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Reducing the dissymmetry of load currents in electrical networks 0,4/0,23 kV using artificial neural networks

***Abstract**. A method for load distribution in the network 0,4/0,23 kV using artificial neural networks is proposed. Types of artificial neural networks are analyzed and a solution to this task based on neural network multilayer perception is proposed. A neural network structure is built which makes recommendations for the uniform distribution of loads in the network based on statistical information. On the basis of the neural network, software for the uniform distribution of loads between phases of the network is created.*

***Streszczenie.** W pracy zaproponowano metodę rozkładu obciążeń w sieci 0,4/0,23 kV za pomocą sztucznej sieci neuronowej. Przeanalizowano typy sztucznych sieci neuronowych oraz zaproponowano rozwiązanie wymienionego zadania na podstawie wielostrefowego perceptronu. Opracowano strukturę sieci neuronowej, która daje polecenia, co do równomiernego rozkładu obciążeń w sieci, wychodząc z informacji statystycznej. Dzięki sieci neuronowej tworzone jest oprogramowanie do równomiernego rozkładu obciążeń między fazami sieci. (**Zmniejszenie dyssymetrii prądów obciążenia w sieciach elektrycznych 0,4/0,23 kV za pomocą sztucznych sieci neuronowych**).*

Keywords: current unbalance, loss of electrical power, a neural network, a uniform distribution of consumers.
Słowa kluczowe: Asymetria prądów, straty energii elektrycznej, sztuczna sieć neuronowa, równomierny rozkład użytkowników.

Introduction

The problem of the quality of electric energy plays a prominent role in development strategies of virtually every state. In European countries, it is believed that if the electricity losses exceed 7 - 9%, then such a transfer of electric energy is inefficient. Therefore, a need has emerged to develop new methods and measures of reducing the losses and improving the indicators of electric energy quality.

Numerous studies on the analysis of voltage up to 0,4/0,23 kV in rural networks operating modes [1 - 3] showed that current dissymmetry is due to of municipal and household workload, most of which consists of casual switching, single-phase power-consuming equipment that is non-uniformly distributed over the phases.

Knowledge of current values of asymmetry in a network allows specifying its additional power losses comparing to the symmetrical mode and the possibility of applying measures to reduce the losses [2]. The changing load of single-phase residential consumers of electricity is erratic and it is very difficult to predetermine its value at any given time. Boundaries of load change can only be established with a certain probability [4, 5, 6].

Technical and economic characteristics of the network performance deteriorate sharply in single-ended mode: energy losses increase and the voltage deviation from the nominal [7, 8]. Lifetime of asynchronous motors attached to a network also declines sharply. Furthermore, there are a number of adverse electromagnetic effects, both in the network and in the load. Therefore, losses of active energy, resulting in non-uniformity of phase load lines 0,4/0,23 kV and consumer transformers 6-10/0.4 kV, may increase by more than a third compared with the losses that would have occurred with a uniform load [3].

Analyzing two types of asymmetry, systematic, which is caused by a constant uneven phase load over time, and probable, which is determined by randomly varying loads in time, one first of all should pay attention to the former, which can be counteracted by even distribution of the load between the phases.

Analysis of existing power networks shows a large number of active and passive filters, have been developed to date but not widely used in 0,4/0,23 kV networks because of their low reliability and high cost. The uniform distribution of single-phase loads between phases is another serious hindrance. Thus, a uniform distribution of phase loads at a given time does not guarantee an optimum mode at other times as voltage deviations depend on house hold's consuming.

It should be noted that the choice of one or another method for the task solution depends on the information support of the rural 0,4/0,23 kV network. That is, on availability of certain data parameters mode builds the appropriate method and algorithm for equal distribution of customers between the phases.

The aim of this study is a quality improvement of electric energy and loss reduction by means of a uniform distribution of load across the 0,4/0,23 kV network using artificial neural networks.

Experimental

Operation of rural network currents is accompanied by significant vibrations every minute (Fig. 1) during the day. Today, thanks to the development of information technology, it is possible to equip a network of 0,4/0,23 kV with smart meters that will take a reading in real-time hourly daily schedule of load not only on a TS (transformer substation), but also for each customer. Information may be transmitted from each user and TS using PLC-modems (Fig. 2). Then information on the GSM / GPRS-communication channel is transmitted to the control point [9, 10].

