OPTIMAL RECONFIGURATION OF THE DISTRIBUTION NETWORKS IN UNCERTAINTY CONDITIONS

Gheorghe CARTINA[1], Gheorghe GRIGORAS[2]

A method based on the hierarchic clustering techniques, conjunctively with fuzzy modeling, is presented in this paper for improving of the fuzzy models and the estimation of the power losses. Numerical results obtained with many tests demonstrate the ability of the improved fuzzy models to overcome difficult aspects encountered in optimal reconfiguration process of the large distribution networks.

Keywords: optimal reconfiguration, power losses, distribution networks, clustering techniques, fuzzy models.

1. Introduction

A policy for the reduction of losses can contain short and long term actions. The some short-term measures are following [3, 7, 10]: 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, etc.

Also, the some long term measures are following: mapping of complete distribution feeders clearly depicting the various parameters such as nominal voltage, the length of the cables, installed transformation capacity, the number of the transformation points, the circuit type (underground, aerial, mixed), load being served, etc, compilation of data regarding existing loads, operations conditions, forecast of expected loads etc, estimation of the financial requirements for implementation of the different phases of system improvement works.

The aim of this paper is to describe an approach to evaluate the levels of the power losses considering the loads as fuzzy numbers, with a design to determining the minimum losses configuration of radial distribution networks.

2. Clustering analysis

Data analysis underlies many computing applications, either in a design phase or as part of their on-line operations. Cluster analysis is the organization of a collection of patterns (usually represented as a vector of measurements or a point in a multidimensional space) into clusters based on similarity.

[1] Prof., Power Engineering Department, Technical University "Gh. Asachi" of Iasi, Romania
[2] Lecturer, Power Engineering Department, Technical University "Gh. Asachi" of Iasi, Romania

Clustering is the technique of grouping rows together that share similar values across a number of variables. There are two major methods of clustering: hierarchical clustering and k-means clustering.

In hierarchical clustering the data are not partitioned into a particular cluster in a single step. Instead, a series of partitions takes place, which may run from a single cluster containing all objects to n clusters each containing a single object. Hierarchical clustering is subdivided into *agglomerative* methods, which proceed by series of fusions of the n objects into groups, and *divisive* methods, which separate n objects successively into finer groupings. Agglomerative techniques are more commonly used. Hierarchical clustering may be represented by a two dimensional diagram known as dendrogram which illustrates the fusion or divisions made at each successive stage of analysis. Hierachical clustering is appropriate for small tables, up to several hundred rows. Several agglomerative techniques are single linkage clustering, complete linkage clustering, average linkage clustering, centroid method and Ward's hierarchical clustering method.

Differences between methods arise because of the different ways of defining distance (or similarity) between clusters.

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids shoud be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycenters of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. Finally, these algorithms aim at minimizing an objective function, in this case a squared error function.

3. Characterizing of the distribution feeders by clustering techniques

The data about the primary characteristics of the feeders were updated and prepared for the grouping process, including the selection of the variables for a total of 44 feeders belonging to the electrical utility, Fig. 1.

In function of the primary characteristics (the total length of the distribution feeders and the installed power of the transformers), the feeders are divided in representative groups, using a statistical clustering method (centroid method).

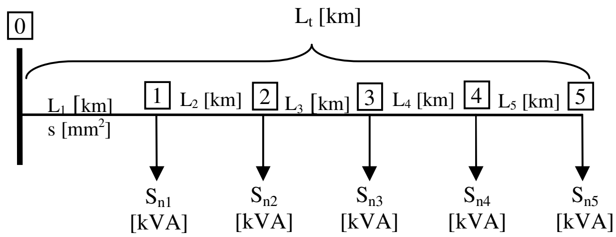

Fig. 1. Simplified representation of a feeder

In this case, the installed power of the feeder is defined as the sum of the nominal power of the transformers served by the respective feeder:

$$S_i^d = \sum_{j=1}^{N_{PT}} S_{nj}^d \; ; \qquad d = 1, \dots , N_d \tag{1}$$

where: S_i^d – installed power of the feeder d, S_{nj}^d – nominal power of a transformer j served by the feeder d, N_{PT} – total number of the transformers served by the feeder d, N_d – total number of feeders in the data base ($N_d = 44$, in this case).

Thus, the eight groups of the distribution feeders were determined, Fig. 2 [2, 3, 7].

