The Efficiency of the Clustering Techniques in the Energy Losses Evaluation from Distribution Networks

Gheorghe Grigoras, Gheorghe Cartina, Marcel Istrate, and Florina Rotaru

Abstract— The reduction of energy losses in distribution networks represents an important issue during planning and operation with important technical and economical implications. Level of energy losses depends upon a number of parameters and variables, such as the nominal circuit voltage, the installed transformer capacity, the number of transformation points, the load level, etc. In this paper is to describe an approach to determine the levels of the energy losses using the K-Means Clustering Method. The methodology is applied to a distribution network with the nominal voltage by 6 kV, but it can also be applied to distribution networks operating at other voltage levels.

Keywords— electric distribution systems, energy losses levels, k-mean clustering method, optimal numbers of clusters.

I. Introduction

In planning and operation of distribution networks a number of goals must be achieved and correspondingly a number of objectives, which often are conflicting, must be optimized.

Frequently, in distribution networks, there are the following three objectives to be optimized: minimization of the power losses, minimization of the investments and improvement of the reliability [1] – [7]. The minimization of power losses is an important issue during planning and operation with important technical and economical implications. The level of energy losses in electricity networks differs from country to country. As for the losses in distribution networks, 10% of the energy supplied to the network can be considered a technically acceptable level. A number of companies in developed countries manage to reach a level not exceeding 5%, but for utilities in many countries 10% remains an objective that is difficult to reach, and there are even countries with the loss level up to 15 %. About 30 to 40 % of total investments in the electrical sector go to distribution systems, but nevertheless, they have not received the technological impact in the same manner as the generation and transmission systems [8] – [11] .

The determination of the power/energy losses depends upon a number of parameters and variables that derive from the design criteria and the operating conditions of the distribution networks. Thus, the feeders have a broad universe of the different variables, such as nominal voltage, the length, installed transformers capacity, the number of the transformation points, the circuit type (underground, aerial, mixed), load being served, etc [2], [4], [12]. Even if a feeder has more power losses compared with other feeders, it does not imply that it is operating out of the normal condition. It may have more length, may be more loaded, may have more transformation points, presenting different constructive or operative characteristics.

The evaluation of energy losses should be based on information from system records and site measurements associated with the various voltage levels of the system. Power losses are incurred as power is transported along distribution wires. Losses increase with line length and square of the power being transported. Average losses can vary from year to year, due to cycles in network utilization, network configuration, the shape of the load profile and the level of reactive power support [1], [2], [7] - [9], [12].

A policy for the reduction of losses can contain short and long term actions. The some short term measures are following [4], [5], [9], [11]:

- Identification of the weakest areas in distribution network and improve them.
- Reduction the length of the distribution feeders by relocation of distribution substation/ installations of additional transformers.
- Installation of shunt capacitors for improvement of power factor, etc.

The some long term measures are following:

- Mapping of complete distribution feeders clearly depicting the various parameters such as nominal voltage, the length, installed transformation capacity, the number of the transformation points, the circuit type (underground, aerial, mixed), load being served etc;
- Replacement of the 6 kV or 10 kV voltage level, with 20 kV voltage level;
- Replacement of the old transformers with the efficient transformers;
- Compilation of data regarding existing loads, operations conditions, forecast of expected loads etc.

For further development of plans of energy loss reduction and for determination of the implementation priorities of different measures and investment projects, analysis of the nature and reasons of losses in the system and in its different parts is needed. A permanent policy for reduction of energy losses implies not only the technical improvement of the network (by introduction of modern equipments and circuit components), but also requires the use of software tools to facilitate the operation process [2], [4].

The aim of this paper is to describe an approach to determine the levels of the power/energy losses using the clustering techniques in the distribution networks. From set of these techniques we chouse to analyze the K-means method.

II. Losses Sources in the Electric Distribution Systems

Estimation of the power/energy losses constitutes an important tool for efficient planning and operation of power systems, especially in a free energy market environment. Overall network losses in the electrical transmission and distribution systems used to supply power to consumers can be as much as 6-9% of the total power generated by large power stations [1], [7], [12], [16], [24].

