Досліджено вплив кліматичних факторів на втрати електроенергії в повітряних лініях електропередачі (ЛЕП) напругою 6–35 кВ. Проаналізовані підходи до розрахунку втрат електроенергії в ЛЕП. Розраховано і запропоновано включити в основне рівняння теплового балансу для проводів ЛЕП коефіцієнти тепловіддачі, що враховують вплив атмосферних опадів. Удосконалено модель теплових процесів, основне рівняння теплового балансу для усталеного теплового режиму та вираз для визначення технічних втрат електроенергії в повітряних ЛЕП. Розроблена модель нейромережі для розрахунку і прогнозування технічних втрат електроенергії в повітряних ЛЕП напругою 6–35 кВ

Ключові слова: нейронні мережі, втрати електроенергії, повітряні лінії електропередач, кліматичні фактори

Исследовано влияние климатических факторов на потери электроэнергии в воздушных линиях электропередачи напряжением 6–35 кВ. Проанализированы подходы к расчету потерь электроэнергии в ЛЭП. Рассчитано и предложено включить в основное уравнение теплового баланса для проводов ЛЭП коэффициенты теплоотдачи, учитывающие влияние атмосферных осадков. Усовершенствована модель тепловых процессов, основное уравнение теплового баланса для установившегося теплового режима и выражение для определения технических потерь электроэнергии в воздушных ЛЭП. Разработана модель нейросети для расчета и прогнозирования технических потерь электроэнергии в воздушных ЛЭП напряжением 6–35 кВ

Ключевые слова: нейронные сети, потери электроэнергии, воздушные линии электропередач, климатические факторы

UDC 621.311.1
DOI: 10.15587/1729-4061.2016.80072

RESEARCH INTO THE INFLUENCE OF CLIMATIC FACTORS ON THE LOSSES OF ELECTRIC ENERGY IN OVERHEAD POWER TRANSMISSION LINES

V. Bakulevskiy
Lecturer, Head of cyclic commission
Cycle commission of electrotechnical disciplines
Mechanics and Technology College of
Odessa National Academy of Food Technologies
Kanatna str., 112, Odessa, Ukraine, 65039
E-mail: bakulevsky_80@mail.ru

1. Introduction

Power losses in electric networks are the most important indicator of their performance efficiency, a clear indicator of state of the system of electricity accounting, efficiency in energy sales activities of electric utility organizations [1]. According to the Ukrainian [2–4] and international experts [5–8], power losses at its transmission and distribution in electrical networks may be considered satisfactory if they do not exceed 4–5 % while at the level of 10 % as maximum permissible from the standpoint of physics of electricity transmission networks.

Sharp aggravation of the problem of reducing energy losses in electric networks requires an active search for new ways of its solution, new approaches to the selection of appropriate measures, to the organization of work to reduce the losses [1, 4, 6, 8]. The world experience shows that in the countries with economy in crisis the losses of electricity in networks tend to grow, which is confirmed in Ukraine, where in many energy systems the losses of electricity grow even when energy consumption reduces [2, 3, 7]. Against the background of the changes in economic mechanism that occur in the energy sector, and crisis in the country's economy, the problem of reducing energy losses in electric networks is one of the tasks of ensuring financial stability of electric utility organizations [1].

One of the main energy saving objectives in Ukraine is, based on the analysis of existing state, to develop the main directions to reduce energy losses and bring this indicator to the level of the advanced countries of the European Union and the United States in energy consumption [1], that is why the improvement of forecasting and calculating the energy losses is a relevant issue of energy saving in the energy sector of Ukraine.

At present, the main formalized means of analysis of functioning and managing the modes of power grids is mathematical modeling, underlying which is a set of mathematical models that adequately reflect the processes that are examined. Increasing complexity of power grids, trend to comprehensive consideration of the processes occurring in them, increasing demands for efficiency of calculations lead to objective difficulties of construction and application of mathematical models that use the language of traditional mathematics. The use of traditional multi-dimensional nonlinear models is ineffective, and partly impossible. In addition, they perform poorly at the partial absence of incoming information. This substantiates the necessity of applying modern mathematical models (in particular, neural networks) to improve the calculation and prediction of energy losses in overhead power transmission lines (PTL) of the energy system.

2. Literature review and problem statement

One of the aspects of improving the prediction of energy losses is to take into account climatic factors (such as ambient temperature, wind, precipitation, etc.) [2, 4, 8, 10]. In [2] it is proposed to better take into account climatic factors, the author [4] proposes to take into account topographic conditions of the terrain, which are directly related to certain climatic factors, in [5], consideration of climatic factors is proposed to replace by defined coefficients, the author [6] offers adaptive short-term forecasting of loads using the weather conditions, ref. [7] proposes short-term forecasting of electric load of the power system dependent on the model of weather. Paper [7] proved by the example that the accuracy of calculation of energy losses in the overhead lines may be significant unless one considers meteodata. Article [10] emphasizes the need for more detailed study of the influence of meteofactors on the losses of electricity in the equipment because there is quite a large percentage of uncertainty in this regard.

The official approach in Ukraine [11] implies taking into account the average annual air temperature in the calculations of load energy losses in overhead PTL and losses to the crown in the overhead lines of 110 kV voltage and higher, while other climatic factors are virtually ignored. This approach should be changed [2, 8, 10, 12].

At present, the calculation models use additional PTL settings for the ambient temperature of 20 °C, but the air temperature may significantly vary throughout the year. In addition, many software tools that are used in modern Ukrainian energy utility companies do not even consider a temperature factor, which leads to considerable errors [3, 9, 12].

In addition, the temperature of the wire is affected by other climatic factors (precipitation, wind direction and strength, etc.), the impact of which on the losses of electricity in the overhead lines requires further research [2, 4–8, 10]. The inclusion of the influence of climatic factors into mathematical model for calculating technical losses of electric power will improve analytical and calculation bases, reduce the accuracy of calculations and forecasting, as well as provide for a fuller understanding of the processes that take place in the overhead PTL. About 85 % of the load losses are accounted for by general losses in modern PTL [1, 2, 8, 10] and hence the research in this direction is relevant.

Papers of Ukrainian [2–4] and foreign specialists [6–10] emphasize the need to improve methodological and technical support, a more accurate and complete account of the factors affecting losses of electricity in equipment, as well as application of improved methods of calculation and prediction of energy losses.

A significant percentage of uncertainty in this issue, as well as improving calculation-analytical base, necessitates the need for research in this direction.

