ENERGY LOSS MINIMIZATION BY LOAD ALLOCATION IN DISTRIBUTION SYSTEMS

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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:

$$P_i\,(t) = x_i P_1^{SE}\,(t)\left\{\alpha_{p_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)^2 + \beta_{p_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right) + \gamma_{p_i}\right\} \quad (3)$$
$$\forall i \in \Omega_L$$

$$Q_i\,(t) = y_i Q_1^{SE}\,(t)\left\{\alpha_{Q_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right)^2 + \beta_{Q_i}\left(u_i\cdot\frac{V_1^{SE}(t)}{V_1^{ref}}\right) + \gamma_{Q_i}\right\} \quad (4)$$
$$\forall i \in \Omega_L$$

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:

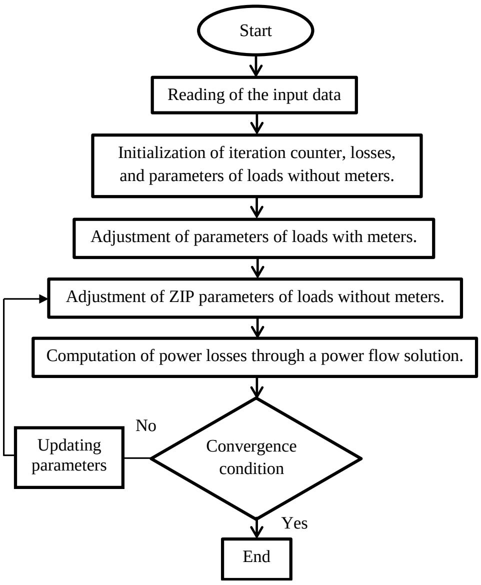

Figure 1. Flowchart of the methodology proposed for the estimation of power losses.

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).

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

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]~~[5]~~. Fig. 2 shows the 23 nodes feeder with a substation at the first node and loads at the remaining nodes.

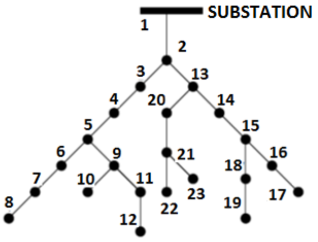

Figure 2. 23 nodes feeder of the case study.

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.

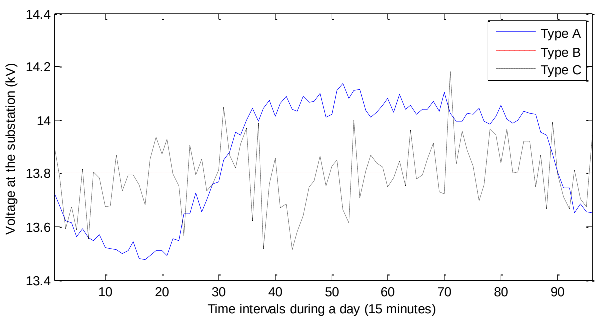

Figure 3. Types of voltage profiles for the case study.

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.

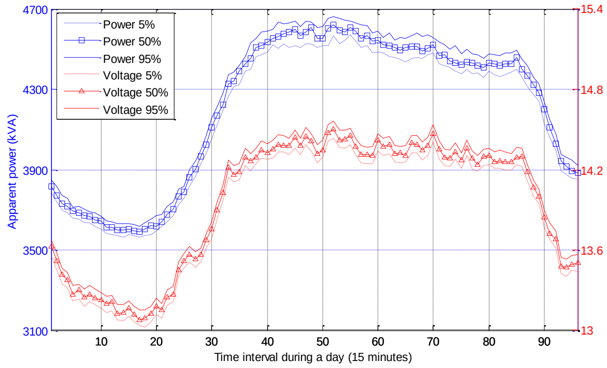

Figure 4. Quantiles for the apparent power and voltage at the substation.

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.

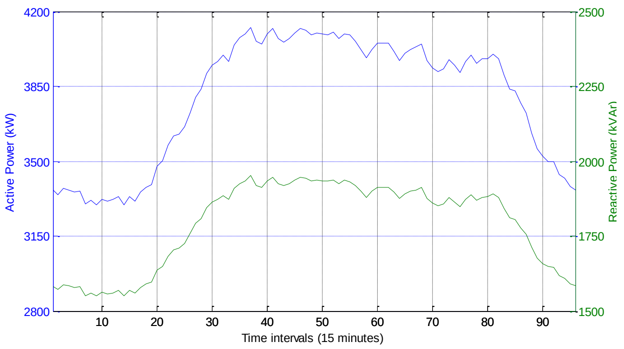

Figure 5. Active and reactive power at the substation for the predicted scenario.

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.

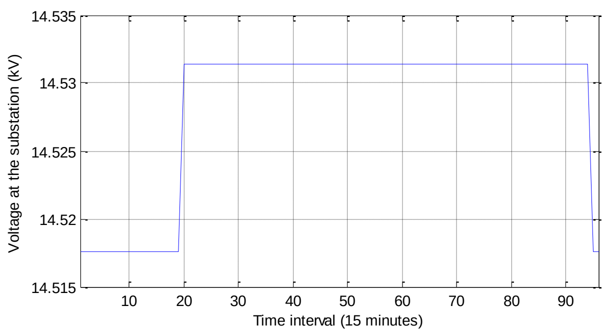

Figure 6. Voltage at the substation for minimum losses in the system for the predicted scenario.

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.

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