This is a postprint version of the following published document:

Velasco, J.A., Amarís, H., Alonso, M. y Miguelez, M. (2019). Energy Losses Estimation in Low Voltage Smart Grids by using Loss Maps. *In WEENTECH Proceedings in Energy,* 4(1), pp. 247-258.

DOI: https://doi.org/10.32438/WPE.5218

© 2018 WEENTECH Ltd.

This work is licensed under a Creative Commons Attribution 4.0 International License.

Energy Losses Estimation in Low Voltage Smart Grids by using Loss Maps

Jose Angel Velasco[a], Hortensia Amarís*[a], Mónica Alonso[a], Mariano Miguelez[b]

[a] Universidad Carlos III de Madrid, SPAIN

[b]Naturgy, SPAIN

[*]Corresponding author's mail: hamaris@ing.uc3m.es

Abstract

Energy efficiency is one of the most important aspects to consider when planning and operating Smart Grids. Consequently, Distribution Systems Operators (DSOs) are focusing in identifying those activities that will increase the efficiency in their distribution networks. An increase in energy efficiency clearly applies a reduction of energy losses. However, the estimation and the calculation of power losses in distribution networks is a process that has not been solved in a satisfactory way. Low Voltage (LV) distribution networks are characterized by a relevant uncertainty in the topology, grid data (length and sections of cables) and customer connection point or customer demand in real time. In this paper, the process of estimating losses is raised as a feeder losses estimator process, where the LV grid's feeders are classified into representative feeders. For each representative feeder a 'losses map' is obtained which will infer the maximum level of losses in the corresponding feeder for different loads demands by Monte Carlo simulations. These losses maps offer the advantage of providing the maximum losses feeder without it being necessary to execute load flows algorithms. Grid data used in this paper belongs to the networks of the Spanish research project OSIRIS. The OSIRIS project is a demonstration project that join industry and academia to unfold the smart grids know-how aiming an optimal supervision. The project is led by the utility Naturgy (former Gas Natural Fenosa) within a national 'smart meter' roll-out. The architecture and configuration of the OSIRIS's distribution networks are heterogenous involving rural as well as urban areas.

Keywords: Feeder Topology Configuration; Generation Expansion Planning; Discriminant Analysis; Clustering

1. Introduction

The estimation and the calculation of power losses in Low Voltage (LV) distribution systems is a process that has not been solved in an efficient way. New approaches for the estimation of losses have to be considered that do not depend heavily on the precision of the measurement systems.

Extensive efforts have been developed in the scientific literature about estimation of losses in distribution networks. Table 1 shows a review of the most relevant research papers. In general, it is necessary to have a detailed knowledge of the network and accurate demand data for each one of the customers.

In this paper, a clustering procedure for power losses estimation is proposed where the LV grid's feeders are clustered according to the maximum power they feed. Therefore, a clustering approach is adopted by applying Linear Discriminant Analysis (LDA) to obtain a generalized loss map applicable to the losses estimation of any feeder. To deliver a generalized loss map, a topology builder heuristic algorithm is formulated to obtain a comprehensive feeder training set based on the characteristics that exhibit a large LV distribution area.

Table 1. Losses estimation methods

References	Methodology	Limitations
[1]	Analytical Equations	Detailed knowledge of the network and its applicability to LV network is limited
[2]-[3]	Load Profile & Regression Analysis	Accurate demand data required, and its applicability to LV network is limited
[4]-[7]	Loss Factor & Load Factor	Requires accurate demand data and ignore topology
[8]	Top Down /Bottom Up Approach	Requires accurate demand data
[9]-[12]	Load Flow Analysis & Regression Analysis	Deep knowledge of the network topology is required
[13]-[18]	Clustering Techniques	High computational complexity

The proposed losses estimation method has been applied in the Spanish smart grids demonstration project OSIRIS. The OSIRIS project is a demonstration project that join industry and academia to unfold the smart grids know-how aiming an optimal supervision. The project is led by the utility Naturgy (former Gas Natural Fenosa) within a national 'smart meter' roll-out.

2. Feeder classification method

The main function of the feeder classification method is to provide a simple and accurate methodology [19] to estimate the maximum power losses level in distribution networks without the need for computing successive power flows. The methodology is based on clustering the different groups of representative feeders.