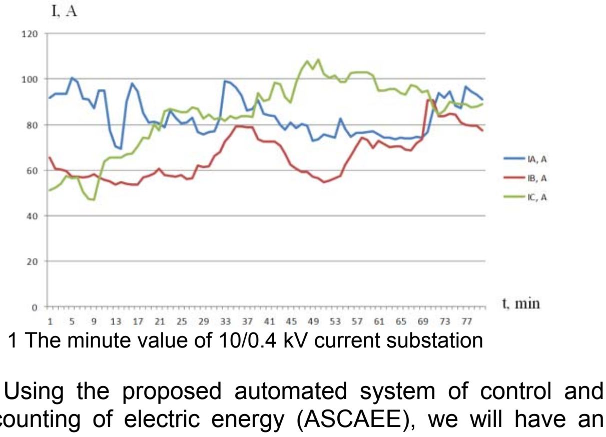

Fig. 1 The minute value of 10/0.4 kV current substation

Using the proposed automated system of control and accounting of electric energy (ASCAEE), we will have an archive of daily and hourly load curves of each consumer for the required period, in this case - six months (winter and summer). To select a current value on the basis of which a consumer will be reconnected to one or the other phase, the mathematical expectation M[I] of the most probable maximum load currents will be used. Thus, for each network user the expectations of current M[I] will be obtained that will meet the most probable value of the current in the peak load mode for the winter and summer season. Based on this information, we propose to develop a method of a uniform distribution of load across the network [11].

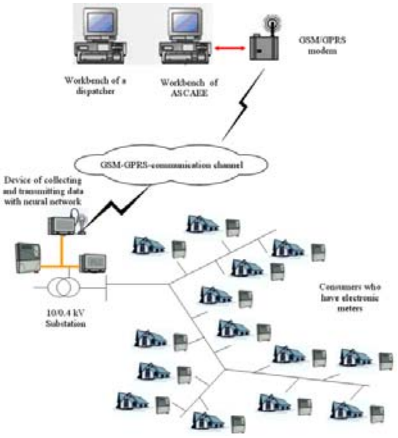

Fig. 2 ASCAEE structure for 0,4/0,23 kV rural network

Obviously, the solution of this problem requires formulation of the optimization problem. Let us define objective functions taking into account existing information sources. Because the network is equipped with smart meters, for the uniform distribution of consumers between the phases we will use archive data basing on hourly current value.

The objective function, which displays the imbalance of load currents across phases in the presence of information from energy meters, has the following form:

$$\sum_{i=1}^{n} M[I_A] = \sum_{i=1}^{n} M[I_B] = \sum_{i=1}^{n} M[I_C], \tag{1}$$

where $M[I_A]$, $M[I_B]$, $M[I_C]$ – the mathematical expectation of the most probable currents in the maximum consumption *i*-x consumers, respectively, for A, B and C phases;

n – number of users in the network, respectively, for A, B and C phases.

Obviously, it is impossible to attain a uniform distribution for each point in time, thereby minimizing of power losses in the daily peak load electricity losses for winter and summer seasons provided the voltage levels within an acceptable range (95% for the duration of the day), is the optimal solution to this problem. In view of the above objective function, electric power loss and voltage levels in the network will have the form:

$$\begin{cases} \sum_{i=1}^{m} W_{A_i} + \sum_{i=1}^{m} W_{B_i} + \sum_{i=1}^{m} W_{C_i} + \sum_{i=1}^{m} W_{N_i} \to \min \\ 0,95U_{nom} \le U \le 1,05U_{nom} \end{cases}, \tag{2}$$

where W_{A_i}, W_{B_i}, W_{C_i}, W_{N_i} – loss of electricity in the *i*-x line section across phase conductors and the neutral wire network;

m – number of sections of the line;

U_{nom} – the rated voltage of the system;

U – voltage on users' terminals.

Since the major electric energy losses in air line conductors falls the peak load hours, the first objective function equation (2) takes into account the loss of electrical power during the peak load period for the winter and summer seasons. The second equation of the objective function (2) specifies:

1. if the voltage is less than at the terminals of the consumer nearest to the substation upper allowable standard minimum limit during the load in the summer season.

2. if the voltage at the most remote user is below the lower permissible limit standard in during the peak load of the winter season.

Results and discussion

As a specific example of the proposed method, we consider the rural feeder network 0,4/0,23 kV (Fig. 3). Its phase diagram contains a mathematical indication of current expectations of the maximum load in the summer season for each user is shown in Fig. 5.