3. Aim and objectives of the research

The aim of the research is to improve the accuracy of taking into account climatic factors when calculating and predicting technical energy losses in overhead power transmission lines (PTL) of voltage 6–35 kV. Technical power losses consist of load losses and losses to the crown that oocur only in PTL of voltage 110 kV and higher [1, 2, 8, 10], so the technical power losses in PTL of 6–35 kV under consideration are the load losses.

To achieve the set aim, the following tasks were formulated and solved:

– study of climatic factors that affect the load power losses in overhead PTL, and approaches that are used for calculation and prediction of losses of electric power in PTL;

– exploration and calculation of heat transfer coefficients, which take into account the impact of precipitation (rain, snow) for the wires of PTL with different sections;

– a detailed analysis of the components of mathematical model of thermal processes in the wires of PTL and the main equation of thermal balance for the thermal regime that was set for the wires of PTL and the expression for calculation of load losses of electricity in the overhead PTL with regard to climatic factors;

– design of a neural network model for calculation and prediction of technical energy losses in the overhead PTL of voltage 6–35 kV taking into account climatic factors: formulation of the problem in a neural basis, a short description of a sample, conducting lowering of dimensionality and selection of data, testing of the input variables, formation of samples (training, control and testing), determining their optimal volumes; selection of the type of architecture of the artificial neural network (ANN), activation function of the network and the ANN learning algorithm.

4. Materials and methods of research into the influence of climatic factors on technical power losses in the overhead PTL of voltage 6–35 kV and development of a neural network model

4. 1. Materials and methods of research into the influence of climatic factors on technical power losses in the overhead PTL of voltage 6–35 kV

Heat transfer in PTL is carries out by all possible ways: by thermal conductivity, emission and convection. There are known laws that determine thermal equilibrium between a conductor in which current flows and parameters of the environment [2, 13]. The peculiarity of heat transfer in the wires of PTL is that the heat, which is transferred from the hot environment inside the wire to the cold surrounding environment, as if expands outside, since the internal surface area of heat transfer is lower than that outside. For this case, the density of heat flow transmitted by heat transfer from the hot heat carrier inside the wire to the cold outside [13]

$$q = K_1 \lambda \left(t_{p1} - t_{p2}\right), \quad (1)$$

where t_{p1}, t_{p2} are, accordingly, the temperatures of the hot and cold heat carriers, K_1 is the linear coefficient of heat transfer through the wire a length of one meter, W/(m·K)

$$K_1 = \frac{1}{1/\alpha_{p1}d_1 + 1/2\lambda \ln\left(d_2/d_1\right) + 1/\alpha_{p2}d_2}, \quad (2)$$

where α_{p1}, α_{p2} are the coefficients of heat transfer by convection, W/(m²·K); λ is the coefficient of thermal conductivity of material of the wire, W/(m·K); d_1, d_2 are the inner and outer diameters of the wire, m, respectively.

The basic equation of heat balance for the thermal regime that was set for the wires of PTL [2, 13]:

$$I^2 R_{20}\left(1 + \alpha\left(t_w - 20\right)\right) + W_r = \pi d\left(\beta_w + \beta_e\right)\left(t_w - t_a\right), \quad (3)$$

where I is the current in the line, A; R_{20} is the wire resistance at 20 °C, Ohm/m; α is the temperature coefficient of wire resistanc, 1/°C, for aluminum $\alpha=4{,}3\cdot10^{-3}$ 1/°C; t_w is the wire temperature, °C; t_a is the ambient temperature, °C; β_w, β_e are the coefficients of wire heat transfer at convection and emission heat transfer, W/(m·°C); W_r is the heat of solar radiation, which is absorbed by 1 m of wire in unit of time, W; d is the diameter of wire, m.

Natural convection plays the main role in cooling the wires of PTL. The coefficient of heat transfer convection β_w is the most undefined parameter of the equation (3), however, it significantly affects the value of permissable load. The amount of heat that is a given by the unit of surface by natural convection is calculated [2, 14]

$$Q_к = \beta_к \Theta, \quad (4)$$

where Θ is the difference between the temperatures of the body and the environment beyond the stream, K; β_k is the coefficient of heat transfer by convection, which depends on the properties of environment that cools, on temperature, shape, and position of the surface that cools, W/(m²·K).

Heat transfer by convection for the wires of PTL is described in a general case by the Newton-Rikhman equation [2, 14]

$$\sigma Q = \beta_к \cdot \Delta t \cdot dF \cdot d\tau, \quad (5)$$

where σQ is the amount of heat that is transferred by thermal conductivity, J; β_K is the coefficient of heat transfer by convection, W/(m²·K); Δt is the average temperature pressure between the wire and the environment, K; F is the wire section, m^2; τ is the time, s.

For the case of stationary heat transfer, equation (5) will take the form [2, 13]

$$\Delta Q = \alpha F \Delta t, \quad (6)$$

where ΔQ is the heat flow, W; α is the variable, the value of which is affected by changes in factors: type of convection, physical properties of the body and the environment, geometric shapes of the immobile wall, the direction of motion of the medium.

They consider three modes of motion of the medium in the middle of the channel of variable form or along the immobile wall: turbulent, laminar and transition [13]. Differential equation of convective heat transfer for the washing medium [13]

$$\lambda \frac{\partial t}{\partial n} = \alpha_p \Delta t, \quad (7)$$

where λ is the coefficient of thermal conductivity of medium in laminar layer or sublayer at the wire temperature, W/(m·K); $\frac{\partial t}{\partial n}$ is the temperature gradient, which is directed towards its growth (vector magnitude) or infinitely low increment of temperature along the normal through a laminar layer or sublayer, K/m; α_p is the convection heat transfer coefficient from the laminar layer to the total volume of the washing medium, W/(m²·K); Δt is the difference of temperatures between the average temperature of the wall and the washing medium.

If the left and the right parts of the equation are simultaneously splitted by the left side, we obtain the main criterion equation of heat transfer, the Nusselt criterion [13], which is fundamental in the theory of heat transfer because it includes the main magnitude of convective heat exchange – the value α

$$Nu = \frac{\alpha \cdot l}{\lambda}. \quad (8)$$

In a general form [13]

$$Nu = f(Re, Pr), \quad (9)$$

where Re is the Reynolds criteria that determines the impact of speed of the cooling medium on convective heat transfer (for air, Re=const in the range of temperatures from –50 to +40 °C.

Heat transfer by convection from the wall of the wire to the free washing air [13]

$$Nu = 0{,}5 Gr^n. \quad (10)$$

In the case of free convection Re=5 [13]

$$Nu = C(Gr \cdot Pr)^n, \quad (11)$$

where C, n are the stable numbers; Pr is the Prandtl criteria that characterizes the similarity of physical properties of the cooling medium in the processes of convective heat exchange; Gr is the Grashof's criterion, which defines the process of heat transfer during the free gravitation motion.

