \beta_{p_i} \left(u_i \cdot \frac{V_1^{SE}(t)}{V_1^{ref}} \right) + \gamma_{p_i} \right\} \quad (1)$$

$$Q_i\ (t) = y_i Q_1^{SE}\ (t) \left\{ \alpha_{Q_i} \left(u_i \cdot \frac{V_1^{SE}(t)}{V_1^{ref}} \right)^2 + \beta_{Q_i} \left(u_i \cdot \frac{V_1^{SE}(t)}{V_1^{ref}} \right) + \gamma_{Q_i} \right\} \quad (2)$$

The proposed methodology uses an optimization model to adjust the parameters of the load model, minimizing, in an iterative process, the square difference between power measured at the substation and the sum of the power allocated for each load plus the power losses during the period of analysis. The convergence is achieved when no significant change is observed in the power losses computed in each iteration for each time interval. As a result, the energy losses are a by-product of the proposed method for the corresponding period. Fig. 1 shows the flowchart of the proposed methodology.

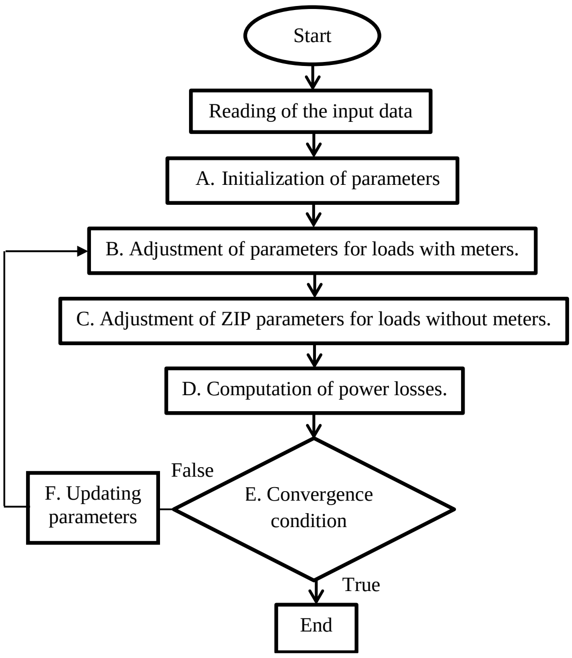


Figure1. Flowchart of the methodology proposed for the estimation of power losses.

Each stage of the process is explained as follows.

. Initialization of parameters

Consider an iteration counter k set to zero. The active ıd reactive power losses at iteration k must be set to zero ır each time interval of the period of analysis. The ırameter u_i must be set to one for each load i without meter stalled.

. Adjustment of parameters of the loads with meters

Before the adjustment process, some constraints for the ad parameters, with or without meters, must be described:

1) Constraints for $\boldsymbol{x}$ *and* $\boldsymbol{y}$*:* The parameters x_i and y_i are ;ed to allocate the active and reactive power at the substation to each load i. In order to reduce the search space, the x_i and y_i are bounded around the relation between the power of the load and the power at the substation, both in nominal conditions as shown in (3) and (4).

$$LB_i\cdot\frac{P_i^{nom}}{P_1^{SE\,(nom)}} \le x_i \le UB_i\cdot\frac{P_i^{nom}}{P_1^{SE\,(nom)}},\ \forall i\in\Omega_L \qquad (3)$$

$$LB_i\cdot\frac{Q_i^{nom}}{Q_1^{SE\,(nom)}} \le y_i \le UB_i\cdot\frac{Q_i^{nom}}{Q_1^{SE\,(nom)}},\ \forall i\in\Omega_L \qquad (4)$$

The LB_i and UB_i are boundary factors to define the lower and upper bound of the search space x_i and y_i.

2) Constraints for the ZIP parameters: As usually done for traditional ZIP model, for each load i the sum of the parameters α_i , β_i and γ_i is equal to one for the active and reactive component.