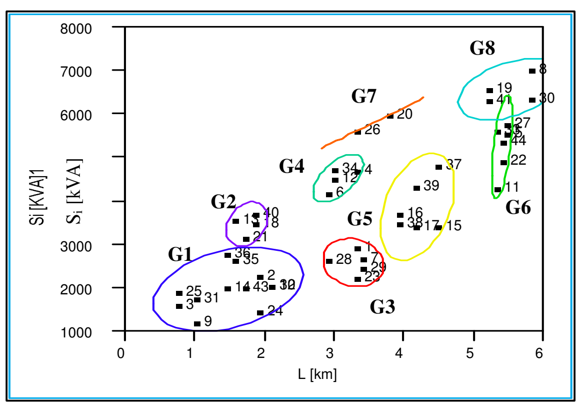

Fig. 2. Result of the grouping of the feeders

In the Table 1 are indicated the average values and the standard deviations corresponding the total length (L) and the installed power (S_i), for the eight groups of feeders.

Using the fuzzy modeling based on the clustering techniques, [2, 3] we defined the following linguistic categories: for the length (L), **Low (LL)**, **Medium (ML)** and **High (HL)**, and for the installed power (S_i), **Low (LS)**, **Medium (MS)** and

High (HS). Thus each group will be characterized by a linguistic category of these primary variables, Fig. 3 and Fig. 4.

Table 1

The average values and the standard deviations for L and S_i

Group	Length (L) [km]		Installed Power (S_i) [kVA]	
	m_L	d_L	m_{Si}	d_{Si}
G1	1.492	0.501	1975	452.33
G2	1.765	0.139	3447.5	239.08
G3	3.289	0.202	2590	259.33
G4	3.077	0.169	4535	255.93
G5	4.214	0.248	3870	575.95
G6	5.427	0.069	3477.5	239.08
G7	3.568	0.344	5805	275.77
G8	5.537	0.343	6577.5	327.65

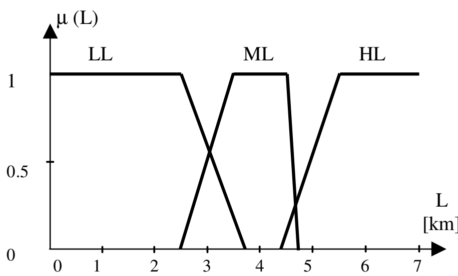

Fig. 3. μ (L) membership functions

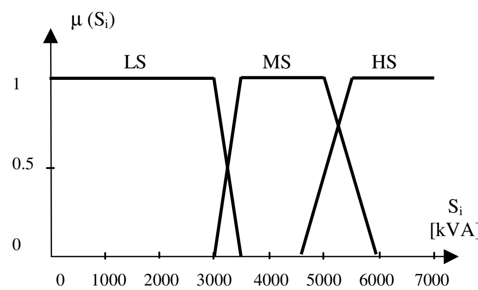

Fig. 4. μ (S_i) membership functions

For example, the first group, G1, is characterized by LL, for length, and LS, for installed power.

4. Modeling of the distribution network loads using fuzzy techniques

The main difficulties in modeling of loads at receiving buses in distribution systems result from the random nature of loads, diversification of load shapes on different parts of the systems, the deficiency of measured data and the fragmentary and uncertain character of information on loads and customers.

The fuzzy models can be used to represent the uncertain knowledge about load behavior either for active and reactive powers. If for some substations there are sufficient database, for a good forecasting of the load, for the other substations the forecasting of the load can be make using the correlation study [1 - 3].

For modeling of the loads in the distribution systems, two fuzzy variables are considered: the loading factor kI (%) and power factor cosφ, so that the fuzzy representation of the active and reactive powers result from relations [1 - 3, 7]:

$$P = \frac{kI}{100} \cdot S_n \cdot \cos\varphi, \quad Q = P \cdot \tan\varphi \tag{2}$$

where S_n [kVA] is the nominal power of the distribution transformer from the distribution substations.

The fuzzy variables, kI and cosφ, are associated to trapezoidal membership functions. The two fuzzy variables must be correlated, just like that fuzzy variables P and cosφ.

Because the most electric utilities have not historical records of the loads, in the distribution substations, linguistic categories are used. Therefore, the variables kI and cosφ were divided into five linguistic categories and the active losses will be calculated for each one of these, [1 - 3, 7]:

- **Very Small – VS**: kI – VS and cosφ – VS;
- **Small – S**: kI – S and cosφ – S;
- **Medium – M**: kI – M and cosφ – M;
- **High – H**: kI – H and cosφ – H;
- **Very High – VH**: kI – VH and cosφ – VH.

Table 2

Loading levels as function of kI and cosφ

Linguistic Declaration		x		Linguistic Declaration		x	
		kI(%)	cos φ			kI(%)	cos φ
VS	x_1	10	0.75	M	x_3	55	0.87
	x_2	10	0.77		x_4	65	0.89
	x_3	15	0.79	H	x_1	55	0.87
	x_4	25	0.81		x_2	65	0.89
S	x_1	15	0.79		x_3	75	0.91
	x_2	25	0.81		x_4	85	0.93
	x_3	35	0.83	VH	x_1	75	0.91
	x_4	45	0.85		x_2	85	0.93
M	x_1	35	0.83		x_3	95	0.95
	x_2	45	0.85		x_4	95	0.97

For the loading levels considered in Table 2, the statistical characteristics for the power losses were calculated. Using these information, for the power losses (dP) five linguistic categories were defined, applying the fuzzy modeling based on the clustering techniques, Fig. 5: **Very Small** – **VS_dP** (6 – 20 kW), **Small** – **S_dP** (15 – 35 kW), **Medium** – **M_dP** (35 – 60kW), **High** – **H_dP** (55 – 105 kW) and **Very High** – **VH_dP** (95 – 160 kW).

