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Intelligent Forecasting of Electricity Consumption in Managing Energy Enterprises in Order to Carry out Energy-Saving Measures

Abstract

The concept of "Digital Transformation 2030", which defines the national goals and strategic objectives of the development of the Russian Federation for the period up to 2030, specifies specialized goals and objectives that are an important message for the introduction of intelligent information management technologies in the electric power industry. The main challenges for the transition to digital transformation are the increase in the rate of growth of tariffs for the end consumer, the increasing wear and tear of the network infrastructure, the presence of excessive network construction and the increase in requirements for the quality of energy consumption. The determining factor in the possibility of developing an effective energy policy is the forecasting of electricity consumption using artificial intelligence methods. One of the methods for implementing the above is the development of an artificial neural network (ANN) to obtain an early forecast of the amount of required (consumed) electricity. The obtained predictive values open up the possibility not only to build a competent energy policy by increasing the energy efficiency of an energy company, but also to carry out specialized energy-saving measures in order to optimize the organization's budget. The solution to this problem is presented in the form of an artificial neural network (ANN) of the second generation. The main advantages of this ANN are its versatility, fast and accurate learning, as well as the absence of the need for a large amount of initial da-ta for a qualitative forecast. The ANN itself is based on the classical neuron and the error back-propagation method with their further modification. The coefficients of learning rate and sensitivity have been added to the error backpropagation method, and the coefficient of response to anomalies in the time series has been introduced into the neuron. This made it possible to significantly improve the learning rate of the artificial neural network and improve the accuracy of predictive results. The results presented by this study can be taken as a guideline for energy companies when making decisions within the framework of energy policy, including when carrying out energy saving measures, which will be especially useful in the current economic realities.

Keywords: *neural networks, artificial intelligence, intelligent forecasting of electricity consumption, data mining, energy efficiency, management in the energy sector*

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Интеллектуальное прогнозирование потребления электроэнергии при управлении энергетическими предприятиями на основе нейросетевых технологий*

В концепции "Цифровая трансформация 2030", определяющей национальные цели и стратегические задачи развития Российской Федерации на период до 2030 года, указаны специализированные цели и задачи, являющиеся важным посылом для внедрения интеллектуальных информационных технологий управления в сферу электроэнергетики. Основными вызовами для перехода к цифровой трансформации являются увеличение темпов роста тарифов для конечного потребителя, нарастающий износ сетевой инфраструктуры, наличие избыточного сетевого строительства и повышение требований к качеству энергопотребления.

Определяющим фактором возможности разработки эффективной энергетической политики является прогнозирование потребления электроэнергии с использованием методов искусственного интеллекта. Одним из методов реализации вышесказанного является разработка искусственной нейронной сети (ИНС) для получения заблаговременного прогноза количества требуемой (потребляемой) электроэнергии. Полученные прогнозные значения открывают возможность не только выстроить грамотную энергетическую политику путем повышения энергоэффективности энергетической компании, но и проводить специализированные энергосберегающие мероприятия в целях оптимизации бюджета организации.

Решение данной проблемы представлено в виде искусственной нейронной сети второго поколения. Основными преимуществами данной ИНС являются универсальность, скоростное и точное обучение, а также отсутствие необходимости в большом количестве исходных данных для качественного прогноза. За основу самой ИНС берутся классический нейрон и метод обратного распространения ошибки с их дальнейшей модификацией. В метод обратного распространения ошибки добавлены коэффициенты скорости обучения и чувствительности, а в нейрон внедрен коэффициент реагирования на аномалии во временных рядах. Это позволило существенно улучшить скорость обучения искусственной нейронной сети и повысить точность прогнозных результатов.

Представленные в настоящем исследовании результаты могут быть взяты в качестве ориентира для энергетических компаний при принятии решений в рамках энергетической политики, в том числе и при проведении энергосберегающих мероприятий, что будет особенно полезным в текущих экономических реалиях.

Ключевые слова: *нейронные сети, искусственный интеллект, интеллектуальное прогнозирование потребления электроэнергии, интеллектуальный анализ данных, энергоэффективность, управление в энергетике*

Introduction

Energy forecasting (in particular electricity consumption forecasting) is an integral part of energy system management processes [1—4]. At the same time, stable and accurate electricity consumption forecasts are very important both for the individual utility and for the energy sector as a whole due to increased network capacity and maintaining the balance of supply and demand in the electricity market [5]. Conversely, inaccurate electricity consumption forecasts increase start-up and forecast financial costs, which can reduce the investment attractiveness of energy companies as well as pose serious threats to the security, efficiency and quality of energy systems [6].