Before the parameters adjustment in the proposed methodology, an estimation of u_j in for each load j with meter installed should take place. This adjustment is done by using the Least Square method, in which u_j is calculated by the relation between the voltage measured at load j and the voltage at the substation, as shown in (5):

$$\min_{\boldsymbol{u}}\left\{\sum_{t\in\Omega_T}\left[\frac{V_j^{msr}(t)-u_j\cdot V_1^{SE}(t)}{V_j^{msr}(t)}\right]^2\right\},\ \forall j\in\Omega_M \qquad (5)$$

In addition, the parameters of the loads with meters are adjusted using the Least Square method to minimize the error between the power measured of the loads with meters and their allocated power computed by the proposed model as follows:

$$\min_{\substack{x,\alpha_P,\beta_P,\gamma_P,\\ y,\alpha_Q,\beta_Q,\gamma_Q}}\left\{\sum_{t\in\Omega_T}\left(\left[\frac{P_j^{msr}(t)-P_j(t)}{P_j^{msr}(t)}\right]^2+\left[\frac{Q_j^{msr}(t)-Q_j(t)}{Q_j^{msr}(t)}\right]^2\right)\right\},\forall j\in\Omega_M \qquad (6)$$

C. Adjustment of the loads parameters without meters

The Least Squares method is applied to minimize the error between the power measured at the substation and the sum of power in each load and the power losses calculated in the previous iteration for all time intervals of the period of analysis. Then, for $k = k + 1$:

$$\min_{x,\alpha_P,\beta_P,\gamma_P}\left\{\sum_{t\in\Omega_T}\left[\frac{P_1^{SE}(t)-\sum_{i\in\Omega_M}P_i(t)-\sum_{j\in\Omega_{NM}}P_j(t)-L_P^{k-1}(t)}{P_1^{SE}(t)}\right]^2\right\} \qquad (7)$$

$$\min_{y,\alpha_Q,\beta_Q,\gamma_Q}\left\{\sum_{t\in\Omega_T}\left[\frac{Q_1^{SE}(t)-\sum_{i\in\Omega_M}Q_i(t)-\sum_{j\in\Omega_{NM}}Q_j(t)-L_Q^{k-1}(t)}{Q_1^{SE}(t)}\right]^2\right\} \qquad (8)$$

D. Computation of power losses

After the steps presented, the power losses are recalculated through a power flow method using the power allocated to the loads in step C and the measurements of the voltage at the substation.

E. Verification of the convergence condition

In this step, the absolute comparison between the power losses computed in the current iteration and the previous interaction is verified according to the following expressions:

$$\left|L_P^k(t)-L_P^{k-1}(t)\right|<Tolerance,\ \forall t\in\Omega_T \qquad (9)$$

$$\left|L_Q^k(t)-L_Q^{k-1}(t)\right|<Tolerance,\ \forall t\in\Omega_T \qquad (10)$$

If the both conditions are satisfied, then the convergence is reached. Otherwise, the process must continue, readjusting the vectors $(\boldsymbol{x}, \boldsymbol{\alpha_P}, \boldsymbol{\beta_P}, \boldsymbol{\gamma_P}, \boldsymbol{y}, \boldsymbol{\alpha_Q}, \boldsymbol{\beta_Q}$ and $\boldsymbol{\gamma_Q})$ of parameters.

F. Updating the parameters u

In each iteration, the vector of parameters $\boldsymbol{u}$ for loads without meter must be updated. The criterion adopted to obtain a representative value was the average of the set of relation values between the computed voltages of the load and the voltages at the substation for the corresponding time intervals as shown in (11)

$$u_j = \frac{1}{T} \sum_{t \in \Omega_T} \frac{V_j^{cal}(t)}{V_1^{SE}(t)}, \forall j \in \Omega_{NM} \quad (11)$$

Where T represents the number of time intervals.