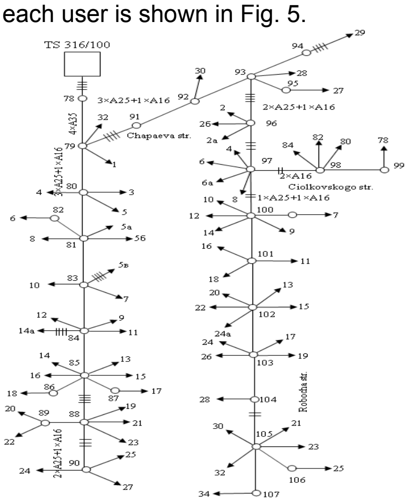

Fig. 3 Feeder's scheme power grid substation 100 kVA № 316

Table 1 shows values of mathematical expectations in the current peak load hours of each consumer in the summer season for the circuit shown in Fig. 3.

Table 1. Initial phase segregated connection of consumers

№ of the accession	M[I]. A on phases			№ of the accession	M[I]. A on phases			№ of the accession	M[I]. A on phases		
	A	B	C		A	B	C		A	B	C
1	-	1.28	-	24	1.15	-	-	47	0.59	-	-
2	-	0.91	-	25	-	-	0.82	48	1.30	-	-
3	-	-	1.06	26	1.10	-	-	49	-	0.78	-
4	1.32	-	-	27	-	-	1.27	50	0.87	-	-
5	-	0.86	-	28	0.48	-	-	51	-	1.24	-
6	-	-	0.67	29	-	-	0.72	52	0.76	-	-
7	-	-	0.51	30	-	-	1.65	53	-	-	1.37
8	-	-	1.08	31	0.90	-	-	54	1.46	-	-
9	-	-	1.32	32	1.20	-	-	55	0.85	-	-
10	0.96	-	-	33	1.36	-	-	56	1.49	-	-
11	-	-	0.87	34	-	-	0.96	57	0.61	-	-
12	-	-	1.30	35	-	-	1.12	58	0.97	-	-
13	-	0.57	-	36	0.95	-	-	59	-	1.42	-
14	-	-	0.93	37	0.82	-	-	60	-	-	1.27
15	0.50	-	-	38	0.72	-	-	61	-	-	1.02
16	-	-	1.40	39	-	1.38	-	62	1.12	-	-
17	0.74	-	-	40	-	1.31	-	63	0.56	-	-
18	-	-	1.09	41	0.48	-	-	64	1.15	-	-
19	1.85	-	-	42	-	-	0.74	65	1.20	-	-
20	0.76	-	-	43	-	-	0.86	66	-	1.25	-
21	-	-	1.31	44	0.70	-	-	67	-	1.47	-
22	0.78	-	-	45	0.68	-	-	68	-	1.06	-
23	-	-	0.97	46	0.55	-	-	69	-	0.81	-
Total mathematical expectation of current M [I] in phases. A											
$\Sigma M[I_A]$				$\Sigma M[I_B]$				$\Sigma M[I_C]$			
30.93 A				14.35 A				24.33 A			

To clearly illustrate changes of current unbalance, we model the operation of the network (Fig. 4) in Multisim [12]. To this end, each consumer will be loaded with currents that meet their mathematical expectation in the maximum load for the entire analyzed period. As a result of the simulation, values of the phase currents in the head line of I_A = 30.93 A, I_B = 14.35 A, I_C = 24.33 A, and the current in the neutral wire will be I_N = 14.1 A.

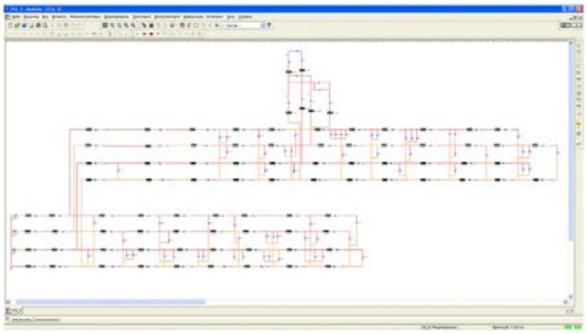
Fig. 4 Simulation of 0,4/0,23 kV network in Multisim

To solve this problem, it is important to note that a transformer substation 10/0.4 kV joins dozens of consumers, with hundreds of such plants for each region , so it is important to choose an appropriate mathematical apparatus that could handle massive amounts of data. In this connection, the question arises about the possibility of parallelization of the calculation process at the program level. With this in mind, we use mathematical tools based on artificial neural networks [13, 14]. The main feature of the neural network is the parallel processing of information from units, which can significantly speed up the process. Taking into account the aforementioned, we propose to use the well-known method of BACKPROPAGATION, the genesis of which is shown in [15, 16].