The Romanian distribution network was significantly expanded during the late 1960s and early 1970s. Really, in distribution networks from Romania, there are three levels of voltage: 6, 10, and 20 kV.

The 6 kV level is the first who was developed and the availability of this in urban centres and other areas of concentrated demand for power is still quite high. Perspective to maintain the level of 6 kV is full of difficulties because the networks are very old, some distributors are loaded close to maximum capacity and energy losses are very high. The electric equipments installed in these networks now approach the end of their useful life and need to be replaced. But after replacing, the lifetimes of primary components are long and the networks built today will still be in use after several decades. The same problems in electric distribution networks are occurring during past years all over the world. The 10 kV level included still very small areas of urban networks. The 20 kV level appeared later and covered the rest of urban and rural distribution areas.

For example, in the Figs. 1 and 2 it is location by components of energy losses in a Distribution Company from Romania.

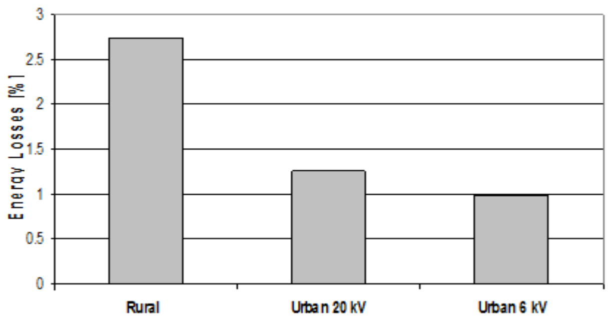


Fig. 1 The total energy losses in a distribution company (expressed in percentage of total energy from network)

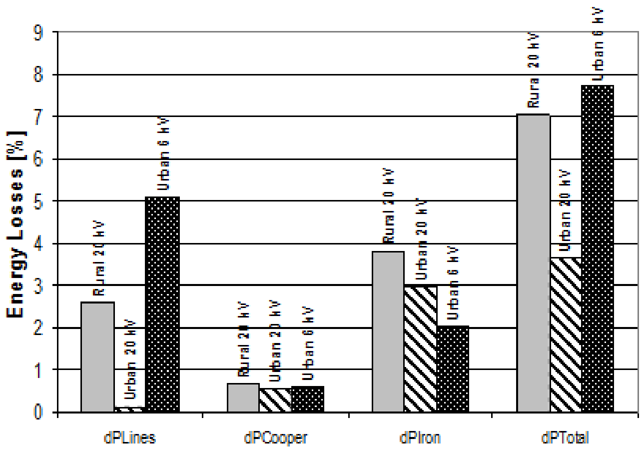


Fig. 2 The total energy losses in a distribution company (expressed in percentage of energy circulating in the every type of network)

From these figures it can observed that a important part of the energy losses of a distribution system are the energy losses in the 6 kV distribution networks. It should be noted that energy losses in the 6 kV networks have about the same percentage as the 20 kV networks (1.25 % vs. ≈ 1 %), even if their total length is much smaller (report lengths, respectively the number of transformers is about 1 to 3).

Based on these issues by replacement the voltage of 6 kV level to 20 kV can be done in order to improve reliability and to minimize power losses in electrical distribution networks. On the other hand, most of Romania's power distribution infrastructure in urban areas is underground, so if excavation work is done to lay new distribution feeders, it makes much more economic sense to deploy 20 kV distribution lines that have about three times the capacity of 6 kV lines.

Another solution that can be applied to minimize the power losses, correlated with the above is the use of efficient transformers. The distribution transformer is the most important single piece of electrical equipment installed in electrical distribution networks with a large impact on the network's overall cost, efficiency and reliability. Selection and acquisition of distribution transformers which are optimized for a particular distribution network, the utility's investment strategy, the network's maintenance policies and local service and loading conditions will provide definite benefits (improved financial and technical performance) for both utilities and their customers [13], [14]. For an electric utility (Distribution Company) that has numerous distribution transformers in its network, there is an opportunity to install high efficient distribution transformers that have less total energy losses than less efficient transformers, so they pollute the environment less.