III. CASE STUDY

To evaluate the performance of the proposed methodology, a real feeder from a utility company of State of São Paulo-Brazil was used. The nominal voltage and power of this system are 13.8kV and 4500kVA. Fig. 2 shows the 23 nodes feeder with a substation at the first node and loads at the remaining nodes. The buses and lines data for this system are presented in Table I and Table II respectively. More information of the feeder can be found in [6].

For this case study, a database was generated by computing a power flow solution for 50 days with a 15-minute time interval and considering different types of load models for each distribution transformer (node) on the feeder. The load factor profile during a day was obtained according to [7]. To highlight the features of the proposed methodology, the voltage and power load profile at the substation are strongly correlated, with a maximum variation of 5% around the nominal voltage. Fig. 3 shows the 5, 50 and 95% quantiles of the daily apparent power and voltages at the substation along the 50 days. Additionally, the voltage of each load are between 0.975% and 1.025% of its nominal value. With all information, the theoretical energy losses can be calculated through a power flow solution. This value is used in this section to validate the proposed methodology and to compare the results with other representative methods estimation.

TABLE I. BUSES DATA

Buses	Active load (kW)	Reactive load (kVAr)
2	1229	505
3	80	39
4	36	17
5	671	325
6	176	85
7	64	31
8	266	129
9	72	35
10	108	52
11	124	60
12	28	14
13	52	25
14	308	149
15	16	8
16	32	16
17	56	27
18	68	33
19	72	35
20	28	13
21	72	35
22	36	17
23	36	17

TABLE II. LINES DATA

Initial node	Final node	Resistance (ohm)	Reactance (ohm)	Length (m)
1	2	0.1104	0.1415	300
2	3	1.1773	1.5094	3200
3	4	1.2141	1.5566	3300
4	5	0.3532	0.4528	960
5	6	0.1112	0.1018	200
6	7	0.3893	0.3562	700
7	8	0.8343	0.7634	1500
5	9	0.5224	0.6698	1420
9	10	0.4783	0.6132	1300
9	11	2.8358	1.4145	2700
11	12	2.7308	1.3621	2600
2	13	1.2604	0.6287	1200
13	14	4.5163	2.2528	4300
14	15	2.3107	1.1526	2200
15	16	3.3610	1.6765	3200
16	17	4.8314	2.4099	4600
15	18	12.4976	4.1793	7300
18	19	8.3888	2.8053	4900
13	20	0.4831	0.2410	460
20	21	6.0917	3.0386	3480
21	22	2.7308	1.3621	2600
21	23	2.9408	1.4669	2800

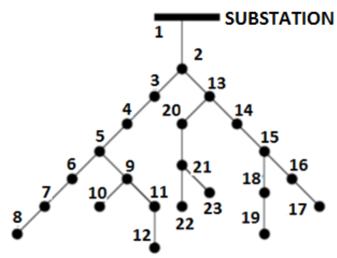


Figure 2. 23 nodes feeder of the case study.

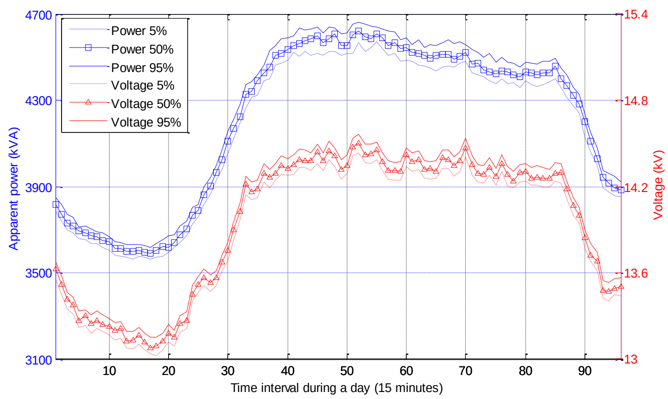


Figure 3. Quantiles for the apparent power and voltage at the substation.

