ENGINEERING MATHEMATICS

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ELECTRICAL ENERGY CONSUMPTION PREDICTION OF THE FEDERAL DISTRICT OF RUSSIA ON THE BASED OF THE RECCURENT NEURAL NETWORK

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The paper considers the prediction of electrical energy consumption using the recurrent neural network. Neural network is built on the base of the energy consumption data of the major Russian federal districts over the past 13 years. When developing the model, the following dominant factors were taken into account: data on energy consumption over the forecast period; meteorological factors (air temperature, cloudiness, amount of precipitation, wind speed, length of daylight, etc.); date (day, month); data of production calendars (information on the day of the week: weekday / weekend / holiday / shortened); specificity of the industry in the district under consideration (combining statistical information on major centers of federal districts). The factor were selected on the basis of test runs through the neural network of fixed configuration. The relevance of the study is explained by the practical importance of searching for the most accurate methods for predicting the main parameters of the energy market conducted by scientists in most developed countries of the world. The constructed recurrent neural network has yielded more accurate prediction results than the widely used mathematical prediction models based on regression dependencies. The obtained scientific result will help to reduce costs and increase the energy efficiency of the electro-energy subjects in the wholesale electric energy and capacity in Russia.

Keywords: neural network; neural forecast; recurrent neural network; RNN; power industry.

Introduction

Scientists of many countries carry out research in the field of production, transmission and distribution of electric energy. The problem of increasing the accuracy of prediction the main parameters of the energy market play a special role in these researches. Different methods of forecasting are used to achieve this goal. Both domestic and foreign authors use traditional methods of economic analysis the energy market [1–8]. Authors [9–11] use methods of mathematical modeling based on one-dimensional and multi-dimensional regression models, models based on the periodic Fourier series, Markov chain model. Prediction the parameters of the energy market using the Maximum Likelihood Estimation (MLE), which gives more accurate predictions than the previous group of models, is used in [12–14]. In the last decade, special research was developed in the field of predicting the energy market parameters based on neural network models [15–19]. The last of the presented group of methods gives the most accurate results of predictions for today, which is especially important for Russian practice. Because of the current rules of Russian wholesale market for electricity and power, the error in the prediction is equivalent to the work of the electric power industry subjects in the price zone of the more expensive tariffs of the balancing electricity market. The paper presents the results of the latest author's research in the field of building the most variable and relatively simple neural network model for predict the main parameters of the regional electricity market.

1. Aims and Goals of the Research

The purpose of this study was to determine the best neural network architecture, its input data for predicting energy consumption by wholesale market subjects and a comparative evaluation of the machine learning algorithm effectiveness against of mathematical prediction models based on linear regression.

Research objective:

1) research of the various factor's correlation for the formation of a train dataset;

2) research of the neural network configuration's effect of on prediction accuracy, determination of the optimal configuration according to the statement of the problem;

3) testing, effectiveness evaluation.

2. Determination of the Input Data

The developed system should be multifactorial to achieve high predictive accuracy. The following factors were chosen for the analysis of the significance:

1) data on energy consumption over the prediction period;

2) meteorological factors (air temperature, cloudiness, amount of precipitation, wind speed, length of daylight, etc.);

3) date (day, month);

4) data of production calendars (information on the day of the week: weekday / weekend / holiday / shortened);

5) specificity of the industry in the district under consideration (combining statistical information on major centers of federal districts).

The modeling was carried out on the basis of statistical data for the last 14 years: from the beginning of 2004 to the end of 2017. All data were obtained from following open sources:

1) system operator of the unified energy system of Russia [20];

2) National Oceanic and Atmospheric Administration [21];

3) service for providing the time of sunrise and sunset on geographical coordinates [22];

4) legal information system "GARANT.RU" [23].

The data were consolidated into a single form of a single selection (fetch; data selection) for the RF districts. Non-numeric factors have been transformed into numerical by coding for interpretation by a neural network. Data on electricity consumption were normalized for each district. All other data were normalized to the maximum and minimum values throughout the dataset.

The selection of factors was carried out in two ways:

1) selection based on the value of the Pearson correlation coefficient [24];

2) selection based on test runs through the neural network of fixed configuration.

Calculation of the correlation coefficient was performed using the library "pandas" [25]. Selection based on the values of the Pearson correlation coefficient did not give unambiguous results. Of the factors considered, only two had a high degree of correlation with the amount of energy consumption: air temperature (0.784159) and length of daylight hours (0.752309). The values of correlation coefficients of the remaining factors did not exceed 0.3, which indicates a weak linear relationship of factors. This allows us to propose the assumption of a complex nonlinear dependence between the factors under consideration.

To test this assumption, a full test run platform was prepared: training, testing based on the neural network of a fixed configuration.