In order to calculate the value α for a particular physical problem of the heat transfer by convection, it is necessary to find in [13] a dependence in criterial form, which describes this problem; to calculate determining criteria; to identify the defining criterion of Nusselt and to determine the value α. We wiil consider below some climatic factors that affect thermal processes and electric power losses in PTL.

The air temperature. The air temperature is the major factor that must be taken into account when calculating the energy losses. Losses of active power in any element of the network are determined by [2, 8, 10]

$$\Delta P = I^2 R, \quad (12)$$

where R and I are the active resistance, Ohm, and current of the given element, A, respectively.

It follows from (12) that the more precisely R is set, the more accurate is the calculation of the losses. It is known that active resistance of metal conductors depends on temperature [2, 12]

$$R = R_o(1 + a(\theta_a + \theta_e)), \quad (13)$$

where R_o is the conductor resistance at 0 °C, Ohm; a is the temperature coefficient of resistance; θ_a is the ambient temperature, K; θ_e is the excess of the conductor temperature above ambient temperature, K.

The active resistance of the wire of overhead line R in many software tools is in general considered as constant magnitude that is computed [12]

$$R = R_0 L, \quad (14)$$

where L is the length of an overhead line, km.

But active resistance depends on temperature, which is why for the wires of PTL [12]

$$R = R_0 L\ [1 + a(t_w - 20°)], \tag{15}$$

where R_0 is the specific active resistance of conductor at a temperature of 20 °C, Ohm/km; a is the temperature coefficient, which for the AC wires equals 0.004, i. e., 4 % per 10 °C; t_w is the wire temperature, °C.

Reactive resistance of PTL is determined by the relative position of wires and their geometric dimensions and it is not dependent on climatic conditions (for the overhead PTL of voltage 6–35 kV, the values X=0.38–0.4 Ohm/km), [11, 12].

Temperature of the conductor is determined by the current that flows in it. But current varies during 24 hours and depends on the magnitude of the load of consumer, which may be different. Therefore, in the calculation of energy losses, in order to reduce the errors, the method of mean loads is applied.

But the main factor that determines the wire temperature is ambient temperature. It is known that if the line load does not exceed 70–80 % of permissible under conditions of heating, then the wire temperature when calculating the losses is taken equal to average annual temperature [2, 10, 12]. The official approach [11], in which active resistances of overhead PTL are calculated with regard to the average annual temperature, is quite dubious and needs checking. The feasibility of the study is predetermined by considerable fluctuation in a monthly average temperature throughout the year, as well as some deviation of average annual temperature from the accepted over recent years. The research was conducted into the dynamics of change in the average temperature throughout the year and deviation of average annual temperature from the generally accepted for 2006–2008 (the averaged values over 3 years) for the weather station Lyubashivka (Ukraine), using the meteodata [14].

Direction and strength of wind. Wind is one of the main factors, which influence convective heat transfer in overhead PTL by cooling wire. Under the real conditions, there is always a certain air motion. When cooling the wires by wind, they apply equations (9)–(11). The coefficient of heat transfer by convection β_w (3) significantly affects the value of permissable load. It is calculated under condition that the wire of overhead PTL is considered as a cylinder in air flow [2, 12]

$$\beta_k = 3{,}5 k_\psi \sqrt{\frac{v}{d}} = 3{,}5 k_\psi \sqrt{\frac{v}{\sqrt{s/0{,}785}}}, \tag{16}$$

where k_ψ is the coefficient of dependence of heat transfer at convection heat transfer on the angle of wind attack, as the overhead lines are usually located at a considerable distance from earth and buildings, it is accepted k_ψ=1; v is the wind speed, m/s; d is the wire diameter, m; s is the wire section, mm^2.

Precipitation. When considering this issue, we propose the approach based on heat exchange processes [13]. Precipitation in the course of interaction with the wire of overhead lines forms the two-phase medium “solid particles – fluid”. At cooling the wire by precipitation such as rain and snow, as well as wind, empirical dependence is applied [13]

$$Nu_2 = 0{,}019 Re^{0{,}83}, \tag{17}$$

where Nu_2 is the Nusselt number (criterion) for the given two-phase medium.

On the other hand [13]

$$Nu = \alpha_0 d / \upsilon, \tag{18}$$

where d is the diameter of wire, mm; υ is the thermal conductivity (for water υ_w=0,6 at 15 °C, for snow υ_s=0,55 at 0 °C), [13].

It is known that the Nusselt number for this two-phase medium is Nu_2=20–25 for rain and Nu_2=5–10 for snow [13]. Then the coefficient of heat transfer on the surface of the PTL wire per 1 km of length

$$\alpha_0 = (Nu\vartheta / d) \cdot 10^3 = \left(Nu\vartheta \Big/ \sqrt{\frac{S}{0{,}785}} \right) \cdot 10^3. \tag{19}$$

After conversion:

– for rain at 15 °C

$$\alpha_0 = \left(20 \cdot 0{,}6 \Big/ \sqrt{\frac{S}{0{,}785}} \right) \cdot 10^3 = \left(10{,}63 / \sqrt{S}\right) \cdot 10^3; \tag{20}$$

– for snow at 0 °C

$$\alpha_0 = \left(5 \cdot 0{,}55 \Big/ \sqrt{\frac{S}{0{,}785}} \right) \cdot 10^3 = \left(2{,}44 / \sqrt{S}\right) \cdot 10^3. \tag{21}$$

To test the adequacy of the obtained results based on technical, reference and meteodata [14], we conducted comparative analysis of energy losses at the overhead PTL of voltage 35 kV of section Lyubashivka-Demidove (wire of the brand AC-50) and PTL of 10 kV of section Demidove-Bobrik (AC-25) of Kotovsky electrical networks of Ukraine [4] over 2008. In this case, the losses at PTL are calculated according to different approaches: approach 1 – the losses are calculated without taking into account climatic factors; approach 2 is the official approach; approach 3 – the losses are calculated taking into account the average monthly temperature and other climatic factors by (41) – the author’s approach. The results of calculations are compared to the APCAS (Automatic power control and accounting system) data of an overhead PTL, which are taken as the reference.

4. 2. Materials and methods of developing the model of neural network of calculation and prediction of the technical energy losses in the overhead PTL of voltage 6–35 kV

Artificial neural network (ANN) is a set of models of biological neural networks. This is a network of elements, artificial neurons, interconnected by synaptic connections. The network processes incoming information and in the process of changing its status over time creates a set of output signals.