Thus, a trained neural network, on the basis of historical data on currents in the network in winter and summer seasons, can provide recommendations on a uniform distribution of consumers between the phases.

Let us consider a particular case, considering that a two-layer neural network [18] contains a number of L hidden neurons and one output [16].

In this case, the function's errors are dependent on the vectors of weights of the hidden layer and weights of the vectors associated with the output neuron.

(3) $$o_i^k = \frac{1}{1+e^{-w_i^T x^k}},$$

w_i – weight vector associated with the i-th hidden neuron, i = 1, 2,..., L.

The rule adjusting weights in a neural network under consideration is also based on the minimization of the quadratic error function gradient method, derived from the expression [16-21]:

(4) $$w_i := w_i - \eta \frac{\partial E_k(W,w)}{\partial w_i},$$

where $\eta = const$ – learning rate factor (0 < η < 1), i = 1, 2,…, L.

Using the rule of differentiating a composite function and the expression for the derivative of the sigmoid (logistics) activation function, we obtain:

(5) $$\frac{\partial E_k(W,w)}{\partial W} = \frac{1}{2}\frac{\partial}{\partial W}\left(y^k - \frac{1}{1+e^{-W^T o^k}}\right)^2 =$$
$$= -\left(y^k - O^k\right)O^k\left(1-O^k\right)o^k,$$

whence (in a discrete space)

(6) $$W_i := W_i + \eta \delta_k o_i^k, \; i = 1, 2, \ldots, L.$$

where

(7) $$\delta_k = \left(y^k - O^k\right)O^k\left(1-O^k\right).$$

Solving coincidently (3) - (7), we will finally write in the vector form:

$$w_{ij} := w_{ij} + \eta \delta_k W_i o_i^k \left(1-o_i^k\right)x_j^k,$$

(8) i = 1, 2,…, L, j = 1, 2,…, n.

Consequently, we construct a neural network structure to solve the problem of uniform redistribution of consumers between the phases (Fig. 5).

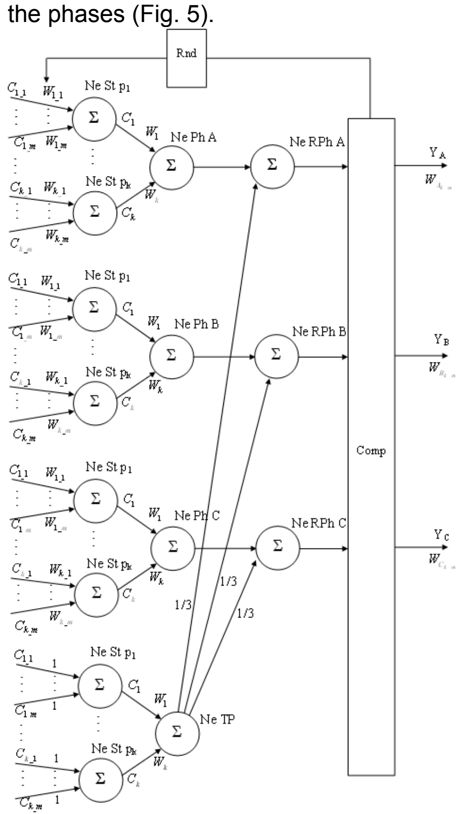

Fig. 5 Structure of the neural network for uniform redistribution of customers between phases

The following notations were made on Figure 5:

C_{1_1} – C_{k_m} – current consumption by consumers (k - support number, m - number of the consumer on the k-th pole);

W_{1_1} – W_{k_m} – weighting factors (0 or 1 - depending on whether the load is connected to the corresponding phase);

Ne St p_1 – Ne St p_k – input layer neurons;

C_1 – C_k – total current consumers connected to the k-th support;

W_1 – W_k – the remoteness factor of a user (support) from the TS;

Ne Ph A, Ne Ph B, Ne Ph C, Ne TP – neurons in the hidden layer;

Ne RPh A, Ne RPh B, Ne RPh C – the output layer neurons;

The comparing block checks if the phases A, B or C load exceeds the optimum value (if exceeded, it occurs randomly sorting load. If the result meets the predetermined request, then a recommended load is issued and the reading process occurs of load values connected to phases A, B and C);

Rnd – a random number generator;

Y_A, Y_C, Y_C – recommended load for phase A, B and C, respectively;

$W_{A_{k\_m}}$, $W_{B_{k\_m}}$, $W_{C_{k\_m}}$ – issuing consumer numbers on the *k*-th pole, whose connection to the phases A, B and C, respectively, is recommended.

