A STOCHASTIC METHOD FOR CALCULATING ENERGY LOSSES IN LOW VOLTAGE DISTRIBUTION NETWORKS USING GENETIC ALGORITHMS

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ABSTRACT. Currently, electrical distribution networks supply a growing number of single-phase customers with unbalanced phase distribution, which determines inefficient operating conditions for these networks. This paper presents a method for calculating active energy losses in a real distribution network based on a stochastic approach.

Keywords: power distribution network, power losses, optimization, genetic algorithms.

1. INTRODUCTION

This paper deals with an issue of major interest to electricity suppliers and distributors: energy losses in low voltage (LV) electrical networks. Currently, electrical distribution networks supply a growing number of single-phase customers with unbalanced phase distribution, which determines inefficient operating conditions for these networks.

The traditional approach calculates the energy losses using coefficient $\tau$ known as „time of losses” and the maximum load $S_{\text{max}}$ in the network for the period of analysis. The major drawback of this approach consists in a very subjective value of parameter $\tau$ and significant errors in the assessment of $S_{\text{max}}$. For instance, standard PE 132/2003 recommends values of parameter $\tau$ in a broad spectrum between 1700÷2500 hours per year, and engineers frequently consider an average value of 2000 hours per year [1, 4].

A recent approach for evaluation of energy losses in conditions of uncertainty about the networks, by using regression models is presented in paper [2]. The authors propose a methodology to group networks in representative clusters and assess power/energy losses based on characteristic values associated to each cluster.

On the other hand, paper [3] proposes to use network measurements for generating typical load profiles, able to characterize the load profiles of different type of customers. These profiles are then used to model loads in LV distribution networks and compute energy/power losses.

This paper presents a method for assessing active power and energy losses in LV distribution networks, useful when there is no clear evidence of customer phase distribution, or the network is not fully supervised and there are uncertainties regarding customer location in the network.

This paper is structured in five sections. In section 2, the methodology of determining the consumers’ load profiles based on the consumers’ daily energy consumption and typical load profiles is presented. Section 3 describes the genetic algorithm approach used for customer phase distribution, based on the consumption measured at the MV/LV substation. The stochastic method used for distributing the consumers in the network is presented in Section 4. Section 5 is a study case with results from applying the proposed method for calculating the losses in a real LV distribution network. Section 6 presents the conclusions.
2. CUSTOMER LOAD PROFILES

The first step is the generation of customer hourly load profiles. For this, based on the typical load profiles and daily energy consumption of each customer supplied in the LV network, the load profiles are computed by applying:

\[ PD(h, k) = W(k) \times PT(h, c) \]  

where:
- \( PD(h, k) \) – the denormalized load profile at customer \( k \), for 24 hours, \( h=1..24 \);
- \( k \) – current customer index \( k=1..N_c \);
- \( c \) = Type\( (k) \) – the type of the \( k \)th customer, \( k=1..N_c \);
- \( PT(h, c) \) – typical load profile for the \( c \) type of customer, for 24 hours \( h=1..24 \);
- \( W(k) \) – daily energy consumption for customer \( k \);
- \( N_c \) – total number of customers.

Next, the denormalized profiles calculated above are adjusted by using the hourly measured values at the main feeder of the MV/LV substation, as follows:

\[ P_{calc}(h) = \sum_{k=1}^{N_c} PD(h, k) \]  

\[ P_{max}(h) = \sum_{f=1}^{3} PM(h, f) \]  

\[ \Delta P(h) = P_{calc}(h) - P_{max}(h) \]  

\[ PD_{cor}(h, k) = PD(h, k) \cdot \left( 1 + \frac{\Delta P(h)}{\sum_{k=1}^{N_c} PD(h, k)} \right) \]  

where:
- \( PM(h, f) \) - three-phase feeder measured load profile for the analyzed time interval;
- \( \Delta P(h) \) - deviation between the measured and computed load profile for the analyzed time interval;
- \( PD_{cor}(h, k) \) - denormalized load profiles adjusted by measured load profiles for the analyzed time interval;

3. GENETIC ALGORITHM FOR CUSTOMER PHASE DISTRIBUTION

Genetic algorithms are adaptive heuristic search techniques based on the principles of genetics and natural selection. A genetic algorithm (GA) is a computer model that emulates biological evolution to solve optimization or search problems. GA uses a population or set of solutions represented as strings and the biological operators of selection, crossover and mutation [5, 7, 9]. During the evolution process, the most promising chromosomes are evaluated by a fitness function and progressively refined, looking for better solutions.

**Representation of chromosomes** – for solving the customer phase distribution problem, the chromosome length was chosen as equal to the number of customers in the network. Genes in a chromosome can take the values of 1, 2 or 3, which means that the customer is connected to in the network. For highlighting the three phase customers, an additional mask vector is introduced, whose elements can have values of 1 or 3, which means that the total number of phases is either single-phase or three-phase.