Neural network approach [15, 16] is based on the study of biological neuron (component of biological nervous system). Mathematical neuron, similar to biological, consists of the basic elements of three types: multipliers (synapses), adder, and transformer. Synapses perform connections between neurons, multiply the signal by the number that characterizes the strength of connection – the weight of the synapse. Adder assembles the signals that come through synaptic connections from other neurons and external input signals. Transformer implements the function of one argument – output of adder. This feature is called “activation function”. Neuron as a whole implements scalar function of vector argument. Mathematical model of neuron [15, 16]

$$S = \sum w_j x_j + b, \tag{22}$$

$$y = f(S), \tag{23}$$

where w_j is the weight of the synapse (j=l, 2..N); b is the value of shift; S is the result of summation; x_j is the component of the input vector (input signal), j=l, 2..N; N is the number of inputs of neuron; f is the activation function.

In the research, the measure of error of the model is determined by the mean square error [15, 16]

$$E = \sqrt{\frac{\sum_{i=1}^{M}(d_i - y_i)^2}{M}}, \quad (24)$$

where M is the number of examples in the corresponding set (sample).

The value E is calculated by (24) for the training, control and testing samples (further denoted as error of training, control and testing errors, respectively).

ANN modeling for the task of planning technical energy losses at overhead PTL is carried out by the algorithm, which implies consistent implementation of the following stages [15, 21]:

1) formulation of the task in a neural network basis;
2) formation of training, control and testing samples;
3) selection of the ANN architecture, including parameters of network elements (identification of the structure of the model);
4) training ANN (assessment of the model parameters);
5) testing ANN in order to establish the adequacy of the resulting model.

The research is conducted in the operating system STATISTICA Neural Networks by the American company StatSoft.

The latest studies in the field of evaluation in the course of planning of electric power losses revealed that it is necessary: to take into account when calculating all the known constituents of energy losses, to take into account various factors affecting the losses of electricity, to facilitate the processes of preparation of initial data and the results of calculation. That is, the input vector should contain factors that depend on voltage of the network and physical nature of technical losses with regard to the dynamics of the process of transmission and distribution of electricity in the power system, as well as meteofactors [17, 19]. We propose the following formulation of the task of forecasting and analysis of technical energy losses based on the ANN apparatus for the overhead PTL of voltage 6–5 kV:

– the input vector X: rated voltage, daily load of PTL, length of PTL, type of the PTL wire, daily average values of air temperature and wind force, dominant precipitation (or their absence). In most classic models, reactive load is not considered to be an input vector, in addition, neural networks operate under conditions of incompleteness of incoming information, that is their considerable advantage [18, 19];

– the output vector Y – technical power losses at PTL (for maximum precision, taken as the difference in the APCAS data at the beginning and at the end of PTL).

Then we examined the input variables in order to determine the appropriateness of their inclusion to the input vector of ANN. Simulation of the sample is carried out by means of load change and meteodata, which create the input vector. The sample comprised 732 daily observations, chosen for the PTL of voltage 10 and 35 kV during the whole of 2008 to include in the model an entire seasonal interval, thereby reducing errors and uncertainty. In the proposed model we make assumptions, such as constant parameters of alternative schemes and operational status of the scheme, that is, when forming the input vector for modeling ANN we do not apply data preprocessing because the model is built in the program – neuro simulator Statistica Neural Networks [21]. One may predict that the input parameters correlate, considering their physical nature, so it is necessary to use one of the methods of lowering dimensionality and selection of data – testing the input variables using attempts and errors [20, 21]. In this case, the network input was exposed to their various combinations followed by the stage of building and training ANN. For solving the problem, here was involved the automatic network designer, which is a function of the package Statistica Neural Network [21], with which the following ANN was built: type – multi-layer perceptron with 6 input neurons, 5 hidden neurons in the hidden layer and 1 original neuron; activation function is linear, the sample was automatically divided into 3 parts: 366 observations – training sample, 183 – control, 183 – testing. Conclusion about appropriateness of using the variable is drawn based on the value of the lowest error of the model, calculated by (24) for the training, control and testing samples.

Then we examine reasonable amounts of the training, control and testing samples of ANN under design. The training data set is a set of observations, for which the values of input and output variables are specified. Based on the study of the training sample, it is necessary to make conclusions about the general totality, and in this case it is necessary to know the degree of reliability of these conclusions. If the training sample includes all the objects of the general totality, that is, they coincide, then the accuracy of conclusions will be the highest (all other things being equal). If the training sample is very small, it is unlikely to become the base for drawing credible conclusions about the general totality [15, 20]. But representativeness depends not only on the volume but also on the structure of the training sample [15, 20, 21]. In this regard, we will later consider necessary characteristics and conditions for the training sample.

Completeness of the training sample is the ratio of the number of training sets for a class to the number of attributes of the class that is applied in the set, which varies within 3–5. Completeness is defined by the provision of classes with training sets

$$F_{HB} = N_F / N, \quad (25)$$

where N_F is the number of classes that satisfy the specified condition, N is the total number of classes.

Equability of the training sample shows how evenly the training sets are distributed in classes

$$\Delta C = \sqrt{\frac{\sum_{i=1}^{K}\left([C_i]-[C_K]\right)^2}{K-1}}, \quad (26)$$

where $[C_i]$ is the number of training sets for the class i.

Irregularity of the training sample

$$R_{HB} = \sqrt{\frac{\sum_{i=1}^{K}\Delta C_i}{K}}. \quad (27)$$

Contradiction of the training sample is an indicator that describes the number of identical objects that belong to different classes

$$A_{HB} = N_A / N, \quad (28)$$

where N_A is the number of conflicting sets in the sample, N is the total number of sets.

Repeatability of the training sample is an indicator that describes the number of identical sets within a single class

$$P_{HB} = \frac{1}{n_c} \sum_{K=1}^{n_c} \frac{n_K^P}{n_K^C}, \quad (29)$$

where n_K^P, n_K^C are the number of sets that are repeated, respectively, and the total number of sets for the class k, n_c is the number of classes in the training sample.

The testing sample is used to test the adequacy of the constructed model, so one should reject at once a hypothesis that the volume of the testing sample is insufficient for its representativeness. Thus, it is assumed that the testing sample is indicative. To test hypotheses about sufficiency of the volume of the training sample, they use the theory of "learning curves" [15, 20, 21]. Therefore, if the volume of the training sample is inadequate for the control and testing errors to reach one asymptotic level, then it is necessary to increase volume of a training sample or use a less complex model. For examining reasonable volumes of the training, control and test samples, in Statistica Neural Network we built ANN with parameters, identical to the above-considered task of studying the input variables. The data set of ANN (732 observations) was divided into 3 parts: the training data set (changed manually), control and testing sets (changed automatically depending on the change in the volume of the training sample).