In this classification problem, there are dependent and independent variables. The dependent variable is defined as the level of maximum power losses referred to the capacity of the secondary distribution transformer. The independent variables are defined according to the feeder topology configuration and the power demand through the feeder [20].

Linear Discriminant Analysis provides the linear combination of independent variables and it is called discriminant function or classification function [21]. The discriminant function is represented in this paper by a "map", which allows inferring the correspondence between a feeder and a group of losses by means of the input parameters, which are the independent variables. This map is called 'loss map'.

A. Key parameters of the feeders

The parameters that characterize the feeders are the following:

- **Relative lateral branch length $\boldsymbol{L_{D,i}}$**: is the total length of the lateral branch l_i in relation to the total length of the feeder L_S as indicated in (1). If a lateral branch consists of several sections, the total length of the lateral branch is the sum of the length of every section N_k.

$$L_{D,i} = \frac{l_i}{L_S} = \frac{\sum_{k}^{N_k} l_{i,k}}{L_S} \qquad (1)$$

- **Relative lateral branch position $\mathbf{K_{D,i}}$**: is the total length between the connection of the lateral branch to the main branch k_i in relation with the total length of the feeder L_S as it is indicated in (2).

$$K_{D,i} = \frac{k_i}{L_S} \qquad (2)$$

- **Weight of the lateral branch $\mathbf{W_{D,i}}$:** is the total sum of the maximum active power demand p_i of every load connected to the lateral branch N_D in relation to the total active power demand of the whole feeder p_T as it is indicated in (3).

$$W_{D,i} = \frac{p_i}{P_T} = \frac{\sum_{k=1}^{N_D} p_{i,k}}{P_T} \qquad (3)$$

An illustrative example of feeder with laterals is shown in Fig. 1 where four lateral branches exist. In this example, there are 38 equal consumption points, each of 15 kW. In Table 2 the key data for all feeders are shown which will be used for obtaining the characteristic parameters for every feeder.

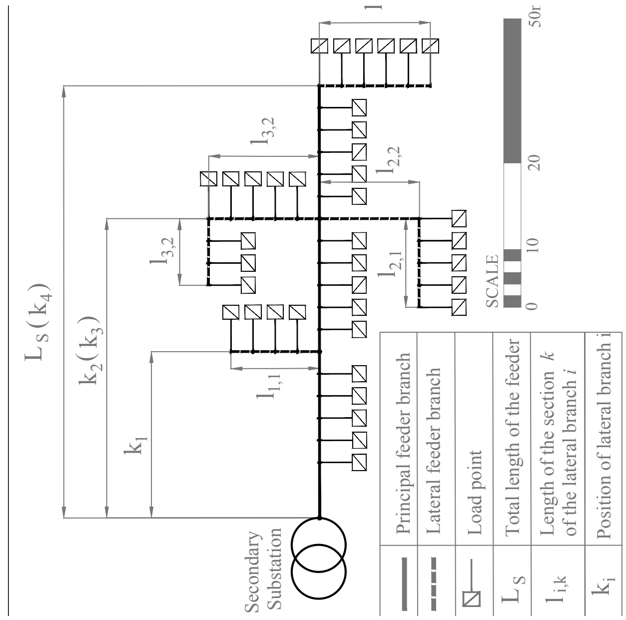

Fig. 1. Illustrative example

Table 2. Data for the illustrative example

Lateral Feeder i	N_k	l_i (m	k_i (m)	p_i (kW)	L_D	K_D	W_D
1	1	40	75	60	0.20	0.38	0.10
2	2	80	135	75	0.41	0.69	0.13
3	2	90	135	120	0.46	0.69	0.21
4	1	50	195	90	0.25	1.00	0.16

B. Classification parameters of the laterals

For each feeder, i^{th}, the classification parameters are obtained based on the parameters that characterize the feeders ($L_{D,i}$, $K_{D,i}$, $W_{D,i}$). The classification parameters defined for each feeder are obtained by (4) and (5).

$$r_{1,i} = L_{D,i} \cdot W_{D,i} \quad (4)$$

$$r_{2,i} = K_{D,i} \quad (5)$$

C. Coordinates of the feeder

The classification of a feeder is carried out by means of the parameters $r_{1,i}$ and $r_{2,i}$ for every lateral branch connected to the feeder. The location of the feeder in the map is defined as the arithmetic mean of their laterals coordinates. The coordinates X_F and Y_F in the map of every feeder are defined by (6) and (7).

