

Modified Fuzzy Clustering Method for Energy Loss Calculations in Low Voltage Distribution Networks

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Introduction

Determination of electrical energy losses in low voltage distribution networks is very important for any electrical utility. The proper calculation of energy losses is one of the most complex problems in power distribution systems analysis, demanding consideration of many factors. The accessibility and credibility of data used in calculations is of the greatest importance here.

The accessibility and credibility of parameter's database are very low for low voltage networks. This problem can be solved by further involvement on reviewing database. The other very difficult problem is small number of measurements in low voltage networks. Therefore, the data about low voltage loadings does not exist. The delivered energies and peak loadings of distribution transformers, are usually the only available measured data.

The problem of losses calculation is simplified in [1,2] classifying low voltage networks in two groups: town's and village's. Regression method is also proposed in [2] for calculation of losses in low voltage networks. Fuzzy arithmetic [3], clustering and fuzzy clustering techniques are used for calculation of energy losses in medium voltage distribution networks [4, 5, 6].

A method for energy loss calculations in low voltage distribution networks is developed in this paper. The method is based on the modified fuzzy clustering technique. Process of clustering is made on a space consisting of objects with following attributes: lengths of lines, number of line segments, number of customers, conductor's cross section area, conductor's material, electrical energy delivered by distribution transformers and load factors.

Fuzzy Clustering Algorithm

Clustering is one of the most fundamental issues in pattern recognition. Given a finite set of data X , the problem of clustering is to find several cluster centres that

can properly characterize relevant classes of X . In classical cluster analysis, these classes are required to form a partition of X such that degree of association is strong for data within blocks of the partition. When the requirement of a crisp partition of X is replaced with a weaker requirement of a fuzzy partition or a fuzzy pseudopartition of X , we refer to the emerging problem area as fuzzy clustering [3]. Fuzzy pseudopartitions are often called fuzzy c partition, where c designates the number of fuzzy classes in the partition. There are two basic methods of fuzzy clustering. One of them, which is based on fuzzy c partitions, is called fuzzy c -means clustering method.

Let $X = \{x_1, x_2, \dots, x_n\}$ be a set of given data. A fuzzy pseudopartition or fuzzy c partition of X is a family of fuzzy subsets of X , denoted by $P = \{A_1, A_2, \dots, A_c\}$ which satisfies:

$$\sum_{i=1}^c A_i(x_k) = 1, \quad k \in N_n, \quad (1)$$

for $N_n = \{1, 2, \dots, n\}$, and

$$0 < \sum_{k=1}^n A_i(x_k) < n \quad i \in N_c, \quad (2)$$

where c is positive integer and N_c set of integers $N_c = \{1, 2, \dots, c\}$. Given a set of data $X = \{x_1, x_2, \dots, x_n\}$, where x_k in general is a vector:

$$x_k = [x_{k1}, x_{k2}, \dots, x_{ka}] \in R^a \quad (3)$$

for all $k \in N_n$, the problem of fuzzy clustering is to find a fuzzy pseudopartition and associated cluster centres by which the structure of the data is represented as best as possible.

The c -means algorithm is based on the assumption that the desired number of clusters c is given and, in addition, a particular distance, a real number $m \in (1, \infty)$,

and a small positive number ε , serving as a stopping criterion, are chosen. The algorithm consists of four steps:

Step 1.

Let $t = 0$. Select an initial fuzzy pseudopartition $P^{(0)}$.

Step 2.

Calculate the c cluster centers $v_1^{(t)}, \dots, v_c^{(t)}$ by relation:

$$v_i = \frac{\sum_{k=1}^n [A_i(x_k)]^m x_k}{\sum_{k=1}^n [A_i(x_k)]^m} \quad (4)$$

for $P^{(t)}$ and the chosen value of m .

Step 3.

Update $P^{(t+1)}$ by the following procedure: For each $x_k \in X$, if $\|x_k - v_i^{(t)}\|^2 > 0$ for all $i \in N_c$, then define

$$A_i^{(t+1)}(x_k) = \left[\sum_{j=1}^c \left(\frac{\|x_k - v_i^{(t)}\|^2}{\|x_k - v_j^{(t)}\|^2} \right)^{\frac{1}{m-1}} \right]^{-1}. \quad (5)$$

If $\|x_k - v_i^{(t)}\|^2 = 0$ for some $i \in I \subseteq N_c$, then define

$A_i^{(t+1)}(x_k)$ for $i \in I$ by any non-negative real numbers satisfying

$$\sum_{i \in I} A_i^{(t+1)}(x_k) = 1, \quad (6)$$

and define $A_i^{(t+1)}(x_k) = 0$ for $i \in N_c - I$.

Step 4.