Figure 1 describes an example of such a chromosome.

**Generation of initial population** - is made by taking into account the consumer type (single-phase or three-phase). Moreover, portions of the electrical network uses two or one active conductors. These restrictions have to be considered also.

**Selection** - perpetuates the best chromosomes in the population by using the roulette rule [6]. This involves selecting an individual in the new generation with a probability proportional to its fitness function.

**Crossover** - using the arithmetic rule, two parent chromosomes are randomly chosen from the initial population. By crossing in \( n \) points, offspring chromosomes will result, where \( n \) is user-chosen, set to 3 in this paper.

**Mutation** - with some probability, choose a gene from the chromosome and change its value within the network structure restrictions described above. This increases the diversity inside the population, with an adverse effect to the selection operator, that reduces diversity.

**Evaluation of chromosomes (calculation of the fitness function)** – using the customer phase distribution encoded in each chromosome, the three phase feeder load profiles for the analyzed time interval of the current chromosome are aggregated:
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\[ P(h, f) = \sum_{k \in C_f} PD_{cor}(h, k) \]  

(6)

where:

- \( f \) – phase A, B or C;
- \( P(h, f) \) – load profile on phase \( f \);
- \( C_f \) – the set of customers connected to phase \( f \) as represented by the current chromosome.

The fitness function [5] is the maximum absolute deviation between the real measurements taken at the main feeder of the MV/LV substation and the sum of profiles calculated and adjusted for all the customers connected on that feeder:

\[ fd = \max_f(\max_h(\text{abs}(P(h, f) - PM(h, f)))) \]  

(7)

4. CUSTOMER LOCATION IN THE NETWORK BASED ON A STOCHASTIC APPROACH

Since the actual location of customers in the network is unknown, a probabilistic model was used for modelling customer location scenarios. Thus, taking into account the energy consumption and the electrical distance of each customer from the MV/LV substation, its location in the network was determined by a stochastic approach, based on a threshold probability \( ps \in [0, 1] \), with a predefined value.

For example, consider the network portion in Figure 2. The customers’ electrical distances from MV/LV substation is encoded in ascending order in the vector \( \mathbf{R} = [R_1, R_2, R_3, R_4, R_{75}, R_{76}, R_5, R_6] \).

A matrix \( \mathbf{S} \) is created which contains the apparent power consumption for all the customers belonging to the feeder, sorted descendingly with respect to total energy consumption. The next step is the creation of matrix \( \mathbf{S}_{ord} \) sorted by the electrical distance of each customer. The following algorithm is used:

For each consumer in matrix \( \mathbf{S} \):

1. Generate a random number \( p \) in the range \([0, 1]\);
2. If \( p < ps \), the matrix \( \mathbf{S}_{ord} \) will receive on the column corresponding to the position of \( R_i \) from the vector \( \mathbf{R} \), the last column of the matrix \( \mathbf{S} \), corresponding to the not yet placed customer which consumed the smallest amount of energy;
3. If \( p \geq ps \) (predefined threshold), the matrix \( \mathbf{S}_{ord} \) will receive on the column corresponding to the position of \( r_i \) from the vector \( \mathbf{R} \), the first column of the matrix \( \mathbf{S} \) corresponding to the not yet placed customer which consumed the biggest amount of energy;
4. Remove from \( \mathbf{S} \) the column associated to the placed customer;
5. CASE STUDY

The energy losses in the low voltage network were computed using the Newton-Raphson load flow algorithm [6, 9] and the consumer location in the network and phase distribution determined with the above methods. The case study was conducted on an existing electrical network in Romania. The studied grid has a total length of 1370 m and feeds 129 households and the public lighting. The network one-line diagram is presented in Figure 3. The line length between 2 busbars was considered as 40 m, as specified in Romanian standards. The simulation was conducted for a total time interval of a week, with measurement samples taken every 10 minutes, which means 1008 load flow calculations. Because of the heavy data volumes and limited paper space, the results will be presented only as charts.

As input data, the measured three phase active power and voltage levels on the feeder in the MV/LV substation were used. The consumer node and phase distribution were determined and the load flow algorithm was run for the entire study period, finding the energy losses and voltage levels across the network. For the marked bus (*) from the one-line diagram in Figure 3, Figures 4, 5, 6 and 7 present the voltage levels for parameter \( ps \in \{0.3, 0.5, 0.7, 0.9\} \) respectively. For comparison purposes, Figure 8 presents the measured voltage levels at the same bus in the network.