The issues of electricity consumption forecasting are still relevant today, not only for financial reasons, but also because of the lack of the necessary universal designers of such solutions in the form of intelligent system technologies for managing organizations and companies in general. These intelligent technologies and systems would help to optimize energy consumption (including energy efficiency). Over the last decades, a huge number of theoretical and practical specialized solutions aimed at predicting energy consumption have been presented by scientists and researchers. At the same time, they can be divided to several types: regression (statistical) [7], Gray's prediction models [8], hybrid models [9—11] and neural network

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(intelligent) models [12], which have three serious common limitations:

1) specificity there is no universality regarding forecasting in all electrical systems. I.e. each smart model/system will have to be redesigned for each specific case;

2) forecasting requires a large amount of retrospective data: amount of electricity consumed and facilities on the grid, types of power grids, number of appliances connected to one power grid facility, capacity of each appliance, specific legal entities (companies) and their operating schedule, season (summer, autumn, winter or spring), holidays and weekends, forecast air temperature values;

3) quite resource-intensive intelligent forecasting models: when providing effective forecasting in remote and isolated energy districts without access to an external global Internet network, this limitation may be critical.

Thus, the main objective of this study is to develop a versatile solution in the electricity sector (taking into account the shortcomings described above) for forecasting electricity consumption in advance in energy companies. This will allow specialized organizations and services, as well as governing bodies, to make decisions, in particular energy saving measures, in the shortest possible time, under conditions of increasing economic uncertainty.

In this study, to minimize the above limitations, we propose to implement an artificial neural network to predict electricity consumption with the following advantages and scientific novelty:

1) the universality of the structure of the proposed solution due to automatic formation of the number of layers and neurons, as well as a modified method for training the artificial neural network. This will allow to integrate the ANN model into the production process without re-designing;

2) modified training method based on the method of back propagation of error. The main changes are:

addition of an ANN learning rate coefficient, which will increase the speed of calculation of predictive values;

addition of sensitivity coefficient $\varphi = 0.01, ..., 0.99$. The main point of the change is to create a range of synaptic connection weights (weight coefficients). This will make it possible to avoid sharp fluctuations in the matrix of weight coefficients, which will have a positive effect on the accuracy of the calculation of predictive values;

3) modified neuron. The essence of the modification (in contrast to the classical neuron [13]) is to add a response coefficient to anomalies in the time series, which also has a positive effect on the accuracy of the output forecast values;

4) small amount of data for training. The proposed ANN model uses retrospective training data for the last 4 years (25,903 values): electricity consumption and air temperature. This makes it possible to accurately predict without historical data for earlier dates.

Management of electricity consumption in electricity distribution grids

At power distribution network enterprises, as well as at any other enterprises, on the basis of certain corrective actions managers formulate goals and objectives of management, the solution of which is achieved through the performance of a certain sequence of functions of the management process. With regard to electric distribution grids, the functions of the management process are: development of an action program; implementation of planned work; evaluation of work results; formation of corrective actions. Thus, the management process in electricity distribution grids can be represented as a Deming cycle in Fig. 1.

Section "plan" — "development of action program". This section of the cycle implies the formation of plans for technical maintenance and repair of distribution networks, where the basis for planning is the information on the condition of equipment and the frequency of preventive maintenance indicated in the regulatory documentation. This section also includes forecasting of power consumption, which depends on a large number of different factors (e.g., air temperature, seasonality, etc.) that have a significant impact on the volume of power consumption.

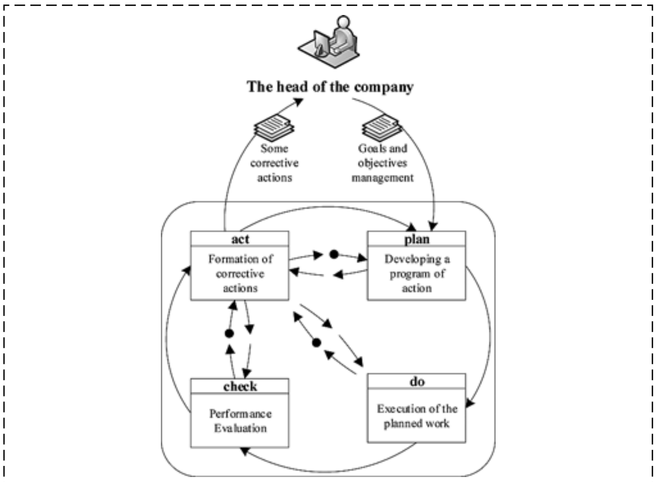

Fig. 1. Formal model of the control process in electrical distribution networks

Section "do" — "performance of planned works". This section of the cycle is to ensure the reliable and efficient operation of power grid facilities (power transmission lines, transformer substations, power substations, etc.), as well as the uninterrupted supply of electricity to consumers.

Section "check" — "performance evaluation". This section in the cycle is related to determining the deviations between the values of the volumes of electricity provided by the distribution networks and received by the end users. The total volume of electric power provided by distribution grids is the sum of the volume received by end users and the volume of various kinds of losses arising in the grid. In reality, electricity losses can occur in any part of the power grid in Fig. 2.