In order to improve the approach of the estimations, the model was applied to three different level of loads during the day (light, medium and peak load), organized by clusters. Note that for each cluster, every load on the feeder has one load model for active and reactive power. Using the three clusters aforementioned, two tests were performed to estimate the energy losses using the Optimization Toolbox of MATLAB [8] to adjust the parameters. The first one considers that there is just one meter at the substation. Therefore, the input data only has values of voltage, active and reactive power at the substation. The second one considers meters at the substation and at the nodes 2 and 18, i.e., the input data contains also measurements of voltages and power consumed by loads connected at the nodes 2 and 18. These tests are called STDA 1 and STDA 2, respectively. In both, the following considerations were taken into account:

For the constraints (2) and (3), a lower and upper bound factor are 0.8 and 1.2 for every load in the system.
For the convergence conditions expressed in (8) and (9), it was used a tolerance of 0.45W and 0.45VAr for the active and reactive power, which represents 10^{-5}% of the peak load measured at the substation.

After applied the proposed methodology for the STDA 1 and STDA 2, the methodology performance is represented by the information in Table I. From this table, it can be seen that the number of iterations for convergence of each cluster is relatively small, however the computation time is longer because the number of power flow computation and the minimization processes of the methodology. The computation time is proportional to the size of the system and the amount of input data.

TABLE III. METHODOLOGY PERFORMANCE

	Iterations performed for each cluster	
	STDA 1	***STDA 2***
Light demand	8	11
Medium demand	10	12
Peak demand	12	8
Computation time (seconds)	490.80	386.45

The optimization result of the parameter *x* for each load ljusted for STDA 1 and STDA 2 is presented in Fig. 4 and .g. 5. In these figures, it is appreciable that the orresponding values of the loads in the buses 2, 5, 8 and 14 dicate that the loads connected to those nodes demand ore power from the system, which agrees with their ominal values presented in Table I. For the sake of space, e results are presented only for the active power omponent. However, it is important to highlight that a milar behavior can be observed for the vector of reactive ower ***y***.

The results of the parameter *u*, adjusted for STDA 1 and TDA 2, are shown in Fig. 6 and Fig. 7. As seen in the figures, the values are less than 1 because they are limited to the voltage at the substation and the lowest values (e.g. nodes 12 and 19) indicate the more distance nodes from the substation.

Fig. 8 and Fig. 9 show the results of the active load parameters adjusted for the light demand for STDA 1 and STDA 2. From these figures it is observed that more weight is given to the power constant type of load, represented by the gamma parameter. This happens because the search space of the power is larger than the search space of the voltage, which leads the algorithm to focus in this parameter in most nodes. A similar behavior was observed for medium and peak load tests.

After the parameters adjustment, the power losses, which are a by-product of the model, can be compared with to the real power losses from the database used. Table IV shows the mean absolute percentage error (MAPE) obtained of the active power losses in each test performed between the estimated model and the theoretical value.

Additionally, the results obtained with the proposed methodology are compared to those estimated using the New Top-Down (NTD) methodology [3] and the current methodology applied in Brazil and established by the ANNEL [5]. The NTD methodology estimates the energy losses by calculating a product of a loss factor (based on the power supplied by the substation), the power losses for maximum demand conditions through a power flow solution and the number of time intervals along the period of analysis. The ANNEL methodology estimates the energy losses by calculating the product of a loss coefficient (based on the power supplied by the substation), the average power loss computed by a multiple linear regression equation (established by the ANNEL) and the number of time intervals along the period of analysis.

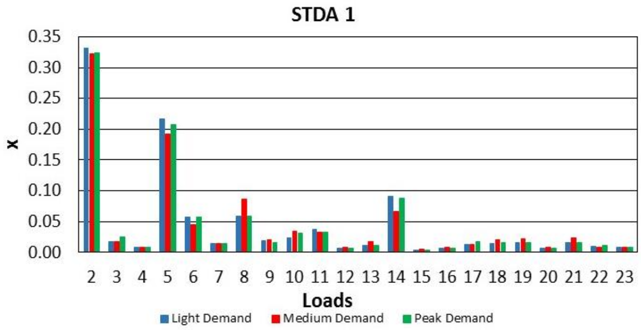


Figure 4. Results of the x parameter for the test STDA 1.