Compare $P^{(t)}$ and $P^{(t+1)}$. If $|P^{(t+1)} - P^{(t)}| \leq \varepsilon$, then stop; otherwise, increase t by one and return to Step 2.

In Step 4, $|P^{(t+1)} - P^{(t)}|$ denotes a distance between $P^{(t+1)}$ and $P^{(t)}$ in the space $R^{n \times c}$. An example of this distance is

$$|P^{(t+1)} - P^{(t)}| = \max_{i \in N_c, k \in N_n} |A_i^{(t+1)}(x_k) - A_i^{(t)}(x_k)|. \quad (7)$$

For energy loss calculations in low voltage distribution networks we have developed a modified c -means method. Modification of fuzzy c -means method is using of known cluster centres. Therefore, algorithm has only three steps (Step 2 of presented algorithm is not comprehended), and if inequality into Step 4 is not satisfied, we should return to Step 3.

Table 1. Input database for 60 test networks

Test network	Number of sections	Line length [m]	S_p max [mm]	S_n max [mm]	S_p min [mm]	S_n min [mm]	Material of conductor	Delivered energy W [kWh]	T_m [h]	ΔW [%]
1	24	815	35	35	16	16	Al	109021	2632.7	3.375
2	24	670	70	70	10	10	Al	162374	2060.5	2.371
3	25	920	50	50	25	25	Al	184620	1212.4	4.675
4	28	765	70	70	16	16	Al	191987	4684.9	2.758
5	4	90	150	150	6	6	Cu	246451	3638	0.55
6	28	2005	70	70	10	10	Al	105591	4766.4	9.048
7	24	1325	50	50	16	16	Al	134996	2853.7	8.016
8	50	1435	70	70	10	10	Al	280943	2104.2	4.631
9	37	1445	70	70	10	10	Al	226103	2721.4	6.949
10	23	640	70	70	6	6	Al	230611	4385.4	3.131
11	26	665	70	70	10	10	Al	147180	3864.0	1.249
12	24	1055	50	50	25	25	Al	63065	1615.2	2.391
13	43	1140	30	30	10	10	Al	382195	6028.6	7.546
14	33	1865	50	50	10	10	Al	89099	2627.9	5.068
15	17	640	70	70	10	10	Al	40852	2736.0	0.459
16	27	815	25	25	10	10	Al	43278	4069.7	0.748
17	10	455	35	35	10	10	Al	45039	3727.5	0.493
18	8	695	35	35	25	25	Al	32361	1361.7	2.143
19	6	205	25	25	10	10	Al	35914	1147.0	2.593
20	8	66.8	95	95	95	95	Al	216714	2715.0	0.224
21	25	920	50	50	25	25	Al	184648	1239.8	4.794
22	6	67	95	95	95	95	Al	159202	3794.7	0.448
23	12	568	95	95	25	25	Al	159976	1410.7	4.359
24	4	1190	25	25	25	25	Al	46898	2575	4.17
25	5	1410	25	25	25	25	Al	50733	2380	4.76
26	3	2680	25	25	25	25	Al	52970	1941	11.17
27	11	6315	35	35	25	25	Al	225020	7738	20.41
28	8	5130	35	35	25	25	Al	196906	4824	38.79
29	1	290	50	50	50	50	Cu	60599	1358	1.11
30	3	160	150	150	70	70	Cu	203882	5518	0.50
31	2	135	150	150	95	95	Cu/Al	131338	5171	0.40
32	1	20	16	16	16	16	Cu	63430	3272	0.68
33	5	1040	25	25	16	16	Al	80056	3196	19.79
34	8	2225	25	25	16	16	Al	64009	2620	16.05
35	3	156	35	35	35	35	Cu	149042	2273	1.40
36	1	85	70	70	70	70	Al	51901	1812	0.35
37	13	1850	35	35	25	25	Al	66414	3647	2.74
38	3	45	150	150	50	50	Cu	752115	6250	0.34
39	1	10	120	120	120	120	Al	77935	887	0.05
40	1	550	25	25	25	25	Al	32236	5494	11.68
41	3	1290	25	25	25	25	Al	25536	2790	1.73
42	6	2940	25	25	25	25	Al	117494	2491	25.46
43	1	70	70	70	70	70	Cu	98528	2484	0.28
44	2	380	50	71.5	50	71.5	Al	91949	1959	2.15
45	3	910	70	71.5	25	25	Al	72514	1635	3.50
46	3	1440	25	25	25	25	Al	70219	7297	6.11
47	7	2080	50	50	25	25	Cu/Al	269400	5690	11.84
48	4	1050	70	70	25	25	Cu/Al	131606	3834	9.42
49	6	1050	35	35	35	35	Al	138332	3770	12.39
50	6	1250	35	35	16	16	Al	93512	3039	6.47
51	3	1040	50	50	25	25	Cu/Al	131612	2780	7.03
52	3	1100	35	35	25	25	Al	118829	2510	12.60
53	1	250	70	70	70	70	Al	304431	8297	6.26
54	1	200	70	70	70	70	Cu	293935	8010	2.91
55	12	2170	35	35	25	25	Al	58023	2985	3.31
56	2	334	70	70	70	70	Cu	79494	1948	0.75
57	3	165	70	70	25	25	Cu/Al	100316	1926	0.51
58	12	1570	50	50	25	25	Al	43549	1915	3.70
59	13	910	50	50	25	25	Al	367256	6125	8.68
60	7	2290	35	35	16	16	Al	7815	788	2.75