In Fig. 2, let us introduce the following notations:

— EDN is the electric distribution network;

— PS_a — a power substation with order number a, such that $a = \overline{(1, \ldots, n)}$, where n — is the number of power substations;

— TS_{ab} — a transformer substation with ordinal number b, connected to a power substation with ordinal number a, where $b = \overline{(1, \ldots, m)}$, where m — is the number of transformer substations, k — is the intermediate ordinal number of the transformer substation;

— UC_{abd} — the final consumer with serial number d, connected to the transformer substation with serial number b and to the power substation with serial number a, where d — is the serial number of the final consumer, such that $d = \overline{(1, \ldots, t)}$, where t — is the number of final consumers, p — is the intermediate serial number of the final consumer.

Based on the above and Fig. 2, electric power losses can be classified into the following groups: losses on electric lines connecting power distribution networks and power substations; losses at power substations; losses on electric lines connecting power and transformer substations; losses at transformer substations; losses on electric lines connecting transformer substations with the end consumer, and losses at the end consumer points.

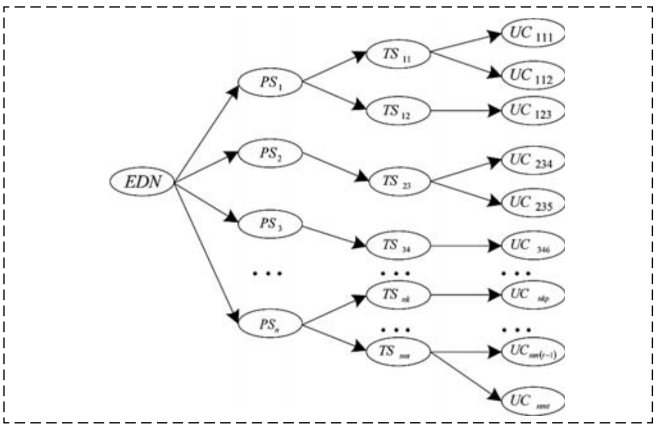

Fig. 2. Scheme of distribution of electricity over the network

In the event of electrical losses, end users compensate only for normative losses, and the difference between the values of actual and normative losses, often caused by malfunction and operation of obsolete equipment, emergence of emergency situations, and complex modes of power transmission have to be paid by distribution grids. If the actual volume of power losses exceeds the permissible normative value, the reason should be identified and eliminated.

It is worth noting that significant changes in consumption volumes caused by various factors, such as temperature conditions, humidity, etc., affect the change in the energy consumption factor value in the base period, but this does not change the reliability of the forecast. At the same time, the high requirements imposed on the electric power industry, including forecasting quality indicators (accuracy, reliability, timeliness, etc.), make it necessary to develop and apply new solutions related to the application of artificial intelligence and taking into account the current level of information support, and to ensure effective energy saving.

It is also important to understand that the activities of power distribution grids depend not only on technological, but also on economic indicators. Moreover, the task of forecasting has become particularly important since the emergence in the Russian Federation of the wholesale electricity and capacity market, whose rules provide for the sale of electricity with changes in hourly cost. Inaccurate electricity consumption forecasting has a negative impact on the quality of the management process in electricity distribution grids, as well as entailing an inflated cost of electricity. At the same time, participants of the wholesale electricity and capacity market may be subjected to penalties associated with the presence of significant deviations of actual electricity consumption from the forecast values. The reason for this is an increase in the forecast values of electricity consumption, which is the basis for the costs associated with the maintenance of excess reserve capacity. Decrease in forecast values relative to actual consumption requires additional commissioning of emergency power plants.

Thus, correct and timely forecasting of electricity consumption indicators using artificial intelligence ensures the achievement of reliability and efficiency of the unified energy system as a whole by making effective management decisions by the heads of energy companies. This will enable a more efficient use of finances both for energy companies and their customers (individuals and legal entities).