Worldwide there are programs on MEPS for to reduce energy losses associated with transformer operation in the electricity distribution system. Since the original MEPS levels were specified there has been significant development in transformer efficiency standards and requirements in other countries including the USA, European Union, Canada, Japan, China, Mexico and India [15].

Several European projects have shown the interest in acquiring efficient transformers. The Thermie project (1999, co-financed by the European Commission) estimated that energy efficient transformers could save approximately 22 TWh per year by means of C-C' units; amorphous core transformers could save even more. The Prophet project continued this task in 2004 and arrived at similar conclusions; furthermore, it showed a rising trend in the installation of amorphous transformers in Japan and China, and India and USA install them too. In USA, 10% of new transformer sales are amorphous transformers (about 100,000 new amorphous transformers per year); 15% of new pole transformer sales in Japan are amorphous transformers (about 350,000 amorphous transformers were in service in 2003 [16]. Today, another EU project is working to highlight energy efficiency on Distribution Transformers. The SEEDT project represents one of the projects in the Intelligent Energy Europe programme. The aim of this project is to promote the use of energy-efficient distribution transformers, which can be profitable for investors, and, by contributing to European Community energy savings, may help to fulfill EU energy policy targets [17].

There are a number of factors that will enable the achievement of higher efficiencies and support the increase in the current minimum efficiency performance standards levels [15], [16]:

- Better use of traditional materials to achieve loss reduction and improvement of efficiency;
- Better computer-aided design of transformers to reduce losses and improve efficiency;
- Use of low loss core materials such as amorphous metals;
- New lower loss core configuration designs such as the "Hexaformer";
- Improved operational applications of transformers to optimize energy efficiency in operation;
- Consideration of total life cost of transformers: purchase cost plus operational energy losses;
- The effect of increasing harmonic levels from non-linear loads in increasing losses and reducing efficiency;
- Increased transformer life resulting from lower operating temperature with more efficient transformers.

The savings brought about by loss reduction not just about the monetary value of the energy saved: the released capacity of the system can serve to delay a costly expansion and reduce ageing of the components.

The worldwide experience shows that in utilities with high network loss level, 1 $ expended for loss reduction saves 10 - 15 $ to the utility [7].

III. K-MEANS CLUSTERING METHOD

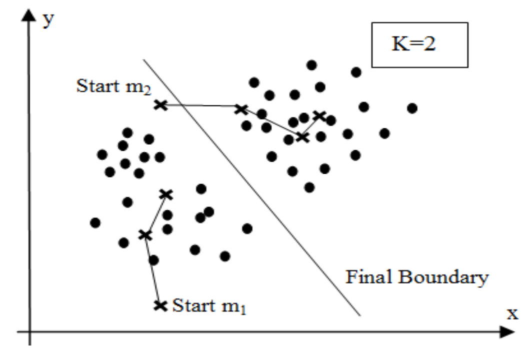
The K-means clustering is an algorithm to classify or to group your objects based on attributes/features into K number of group. K is positive integer number. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid [12], [18] – [20].

$$\min(E) = \min\left(\sum_{i=1}^{k} \sum_{x \in C_i} d(x, z_i) \right) \tag{1}$$

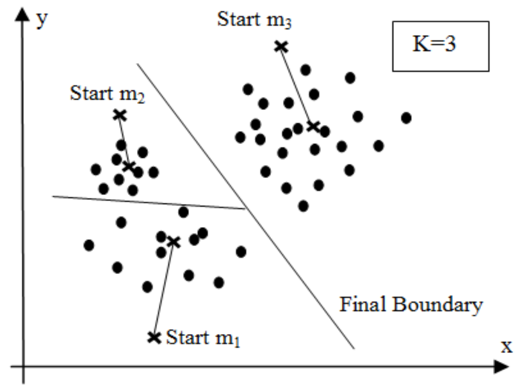
where z_i is the center of cluster C_i, while $d(x, z_i)$ is the Euclidean distance between a point x and z_i.