$$X_F = \frac{\sum_{k=1}^{N_D} r_{1,k}}{N_D} \qquad (6)$$

$$Y_F = \frac{\sum_{k=1}^{N_D} r_{2,k}}{N_D} \qquad (7)$$

3. Classification of feeder's selection in the OSIRIS project

To illustrate the process of classification, a set of representative feeders from the OSIRIS distribution networks were selected and are shown in Fig. 2, where all customers have a contractual power of 15 kW and the power factor is 0.9 (ind). The area of distribution of the study comprises 31,000 residential and industrial customers with a total contracted power of 155 MW distributed in 750 feeders having an accumulated length of 164 km.

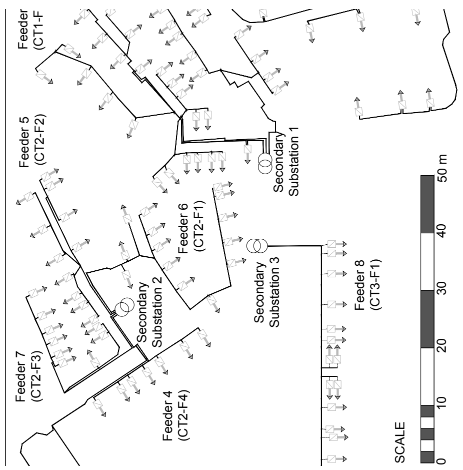

Fig. 2 Set of representative feeders (OSIRIS project)

The characteristic parameters of every lateral branch are calculated for the representative feeders by using (1), (2) and (3). Then, the classification parameters for laterals are calculated with (4) and (5) (see Fig. 3). The coordinates X_F and Y_F for each feeder are computed by applying (6) and (7) and the results are showed in Fig. 4

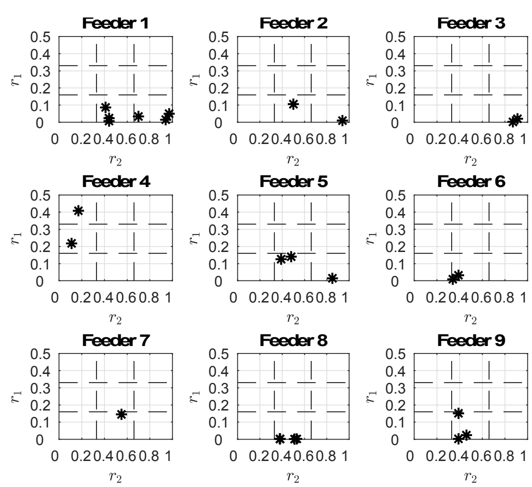

Fig. 3 Classification of the lateral branch of the illustrative feeder's group (OSIRIS project)

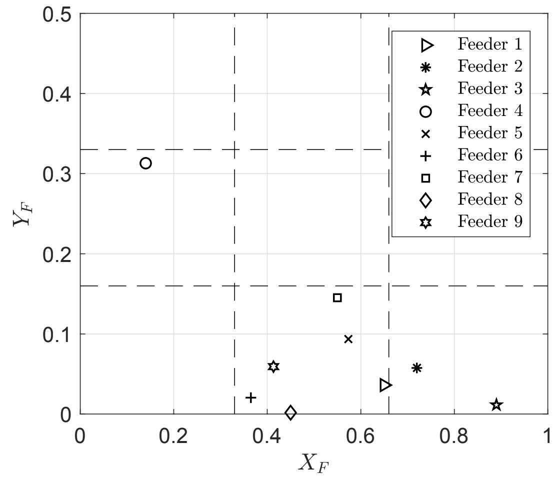

Fig. 4 Coordinates of the selected feeders (OSIRIS project)

4. Feeders training set

In order to obtain a loss map applicable to any distribution feeder under a diversity of demand conditions, a heuristic algorithm to generate the distribution feeder's topologies will be used as the training set. The algorithm designed is based on the expertise acquired in the OSIRIS research project and reproduce the characteristics of the distribution network topologies of a large distribution area of Madrid. The feeders are underground and consist of aluminium cables with a cross-section area of 240 mm^2.