Calculation of Energy Losses

Presented fuzzy clustering algorithm and its modification can be used for energy loss calculations in low voltage distribution networks. Following steps should be made for set of N_n low voltage networks:

Step 1

Select N_t test networks. Make additional measurements that enable to determine technical losses for test networks using well known methods.

Step 2

Form a space consisting of N_t objects. Any object has N_a attributes, whereat value of energy losses is one attribute (absolute or percentage).

Step 3

Calculate cluster centres for chosen number of clusters c and real number $m \in (1, \infty)$. Store objects that represent cluster centres in memory.

Step 4

Form a spice that consists of $N_n - N_t$ objects. Any object has $N_a - 1$ attributes because of energy losses are not considered as attribute.

Step 5

Determine pseudopartition of formed space by the modified c -means method for cluster centres determined in step 3 (energy losses attributes of cluster centres are not considered).

Table 2. Input database for 90 low voltage networks for which we will calculate losses

network	Number of sections	Line length [m]	S_p max [mm]	S_n max [mm]	S_p min [mm]	S_n min [mm]	Material of conductor	Delivered energy W [kWh]	T_m [h]	ΔW [%]	network	Number of sections	Line length [m]	S_p max [mm]	S_n max [mm]	S_p min [mm]	S_n min [mm]	Material of conductor	Delivered energy W [kWh]	T_m [h]	ΔW [%]
1	8	2225	25	25	16	16	Al	64009	2620	16.05	46	23	640	70	70	6	6	Al	230611	4385.4	3.131
2	34	1080	70	70	10	10	Al	180388	2905.0	1.213	47	1	20	35	35	35	35	Cu	55460	3228	0.83
3	6	2940	25	25	25	25	Al	117494	2491	25.46	48	1	20	120	120	120	120	Al	128106	2815	0.08
4	34	1080	70	70	10	10	Al	260231	3095.2	1.913	49	4	80	140	140	50	50	Cu	656249	2695	0.59
5	8	5130	35	35	25	25	Al	196906	4824	38.79	50	24	815	35	35	16	16	Al	109021	2632.7	3.375
6	46	1215	70	70	16	16	Al	246170	3202.1	3.038	51	1	180	70	70	70	70	Cu	65114	2600	1.38
7	8	695	35	35	25	25	Al	32361	1361.7	2.143	52	3	1440	25	25	25	25	Al	70219	7297	6.11
8	38	2130	50	50	10	10	Al	183465	3006.3	6.113	53	8	2090	25	25	25	25	Al	45457	2073	23.30
9	1	200	70	70	70	70	Cu	293935	8010	2.91	54	12	568	95	95	25	25	Al	159976	1410.7	4.359
10	1	20	16	16	16	16	Cu	63430	3272	0.68	55	8	66.8	95	95	95	95	Al	216714	2715.0	0.224
11	6	67	95	95	95	95	Al	159202	3794.7	0.448	56	17	640	70	70	10	10	Al	40852	2736.0	0.459
12	1	70	70	70	70	70	Cu	98528	2484	0.28	57	3	810	25	25	25	25	Al	73401	5487	9.37
13	24	695	70	70	35	35	Al	131899	1875.7	2.530	58	5	1300	35	35	25	25	Al	92489	5118	11.29
14	21	495	50	50	25	25	Al	74334	1737.7	1.825	59	5	1210	25	25	25	25	Al	67497	3940	8.86
15	3	160	150	150	70	70	Cu	203882	5518	0.50	60	1	40	70	70	70	70	Cu	145969	3769	0.17
16	17	149	95	95	95	95	Al	410521	4845.3	1.154	61	3	1400	50	71.5	35	71.5	Al	236347	3730	8.08
17	1	10	120	120	120	120	Al	77935	887	0.05	62	2	570	25	25	25	25	Al	10696	3255	2.04
18	30	665	35	35	16	16	Al	43673	2575.0	1.064	63	1	110	50	50	50	50	Cu	65819	2983	0.41
19	15	540	50	50	10	10	Al	30640	2552.0	1.125	64	1	130	70	70	70	70	Cu	200634	2714	1.01
20	2	380	50	71.5	50	71.5	Al	91949	1959	2.15	65	4	710	50	71.5	35	71.5	Al	202955	2686	3.48
21	28	2005	70	70	10	10	Al	105591	4766.4	9.048	66	24	670	70	70	10	10	Al	162374	2060.5	2.371
22	7	2080	50	50	25	25	Cu/Al	269400	5690	11.84	67	24	1055	50	50	25	25	Al	63065	1615.2	2.391