Thus, the criterion function E attempts to minimize the distance of each point from the center of the cluster to which the point belongs. More specifically, the algorithm begins by initializing a set of K cluster centers. Then, it assigns each object of the dataset to the cluster whose center is the nearest, and recomputed the centers. The process continues until the centers of the clusters stop changing.

It is obvious in this algorithm that the final clusters will depend on the initial cluster centers chooses and on the values of K. As example, in Fig 3 these aspects are presented.



a.



b.

Fig. 3 Influence the choice of initial cluster number

The steps of the algorithm are the following [12], [19]-[21]:

- **Step 1**. Choose K initial clusters centres $z_1^{(0)}, z_2^{(0)}, \ldots, z_k^{(0)}$;
- **Step 2**. At the k-th iterative step, distribute the samples $\{x\}$ among the K clusters using the relation:

$$x \in C_i^{(k)} \text{ if } d(x, z_i^{(k)}) < d(x, z_j^{(k)}) \tag{2}$$

$$i = 1, 2, \dots, K; \quad i \neq j$$

where $C_i^{(k)}$ denotes the set of samples whose cluster centre is $z_i^{(k)}$.

- **Step 3**. Compute the new cluster centers $z_i^{(k+1)}$, $j = 1, 2, \dots, K$. The new cluster centre is given by:

$$z_i^{(k+1)} = \frac{1}{n_i} \sum_{x \in C_i^{(k)}} x, \quad i = 1, 2, \dots, K \tag{3}$$

where n_i is the number of objects in $C_i^{(k)}$.

- **Step 4**. Repeat steps 2 and 3 until convergence is achieved, that is until a pass through the training sample causes no new assignments.

For defining of the optimal number of clusters $N_{c\ opt}$ it can used the following algorithm [18], [20], [25]:

- Determination of the maximum optimal of clusters $N_{c\ max}$. The maximum optimal of clusters $N_{c\ max}$ should be set to satisfy $2 \leq N_{c\ max} \leq \sqrt{n}$, where n is the clustered objects from data base [19], [22].
- For set of objects from data base, the *K*-means clustering method of with given N_c ($2 \leq N_c \leq N_{c\ max}$) is used.
- According to the obtained clusters structure, determinate partition quality is evaluated. In the paper, this is achieved through silhouette global coefficient.
- Increase the number of clusters N_c to the $N_{c\ max}$ to see if *K*-means method find a better grouping of the data. (To repeat the steps 2 ÷ 3).
- Show number of clusters that has obtained the optimal value of the silhouette global coefficient.

Evaluating and assessing the results of the K-means algorithm represents the main subject of cluster validity. In the process of cluster analysis the following properties of clusters are being examined: density, sizes and form of cluster, separability of clusters, robustness of classification. There are three main approaches to cluster validation [23]:

- *external tests* – the results of classification of input data are compared with the results of classification of data not participating in the basic classification.
- *internal tests* – only input data is used for the evaluation of classification quality. It is used for validation of the separate cluster, results of hierarchical and iterative classification.
- *relative tests* – several different classifications of one set of data are compared using the same algorithm of classification with different parameters.

Internal cluster validation tests are more popular in practice of cluster analysis. From these, the test based on the Silhouette Global Index calculation is one of the most used. This calculates the silhouette width for each sample, average silhouette width for each cluster and overall average silhouette width for a total data set. Using this approach each cluster could be represented by so-called silhouette, which is based on the comparison of its tightness and separation. The average silhouette width will be applied for evaluation of clustering validity and also will be used to decide determination of optimal number of clusters.

$$SC = \frac{1}{N_c} \sum_{j=1}^{N_c} S_j \tag{4}$$

where:

S_j - silhouette local coefficient is defined as:

$$S_j = \frac{1}{r_j} \sum_{i=1}^{r_j} s_i \tag{5}$$

s_i - the silhouette width index for *i*-object is:

$$s_i = \frac{b_i - a_i}{\max\{b_i\ , a_i\}} \tag{6}$$

a_i – mean distance between object i and objects of the same class j,

b_i – minimum mean distance between object i and objects in class closest to class j.