Then we performed research and selection of the appropriate type of ANN architecture. The criteria for this selection are determined by the minimum error of the model that is calculated by (24), and the complexity of the network architecture [16, 17, 21]. To do this, in the program – neuro simulator STATISTICA Neural Networks we built 10 best ANN with the help of architectures that are appropriate to use in this case [17, 21]:

– multi-layer perceptron (MP) – simulates response function using the function of «sigmoid slopes». Mathematically, the function that is implemented at the output of the perceptron, takes the form

$$f(x) = \mathrm{sign}\left(\sum_{i=1}^{n} \omega_i x_i - \theta\right), \quad (30)$$

where ω_i is the weight of connection, takes a value in the range {–1; 0; +1};

– radial – basic function (RBF) is the surface of response, it is a Gaussian function, with the peak in the center and decreasing to the edges

$$f(x) = \phi\left(\frac{x^2}{\delta^2}\right), \quad (31)$$

where x is the vector of input signals of neuron, σ is the width of the function window;

– reverse propagation of neural network (RPNN) or generalized-regression network is the class of networks, based on the method of approximation of probability density with the help of nuclear functions, where the Gaussian function fits location of each training measure.

A study of selection of expedient activation function of ANN under design consists in finding and comparing an error of the model that is calculated by (24), in the received ANN with different activation functions. To solve the problem, we built ANN with selected expedient architecture and volume of samples. We analysed the following activation functions, which is predetermined by specificity of the task [15, 20, 21]

– linear

$$y = f(x); \quad (32)$$

– logistic

$$y = f\left(\frac{1}{1+e^{-x}}\right). \quad (33)$$

To select the appropriate algorithm of ANN training, we built ANN with selected appropriate architecture, volume of the sample and activation function.

The training of ANN under design was carried out using the following algorithms [15, 20, 21]:

– reverse propagation (RP) – when training, it computes local gradient of each weight for each observation. The weight is determined after processing each observation

$$\Delta\omega_{ij}(t) = \eta \cdot \delta_j \cdot \theta_i + a \cdot \Delta\omega_{ij}(t-1), \quad (34)$$

where η is the learning rate; δ is the local gradient of error; θ_i is the original value of the i-th element; a is the coefficient of inertia;

– fast propagation (FP) – it acts on assumption that the error's surface is locally quadratic. The change of weights are calculated by the formula of fast propagation

$$\Delta\omega_{ij}(t) = \frac{s(t)}{s(t-1)-s(t)} \Delta\omega(t-1), \quad (35)$$

where s(t) is the gradient of errors' surface with respect to the given weight;

– descent by linked gradients (DLG) is applied in all cases where the reverse propagation method is applied. The initial direction of the search

$$d_O = -g_O. \quad (36)$$

In further steps, the search direction is corrected by using the Polak Ribiere formula

$$D_{j+1} = -g_{j+1} + \beta_j d_j. \quad (37)$$

The search in the specified direction is performed by the Brent's iterative method of linear search, in which for quick localization of the minimum, a parabolic interpolation is used;

– Levenberg-Marquardt (LM), developed in such a way as to minimize mean square error function

$$\Delta\omega = -(Z^T Z + \lambda I)^{-1} Z^T \varepsilon, \quad (38)$$

where ε is the vector of errors on all observations, Z is the matrix of private derivatives from these errors by weights.

An algorithm of learning, characterized by minimal error of the model by (24) and the time of learning will be expedient [16, 17, 21]. At first ANN under design was trained in one stage by different algorithms, the results were analysed and inefficient algorithms that have unacceptable errors were excluded. Then the training of the network was conducted in two stages by analyzing all possible combinations of the algorithms of learning.

5. Results of research into the influence of climatic factors on technical power losses at the overhead PTL of voltage 6–35 kV and development of a model of neural network

5. 1. Results of research into the influence of climatic factors on technical power losses at the overhead PTL of voltage 6–35 kV

Results of the study of dynamics of change in average monthly temperature throughout the year and deviations of average annual temperature from the generally accepted for 2006–2008 (averaged values over 3 years) for the weather station Lyubashivka, using meteodata [14], are given in Table 1.

Table 1

Dynamics of change in average monthly temperature throughout the year and deviations of average annual temperature from the generally accepted for 2006–2008 (averaged values over 3 years) for the weather station Lyubashivka

Month	Temperature, °C	Month	Temperature, °C
January	–4,43	July	21,14
February	–2,10	August	21,70
March	4,83	September	15,20
April	8,60	October	10,17
May	15,00	November	2,80
June	19,77	December	–0,70
Average annual temperature in 2006–2008			9,3
Generally accepted average annual temperature			8,2
Deviation of average annual temperature from the generally accepted in 2006–2008			1,1

As a result of comparative analysis of the deviation of estimated energy losses at overhead PTL by the approaches that take into account temperature factor, from the official approach [11] based on technical and reference data, as well as meteodata [14] for the period of 2006–2008 (averaged values over 3 years), it was found [22]:

– deviation of energy losses at the overhead PTL, calculated by the approach, in which the losses are calculated without taking into account temperature, compared to the official approach is 5 %;

– application of the approach, in which the losses are calculated with regard to average annual temperature in 2006–2008, allows obtaining an insignificant (0.5 %) deviation from the official approach;

– the approach, in which the losses are calculated taking into account average monthly temperature, has over one year a deviation from the official approach in the range of 0.17–5.67 % and totally for the year – 3.32 %. With regard to the obtained results, one may predict that this approach is more accurate compared to the official approach, which was consequently confirmed after checking the adequacy of the received results (Table 3). This approach is accepted as basic for further research.

Table 2 displays values of coefficient of heat transfer during rain and snow on the surface of the wires of the AC mark with different sections of overhead PTL, 1 km long, which are calculated by (20) and (21).

Table 2

Value of coefficient of heat transfer during atmospheric precipitation on the surface of the wires of the AC mark with different sections of overhead PTL of length 1 km

Wire section, S, mm^2	α W/m^2·K	
	Rain	Snow
10	3361,5	771,6
16	2657,5	610,0
25	2126,0	448,0
35	1796,8	412,4
50	1503,3	345,1
70	1270,5	291,6
95	1090,6	250,3
120	970,4	222,7
150	867,9	199,2
185	781,5	179,4
240	686,2	157,5

With regard to the proposed approach to the selection of temperature for calculations and estimated coefficients of heat transfer during atmospheric precipitation on the wires' surface, the basic equation of heat balance for the thermal mode that was set, for the PTL wires [2, 13, 23]

$$I^2 R_{20} k_f^2 \left(1+\alpha\left(t_w-20\right)\right)+W_r = \\ =\pi d\left(\beta_w+\beta_e+\alpha_0 l\right)\left(t_w-t_a\right), \quad (39)$$

where α_0 is the heat transfer coefficient, which takes into account the impact of atmospheric phenomena; k_f is the coefficient of diagram's form; l is the length of the wire, km.