23	23	750	35	35	10	10	Al	89801	3748.3	1.351	68	2	410	25	25	10	10	Cu	58872	2344	2.29
24	3	45	150	150	50	50	Cu	752115	6250	0.34	69	2	690	50	71.5	50	71.5	Al	129307	2204	3.88
25	6	1050	35	35	35	35	Al	138332	3770	12.39	70	10	455	35	35	10	10	Al	45039	3727.5	0.493
26	26	665	70	70	10	10	Al	147180	3864.0	1.249	71	1	290	50	50	50	50	Cu	60599	1358	1.11
27	1	85	70	70	70	70	Al	51901	1812	0.35	72	3	156	35	35	35	35	Cu	149042	2273	1.40
28	19	571	50	50	25	25	Al	124494	1190.3	0.393	73	5	1950	25	25	25	25	Al	66814	797	10.86
29	6	39	95	95	95	95	Al	120109	5261.7	0.132	74	6	205	25	25	10	10	Al	35914	1147.0	2.593
30	3	770	35	50	25	25	Al	182613	4138	6.64	75	1	400	120	120	120	120	Al	296955	3920	3.32
31	4	170	95	95	95	95	Cu	200768	3854	0.47	76	2	1080	25	25	25	25	Al	109839	3866	11.54
32	1	360	70	70	70	70	Al	114811	3278	2.60	77	25	920	50	50	25	25	Al	184648	1239.8	4.794
33	1	90	35	50	35	50	Al	62691	2086	0.71	78	2	135	150	150	95	95	Cu/Al	131338	5171	0.40
34	3	2680	25	25	25	25	Al	52970	1941	11.17	79	1	350	120	120	120	120	Al	148842	1849	2.06
35	28	765	70	70	16	16	Al	191987	4684.9	2.758	80	1	320	25	25	25	25	Al	60668	1464	4.49
36	3	910	70	71.5	25	25	Al	72514	1635	3.50	81	50	1435	70	70	10	10	Al	280943	2104.2	4.631
37	43	1140	30	30	10	10	Al	382195	6028.6	7.546	82	1	200	150	150	150	150	Al	79848	5328	0.77
38	3	1040	50	50	25	25	Cu/Al	131612	2780	7.03	83	12	1880	25	25	25	25	Al	141541	4041	7.54
39	3	100	150	150	70	70	Cu	221679	5092	0.24	84	5	460	70	70	35	35	Cu	83812	3813	0.34
40	3	200	50	50	50	50	Cu	526029	4967	4.95	85	1	120	70	70	70	70	Cu	233238	2637	0.92
41	6	1760	25	25	16	16	Al	184644	4762	14.33	86	13	3936	25	25	25	25	Al	46927	2346	8.80
42	3	170	95	95	95	95	Cu	251863	4731	0.90	87	16	5500	25	25	25	25	Al	44849	2324	7.99
43	1	100	70	70	70	70	Cu	256222	4344	0.71	88	1	80	70	70	70	70	Cu	93062	2109	0.28
44	3	160	120	120	50	50	Cu/Al	879374	4013	2.34	89	11	1730	25	25	25	25	Al	45045	2059	6.20
45	4	90	150	150	6	6	Cu	246451	3638	0.20	90	18	925	35	35	25	25	Al	154758	1707	3.40

Step 6

Calculate absolute or percentage energy losses for any low voltage network summing the memberships values multiplied by the attributes of corresponding centre of cluster that represent energy losses.

The following questions required answer:

- What is optimal number of clusters?
- What is optimal value of real number m ?
- Which attributes do we consider in analyses?

These questions have do not have unique solution, and as will be seen from the following example, answers depend on accessibility of input data.

Test Example

Presented method is applied for energy loss calculation on the set of real low voltage networks, for which the measuring data is available. At first we select 60 test networks from this set of networks by generating random numbers. The input data for test networks is shown in Table 1.

The following data is comprehended in analysis:

1. Number of line sections;
2. Maximal median cross section area of line $(3 \cdot S_{p\max} + S_{n\max})/4$;

3. Minimal median cross section area of line $(3 \cdot S_{p\min} + S_{n\min})/4$;
4. Resistivity of conductor's material,
5. Energy delivered by distribution transformers W ,
6. load factor ($LF = T_m/8760$).

where S_p and S_n are cross section areas of phase and neutral conductors respectively.