The flowchart of the aforementioned algorithm is shown in Fig. 5 where decisions about the composition of the feeder have to be taken based on the historical data and statistics of the distribution area. The distribution function or cumulative distribution function (cdf) and the density function or probability density function (pdf) are shown in Fig. 6 for the following variables: number of segments in a feeder, total length of the feeder, the length of a segment, the total number of loads in a feeder, the number of lateral branches in a feeder and the maximum power demand. The density and distribution functions are estimated by means of Kernel Density Function (KDE) [22].

The characteristic parameters L_D, K_D and W_D and the classification parameters r_1 and r_2 are calculated to obtain the coordinates of the feeder by means of (6) and (7). With this information, a power flow is carried out for every feeder to obtain the maximum network losses level and the maximum voltage drop. To ensure that the maximum level of power losses have been found a Monte Carlo simulation is performed modelling the demand of each load point as a random variable following a normal distribution. The procedure of creation of the load demand scenarios for the Mote Carlo simulation is showed in Fig. 7.

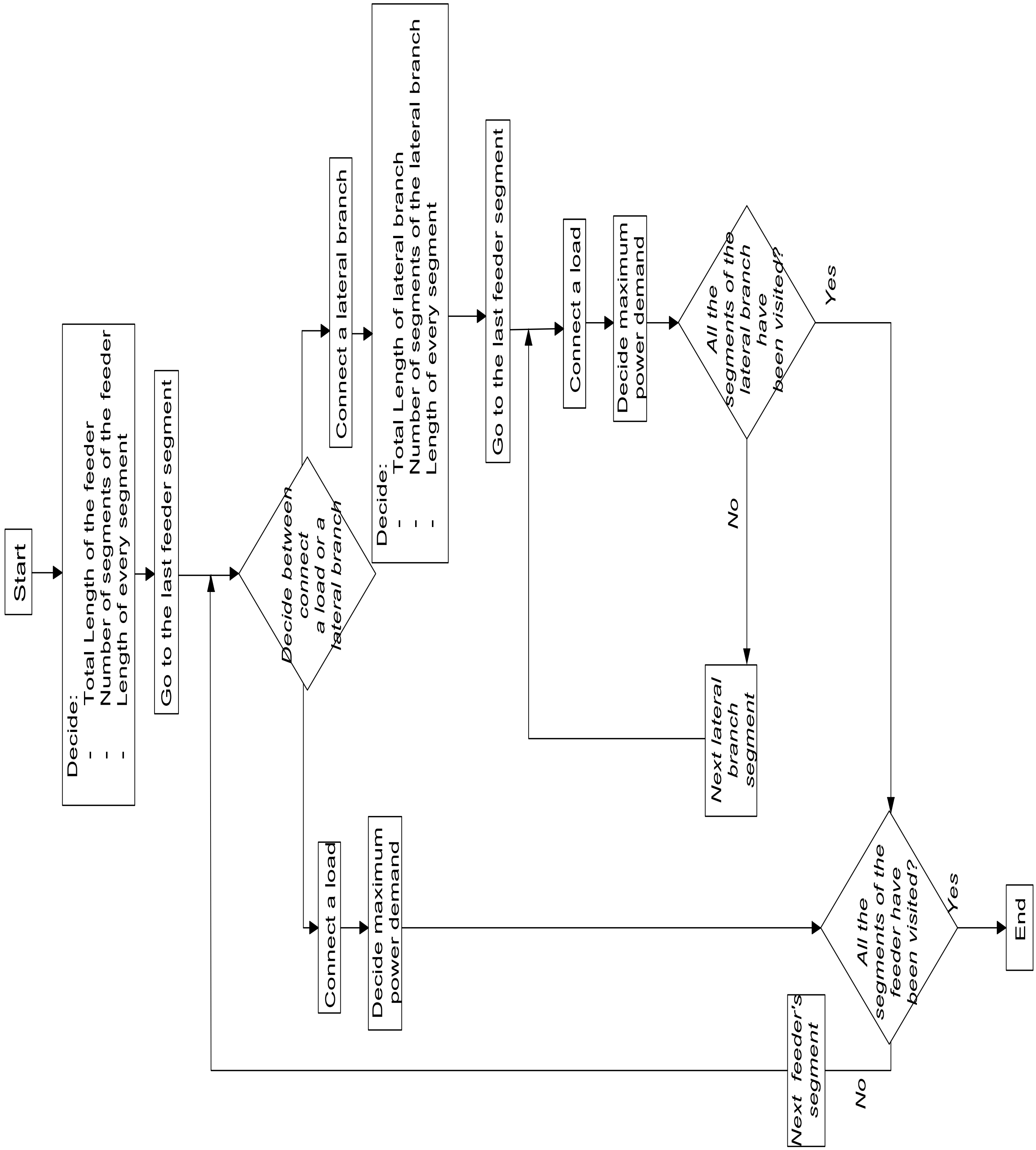

Fig. 5 Flowchart of the topology builder heuristic algorithm

Simulations where the feeder voltage exceeds the maximum voltage limit (5% in the Spanish case) are discarded. However, simulations where there are no voltage violations in the feeders are labelled with the maximum power losses level and their coordinates are included in the loss map.

5. Results

The obtained loss map considers the uncertainty of demand. The histogram of maximum load demand of the area of study shown in Fig. 8. which describes that 95% of the customers have a power demand equal or less than 15 kW. With this information a probability distribution for maximum power demand is fitted with the KDE method. The consequent loss estimation for the feeders training set selected are shown in Fig. 9. Finally, the loss map (Fig. 10) is obtained for the representative feeders and it can be a that six power loss regions are found which have the same power loss percentage. For example, it can be inferred that knowing the feeder 4 coordinates (X_F=0.18, Y_F=0.32) the expected power loss in that feeder is 2.5%, because feeder 4 is found to be located in the 2.5% power loss region of the map. For the same feeder (feeder 4) a power flow using the real topology data and maximum power demand gives technical power losses of 2.96%, which means a power loss error (results of power flow vs. expected power losses in the loss map) of 15%. The rest of the feeders (except for feeder 4 and feeder 7) are found in the 0.5% power loss region.