The wire temperature is determined through ambient temperature, taking into account current in it, as well as cooling the wire by precipitation and wind, using the recommended method of mean loads with consideration of the proposed approach to the selection of temperature for calculations and the calculated heat transfer coefficients during atmospheric precipitation on the wires' surface [2, 13, 23]

$$\left(1+\alpha\left(t_w-20\right)\right)= \\ =\left[1+\alpha\left(t_a+\frac{1+\alpha\left(t_a-20\right)I^2R_{20}k_f}{2\alpha_o\sqrt{\pi F}}-3{,}5k_\psi\sqrt{\frac{v}{\sqrt{S/0{,}785}}}\right)\right]\Delta t. \quad (40)$$

Then the proposed expression for the calculation of the load energy losses at overhead PTL, taking into account the above-enumerated [23]

$$\Delta W = I^2 R_{20} k_f^2 \times \\ \times\left[1+\alpha\left(t_a+\frac{1+\alpha\left(t_a-20\right)I^2R_{20}k_f}{2\alpha_o\sqrt{\pi F}}-3{,}5k_\psi\sqrt{\frac{v}{\sqrt{S/0{,}785}}}\right)\right]\Delta t, \quad (41)$$

where s, F are the section and area of wire's surface, respectively (calculated as the surface area of cylinder)

$$F = \pi dl = \pi\sqrt{S/0,785}. \quad (42)$$

Expression (41) may be applied for the calculation of energy losses at overhead PTL over the daily and monthly periods. The total losses during the respective periods add up to the yearly ones.

Results of the calculation of deviation in energy losses, which are calculated by different approaches, at the overhead PTL of voltage 35 kV (AC-50 wire) and of 10 kV (AC-25 wire) from the APCAS data in 2008 (to verify the adequacy of the obtained results) are demonstrated in Table 3.

The example we have considered demonstrates that the proposed approach, compared with the official, turned out to be more accurate on average by 4.58 % when calculating annual energy losses at the overhead PTL of 35 kV in Lyubashivka-Demidove (AC-50 wire) and by 3.07 % when calculating annual energy losses at the overhead PTL of 10 kV in Demidove-Bobrik (AC-25 wire), as well as by 6.04 % for the coldest month of the year and by 4.73 % for the warmest month when conducting analysis over 3 years for the section Lyubashivka-Demidove [23].

5. 2. Results of development of a model of neural network for calculation and prediction of technical energy losses at the overhead PTL of voltage 6– 35 kV

Table 4 displays values of errors in the calculation of energy losses and the following designations are introduced [24]: P – active load of OL; U – rated voltage of OL; S – section of OL wire; L – length of OL wire; T – average daily air temperature; V – wind speed; O – availability of precipitation.

We conducted analysis of the levels of significance of the sets of input variables assigned after training ANN by the program – neuro simulator, based on the values of errors in the calculation of losses, received as a result of constructing and training ANN [24], from which it follows:

– the sets of input variables PUSLVO (excluding temperature) and USLTVO (excluding load) cannot be used as an input vector, which is due to a large error;

– the most significant variables are active load of OL and the average daily air temperature, which must be included in the set of input variables by all means;

– all other variables are also expedient to include in the constructed ANN for the following reasons: first, their total level of significance is practically the same, second, the inclusion of data of the variables will reduce the error of forecasting and improve result.

Table 3

Results of the calculation of deviation in energy losses, which are calculated by different approaches, at the overhead PTL of voltage 35 kV (AC-50 wire) and 10 kV (AC-25 wire) from the APCAS data in 2008

Month	Energy losses, thous. kW·year							
	Overhead PTL of 35 kV (AC-50 wire)				Overhead PTL of 10 kV (AC-25 wire)			
	APCAS thous. kW·year	Approach 1, thous. kW·year	Approach 2, thous. kW·year	Approach 3, thous. kW·year	APCAS thous. kW·year	Approach 1, thous. kW·year	Approach 2, thous. kW·year	Approach 3, thous. kW·year
January	2,924	3,515	3,326	3,133	0,861	0,935	0,839	0,873
February	3,154	3,612	3,401	3,247	0,813	0,746	0,783	0,826
March	2,837	3,437	3,124	3,015	0,722	0,810	0,809	0,678
April	2,753	3,215	2,970	2,835	0,921	0,750	0,794	0,969
May	2,875	3,502	2,994	2,982	1,183	1,023	1,065	1,267
June	2,265	2,751	2,587	2,374	1,184	1,019	1,109	1,252
July	2,132	1,678	1,794	1,908	1,019	1,019	0,889	0,947
August	2,378	2,874	2,675	2,559	1,678	1,453	1,787	1,779
September	2,252	2,736	2,495	2,412	1,050	0,908	0,979	1,103
October	2,315	2,795	2,428	2,406	1,461	1,235	1,256	1,587
November	2,453	2,902	2,688	2,612	0,516	0,413	0,422	0,478
December	2,518	3,023	2,869	2,694	0,545	0,648	0,482	0,563
Mean relative deviation of approach, %	–	20,04	10,45	5,87	–	8,302	6,172	3,102

Table 4

Errors in the calculation of losses depending on the set of input variables

Error/set of input variables	PUSLTV (without regard to precipitation)	PUSLTO (without regard to wind speed)	PUSLVO (without regard to temperature)	PUSTVO (without regard to wire length)	PULTVO (without regard to wire section)	PSLTVO (without regard to voltage)	USLTVO (without regard to load)
Error of training	0,067494	0,061896	0,110904	0,050740	0,063761	0,056326	0,156492
Control error	0,049753	0,059727	0,124642	0,071494	0,055463	0,057126	0,178821
Testing error	0,057444	0,066974	0,109739	0,067247	0,059764	0,072795	0,192722

As a result of research into reasonable volumes of the training, control and testing samples, the errors were received that are presented in Table 5.

Table 5

Errors in the calculation of losses depending on volume of the training sample

Volume of the training sample	Error of training	Control error	Testing error
100	0,113832	0,109299	0,126672
150	0,104773	0,143514	0,104490
200	0,063827	0,075923	0,061595
250	0,051757	0,067472	0,072237
300	0,058532	0,068606	0,070284
350	0,062869	0,061484	0,059147
400	0,066695	0,066691	0,072729

Appropriate training sample volume for the given ANN under design at the set parameters amounted to 250 observations, the volumes of control and testing samples are taken equal to 250 and 332 observations, respectively.