For this set of test networks we determined cluster centres for 23 different combinations of parameter m (1.05-1.75), number of clusters (6-20), and chosen data set comprehended in analysis (selection 1,2 or 3). Selection 1 comprehend all accessible data. Selection 2 does not comprehend resistivity of conductors, and selection 3 does not comprehend load factors.

Table 2 gives data for 90 networks for which we will calculate energy losses. The column $\Delta W\%$ of the Table 2 gives the measured percentage losses. We will compare losses calculated using presented method with losses given in this column in order to show applicability of the method. Total energy losses (for all 90 networks) determined from measuring are 3.81%. Table 3 shows results of calculation for second and third selection of input data and different number of clusters as well as different values of parameter m .

Table 3. Results of energy loss calculations for selections 2 and 3 of input data

m	selection 2						selection 3					
	1.05			1.2			1.05		1.2		1.4	
	cl. num.	6	12	20	10	15	20	10	20	12	20	12
1	6.36	14.4	16.8	16.4	20.4	17.4	15.6	18.1	16.0	9.79	15.6	13.7
2	3.52	4.54	3.20	3.55	4.50	3.15	4.45	2.55	3.28	3.09	3.31	3.15
3	6.36	14.5	25.5	16.3	18.9	17.6	15.6	18.1	15.4	25.4	13.5	25.5
4	3.52	4.54	3.20	3.56	4.50	3.13	4.45	5.25	3.28	3.68	3.32	3.70
5	29.3	32.1	38.8	29.6	29.6	38.8	29.6	38.8	29.6	38.8	29.5	29.5
6	3.52	4.54	3.20	3.56	4.50	3.13	4.45	5.25	3.28	3.68	3.32	3.70
7	6.33	1.93	2.78	3.87	2.39	2.85	3.29	12.0	3.57	2.00	3.45	7.02
8	6.34	4.88	9.29	13.2	8.06	6.23	6.15	6.73	5.04	6.55	6.62	7.00
9	2.01	3.17	4.59	4.58	4.59	4.59	1.19	2.91	1.19	1.31	1.28	1.29
10	6.36	1.93	0.64	4.39	2.19	0.67	1.19	1.06	1.22	1.06	1.84	1.05
11	0.47	0.32	0.24	0.24	0.24	0.24	1.89	0.24	0.24	0.24	0.27	0.62
12	0.47	0.93	0.93	0.93	0.93	0.93	1.19	0.52	1.19	1.31	1.21	1.26
13	3.52	2.63	2.24	3.46	2.63	2.29	4.45	2.55	3.28	2.48	3.59	2.93
14	3.52	2.63	2.78	3.81	2.64	2.87	3.29	12.2	3.84	3.11	4.43	6.37
15	2.01	0.32	0.50	0.41	0.45	0.45	0.42	0.50	0.42	0.50	0.48	0.50
16	2.01	0.38	0.25	0.77	0.96	1.10	1.89	6.12	0.35	4.55	0.99	0.90
17	0.47	0.32	0.24	0.24	0.24	0.24	0.05	0.24	0.24	0.24	0.29	0.06
18	6.36	1.93	3.55	3.84	2.17	8.24	3.29	3.18	3.57	1.90	3.40	1.96
19	3.52	1.93	3.65	3.86	2.87	5.71	3.29	3.33	3.80	2.22	4.38	3.94
20	3.52	0.93	0.93	0.93	0.93	0.93	1.89	1.25	2.92	1.25	2.86	2.48
21	6.91	4.54	9.23	6.42	4.52	9.18	4.45	6.73	3.97	6.43	4.66	5.50
22	6.91	9.36	9.69	6.45	9.34	11.8	7.20	11.8	7.19	9.43	7.14	11.8
23	6.36	1.93	0.64	4.24	3.65	0.97	3.29	3.19	3.58	1.91	3.62	2.40