Using the fuzzy rules with respect to the linguistic description of the inputs, (length, installed power and loading level), it is possible to evaluate the power losses [1 - 3, 7].

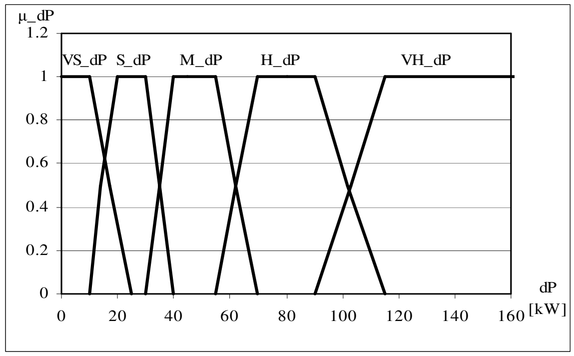

Fig. 5. Membership functions for dP

5. Optimal reconfiguration of the distribution networks

Distribution systems should operated at minimum cost, subject to a number of constraints: radial configuration, all loads are served, lines, transformers, and other equipment operate within current capacity limits, overcurrent protective devices are coordinated and voltage magnitudes are within limits.

Distribution feeders are usually radial to simplify overcurrent protection. To help restore power to customers following a fault, most feeders have several interconnecting tie switches to neighboring feeders. Configuration alternations may be performed by changing the status of network switches (open/close), in such a way that radiallity is always re-established after the operations are completed.

Network reconfiguration can also be used in planning studies, in order to determine the optimal configuration of the network during the overall planning procedure.

Since a typical distribution system may have hundreds of switches, a combinatorial analysis of all possible options is not a practical solution. Therefore, most of the algorithms in literature are based on heuristic search techniques, using either analytical or knowledge-based engines.

The proposed solution method starts with a meshed distribution network obtained by considering all switches closed. Then, the switches are opened successively to eliminate the loops. The opening criterion is based on minimum total power loss increase, and is determined using a power-flow program. A refinement on the above procedure is made using the branch exchange technique, involving neighboring open switches.

These methods allow finding a solution after a relatively small number of searches. The improved configuration can be found through branch exchange so that the radial structure is kept and the active losses are diminished. This method is known as the “branch exchange” method [1, 11-13].

The algorithm starts with the calculation of the active losses for the initial configuration (meshed). The next step is to generate all possible configurations for the network by permuting each branch of the network. The one with the least difference between it and the initial configuration is selected (if such a configuration exists). This becomes the next variant and the network is reconfigured. The final solution is obtained when the current schema can’t be improved any more [16].

For example, in Fig. 6 a comparison between the average power losses in the cable and the average power losses in the feeders, for the group G6, as function of loading levels it is presented. In Fig. 7 it is presented the influence of the sectors on the average power losses in cable, for each feeder from G6.

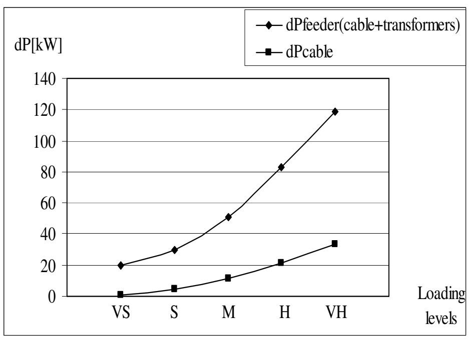

Fig. 6. Average power losses in the cable vs. feeders, group G6

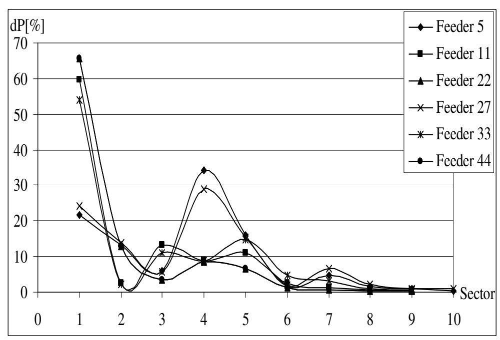

Fig.7. Power losses for feeders of the group G6

Table 3

Power losses by sector with branch exchange for Feeder 22 (group G6)