Results of the best architectures of networks that were obtained in STATISTICA Neural Networks [21, 24] are given in Table 6. Abbreviations to Table 6: multi-layer perceptron (MP), radial basic function (RBF) and reverse propagation of neural network (RPNN) or generalized-regression network.

Table 6

Results of the best architectures of networks that were obtained in STATISTICA Neural Networks

Architecture of network	Error of training	Control error	Testing error	Input	Hidden layers	
					Layer 1	Layer 2
RPNN 7:7–250–2–1:1	4,274141	4,346222	3,669047	7	250	2
RBF 7:7–14–1:1	3,833628	3,995193	3,101599	7	14	0
RPNN 7:7–250–2–1:1	3,384848	3,712948	3,150827	7	250	2
RBF 7:7–29–1:1	2,303887	2,428618	1,958460	7	29	0
MP 1:1–6–5–1:1	0,189972	0,205554	0,200392	1	6	5
MP 1:1–6–4–1:1	0,191509	0,202157	0,198880	1	6	4
MP 5:5–4–1:1	0,067834	0,080368	0,065184	5	4	0
MP 5:5–5–1:1	0,067084	0,071118	0,065293	5	5	0
MP 7:7–5–1:1	0,059038	0,069098	0,065109	7	5	0
MP 7:7–10–6–1:1	0,067096	0,066738	0,054334	7	10	6

Using the obtained results of the program – neuro simulator and based on the criteria of choosing the best type of architecture of ANN, based on comparative analysis by the criteria of significance, we can conclude [24]:

– the use of generalized-regression network and radial basic function is inexpedient because the errors of these architectures of networks are considerably larger than the corresponding errors, obtained by using the multilayer perceptron;

– for this type of task, the best type of ANN architecture is the multi-layer perceptron, which compared to other architectures is characterized by the smallest errors and complexity of the network;

– we take ANN with the following architecture as basic: multi-layer perceptron, 7 neurons in the input layer, 5 neurons in the hidden layer and one output neuron.

After the performed research, it was determined [24] that the expedient activation function for this ANN is logistic function (Table 7).

Table 7

Selecting the activation function for ANN

Activation function	Error of training	Control error	Testing error
Linear	0,084740	0,099548	0,092458
Logistic	0,057665	0,059522	0,058583

Results of examination of errors of the ANN learning algorithms in one and two stages [24] are presented, respectively, in Tables 8, 9.

As a result of examination of errors in the ANN learning algorithms in one stage (Table 8), it was found that for the further study of the ANN learning algorithm, reverse propagation and the Quasi-Newton algorithm are not valid because they have large errors. Other algorithms provide for the acceptable errors.

As an appropriate training algorithm for the given task, we accept the ANN training in 2 stages: at the first stage we apply the method of fast propagation, at the second – the Levenberg-Marquardt method (has rapid convergence and the least error).

Table 8

Results of examination of errors in the ANN learning algorithms in one stage

Error/Results of training	Methods (algorithms) of training ANN				
	reverse propagation (RP)	fast propagation (FP)	descent by linked gradients (DLG)	Levenberg-Marquardt (LM)	Quasi-Newton (QN)
Error of training	0,112562	0,080551	0,046875	0,091003	0,112388
Control error	0,134033	0,089106	0,067834	0,068000	0,100995
Testing error	0,126493	0,073998	0,055933	0,085069	0,115200
Training time, s	2	3	4	4	4

Table 9

Results of examination of errors of the ANN learning algorithms in two stages

Error/Results of training	Methods (algorithms) of training ANN (first/second stages)								
	FP/FP	LM/LM	DLG/DLG	FP/LM	LM/ DLG	DLG/FP	LM/FP	DLG/LM	FP/DLG
Error of training	0,060728	0,043001	0,054755	0,039913	0,062569	0,094558	0,123173	0,282422	0,059506
Control error	0,073110	0,057539	0,065078	0,058128	0,063272	0,097877	0,131407	0,301171	0,066908
Testing error	0,069919	0,066846	0,064994	0,064644	0,066113	0,087794	0,156572	0,342226	0,075725
Training time, s	4	5	5	5	5	5	5	5	5

6. Discussion of results of research into the influence of climatic factors on technical power losses at the overhead PTL of voltage 6–35 kV

When examining [11] in detail, the first question is “why does the official method of determining energy losses take into account only the annual average air temperature for the given region while neglecting all other climate factors? And why, when calculating energy losses in such different months as, for example, January and July, do we need to use the data of annual rather than monthly average air temperature (Table 1)?” We conducted research into these issues and recommend using, when calculating and forecasting the power losses, the approach, which uses value of the average monthly temperature for the particular region, as the more accurate compared to the official approach (Table 3).

In addition, to reduce the error in prediction and calculation of energy losses at overhead PTL, we analyzed and explored other climatic factors (wind, precipitation, etc.) and proposed to include in the basic equation of thermal balance, which was established, for the PTL wires, coefficients of heat transfer that take into account the impact of precipitation (rain, snow), which were calculated (Table 2).

In view of the above said, we improved the main equation of thermal balance, which was established, and the expression for calculating technical energy losses for the PTL of voltage 6–35 kV (22, 24).

With regard to this, we developed an appropriate neural network model for the calculation and prediction of technical energy losses at overhead PTL of voltage 6–35 kV, which has many advantages compared with many obsolete models that are still widely used in the Ukrainian energy systems [2, 3, 8, 10].

In the course of developing this issue, using mainly the type of the task and the least errors, with the help of the program-neuro simulator STATISTICA Neural Networks, we examined and selected the expedient: set of input variables (Table 4), volumes of the samples (Table 5), network architecture (Table 6), activation function (Table 7), network learning algorithm (Tables 8, 9).

Further research in the direction of taking into account climatic factors in forecasting and calculating energy losses at overhead PTL is a promising task [3, 8, 10]. In this case, in the future studies it would be appropriate to include additional factors such as topographical conditions of terrain, air humidity, pressure, etc. [3, 4, 8, 10, 12]. It is also worthwhile examining different classes of voltage at overhead PTL, which would complement the research, as the analysis of this issue was performed only for the overhead PTL of 6–35 kV. Another limitation of the study is that it was conducted for the moderate climate of the South of Ukraine with corresponding climatic conditions. In future, it is planned to continue the study of this problem with regard to these aspects.

A certain shortcoming of the study is that we did not use in the simulation of artificial neural network the hybrid, as well as some advanced, methods (for example, simulation based on the particle swarm optimization algorithm, etc.).