In (6) if the object i is the single object of a cluster, then the silhouette $s_i = 0$.

In [25] is proposed the following interpretation of the *SC* coefficient:

- 0.71 – 1.0 A strong structure has been found;
- 0.51 – 0.7 A reasonable structure has been found;
- 0.26 – 0.5 The structure is weak and could be artificial;
- < 0.25 No substantial structure has been found.

Cluster validity checking is one of the most important issues in cluster analysis related to the inherent features of the data set under concern. It aims at the evaluation of clustering results and the selection of the scheme that best fits the underlying data.

IV. Evaluation of Energy Losses in Electric Distribution Networks

In the worldwide practice, in networks with high level of losses the metering system is usually poor measurements are fairly inaccurate or they are missing at all. It is obvious that due to poor provision with information such utilities have to apply simplified methods for calculation of technical losses basing primarily on energy metering. The energy data are sometimes partially supported by measurements of currents in outgoing medium-voltage feeders.

Average losses can vary from year to year due to cycles in network utilization, network configuration, the shape of the load profile and the level of reactive power support. In principle technical losses in electric distribution networks can be determined by calculations. Choice of the calculation method depends on the character of the network and information available.

For energy losses determination, when the active and reactive energies (W_P and W_Q), respectively the peak load current I_{max} of the feeder(s) are known, it may the following empirical formula:

$$\Delta W_T = \left(\Delta P_L + \Delta P_{TrCo}\right)\cdot \tau + \Delta P_{TrIr} \cdot 8760 \qquad (7)$$

where:

ΔP_L – the power losses at the peak load in the cable;

ΔP_{Tr_Co} – the cooper losses at the peak load in the transformers;

ΔP_{Tr_Ir} – the iron losses in the transformers;

τ - utilization time of power losses.

Determination of utilization time of power losses τ was done for each distribution feeder using the following formulae [4], [6], [7]:

$$\tau = \left(0.124 + \frac{T_{\max}}{10000}\right)^2 \cdot 8760 \qquad (8)$$

$$T_{\max} = \frac{\sqrt{W_P^2 + W_Q^2}}{S_{\max}} \qquad (9)$$

where:

W_P - active power measured during a period T (usually a year);

W_Q - reactive power measured during a period T (usually a year);

S_{max} - peak load load of the feeder;

T_{max} - peak load hours.

V. Study Case

The methodology described in this paragraph enables determination of the levels of the power losses of the different distribution networks based on several circuit configuration variables (length, number of transformers points and the circuit type) and the nodal loads. Even if a feeder has more power losses compared with other feeders, it does not imply that it is operating out of the normal condition. It may have more length, may be more loaded, may have more transformation points, etc., presenting different constructive or operative characteristics.

In the first step of study, the data were updated and prepared for the process, including the selection of the variables for a total of the 96 feeders by 6 kV. The simplified representations of a feeder and an urban distribution network from this network are presented in Figs. 4 and 5.