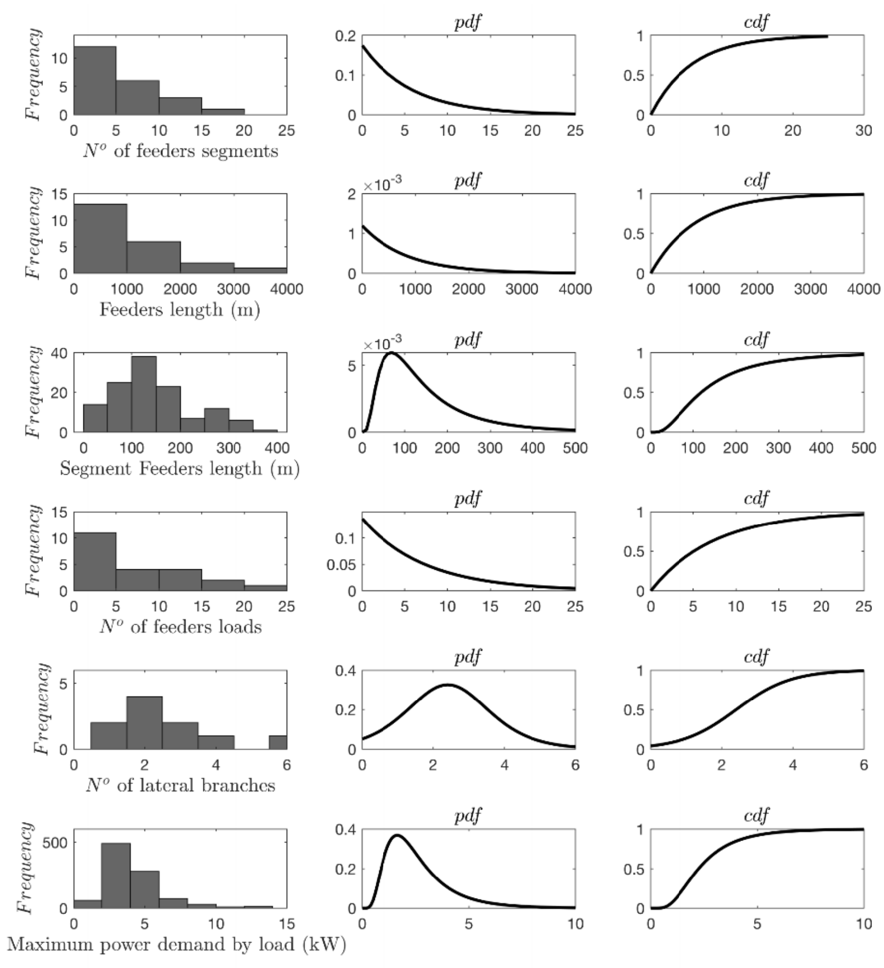

Fig. 6 Distribution feeders statistics of the OSIRIS project

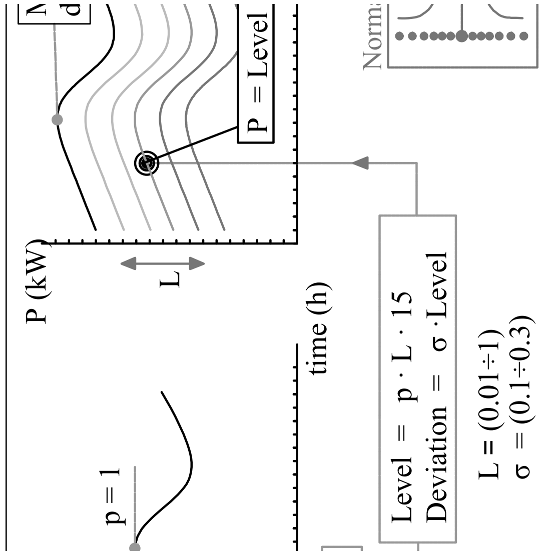

Fig. 7 Modeling demand as a random