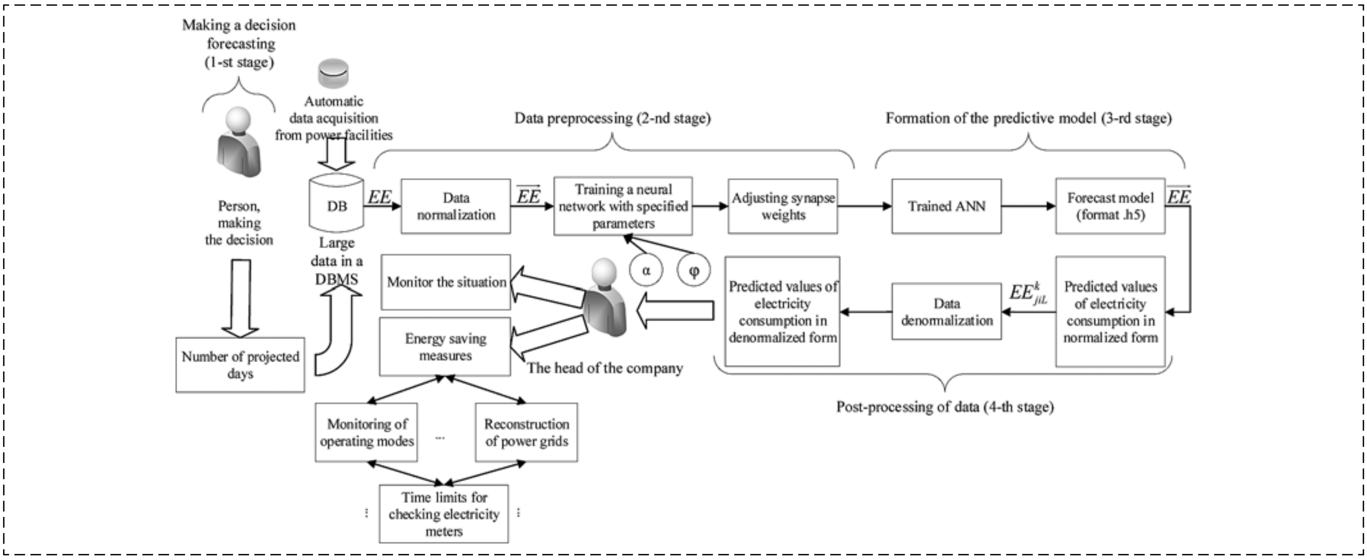

Fig. 3. Scheme of using a neural network to predict the values of electricity consumption

Mathematical model of a neural network

One of the main influencing factors on the various developing and intensively used components (e.g. financial) of enterprises is the state of the electrical grid, in particular the amount of electricity consumed. The amount of electricity consumed in an enterprise can be represented by the notation *EE*. As an example, we took "Kumertau Electric Networks" organization using time series for the past 4 years. For this organization, a forecast with a forecasting horizon of one month during one calendar year was performed. The number of forecasted days of electricity consumption is set by the management of the department/enterprise.

The following notation is used: EE_{ji}^{k} — the value of electricity consumption measured on the k-th meter on the i-th date of the j-th year. Here $k = 1$, ..., n, where n — is the number of electric meters involved in the calculations, j — is the number of the year, i — is the specific measurement date.

The task of advance forecasting consists in calculating, on a particular current i — day of measurement, the value of electricity consumed on $i + 1$ day, that is EE_{ji+1}^{k}, and on $i + 2$ (EE_{ji+2}^{k}), $i + 3$ (EE_{ji+3}^{k}), $i + 4$ (EE_{ji+4}^{k}),..., $i + 31$ (EE_{ji+31}^{k}), or $i + 1$ (EE_{ji+l}^{k}), for $k = 1, \ldots, n$ any, in which case $l = 1, \ldots, 31$.

The proposed method of advance forecasting is based on the application of a second-generation artificial neural network implemented using the following tools and software: high-level Python programming language, PyCharm Professional development environment, free relational MySQL database management system.

The forecasting process itself is proposed to be carried out in four stages (Fig. 3): the decision maker on the forecast number of days, pre-processing of data, formation of the forecast model and post-processing of data. This technique was partially applied in earlier studies [15, 18]. The results of these studies also partially confirm the effectiveness of the proposed artificial neural network.

At the first stage, the decision maker determines for how many days to calculate the forecast values of electricity consumption (depending on the month and various tasks). At the second stage, automatic selection of parameters and training of the ANN is performed.

The training method of second-generation artificial neural network (Fig. 4) proposed by the authors is based on the Backpropagation method for elec-

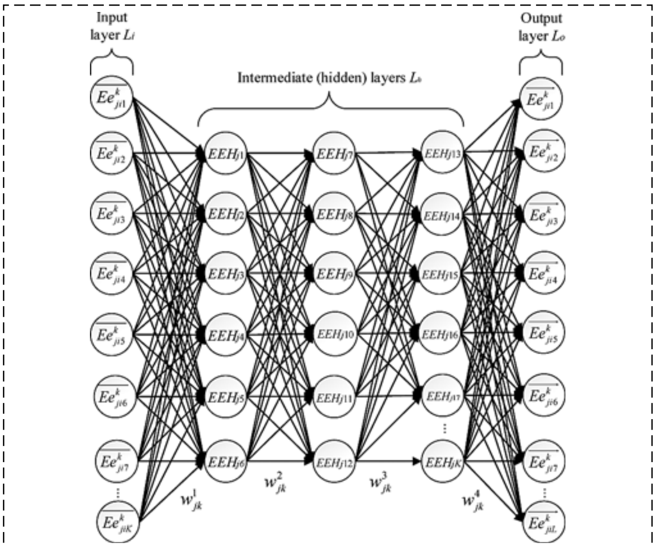

Fig. 4. The structure of the second-generation neural network

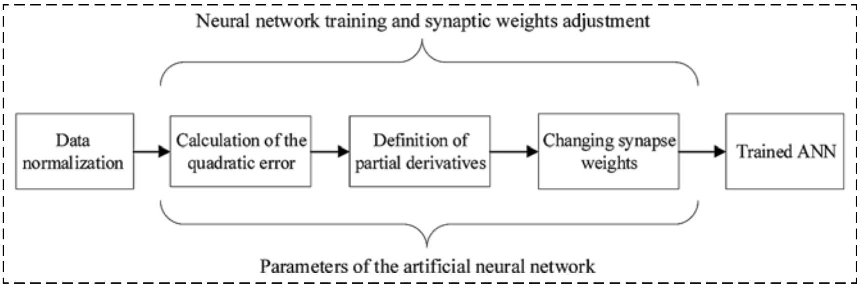

Fig. 5. Sub-stages of neural network training

tric power consumption forecasting. Consequently, when applying the above parameters, it is necessary to normalize the input values of the amount of energy consumed to prevent disappearing and exploding gradients (1):