Sector	dPsector [%dPcable]		
	Case a	Case b	Case c
	Feeder 22 dPcable= 13.1975kW	Feeder 22-Sector 9 dPcable=8.7325kW	Feeder 22+Sector 9 dPcable=18.83kW
1	65.3798	68.9693	62.202
2	13.0839	13.3781	12.727
3	3.4002	3.2407	3.4678
4	8.6834	7.7984	9.2103
5	6.5599	5.1588	7.5292
6	1.3733	0.953335	1.6901
7	0.6194	0.3492	0.8311
8	0.4622	0.13741	0.7873
9	0.4508		1.2453
10			0.3159

For the feeder 22 (case a), of the group G6, we considered another two cases, case b: sector 9 – disconnected and case c: sector 10 (identical with sector 9) – connected, and we calculated the power losses for these cases and compared them. The results are shown in Table 3.

6. Conclusions

By using the heuristic "branch exchange" method, the area of studied variants is narrowed. In addition, the method was improved by considering the loads as fuzzy numbers that reflects better the vagueness about the power demand in distribution networks.

REFERENCES

1. *Gh. Cârţină*, *Y-H Song*, *Gh. Grigoraş*, Optimal Operation and Planning of Power Systems, Casa de Editură VENUS, Iaşi, 2003.
2. *Gh. Cârţină*, Improving of Fuzzy Models by Clustering Techniques Applications in Power Systems, Proc. of the 28th International Conference on Fundamentals of Electrotechnics and Circuit Theory, IC-SPETO'05, **vol. 1**, Gliwice-Ustron, Polonia, 2005, pp. 7a-7h.
3. *Gh. Cârţină*, *Gh. Grigoraş*, *E.C.Bobric*, Tehnici de clustering în modelarea fuzzy. Aplicaţii în electroenergetică, Casa de Editură VENUS, Iaşi, 2005.
4. *G. Chicco*, *R. Napoli*, *F. Piglione*, *P. Postolache*, *M. Scutariu*, *C. Toader*, A Review of Concepts and Techniques for Emergent Customer Categorization, www.telmark.org/2002Sep/ 2-4_Chicco.pdf.
5. *R. Ciric*, *N. Rajakovic*, Restoration of Radial Distribution Networks, European Transaction on Electrical Power, **vol. 7**, no. 1, 1997, pp. 27-34.
6. *F. V. Gomes*, *S. Carneiro*, *J. L. R. Pereira*, *M. P. Vinagre*, *P.A.N. Garcia*, *L.R. Arauj,* A new Heuristic Reconfiguration Algorithm for Large Distribution Systems, IEEE Trans. on Power Systems, **vol. 20**, no. 3, 2005, pp. 1373-1378.
7. *Gh. Grigoraş*, *V. Alexandrescu*, *Gh. Cârţină*, Energy Losses Computation in Distribution Systems using Fuzzy Techniques, International World Energy System Conference, Oradea, 2004, pp. 302-305.
8. *A.K. Jain*, *M.N. Murty*, *P.J. Flynn*, Data Clustering: A Review, www.cermics.enpc.fr/~keriven/vision/ articles.
9. *** JMP Statistics and Graphics Guide, Version 3, SAS Institute Inc., Cary, NC, USA, 1999.
10. *H.M. Khodr*, *J. Molea*, *I. Garcia*, *C. Hidalgo*, *P.C. Paiva*, *J.M. Yusta*, Standard Levels of Energy Losses in Primary Distribution Circuits for SCADA Applications, IEEE Trans. on Power Systems, **vol. 17**, no.3, 2002,pp. 615 - 620.
11. *G.J. Peponis*, *M.P. Papadopulos*, *N.D. Hatziargyriou*, Optimal Operation of Distribution Networks, IEEE Trans. on Power Systems, **vol.** 11, no. 1, 1996, pp. 59- 65.
12. *R. Taleski*, *D. Rajicic*, Distribution Network Reconfiguration for Energy Loss Reduction, IEEE Trans. on Power Systems, **vol.** 12, no. 1, 1997, pp. 398 - 406.
13. *C.J. Wang*, *H.D. Chiang*, *G. R. Darling*, An Efficient Algorithm for Real-Time Network Reconfiguration in Large Scale Unbalanced Distribution Systems, IEEE Trans. on Power Systems, **vol. 11**, no. 1, 1996, pp. 51-56.
14. *** Clustering: An introduction, www.elet.polimi.it/ upload /matteucc/ Clustering/tutorial_html.
15. *** Hierarchical Clustering, www.resample.com/ xlminer/ help/HClst/ HClst.intro.html.
16. *Gh. Cârţină*, *Grigoraş Gh.*, *E.C. Bobric*, *C. Lupaşcu*, Improving of Fuzzy Models by Clustering Techniques in Optimal Reconfiguration of the Distribution Networks, International World Energy System, Torino, 2006, CD-ROM.