24	2.01	3.17	0.34	0.43	0.34	0.34	0.42	0.34	0.42	0.34	0.34	0.34
25	6.36	14.4	9.30	8.71	6.67	14.8	6.12	12.2	7.44	12.8	7.13	12.8
26	3.56	4.54	3.20	3.67	4.50	3.47	4.45	2.55	3.28	2.45	3.32	2.47
27	0.47	0.93	0.93	0.93	0.93	0.93	1.89	1.25	2.92	1.25	2.81	2.40
28	3.52	2.63	2.78	3.79	2.64	2.86	4.30	12.2	3.95	4.87	4.64	6.94
29	1.82	0.32	0.26	0.53	0.55	0.63	1.89	0.24	0.24	0.24	0.27	0.62
30	6.91	7.91	9.30	4.59	5.98	13.2	3.32	12.2	4.79	8.17	5.84	11.0
31	0.47	0.32	0.24	0.24	0.24	0.24	1.19	2.39	1.14	1.31	1.26	1.28
32	0.47	0.93	0.93	0.93	0.93	0.94	1.89	1.25	2.92	1.25	2.81	2.40
46	6.91	4.54	3.20	6.38	4.50	3.15	4.45	2.55	3.28	3.64	3.32	3.46
47	6.35	1.93	0.77	4.29	2.26	8.20	1.19	1.06	1.19	1.06	1.23	1.05
48	0.47	0.32	0.24	0.24	0.24	0.24	0.05	0.24	0.24	0.24	0.28	0.06
49	2.00	0.34	0.34	0.53	0.45	0.46	0.42	0.34	0.42	0.34	0.34	0.34
50	6.36	1.93	9.30	3.85	2.20	8.66	3.29	11.8	3.58	2.04	3.61	7.53
51	0.47	0.93	0.93	0.93	0.93	0.93	1.19	0.52	1.19	1.31	1.21	1.26
52	6.91	8.90	8.90	4.53	8.90	6.11	15.6	3.17	15.9	14.0	14.7	4.33
53	6.36	14.3	4.38	16.2	16.4	16.9	15.6	18.1	16.1	5.33	15.9	12.3
54	3.52	2.63	2.24	3.52	2.67	2.29	4.45	2.55	3.28	2.47	3.48	2.83
55	0.47	0.32	0.24	0.24	0.24	0.24	1.89	0.24	0.24	0.24	0.28	0.62
56	3.52	2.63	2.24	3.55	2.67	2.36	4.45	2.55	3.32	2.46	3.84	2.68
57	6.91	8.90	8.90	4.10	8.9	11.7	3.29	12.2	3.57	7.39	3.43	13.1
58	6.91	8.90	8.89	4.11	8.84	11.6	3.29	3.17	9.70	13.3	7.95	9.97
59	6.36	14.4	2.11	4.85	7.15	12.3	4.56	3.20	3.81	14.0	5.09	10.6
60	0.47	0.93	0.93	0.96	0.99	1.12	1.19	0.52	1.19	1.31	1.21	1.26
61	6.70	4.54	8.98	6.44	5.73	7.81	4.45	6.08	5.28	6.05	5.82	6.28
62	6.36	1.93	0.64	4.91	2.17	1.87	3.29	11.8	3.57	2.05	3.52	5.23
63	3.55	0.93	0.93	1.00	1.04	1.58	1.19	1.06	1.19	1.08	1.19	1.25
64	0.47	0.93	0.93	0.93	0.93	0.93	1.19	2.91	1.19	1.31	1.21	1.26
65	3.52	1.50	9.19	2.76	3.08	5.21	4.45	1.45	3.07	3.27	3.92	4.68
66	3.52	2.63	2.24	3.55	2.64	2.29	4.45	2.55	3.28	2.45	3.31	2.48
67	3.52	2.66	2.78	3.84	2.93	2.85	3.29	5.82	4.50	6.39	4.81	6.52
68	6.36	1.93	2.73	4.09	2.17	4.30	1.19	1.06	1.23	1.06	1.92	1.06
69	3.52	0.93	0.93	0.93	0.93	0.93	1.89	1.25	2.92	1.25	2.92	2.64
70	6.36	1.93	0.64	4.13	2.45	0.65	3.29	3.30	3.57	1.90	3.6	1.97
71	3.52	0.93	0.93	0.94	0.94	0.97	1.19	1.06	1.19	1.08	1.19	1.25
72	4.79	1.93	2.78	3.99	2.31	9.47	1.19	1.06	1.19	1.06	1.22	1.05
73	6.36	6.71	4.37	8.76	6.86	6.10	15.6	18.1	16.1	6.52	16.2	7.12
74	6.33	1.93	2.78	4.23	2.31	2.93	3.29	7.52	3.58	1.91	3.79	2.30
75	0.52	0.32	0.24	0.25	0.25	0.25	0.05	0.24	0.24	0.24	0.29	0.35
76	6.36	14.3	0.98	5.13	5.91	14.4	8.02	12.2	3.84	14	5.04	13.5
77	3.52	2.63	2.78	3.91	2.72	2.90	4.45	6.73	4.17	6.46	5.19	6.65