variable. demand scenario generation

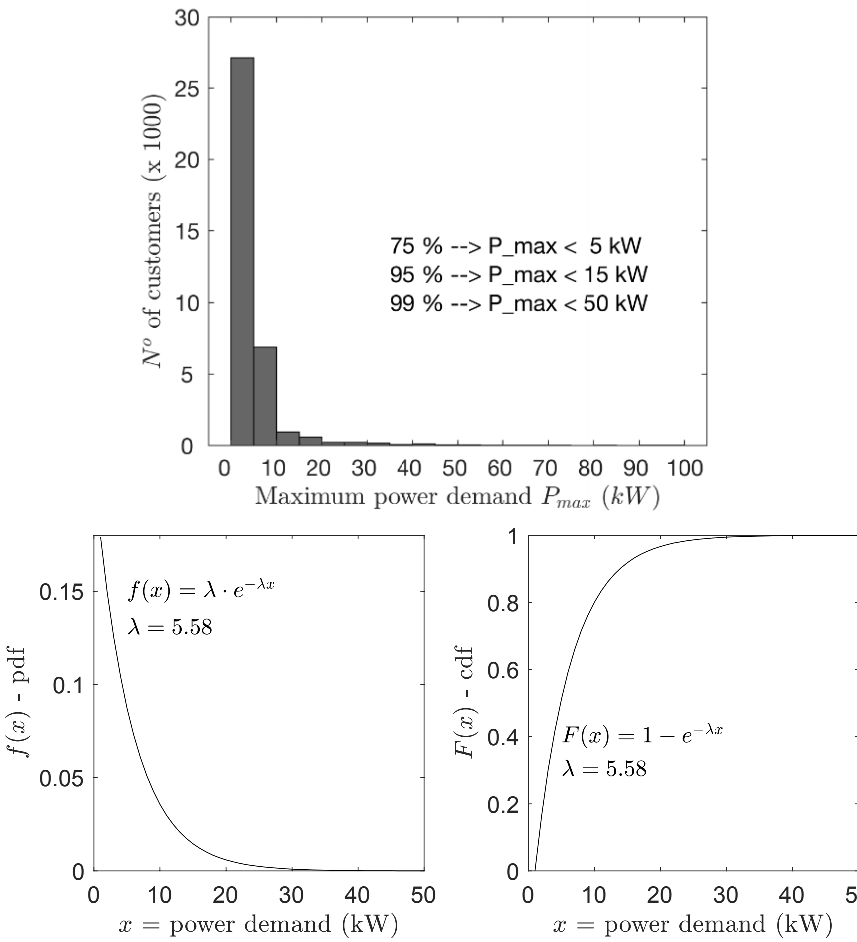

Fig. 8 Histogram of maximum power demand per customer and probability distribution for maximum power demand