$$\overrightarrow{EE^{k}_{ji}} = \frac{\overrightarrow{EE^{k}_{ji}} - \overrightarrow{Ee_{\min}}}{\overrightarrow{Ee_{\max}} - \overrightarrow{Ee_{\min}}}, \tag{1}$$

where $\overrightarrow{Ee_{\max}}$ and $\overrightarrow{Ee_{\min}}$ — minimum and maximum values of the amount of consumed electric energy for all data fed to the input layer of the neural network for all $\overrightarrow{EE^{k}_{ji}}$, where $k = 1, ..., n$.

The sub-stages of neural network training at the preprocessing stage (Fig. 3) are shown in Fig. 5.

Calculation of the quadratic error. As a rule, the inputs of the network are considered as the input vector ($\overrightarrow{EE^{k}_{ji}}$), where $\overrightarrow{EE^{k}_{ji}} = [Ee^{k}_{ji1}, Ee^{k}_{ji2} ..., Ee^{k}_{jiK}]$, and the outputs of the network can be represented as an output vector ($\overrightarrow{EE^{k}_{ji}}$), where $\overrightarrow{EE^{k}_{ji}} = [Ee^{k}_{ji1}, Ee^{k}_{ji2},..., Ee^{k}_{jiL}]$, that said $K = 1, ..., M$, $L = 1, ..., N$, in which M and N are the number of input and output vector values. Correspondingly, the training sample is a set of pairs R of input vectors $\overrightarrow{Ee^{k}_{jiK}}$ and desired (reference) output vectors $\overrightarrow{Ee^{k}_{jiL}}$ (2):

$$R = \{(\overrightarrow{Ee^{k}_{ji1}}, \overrightarrow{Ee^{k}_{ji1}}), (\overrightarrow{Ee^{k}_{ji2}}, \overrightarrow{Ee^{k}_{ji2}}), ..., (\overrightarrow{Ee^{k}_{jiK}}, \overrightarrow{Ee^{k}_{jiL}})\}. \tag{2}$$

With each application $\overrightarrow{Ee^{k}_{jiK}}$ from R to the neural network will calculate the actual output $\overrightarrow{Ee^{k}_{jiL}}$ layer (3):

$$\overrightarrow{Ee^{k}_{jiL}} = f(\sigma_L), \tag{3}$$

where σ — activation function, defined by the relation (4):

$$\sigma(\overrightarrow{Ee^{k}_{jiK}}) = \frac{1}{1 + e^{-\overrightarrow{Ee^{k}_{jiK}}}}, \tag{4}$$

and which is the weighted sum of the outputs of the neuron EEH_j in each intermediate layer L_h (5):

$$\sigma_L = \sum_{j'=1}^{j} w^{j}_{j'k} L_h(EEH^{j}_{j'k}), \tag{5}$$

where w — synapse weight, k — is the k-th neuron in the intermediate layer. Based on this, we can determine the quadratic error for each pair of vectors of the set R by summing the quadratic errors in each output neuron (6):

$$E_l = \frac{1}{2} \sum_{k'=1}^{L} (\overrightarrow{Ee^{k}_{jiK_{k'}}} - \overrightarrow{Ee^{k}_{jiL_{k'}}})^2, \tag{6}$$

and, as a consequence, the total quadratic error E by summing all pairs of inputs and outputs in the training sample (7):

$$E = \frac{1}{2} \sum_{l'=1}^{K} \sum_{k'=1}^{L} (\overrightarrow{Ee^{k}_{jiK_{k'l'}}} - \overrightarrow{Ee^{k}_{jiL_{k'l'}}})^2. \tag{7}$$

Thus, the learning objective is to minimize E by finding an appropriate set of weights w^{1}_{xk} and w^{l}_{jk}, where l varies from 1 to 4.