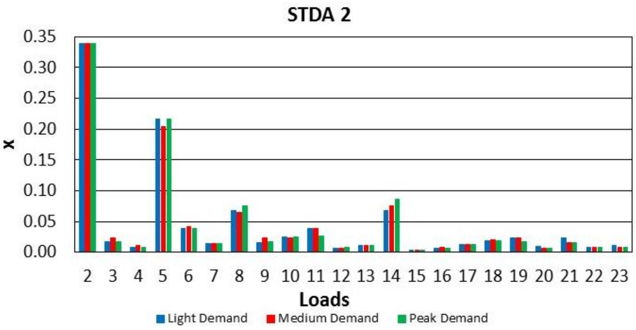


Figure 5. Results of the x parameter for the test STDA 2.

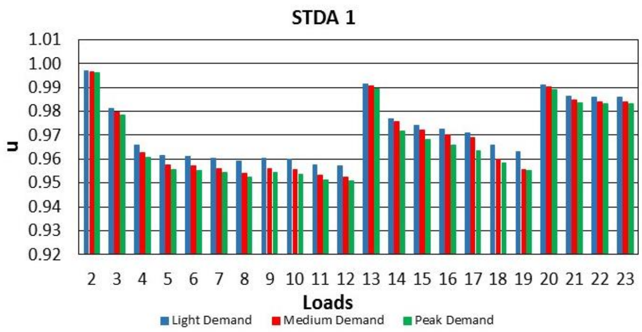


Figure 6. Results of the voltage correlation parameters for the test STDA 1.

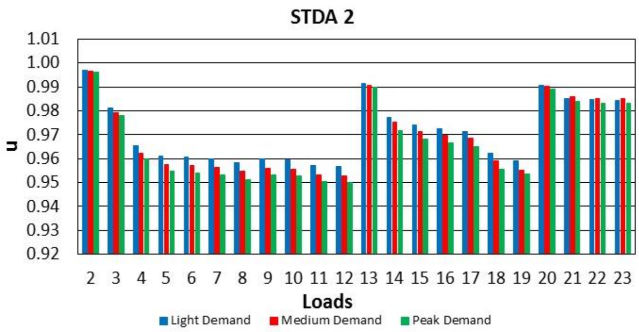


Figure 7. Results of the voltage correlation parameters for the test STDA 2.

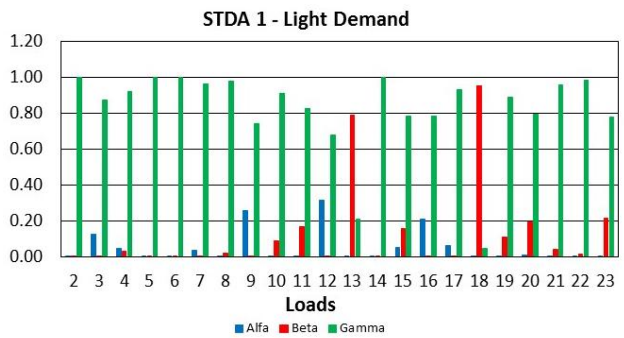
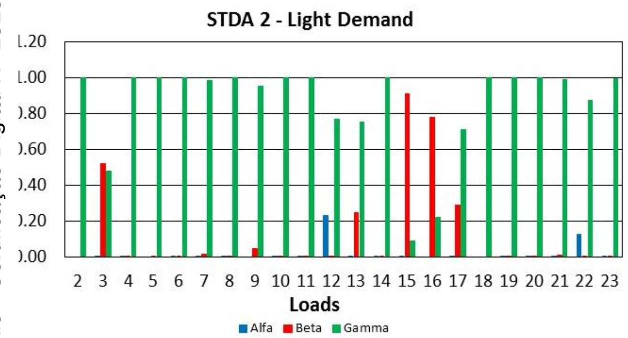


Figure 8. Results of the load parameters for the test STDA 1.