Results of the study may be useful for forecasting and calculation of energy losses at the overhead PTL of voltage 6–35 kV in power supply and designing organizations.

7. Conclusions

1. We analyzed and examined approaches to calculating the losses of electric energy in PTL; after verifying the adequacy of the obtained results, the feasibility was justified of applying the approach, in which the losses are calculated taking into account average monthly air temperature (it is more accurate in comparison to the official approach). This approach is proposed as basic when calculating and forecasting load energy losses at the overhead PTL of voltage 6–35 kV.

2. We examined, calculated and proposed to include in the basic equation of thermal balance, which was established, for the PTL wires, coefficients of heat transfer that take into account the impact of precipitation (rain, snow);

3. The model of thermal processes was improved, as well as the basic equation of thermal balance, which was established, and expression for determining technical energy losses in the overhead PTL of voltage 6–35 kV. The improvement was carried out by the fuller account of meteofactors, taking into account the proposed approach to the selection of air temperature and heat transfer coefficients at atmospheric precipitation on the surface of the wires. This will reduce the error when calculating and predicting load power losses at PTL.

4. We designed appropriate model of neural network for the calculation and prediction of technical energy losses in the overhead transmission lines of voltage 6–35 kV. This model has the following advantages: lower error of calculation, capacity to work with noisy data, ability to use small training samples, quick response of the trained network. Other benefits of the developed model include provision of virtually full mode range of electrical network performance, accounting for a large number of factors, high degree of adequacy of the network modes, etc.

References

1. The Cabinet of Ministers of Ukraine [Text]. – A comprehensive state program of energy saving in Ukraine, 1997.
2. Krasovsky, P. Y. Factors affecting the dynamics of technical losses in power lines [Text] / P. Y. Krasovsky // Proceedings of the Dnipropetrovsk National Mining University, 2006. – 76 p.
3. Miroshnik, A. A. Refined algorithms for calculating the energy losses in networks 0,38 kV in real time [Text] / A. A. Miroshnik // Regional energy issues. – 2010. – Vol. 2, Issue 13. – P. 35–42.
4. Turbin, S. V. Improving methods for determining environmental loads on air routes taking into consideration subject topographical features of the area [Text] / S. V. Turbin // Energy and Electrification. – 2006. – Vol. 3. – P. 33–43.
5. IEC 60287–2–2:1995 Electric cables–Calculation of the current rating–Part 2: Thermal resistance [Text]. – Section 2: A method for calculating reduction factors for groups of cables in free air, protected from solar radiation
6. Gupta, P. C. Adaptive short–term forecasting of hourly loads using weather information [Text] / P. C. Gupta, K. Yamada // IEEE Transactions on Power Apparatus and Systems. – 1972. – Vol. PAS-91, Issue 5. – P. 2085–2094. doi: 10.1109/tpas.1972.293541
7. Panuska, V. Short–term forecasting of electric power system load from a weather dependent model [Text] / V. Panuska // IFAC Symp.1977. Autom. Contr. and Prot. Electr. Power Syst., Melbourne, 1977, 1977. – P. 414–418.
8. Vorotnitsky, V. E. Estimation of variable energy losses error in overhead lines because of the weather conditions neglect [Text] / V. E. Vorotnitsky, O. V. Turkina // Energy systems and electrical networks. – 2008. – Vol. 10. – P. 42–49.
9. Levchenko, I. I. Carrying capacity and monitoring of overhead power lines in extreme weather conditions [Text] / I. I. Levchenko, E. I. Satsuk // Electricity. – 2008. – Vol. 4. – P. 2–8.
10. Zhelezko, Y. S. Loss of electric energy in electric grids, depending on weather conditions [Text] / Y. S. Zhelezko // Power station. – 2004. – Vol. 11.
11. Ministry of Energy and Coal Industry of Ukraine [Text]. – Method for determining the technological power consumption of transshaper and power lines, 2011.
12. Osipov, D. S. Recording of heating of current–carrying parts in the calculation of the power loss and power at non-sinusoidal modes of electric power systems [Text] / D. S. Osipov. – Omsk, 2006.
13. Vragov, A. P. Heat exchange processes and equipment of chemical and petroleum industries [Text] / A. P. Vragov. – Sumy, 2006. – 218 p.
14. Server «Weather of Russia». Archive of weather data [Electronic resource]. – Available at: http://meteo.infospace.ru
15. Rutkovska, D. Neural networks, genetic algorithms and fuzzy systems [Text] / D. Rutkovska, M. Pilinsky, L. Rutkowski. – I.D.M.: Hotline–Telecom, 2006. – 452 p.
16. Zaigraeva, Y. B. Neural network models of assessment and loss electricity planning in power systems [Text] / Y. B. Zaigraeva. – Novosibirsk, 2008. – 215 p.
17. Tsaregorodtsev, V. G. To the definition of informativeness of independent revariables for the neural network [Text] / V. G. Tsaregorodtsev // Neyroinformatika i ee prilozheniya, 2003. – P. 176–177.
18. Srinivasan, D. A novel approach to electrical load Forecasting based on a neural network [Text] / D. Srinivasan et. al. – Singapore: INNC–91, 1991. – P. 1172–1177.
19. Hamid, B. Automated load forecasting using neural networks [Text] / B. Hamid, M. Walter // Proc. Amer. Power Conf. – 1992. – Vol. 54. – P. 1149–1153.
20. Tsaregorodtsev, V. G. A view at the architecture and requirements for the neuroimitator to solve problems of modern industry [Text] / V. G. Tsaregorodtsev // Neyroinformatika i ee prilozheniya, 2003. – P. 171–175.
21. Neural networks. STATISTICA Neural Networks [Text]. – Moscow: Hotline – Telecom, 2001. – 654 p.
22. Bakulevskiy, V. L. Considering the temperature factor in the calculation of technical losses in electricity transmission overhead lines [Text] / V. L. Bakulevskiy // Problems of energy saving in electrical systems. – 2011. – Vol. 1. – P. 172–173.
23. Bakulevskiy, V. L. Improving the accuracy of calculation of load electricity losses in overhead lines with voltage 6–35 kV by taking into account climatic factors [Text] / V. L. Bakulevskiy // Scientific works of Donetsk National Technical University. – 2013. – Vol. 1, Issue 14. – P. 9–14.
24. Bakulevskiy, V. L. The use of neural networks for the calculation of technical losses of electricity in overhead power lines voltage 6–35 kV [Text] / V. L. Bakulevskiy // Journal of Azov Technical University. Engineering. – 2015. – Vol. 30.