Determination of partial derivatives of synaptic weights. On the basis of relation (6) we can note that

$$\frac{dE}{dw^{l}_{jk}} = \overrightarrow{Ee^{k}_{jiK}} - \overrightarrow{Ee^{k}_{jiL}}, \tag{8}$$

in this case, based on (5), we obtain

$$\frac{d\sigma_k}{dw^{l}_{jk}} = L_h(EEH_j). \tag{9}$$

Based on (8) and (9), we determine the partial derivative of E by weight w_{jk} to perform a gradient descent in (10) for synaptic weights between the intermediate and output layers:

$$\begin{aligned} \frac{dE}{dw^{l}_{jk}} &= ((\overrightarrow{Ee^{k}_{jiK}} - \overrightarrow{Ee^{k}_{jiL}})\overrightarrow{Ee^{k}_{jiL}}) \times \\ &\times ((\sigma(\overrightarrow{Ee^{k}_{jiK}}) - \overrightarrow{Ee^{k}_{jiL}}) EEH_{jk}). \end{aligned} \tag{10}$$

If we consider the special case of the derivative E between the input and intermediate layers, all outputs depend on w_{xk} and the partial derivative will be as follows:

$$\begin{aligned} \frac{dE}{dw^{1}_{xk}} &= \sum_{k'=1}^{L} ((\overrightarrow{Ee^{k}_{jiK_{k'}}} - \overrightarrow{Ee^{k}_{jiL_{k'}}})\overrightarrow{Ee^{k}_{jiL_{k'}}}) \times \\ &\times (((\sigma(\overrightarrow{Ee^{k}_{jiK_{k'}}}) - \overrightarrow{Ee^{k}_{jiL_{k'}}})(w^{l}_{jk'} EEH_{jk'})) \times \\ &\times ((1 - EEH_{jk'})\overrightarrow{Ee^{k}_{jiK_{k'}}}). \end{aligned} \tag{11}$$

Thus, equations (8) and (9) give all the necessary values $\frac{dE}{dw}$ to apply (10) and (11) within the gradient descent for all weights of the neural network.

Changing synapse weights. Each weight will be changed to dw to reduce E (12):

$$w(t+1) = w(t) + \Delta w(t), \tag{12}$$

where $\Delta w(t) = -\left.\frac{dE}{dw}\right|_t$, $w(t)$ — synapse weight during t, $w(t + 1)$ — modified (updated) synapse weight. In the present study, in order to increase the learning rate of the neural network, the previously indicated parameter α, and to improve the accuracy of calculations of predictive values, a specialized sensitivity factor (also designated earlier) is setφ:

$$\Delta w(t) = -\left.\frac{dE}{dw}\right|_t + (\varphi(\alpha \Delta w(t-1))). \tag{13}$$

At the third stage, the prognostic model is formed directly, and at the fourth stage, the predicted values of the amount of electricity consumption are calculated. At the same time, it is necessary to renormalizations normalize the obtained forecast values $\overrightarrow{EE_{ji+l}^k}$ (14) in connection with the initial normalization of the data ($\overrightarrow{EE_{ji}^k} \in [0;1]$):

$$\overrightarrow{EE_{ji}^k} = \overrightarrow{Ee_{ji}^k}(\overrightarrow{Ee_{\max}} - \overrightarrow{Ee_{\min}}) + \overrightarrow{Ee_{\min}}. \tag{14}$$

Modification of a classical neuron for time series prediction tasks

As a basis for modification, we chose a classical version of the neuron (Fig. 6, on the example of the input layer), consisting of input values, synaptic connections (synapses), neuron cell, axon and output value.

In Fig. 6 n_{in} — number of neuron inputs, $\overrightarrow{Ee_{ji\,K}^k}$ — normalized value of the amount of energy consumed, $\overrightarrow{EEH_{jK}}$ — the output value of the neuron from the input layer to the intermediate layer.

The modified neuron and its mathematical model are shown in Fig. 7.

From Fig. 7 shows that the modified neuron has an identical structure, except for the addition of the response coefficient $\lambda \in [0.1;\ 0.9]$ (Table 1) on the anomalies in the time series. As such anomalies are considered sharp spikes and drops in the values of electricity consumption, which can lead to inaccurate calculations of forecast data.

With this coefficient, we take into account such spikes and decreases, which allows us to minimize the consequences in the form of inaccuracy of forecast values. Thus, the local convergence of the ANN model increases, and as a consequence, the prediction accuracy increases, as shown in the next section.

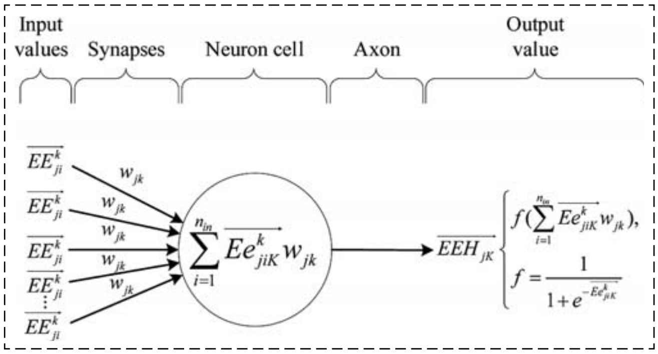

Fig. 6. Classical neuron on the example of the input layer of the developed ANN

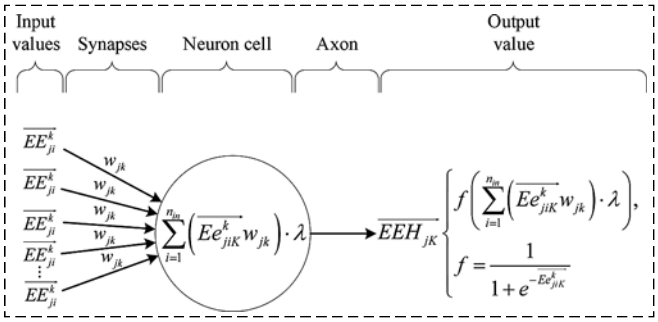

Fig. 7. Modified neuron taking into account the addition of the coefficient of response to anomalies in the time series