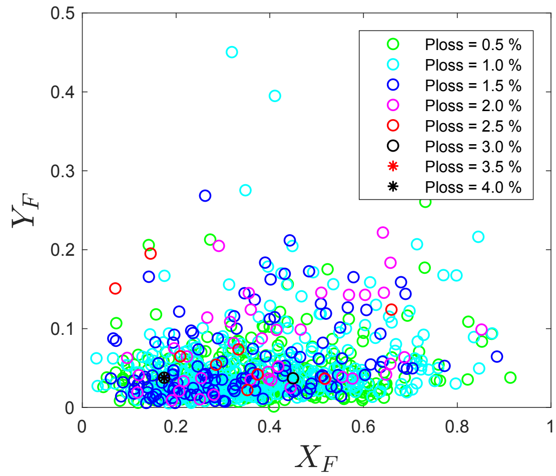

Fig. 9 Scatter plot of the feeders training set with the label of maximum power losses

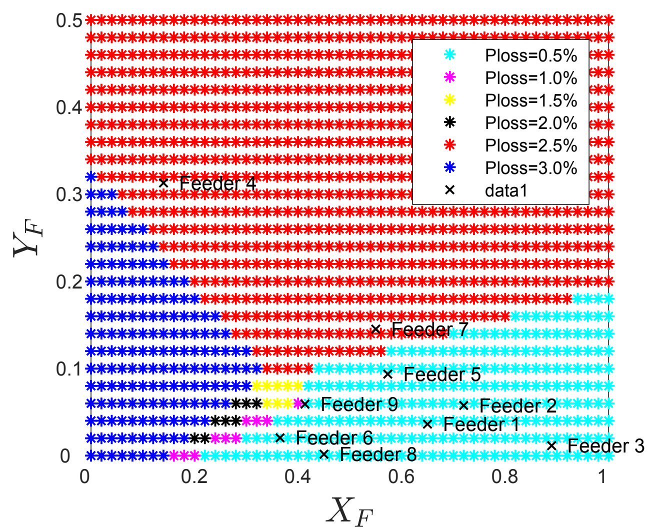

Fig. 10 Generalized loss map for the representative feeder set

6. Conclusions

This article presents a maximum power loss estimation method for distribution feeders. The method presented takes into account the topology, as well as the nature of the power demand. The method exploits the similarity that some feeders present regarding the distribution of the demand along the feeder, in particular, the presence of lateral branches. As has been shown, the characteristics of the feeders defined in this paper keep a close relation with the level of maximum power losses.

The classification parameters allow the representation of every lateral branch in a loss map where the coordinates of the feeder are labelled with a class (level of maximum power losses respect to the capacity of the secondary distribution transformer) and the expected maximum power loss can therefore be deduced.

A clustering approach using Linear Discriminant Analysis (LDA) was adopted to obtain a graphical tool that could support the estimation of maximum level of losses of every distribution feeder. The method presented is based on a heuristic algorithm to provide an extensive feeders training set to obtain a generalized loss map under different conditions of demand. The loss map obtained has been applied to a large LV distribution area of Madrid (Spain).

The proposed method could be used to support the decision-making process related to increase the renewable-based Distributed Generation (DG) presence. Therefore, the method could be used in modelling and solving DG expansion planning problems and hosting capacity.

Acknowledgement

This work has been partly funded by the Spanish Ministry of Economy and Competitiveness through the National Program for Research Aimed at the Challenges of Society under the project OSIRIS (RTC-2014-1556-3).