Continuation of Table 3

33	4.11	1.93	2.78	2.96	2.18	4.10	3.29	12.2	3.72	2.96	4.42	7.91	78	2.01	0.36	0.40	0.86	0.54	0.55	0.05	0.24	0.25	0.26	0.55	0.11
34	6.36	12.9	25.5	16.1	6.95	17.6	15.6	18.1	15.8	25.4	14.2	14.8	79	0.47	0.32	0.24	0.24	0.24	0.24	0.05	0.24	0.24	0.24	0.28	0.06
35	6.91	4.54	7.43	6.44	4.50	5.92	4.45	2.55	3.28	2.48	3.31	2.59	80	6.35	1.93	2.78	4.05	2.20	2.91	3.29	12.2	3.57	1.95	3.66	5.47
36	3.52	2.63	2.24	3.55	2.63	2.29	4.45	2.55	3.31	2.47	3.80	2.71	81	3.52	2.89	3.19	3.56	4.50	3.13	4.45	5.25	3.29	3.68	3.51	3.70
37	6.91	9.36	9.69	6.43	9.34	8.11	4.79	5.25	8.08	8.11	7.99	8.09	82	2.00	0.32	0.40	0.37	0.44	0.45	0.05	0.24	0.26	0.28	0.76	0.18
38	3.52	4.87	9.30	3.93	6.83	5.94	7.20	8.23	7.19	9.43	7.15	5.81	83	6.36	14.4	17.9	15.7	17.0	11.2	15.6	18.1	16.1	12.8	16.1	8.84
39	2.01	0.32	0.50	0.41	0.45	0.45	0.42	0.50	0.42	0.50	0.49	0.50	84	3.52	4.54	9.23	3.54	4.33	7.72	1.19	0.52	1.19	1.23	1.24	1.38
40	6.91	9.36	8.68	6.14	8.79	8.17	1.19	2.91	1.28	1.37	2.05	2.59	85	0.47	0.93	0.93	0.93	0.93	0.94	1.19	2.91	1.19	1.31	1.23	1.26
41	6.91	10.1	9.73	5.56	10.9	10.7	15.6	18.1	16.0	12.8	14.6	9.64	86	6.36	32.1	25.5	15.4	9.58	17.5	29.0	34.6	21.0	25.6	18.1	23.1
42	1.59	0.32	0.24	0.31	0.33	0.36	1.19	2.91	1.08	1.30	1.27	1.29	87	29.3	32.1	37.3	24.6	15.9	34.5	29.6	38.8	29.6	37.4	29.4	29.1
43	0.47	0.98	0.98	2.02	2.28	3.52	1.19	2.91	1.19	1.31	1.24	1.27	88	0.47	0.93	0.93	0.93	0.93	0.93	1.19	0.52	1.19	1.31	1.21	1.26
44	2.01	3.17	0.34	0.99	0.35	0.35	0.42	0.34	1.05	0.49	1.59	2.24	89	6.36	14.4	4.38	14.5	18.8	4.09	15.6	18.0	16.1	5.99	16.1	3.92
45	2.04	4.13	0.50	1.21	2.29	2.64	0.42	0.50	0.43	0.51	1.33	1.07	90	6.31	2.58	2.78	3.89	3.45	2.90	3.30	12.2	4.38	12.0	5.52	13.0

Table 4. Total percentage losses, number of properly, erroneously or not identified networks with large value of energy losses

Input data set	selection 1						selection 2						selection 3										
	1.05		1.2		1.4		1.75		1.05		1.2		1.05		1.2		1.4						
Number of clusters	6	12	20	10	20	6	12	20	6	12	20	6	12	20	10	15	20	10	20	12	20	12	20
Total percentage losses [%]	4.03	3.86	4.12	3.92	3.63	4.06	3.8	3.98	5.02	4.17	4.92	3.91	4.22	4.15	3.67	3.78	4.35	3.53	4.57	3.45	3.95	3.61	3.97
Number of networks with large value of losses, which are not identified	2	0	0	1	6	1	1	0	0	0	0	1	4	5	6	1	1	7	3	5	0	3	2
Number of networks with large value of losses, which are identified properly	22	24	24	23	18	23	23	24	24	24	23	20	20	18	23	23	17	21	20	24	21	22	22
Number of networks on which large value of losses is erroneously identified	0	1	4	1	0	16	3	0	26	9	16	12	1	5	3	1	9	0	12	0	3	1	10

Table 3 shows only a small piece of results, and authors made analysis for different number of networks. Meanings of different colours in tables 3 and 4 are:

- networks with a large value of electrical losses that are not identified,
- networks with a large value of electrical losses that are identified properly,
- networks for which a large value of electrical losses is identified erroneously.

Table 4 shows calculated total energy losses in percents. Additionally, table shows number of networks on which large value of losses are properly or erroneously identified, and number of networks on which large value of losses is not identified. On the basis of results shown in Table 4, we can conclude that the best results are given in the following two cases:

- $m=1.05$, for 12 clusters and all data comprehended,
- $m=1.4$, for 20 clusters and all data comprehended.

Conclusions

A new method for calculation of energy losses in low voltage distribution networks is developed in this paper. The method is based on using fuzzy clustering and modified fuzzy clustering techniques. Besides the database of network parameters, the method requires knowledge of energies delivered by distribution transformers as well as pick loadings of distribution transformers. Additionally, measurements that enable determination of technical losses calculation are required for set of test networks.