Table 1

Values of the coefficient of response λ to anomalies in time series

Value coefficient λ	Spike in power consumption values in the time series, kWh
0.1	50—119
0.2	120—179
0.3	180—239
0.4	240—289
0.5	290—399
0.6	400—899
0.7	900—4999
0.8	5000—8999
0.9	9000—15000

Analysis of the effectiveness of the proposed ANN for electricity consumption forecasting

To analyze the effectiveness of the proposed ANN model as part of the prediction of the amount of electricity consumed, the time series for the past

4 years was used. This data was provided by the production department "Kumertau Electric Networks" from 01.01.2018 to 21.06.2022 in the following form (database, Table 2): date, active electricity consumption, air temperature. Name of the meters used: "Mercury 230 ART".

During the experiment a large number of calculations and iterations were performed in the framework of predicting the amount of electricity consumed. The total array of data used in the experiment is 25,903 values, of which 60 % are fed to the training sample of the neural network and 20 % each to the test and validation sample.

This article presents the results of the experiment to predict the amount of electricity consumed by the enterprise in the period from 01.04.2022 to 01.05.2022. Initially, the predicted values of the amount of electricity consumption were calculated with their subsequent comparison with the real (actual) values of the amount of electricity consumed (Table 3, Fig. 8).

Every day (every day at 8:00 a.m.) data is taken from all electric meters (their current number is 196, i.e. $n = 196$), and entered into the database for further processing in order to calculate the forecast values using an artificial neural network. The start date of the experiment can be considered 01.04.2022, i.e. $I = 1$.

The forecast itself was carried out for the next m (for example, 1—31) days by 1 electricity meter, i.e. $n = 1$. This value of n was taken to reduce the time of the experiment. The next day the actual value of electricity consumption was measured on the same electric meters $EE^{k}_{j,i+m}$. The decision maker (Fig. 3), For example, the head of the department, depending on the requirements of the company, selects the number of days for which the forecast will be carried out. Making forecasts daily until 01.05.2022 inclusive, we obtain for each electricity meter 961 forecast and the actual value of the amount of electricity consumed for each of the n electric meters. To do this, let's introduce an ad-

Table 2

Fragment of the database for the formation of the ANN dataset

Date	Meter number	Consumed electricity, kWh	Air temperature, °C
01.01.2018	1	7156.5	−8.3
02.01.2018		7567.1	−9.4
03.01.2018		8123.2	−14.4
04.01.2018		8119.3	−11.4
05.01.2018		8912.0	−12.2
06.01.2018		7118.4	−11.1
07.01.2018		7945.2	−11.9
08.01.2018		7981.5	−8.1
09.01.2018		8589.0	−13.2
10.01.2018		8611.7	−13.1

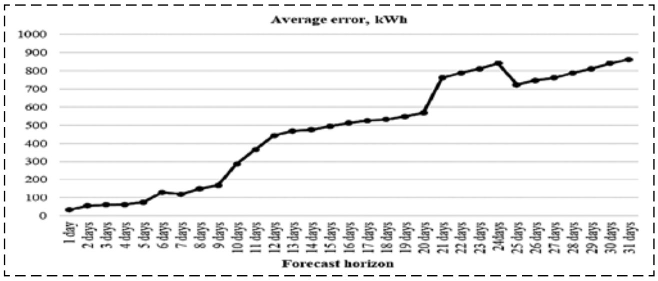

Fig. 8. Change in E^{k}_{ji} depending on $Ee^{k}_{ji+1,...,31,L}$ in the framework of the experiment on the three-phase counter "Mercury 230 ART"

Table 3

Change in the average error E^{k}_{ji} when predicting the proposed ANN of the amount of energy consumed (on the example of the Kumertau Electric Networks enterprise, meter No. 1)