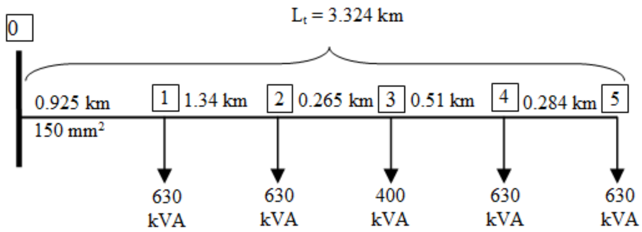


Fig. 4 Simplified representation of an urban feeder

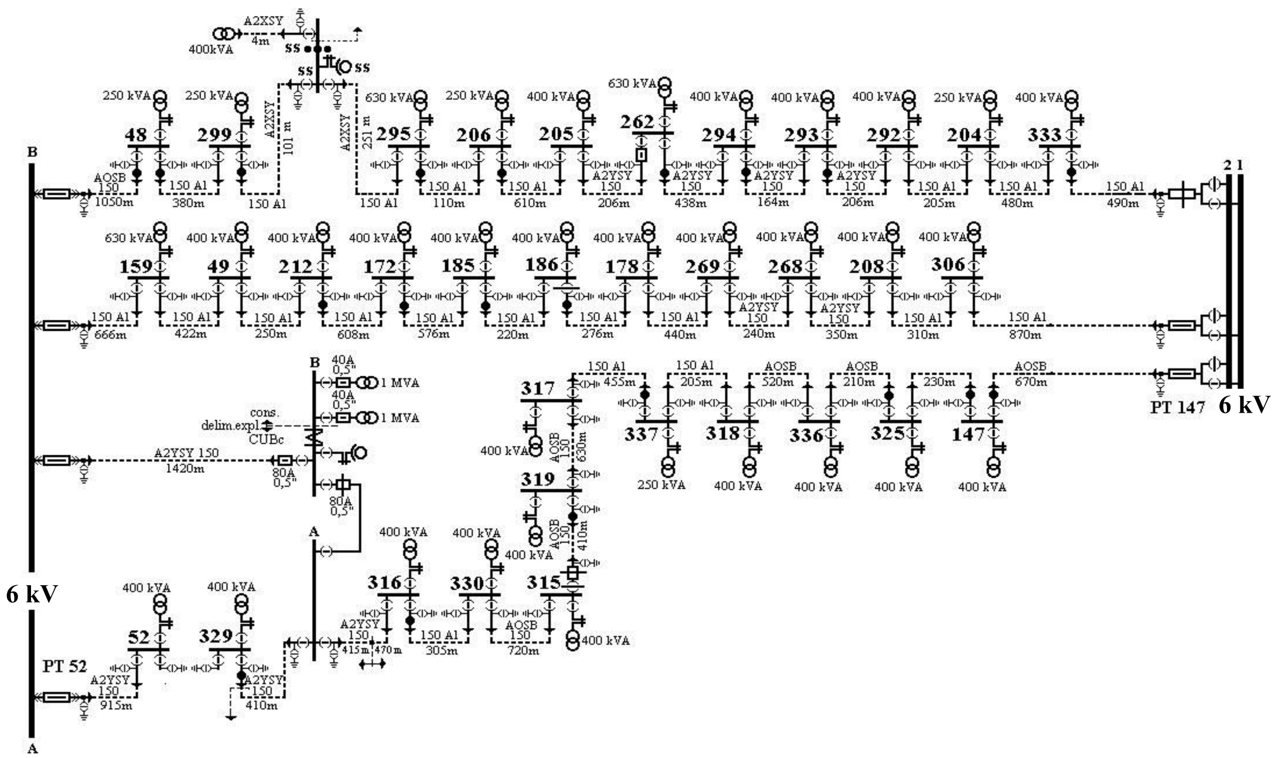


Fig. 5 Representation of the considered urban distribution network

This step includes the calculation of the energy losses for every feeder from the database using the algorithm described in paragraph 4. Then, the distribution feeders were classified according to the energy losses, Table 1 and Fig. 6, and after other selected variables (length, installed power and loading factor), Table 2.

Table 1. Feeders' classification according to energy losses

Energy Losses Level [%]	**Number of feeders**	
	[no.]	**[%]**
Low Losses (< 4.5 %)	55	57.3
Moderate Losses (4.5 % ÷ 6 %)	14	14.6
High Losses (> 6 %)	27	28,1

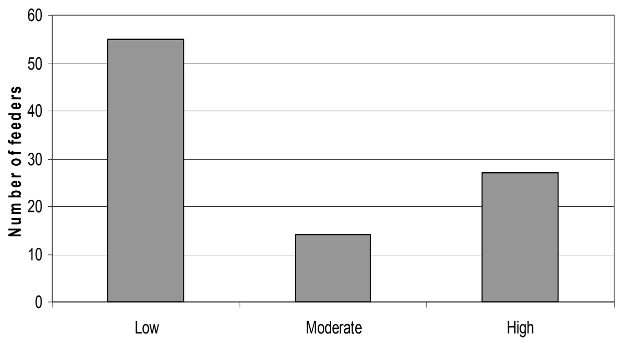


Fig. 6 Repartition of the 6 kV distribution feeders, on the energy losses levels

As shown in Table 1 and Fig. 6, three levels were defined according to the linguistic level of energy losses:

- low losses (< 4.5 %);
- moderate losses (4.5 % ÷ 6 %);
- high losses (> 6 %).