Figrue 9. Results of the load parameters for the test STDA 2.

TABLE IV. MAPE OF THE POWER LOSSES ESTIMATION

MAPE (%)	
STDA 1	***STDA 2***
5.08	1.31

TABLE V. ESTIMATION OF ENERGY LOSSES

Energy losses during 50 days (kWh)				
Real	***STDA 1***	***STDA 2***	***NTD***	***ANEEL***
95703	87494	98249	105126	142357

TABLE VI. PERCENTAGE OF ENERGY LOSS

Percentage of Energy loss on the system (%)				
Real	***STDA 1***	***STDA 2***	***NTD***	***ANEEL***
2.01	1.91	2.15	2.30	3.11

TABLE VII. ABSOLUTE PERCENTAGE ERROR

Absolute percentage errors (%)			
STDA 1	***STDA 2***	***NTD***	***ANEEL***
8.60	2.70	9.84	48.70

Table V shows the real energy losses of the system and the values estimated by the aforementioned methodologies. Table VI shows the percentage of the energy loss to the total distributed energy. Table VII shows the Absolute Percentage Error of the losses between the different methodologies analyzed and the theoretical value.

As it can be seen in Table VII, the best result was reached by applying the STDA method. The results indicated that the more information available from meters allocated in the network, the more accurate the results will be.

IV. CONCLUSIONS

In this paper, a new method, called Statistical Top-Down Approach (STDA), for energy loss estimation in distribution systems was presented. The novelty of the proposed method is the application of a model that considers the voltage drop of the system to estimate the power in each load, taking into account the power flow results to estimate the energy losses. The case study demonstrates that the proposed methodology estimates energy losses more accurately than other methodologies such as the New Top-Down (NTD) approach and the one produced by ANNEL (the Brazilian regulator). The results indicate that the proposed method is promising, particularly considering that the number of meters to be installed in medium voltage distribution networks is likely to rise in the next few years.

REFERENCES

[1] G. Grigoras, F. Scharlatache, “Energy Losses Estimation in Electrical Distribution Networks with Decision Trees-based Algorithm”, in *Proc. 2013 The 8th International Symposium on advanced topics in Electrical Engineering Conf.*, pp. 1-4.

[2] J. Dickert, M. Hable, P. Schegner, “Energy Loss Estimation in Distribution Networks for Planning Purposes”, in *Proc. 2009 IEEE Bucharest Power Tech Conf.*, pp. 1-6.

[3] M. E. Oliveira, A. Padilha-Feltrin, “A Top-Down Approach for Distribution Loss Evaluation”, IEEE Transactions on power delivery, vol. 24, NO. 4, pp. 2117-2124, October 2009.

[4] G. Grigoras, G. Cartina, E. C. Bobric, “An Improved Fuzzy Method for Energy Losses Evaluation in Distribution Networks”, in *Proc. 2010 MELECON 2010 - 2010 15th IEEE Mediterranean Electrotechnical Conf.*, pp. 131-135.

[5] *National Agency of Electric Energy-ANEEL Procedures of Electric Energy Distribution on the National Electric System*, ANEEL Std. 543/2013, Apr. 2013.

[6] G. Sergio, "Cálculo de fluxo de carga em sistemas de transmissão com alimentadores primários de distribuição", MSc. dissertation, Dept. Electric. Eng., Univ. Estadual de Campinas, Brazil, 2005.

[7] C. Grigg, “The IEEE reliability test system: 1996”, IEEE Transactions on power delivery, vol. 14, NO. 3, pp. 1010-1020, August 1999.

[8] T. F. Coleman, Y. Zhang. (2014). Optimization Toolbox: User’s guide. [Online]. Available: https://www.mathworks.com