Software is created on the basis of the developed model of a neural network which allows us to provide advice on the uniform distribution of users in the network. The software has a graphical editor where you can draw a power grid, arrange accommodation and a support can be connected to a number of consumers corresponding to an appropriate phase. In addition to the software product, it is possible to select a brand and wire cross-section on the line, as well as to take into account the distance of each consumer from the TS. In addition, the software calculates the current expectation of each customer for the peak load mode of winter and summer using the archives of daily schedules for each user load. The program automatically recalculates the currents in the power consumed by each consumer. Fig. 6 is an example of the program at work, which shows that the software produces a particular result, which consumer needs to be switched to one or the other phase. In addition, the software gives the value of power (or current) of TS phase loading to redistribution, and information about what amount of power (or current) one or another phase line needs to unload.

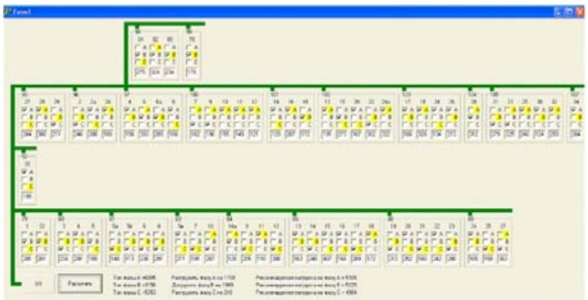

Fig. 6 A software product that allows you to provide recommendations on a uniform distribution of users in the network

Table 2 shows a variant of the connection of consumers corresponding to the optimal redistribution of loads.

Table 2. The decision on connection of consumers

№ of the accession	M[I]. A on phases			№ of the accession	M[I]. A on phases			№ of the accession	M[I]. A on phases		
	A	B	C		A	B	C		A	B	C
1	-	-	1.28	24	1.15	-	-	47	0.59	-	-
2	0.91	-	-	25	-	-	0.82	48	-	1.30	-
3	-	1.06	-	26	-	-	1.10	49	0.78	-	-
4	-	-	1.32	27	-	1.27	-	50	0.87	-	-
5	-	-	0.86	28	-	0.48	-	51	-	-	1.24
6	-	-	0.67	29	-	-	0.72	52	0.76	-	-
7	0.51	-	-	30	1.65	-	-	53	-	1.37	-
8	-	1.08	-	31	-	-	0.90	54	1.46	-	-
9	-	-	1.32	32	1.20	-	-	55	0.85	-	-
10	-	-	0.96	33	-	1.36	-	56	-	-	1.49
11	-	-	0.87	34	0.96	-	-	57	0.61	-	-
12	1.30	-	-	35	-	1.12	-	58	-	0.97	-
13	-	0.57	-	36	0.95	-	-	59	-	1.42	-
14	-	-	0.93	37	-	-	0.82	60	-	1.27	-
15	-	-	0.50	38	0.72	-	-	61	-	-	1.02
16	1.40	-	-	39	-	1.38	-	62	-	-	1.12
17	-	0.74	-	40	-	1.31	-	63	-	0.56	-
18	-	1.09	-	41	-	-	0.48	64	1.15	-	-
19	-	-	1.85	42	0.74	-	-	65	-	1.20	-
20	-	-	0.76	43	-	0.86	-	66	1.25	-	-
21	-	-	1.31	44	0.70	-	-	67	1.47	-	-
22	-	0.78	-	45	0.68	-	-	68	-	1.06	-
23	-	0.97	-	46	0.55	-	-	69	-	-	0.81
Total mathematical expectation of current M [I] in phases. A											
$\Sigma M[I_A]$				$\Sigma M[I_B]$				$\Sigma M[I_C]$			
23.23				23.22				23.16			

To validate this method, we model the operation of the network with a new redistribution of customers in Multisim. The modeling generates the following values of the phase currents in the line head: I_A = 23,23 A, I_B = 23,22 A, I_C = 23,16 A, and of the current in the neutral wire: I_N = 0,07 A.