An analysis of the information contained in Table 1 indicates that approximately 70 % the feeders have the energy losses below 6 % (this value is normal for the feeders with the 6 kV voltage level from Romania).

In terms of primary characteristics, over 70% distributors have a length less than 5 km and an installed power for up to 4500 kVA. An analysis of the factor loading values, only 30 % of feeders have a loading between 30 and 60 % from the nominal power, values considered optimal for economical operation of transformers. Thus, high values of the energy losses are registered for approximately 25 % of feeders with a loading level < 30 % and > 60 %.

In the second step, the feeders were correlated and grouped according to its characteristics. In function by the primary characteristics (the total length of the distribution feeders and the installed power), the feeders will be divided in representative clusters using the K-means clustering method.

Further, it was applied the algorithm for to determine the optimal number of clusters. In the first step, the maximum optimal of clusters $N_{c\ max}$ was calculated ($N_{c\ max}$ = 9). In the next step, for the set of feeders from the database, the K-means clustering method with given N_c ($2 \le N_c \le N_{c\ max}$) is used. In the step three, the silhouette global coefficient is calculated for to assess the partition quality.

The obtained results are presented in the Fig. 7.

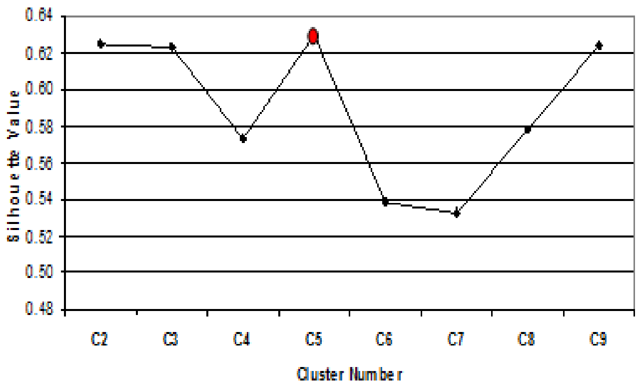


Fig. 7 The silhouette global coefficient for different values of the number of clusters N_c

Table 2. Feeders' classification according to primary variables

Primary Characteristics	**Variables**		**Feeders**			**Total Feeders**	
			Small Loses	**Moderate Losses**	**High Losses**	**[no.]**	**[%]**
Installed Power	**Small**	< 2500 kVA	28	8	14	50	52.1
	Medium	2500 kVA ÷ 4500 kVA	19	5	3	27	28.1
	High	> 4500 kVA	8	1	10	19	19.8
		Total Feeders	55	14	27	96	100
Length	**Small**	< 3 km	18	4	8	30	31.3
	Medium	3 km ÷ 5 km	23	7	11	41	42.7
	High	> 5 km	14	3	8	25	26.0
		Total Feeders	55	14	27	96	100
Loading Factor	**Small**	< 30 %	25	6	17	48	50.0
	Medium	30 % ÷ 60 %	20	5	3	28	29.2
	High	> 60 %	10	3	7	20	20.8

		Total Feeders	55	14	27	96	100

Table 3. Statistical characteristics of the clusters (average (m) and standard deviation (σ))

No. cluster	No. feeders	Length		Installed Power		Energy losses		
		m [km]	σ [km]	m [kVA]	σ [kVA]	m [%]	[%]	Linguistic Level
I	17	4.48	1.05	1430.59	702.91	6.22	3.97	High
II	41	1.55	0.81	1264.15	561.47	4.41	4.39	Low
III	21	5.44	1.00	4269.05	933.29	4.51	1.96	Medium
IV	7	8.72	0.67	6928.00	981.37	6.02	1.03	High
V	10	2.01	0.95	3822.60	932.50	6.51	4.94	High