On the basis of analyses we can conclude the following. All accessible data should be comprehended in calculations. Optimal number of clusters depends on the number of test networks and shall be 15% to 30% of the number of test networks. Minimal number of test networks

is 50. Parameter m that defines fuzziness of clustering gives an optimal value in the range of 1 to 1.5. Optimal value of m increases with increasing the number of clusters. If proposed values of parameter m and number of clusters are used, we can calculate the total technical losses of all networks quite accurately. Additionally, we can identify networks with large value of losses.

References

1. Железко Ю.С. Выбор мероприятий по снижению потери электроэнергии в электрических сетях. – Энергоатомиздат: Москва, 1989. (in Russian)
2. Воротницкий В.Э., Железко Ю.С., Казанцев В.Н., Пекелис В.Г., Файбисович Д.Л. Потери электроэнергии в электрических сетях энергосистем. – Энергоатомиздат, Москва, 1983. (in Russian)
3. Klir G.J., Yuan B. Fuzzy sets and fuzzy logic: Theory and Applications. – Prentice Hall, New Jersey, 1995.
4. Rajaković N., Tasić D., Stojanović M. A Clustering Technique for Distribution Losses Calculation in Deregulated Environment // Proceedings of 2nd Balkan Power Conference. – Beograd, June 19-21, 2002. – P.31– 36.
5. Rajaković N., Stojanović M., Tasić D. An Improved Methods for the Electric Energy Losses Assessment in Distribution Networks // 3rd Mediterranean Conference Med Power 2002, Athens, November 4-6, 2002.
6. Stojanović M., Tasić D. A fuzzy method of distribution energy losses calculation // ICEST 2003, Sofia, October 2003. – P.454-457.

D.S. Tasić, M. S. Stojanović. Modified Fuzzy Clustering Method for Energy Loss Calculations in Low Voltage Distribution Networks // Electronics and Electrical Engineering. – Kaunas: Technologija, 2006. – No. 2(66). – P. 50–55.

There is presented a new method for calculation of energy losses in low voltage distribution networks. The method is based on the fuzzy clustering and modified fuzzy clustering techniques, and requires input data that we can collect easily: lengths of lines, number of line segments, number of customers, conductor's cross section area, conductor's material, electrical energy delivered by distribution transformers, and peak loadings of distribution transformers. Additional measurements that enable exact calculation of energy losses are required for set of test networks. Presented method is tested on the example of ninety low voltage networks. Optimal number of clusters as well as the optimal value of the parameter m that defines fuzziness of fuzzy clustering was determined. Bibl. 6 (in English; summaries in English, Russian and Lithuanian).

Д.С. Тасич, М.С. Стоянович. Модифицированный нечеткий кластерный метод для расчета потерь энергии в распределительных сетях низкого напряжения // Электроника и электротехника. – Каунас: Технология, 2006. – № 2 (66). – С. 50–55.

Предлагается новый метод расчета потери энергии в электрических сетях напряжения 0,4 кВ, который базируется на модифицированной технике нечетких кластеров. Метод требует следующие исходные данные: длине линии, число участки линии, число потребителей, сечения проводов, максимальные нагрузки трансформаторов. Используя предложенный метод, рассчитаны потери энергии для девяноста электрических сетей напряжения 0,4 кВ, и предложены оптимальное число кластеров и оптимальный коэффициент, который определяет нечетность кластеров. Библи. 6 (на английском языке; рефераты на английском, русском и литовском яз.).

D.S. Tasić, M. S. Stojanović. Modifikuotas „fuzzy“ klasterinis metodas nuostoliams žemos įtampos paskirstymo tinkluose apskaičiuoti // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2006. – Nr. 2(66). – P. 50–55.

Pateikiamas naujas metodas energijos praradimams žemos įtampos paskirstymo tinkluose apskaičiuoti. Šis metodas pagrįstas „fuzzy“ klasterių sudarymu ir modifikuoto „fuzzy“ klasterizavimo metodais ir reikalauja pradinių (įėjimo) duomenų, kuriuos galima lengvai surinkti. Tai linijų ilgis, linijų segmentų skaičius, vartotojų skaičius, laidininko skerspjūvio plotas, medžiaga, elektros energija, tiekama paskirstymo transformatorių, bei paskirstymo transformatorių maksimalios apkrovos. Papildomi matavimai, įgalinantys tiksliai apskaičiuoti energijos nuostolius, reikalingi testiniams tinklams. Pateiktas metodas yra testuojamas 90 žemos įtampos tinklų. Nustatytas optimalus klasterių skaičius, taip pat optimali parametro m vertė, kuri nurodo „fuzzy“ klasterizavimo laipsnį. Bibl. 6 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).

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