We perform similar calculations for 0,4/0,23 kV rural feeder network (Fig. 5) in the winter season. As a result of the simulation, we obtain the following values of mathematical expectation in the current I_A line head:I_A = 41,81 A, I_B = 41,76 A, I_C = 41,79 A, and the current in the neutral wire is I_N = 0,05 A.

To assess effectiveness of the proposed method, we present a comparative analysis of seasonal electricity losses in the line for its three modes:

- before load redistribution,
- after redistribution of loads on the existing methodology based on measurements of a maximum load of one time in the season,
- after the redistribution of loads using the proposed method.

These comparative analyses are shown in Table. 3.

Table. 3. Results of the comparative analysis

Season	Phases	Network settings mode	
		Before the loads redistribution	
		The currents in the line head, A	Losses in the line, kW • h
Summer season	A	30,93	28633
	B	14,35	7135
	C	24,33	16062
	N	14,1	13066
The total losses			64898
Winter season	A	47,21	74083
	B	25,57	18463
	C	32,63	41558
	N	19,17	33807
The total losses			167911
Season	Phases	After the loads redistribution on the existing method	
Summer season	A	20,12	23288
	B	25,14	14174
	C	21,35	12514
	N	6,68	9402
The total losses			59378
Winter season	A	37,81	53775
	B	32,34	25239
	C	33,85	45734
	N	6,12	21687
The total losses			146435
Season	phases	after the loads redistribution on the proposed method	
Summer season	A	23,23	16382
	B	23,22	18520
	C	23,16	13305
	N	0,07	3217
The total losses			51424
Winter season	A	35,51	41551
	B	35,86	36554
	C	35,42	43225
	N	0,616	7631
The total losses			128961

The results in Table 3 suggest that after stress redistribution within the method the total quantity of electricity loss in the line is expected to reduce at 8.5% during the summer season and 12.8% for the winter season. Meanwhile, these current values are almost equal in phases after the redistribution of loads when the existing techniques were used, but the values of power losses in each phase line for a season differ greatly from each other. This suggests the necessity to improve the existing techniques, as a redistribution of customers between the phases of the line based on the current measurement in the maximum load does not ensure achievement of an optimal level of electric power losses across the line.

By using the proposed method, when the mathematical expectations of the phases using the most probable peak currents in the load clock for the summer and winter periods are used for uniform reallocation among consumers, the loss of electric power in the network is significantly lower than when the existing methods are applied. Thus, unlike the conventional technique, the total losses will decrease to 20.8% for the summer season and to 23.2% for winter.

It follows from the foregoing that the proposed method will reduce the electrical energy losses in the line by 12.3% during the summer season and 10.4% for the period following winter season compared to the traditional methods.

Conclusions

1. The flexible mathematical theory of the device of artificial intelligence, based on neural networks, allows solving complex stochastic problems of applied electrical engineering with elements of fuzzy sets. Typically, there is a network with a supervisor trained both with the help of field experiments and mathematical models of the objects being studied. On this basis, software has been created that makes it possible to provide recommendations for a uniform redistribution of loads between phases in 0,4/0,23 kV networks. It is based on neural networks mathematical apparatus using multilayer perceptions. The software is built using the mathematical apparatus. The software allows you to provide recommendations for a uniform redistribution of loads between phases in 0,4/0,23 kV networks. For realization of the proposed approach, it is necessary to implement a substation ASCAEE and households should be provided with electronic meters capable of transmitting information to the control room.

2. With the help of the developed software, we calculated the actual 0,4/0,23 kV network to confirm reliability of the data used to simulate the network in Multisim. A comparative analysis of the obtained data in the software and Multisim allows us to posit usefulness of the proposed software for uniform load transfer between the phases in the 0,4/0,23 kV network.

3. To confirm effectiveness of the proposed methodology, a comparative analysis of the options for redistribution of loads was carried out using the existing and the proposed methodologies, which showed that using the proposed methodology, the electric energy losses are lower by 12.3% over the summer season and by 10.4% during winter. Thus, the proposed approach provides a significant reduction in electric energy losses in 0,4/0,23 kV networks. In effect, the proposed approach provides a significant reduction in electricity losses across 0,4/0,23 kV networks.

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