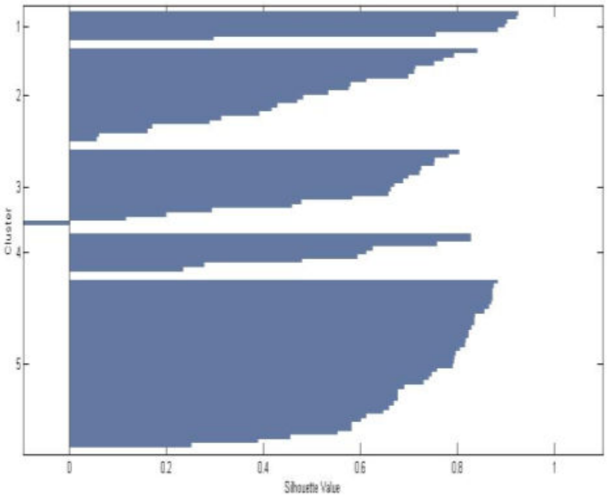


Fig. 8 The silhouette plot for $N_c = 5$

As it seems in Fig. 7 the criterion has given the result with $N_c = 5$. For this value, the silhouette plot is presented in the Fig. 8.

From the silhouette plot, you can see that most points in the five cluster have a large silhouette value, greater than 0.6, indicating that the cluster is somewhat separated from neighboring clusters. However, the second cluster contains many points with low silhouette values, and the other clusters contain a few points with negative values, indicating that those two clusters are not well separated.

Thus, the five clusters of the distribution feeders were presented in the Fig. 9.

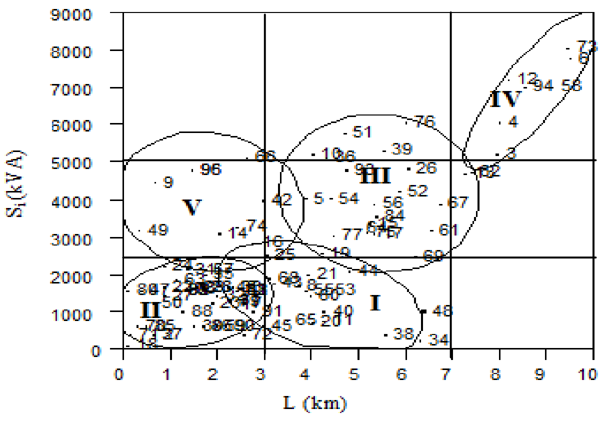


Fig. 9 Clustering of the distribution feeders

In the Table 3 are indicated the statistical characteristics (average values and standard deviations) of the five clusters of feeders corresponding the total length, installed power and energy losses.

If for the installed power, the length, and energy losses are used the linguistic levels presented in the Table 3, each cluster will be characterized by a linguistic level of these variables, Table 4.

Table 4. Characterization by linguistic levels for the clusters of distribution feeders

No. Cluster	Length	Inslalled Power	Energy Losses
I	Medium	Small	High
II	Small	Small	Low
III	Medium	Medium	Moderate
IV	High	High	High
V	Small	Medium	High

From the analysis of the results, several conclusions can be formulated in this case:

- feeders with the very long lengths and high installed powers presented a high level of losses (cluster IV);
- for the short feeders, the high loading condition turned out to be very important, so the losses level is high (cluster V);
- 65 % from the total of the feeders have the low and moderate losses level (cluster II and III), remaining 35 % with de high losses level.

Level of energy losses for a feeder, found in this normal operation state, can be changed if using other configurations. In these situations, a feeder can migrate from one cluster to another cluster.

VI. Conclusions

Level of energy losses represents an important indicator for the planning and operation of electrical distribution networks.

The methodology described in this paper was applied to a group of 96 distribution feeders with the voltage level by 6 kV. Finally, using K-Means method, these feeders were grouping in five clusters according to the constructive characteristics and to determination of the levels of energy losses for each cluster.

This approach can be used to determine the energy losses levels from other distribution networks based on several circuit configuration variables (length, number of transformers points and the circuit type) and the nodal loads.

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