An analysis of the charts presented in Figures 4, 5, 6, 7 and 8 will reveal the following:

1. The simulated voltage levels are in the same range with the measured voltage levels.
2. The simulated voltage levels follow the same trend on all of three phases, while measured voltage levels are irregular.
3. Although the measured voltage levels are irregular, the graphic representations show that the simulated and measured voltage levels have peaks at the same time interval.

The measured three phase active powers on the feeder at the MV/LV substation are shown in Figure 13 and the values simulated with the proposed method are presented in Figures 9, 10, 11 and 12 for customers bus distribution threshold \( ps \in \{0.3, 0.5, 0.7, 0.9\} \).
Fig. 3 The one-line diagram of the analyzed LV network

Fig. 4 Voltage levels at the highlighted bus for threshold \( p_s = 0.3 \)

Fig. 5 Voltage levels at the highlighted bus for threshold \( p_s = 0.5 \)
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Fig. 6 Voltage levels at the highlighted bus for threshold $ps=0.7$

Fig. 7 Voltage levels at the highlighted bus for threshold $ps=0.9$

Fig. 8 Measured voltage levels at the highlighted bus.

Fig. 9 Simulated feeder load profiles for threshold $ps=0.3$.

Fig. 10 Simulated feeder load profiles for threshold $ps=0.5$.

Fig. 11 Simulated feeder load profiles for threshold $ps=0.7$. 
When analyzing the charts from Figures 9, 10, 11, 12 and 13 the following conclusions are obvious:

1. The simulated load profiles on all three phases follow the same trend;
2. The simulated and measured load profiles vary around the same values, having peak and valley loads around the same time intervals;
3. The simulated load profiles follow the same trend on all of three phases, while the measured load profiles are irregular;
4. The measured load profiles irregularity is due to customers with big power requirement over a small time period. This phenomenon affects the results of the simulations because it is practically impossible to
accurately simulate these events when building the corrected consumption profiles. The same influence can be seen in the measured voltage levels representation.

5. On a closer look it can be noticed that there is a considerable difference between the simulated feeder load profiles with different thresholds, which indicates that simulations made with a high ps threshold (the most important consumers placed with preference near the substation) have smaller energy losses [8]. This means that a grid analyzed using the proposed method will have the lowest energy losses possible when ps=1.

The evolution of active power losses in kW for the analyzed network are presented in figure 14, 15, 16 and 17 for ps =0.3, 0.5, 0.7, 0.9.

When analyzing the evolution of power losses, the following conclusions can be drawn:

1. The evolution of power losses and feeder load profiles simulated for every threshold follow each other closely;

2. The lowest values of power losses corespond to the night hours, when their main component is the losses on the public lighting circuit;

The values of total energy losses in kWh and percent values are presented in Table 1.

Table 1. Summary of energy losses.

<table>
<thead>
<tr>
<th>ps</th>
<th>Total energy infeed [kWh]</th>
<th>Total energy losses [kWh]</th>
<th>Total energy losses [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.3</td>
<td>3553.995</td>
<td>169.8579</td>
<td>4.779353</td>
</tr>
<tr>
<td>0.5</td>
<td>3546.338</td>
<td>160.5423</td>
<td>4.526987</td>
</tr>
<tr>
<td>0.7</td>
<td>3484.45</td>
<td>95.52412</td>
<td>2.741441</td>
</tr>
<tr>
<td>0.9</td>
<td>3426.116</td>
<td>52.68288</td>
<td>1.537685</td>
</tr>
</tbody>
</table>

The values from Table 1 show that energy losses presented in this study case are showing an expected behaviour, but this can not be defined as a rule, because of the stochastic nature of the proposed method.

In networks with a small number of heavy loaded customers, due to the stochastic nature of the location assignment algorithm it is possible that energy losses are not always correlated with the variation of parameter ps. In this case we recomend accurate location of these customers, based on on-site inspections and their removal from the list of location assignment algorithm. These customers remain in the list of the phase distribution algorithm.

6. CONCLUSIONS

This paper presented a method suitable for computing the energy losses in LV electrical networks with a high number of connected customers with comparable energy consumption.

This method also gives the advantage of studying the behavior of an electrical network under different circumstances (different load profiles, different slack bus voltages, peak and valley loads), offering the possibility to analyze the network by simulating real loads.

Customer position in the network (bus and phase) influences the energy losses. From this point of view the proposed method gives reasonable results. The energy losses have an expected behavior; when important consumers are placed near the beginning of the feeder the losses are minimal. By choosing the appropriate value for parameter ps and by creating accurate customer load profiles, the method can compute with minimal errors, the power losses and voltage levels for LV networks with unknown consumer location.

Another conclusion that can be drawn from studying the simulated feeder load profiles, is that active power losses in the network can be reduced by balancing the energy infeed on all of three phases. For this purpose the method can be applied to find the optimal balanced distribution of one-phase consumer in a three-phase network.

BIBLIOGRAPHY

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