E^{k}_{ji} (10 days), kWh	E^{k}_{ji} (9 days), kWh	E^{k}_{ji} (8 days), kWh	E^{k}_{ji} (7 days), kWh	E^{k}_{ji} (6 days), kWh	E^{k}_{ji} (5 days), kWh	E^{k}_{ji} (4 days), kWh	E^{k}_{ji} (3 days), kWh	E^{k}_{ji} (2 days), kWh	E^{k}_{ji} (1 day), kWh
286.4	168.7	149.4	119.8	130.5	75.9	62.7	61.4	57.2	34.2
E^{k}_{ji} (20 days), kWh	E^{k}_{ji} (19 days), kWh	E^{k}_{ji} (18 days), kWh	E^{k}_{ji} (17 days), kWh	E^{k}_{ji} (16 days), kWh	E^{k}_{ji} (15 days), kWh	E^{k}_{ji} (14 days), kWh	E^{k}_{ji} (13 days), kWh	E^{k}_{ji} (12 days), kWh	E^{k}_{ji} (11 days), kWh
5812.6	5914.2	5943.0	5600.0	511.3	494.4	475.8	468.9	443.8	366.6
E^{k}_{ji} (30/31 days), kWh	E^{k}_{ji} (29 days), kWh	E^{k}_{ji} (28 days), kWh	E^{k}_{ji} (27 days), kWh	E^{k}_{ji} (26 days), kWh	E^{k}_{ji} (25 days), kWh	E^{k}_{ji} (24 days), kWh	E^{k}_{ji} (23 days), kWh	E^{k}_{ji} (22 days), kWh	E^{k}_{ji} (21 days), kWh
840.2/861.9	811.2	787.0	760.8	746.0	723.8	840.2	811.2	787.0	760.8

ditional notation l — the number of days of the experiment, that is, the value $l_{k,i+m}$ = 31. This makes it possible to determine the average accuracy of the forecast for each k-th electricity meter (15):

$$E_{\text{cp}}^{k} = \frac{1}{l_{k,i+m}} \sum_{r=1}^{l_{k,i+m}} E|EE_{jr}^{k} - EE_{j,i+m}^{k}|. \qquad (15)$$

In this case, the error E_{ji}^{k} (in kWh) on the i-th day of the j-th year of each k-th electricity meter is calculated by the ratio of the absolute difference (16), and the error in percent by the following ratio (17):

$$E_{ji}^{k} = |EE_{ji}^{k} - EE_{j,i+m}^{k}|; \qquad (16)$$

$$Ep_{ji}^{k} = \left(\frac{EE_{ji}^{k}}{EE_{j,i+m}^{k}}\right) \cdot 100\ \%. \qquad (17)$$

Based on the results (Table 3 and Fig. 8) of the experiment, the following conclusions were made:

the average error (Fig. 8) of the predicted electricity consumption E_{ji}^{k} cleft 457.2 kWh (Ep_{ji}^{k} — 7.8 %) on all three-phase static meter № 1 "Mercury 230 ART";

noted that in the forecast on the 6th day (Table 3, Fig. 8) errors E_{ji}^{k} and Ep_{ji}^{k} more than the forecast on day 7. This is a limitation of the modified mathematical apparatus for training the artificial neural network, which requires additional research and improvements;

despite the weak trends of increasing/decreasing power consumption, as well as constant spikes (spikes, anomalies) in the time series, the predicted values are quite accurate due to the coefficients introduced earlier, as confirmed by further experiments.

Moreover, when evaluating the effectiveness, the integral indicator of the effectiveness of the proposed method of prediction is also important: it is necessary to calculate the relative effectiveness of Epo_{ji}^{k} (Table 4) of each forecasting method by the ratio (18):

$$Epo_{ji}^{k} = \left(\frac{Ep_{\text{cp}}^{k}}{Em_{\text{cp}}^{k}}\right) \cdot 100\ \%, \qquad (18)$$

where Ep_{cp}^{k} — average error (kWh) of the proposed forecasting methodl Em_{cp}^{k} — average error (kWh) of the method, with the highest error (kWh).

The relative efficiency (Table 4) of the proposed forecasting method is 84.6 %, which indicates the need for energy capacity reserve in the form of an additional 15.4 %. Consequently, the smaller the percentage of power capacity reserve, the less financial costs for their reservation, which is especially useful in the current economic realities.

Table 4

Calculation of the relative effectiveness of each method (integral indicator)

Neural network	Relative effectiveness, %
INS of the authors of the article	84.6
ARIMA	16.6
SVR	29.1
ARIMAX-GARCH	40.1
MLR	21.5
Single layer perseptron	0
Multilayer Perspectron	47.3
Convergent	75.1
Classic Recurrent	65.0

Thus, the implemented artificial neural network of the authors of the article showed more accurate and stable results, which proves the feasibility of the proposed solution in the framework of electricity consumption forecasting. Due to these forecasts, enterprises will be able to carry out energy-saving activities (starting from the control of operating modes and timing of checking electricity meters and ending with the reconstruction of electrical networks). This will allow energy companies to use financial resources more efficiently, which will positively affect not only electricity tariff plans for individuals and legal entities, but also provide an opportunity to optimize the budget of an energy company.

Conclusion

Given the widespread use of artificial intelligence technologies, this study examines the issue of their effectiveness in predicting electricity consumption. The model of artificial neural network for predicting the amount of electricity consumption was developed and evaluated on the example of the enterprise "Kumertau Electric Networks".

The analysis of the effectiveness of the proposed ANN showed on the basis of retrospective data enterprise "Kumertau Electricity Networks" that the use of artificial neural network in predicting electricity consumption is appropriate and effective, which confirms the calculated integral index.

Thus, the proposed method of forecasting electricity consumption can be especially useful for companies to carry out specialized energy-saving measures, which is especially useful in the current global economic realities.

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