ORCID Id of Authors

Jose Angel Velasco: https://orcid.org/0000-0002-5401-637X
Hortensia Amarís: https://orcid.org/0000-0001-9487-0127
Mónica Alonso: https://orcid.org/0000-0001-9006-8196

References

[1]. N. R. Schultz. (1978) Distribution Primary Feeder I2R Losses. IEEE Transactions on Power Apparatus and Systems, PAS-97, 2, 603-609.
[2]. R. Taleski and D. Rajicic. (1996) Energy summation method for energy loss computation in radial distribution networks. IEEE Transactions on Power Systems, 11, 2, 1104-1111.
[3]. C.S. Chen, J.C. Hwang, M.Y. Cho, Y.W. Chen, (1994) Development of simplified loss models for distribution system analysis. IEEE Transactions on Power Delivery, 6, 1545-1551.
[4]. O. M. Mikic. (2007) Variance-Based Energy Loss Computation in Low Voltage Distribution Networks. IEEE Transactions on Power Systems, 22, 1, 179-187.
[5]. L. M. O. Queiroz, M. A. Roselli, C. Cavellucci and C. Lyra. (2012) Energy Losses Estimation in Power Distribution Systems. IEEE Transactions on Power Systems, 27, 4, 1879-1887.
[6]. X. Fu, H. Chen, R. Cai and P. Xuan. (2016) Improved LSF method for loss estimation and its application in DG allocation. IET Generation, Transmission & Distribution, 10, 10, 2512-2519.
[7]. K. A. Ibrahim, M. T. Au, C. K. Gan, and H. J. Tang, (2017) System wide MV distribution network technical losses estimation based on reference feeder and energy flow model. Int. J. Electr. Power Energy Syst, 93, 440–450.

[8]. C. A. Dortolina and R. Nadira. (2005) The loss that is unknown is no loss at all: a top-down/bottom-up approach for estimating distribution losses. IEEE Transactions on Power Systems, 20, 2, 1119-1125.
[9]. P. S. N. Rao and R. Deekshit. (2006) Energy loss estimation in distribution feeders. IEEE Transactions on Power Delivery, 21, 3, 1092-1100.
[10]. E. Mckenna, I. Richardson, M. Thompson. (2012) Smart meter Data: Balancing consumer privacy concerns with legitimate applications. Energy Policy, 41, 817-814.
[11]. A. J. Urquhart and M. Thomson. (2015) Impacts of Demand Data Time Resolution on Estimates of Distribution System Energy Losses. IEEE Transactions on Power Systems, 30, 3, 1483-1491.
[12]. G. Poursharif, A. Brint, M. Black, M. Marshall. (2018) Using smart meters to estimate low-voltage losses. IET Generation, Transmission & Distribution, 12, 1206-1212.
[13]. Y-Y. Hong and Z.T. Chao. (2012) Development of energy loss formula for distribution systems using FCN algorithm and cluster-wise fuzzy regression. IEEE Transactions on Power Delivery, 17, 794-799.
[14]. A. K. Dashtaki and M. R. Haghifam. (2013) A New Loss Estimation Method in Limited Data Electric Distribution Networks. IEEE Transactions on Power Delivery, 28, 4, 2194-2200.
[15]. S. Wang, P. Dong and Y. Tian. (2017) A Novel Method for Statistical Line Loss Estimation for Distribution Feeders Based on Feeder Cluster and Modified XGBosst. Energies, 10.
[16]. C.T. Hsu, Y. M. Tzeng, C. S. Chen and M. Y. Cho. (1995) Distribution feeder loss analysis by using an artificial network. Electric Power System Research, 34, 85-90.
[17]. M.-S. Kang, C.-S. Chen, C.-H. Lin, C.-W. Huang, and M.-F. Kao. (2006) A Systematic Loss Analysis of Taipower Distribution System. IEEE Trans. Power Syst., 21, 3, 1062-1068.
[18]. A. G. Leal, J. A. Jardini, L.C. Magrini and S. Ahm. (2009) Distribution Transformer Losses Evaluation: A New Analytical Methodology an Artificial Neural Network Approach. IEEE Transactions on Power Systems, 24, 705-712.
[19]. Robert J. Broderick and Joseph R. Williams (2013) Clustering Methodology for Classifying Distribution Feeders. IEEE 39th Photovoltaic Specialist Conference (PVSC).
[20]. Benoît Bletterie, Serdar Kadam and Herwig Renner (2018) On the Classification of Low Voltage Feeders for Network Planning and Hosting Capacity Studies. Energies, 11, 651.
[21]. Krzanowski, W. J. (1998) Principles of Multivariate Analysis: A User's Perspective. New York: Oxford University Press.
[22]. D. C. Montgomery, G. C. Runger. (1999) Applied Statistics and Probability for Engineers. New York. Wiley.