For the implementation, a library bundle "Tensorflow" [26] и "Keras" [27] was used. The configuration was selected according to the highest accuracy of prediction from energy consumption data with the minimum possible number of layers. As a result, a recurrent neural network was obtained. It was consisting of three layers: the first LSTM layer, 32 neurons, activation function hyperbolic tangent, recurrent activation function of hard sigmoid, the second layer Dropout layer with a threshold of 0.15 (prevention of overfitting), the third layer is the Dense layer (obtaining the result). The structure of the neural network is shown in Fig. 1.

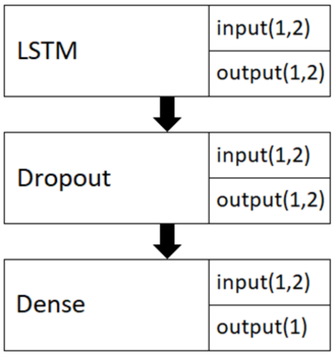

Fig. 1. Network's structure

Because of the "simplicity" of the input numeric data, intentionally, the simplest network configuration was chosen. In addition, network expansion leads to an increase in the probability of network's overfitting or to redundancy, which appear in the slowdown of the network, due to the increase in the number of calculations.

The use of a recurrent neural network is due to the better adaptability of this type of network to the tasks of processing sequences of time data in comparison with other types of neural networks.

The selection of factors was carried out by supplying two factors to the input of the network: main (energy consumption) and the investigated. Network training and testing were conducted. The training was carried out by estimating the increase in the prediction accuracy parameter at each epoch to prevent overfitting, also Mean Squared Error was estimated. For convenience, the process of visualization of learning metrics was automated, as example, the output of the model learning state is shown in Fig. 2.

Train and test dataset were taken from a prepared large dataset in a ratio of 85/15. The decision on the factor's importance was made on the basis of the accuracy of network prediction on the test dataset with and without the investigated factor (prediction only on the basis of data on energy consumption).

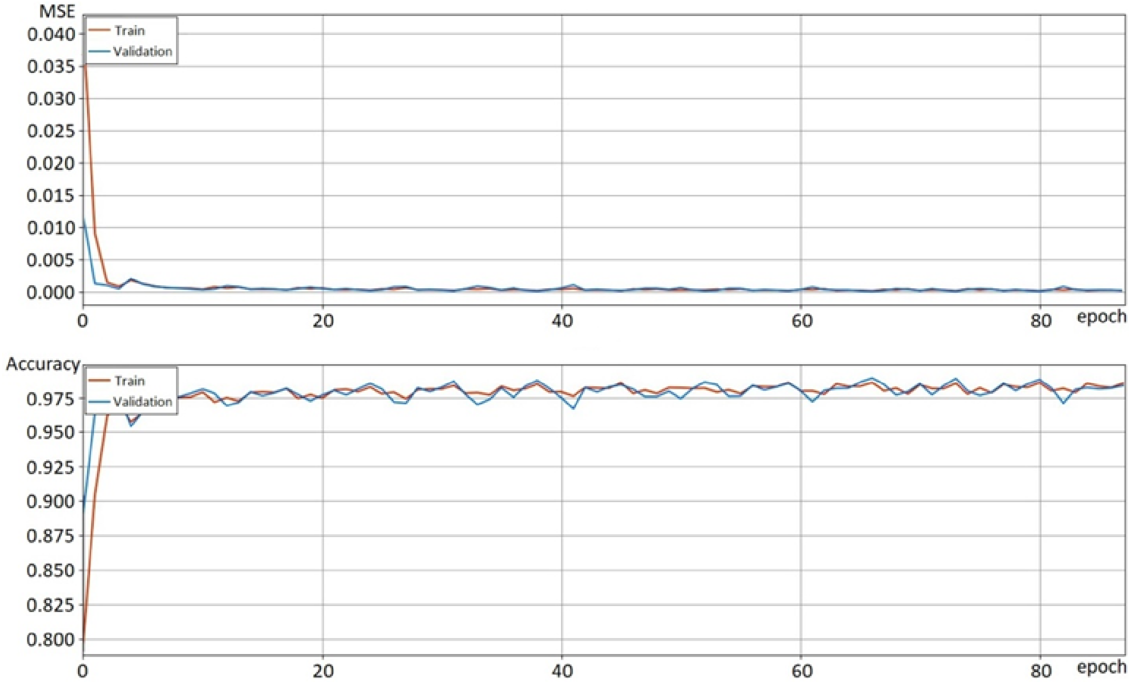

Fig. 2. Visualization of network training metrics

As a result of the study, the following factors were selected:

1) data on energy consumption for the previous prediction period of time;
2) air temperature;
3) length of daylight hours;
4) cloudiness;
5) date;
6) day of the week;
7) type of day: working, festive / holidays, shortened;
8) region.

All of the above factors have increased the prediction accuracy despite the low values of the Pearson correlation coefficients given in Table 1.

Table 1

Values of the Pearson correlation coefficients

Factor	The value of the Pearson correlation coefficient with the value of electrical energy consumption
Cloudiness	0.115061
Date	0.086663
Day of the week	0.102001
Type of day	0.115837
Region	0.031643

The obtained results show the confirmation of the proposed assumption about the complex nonlinear dependence of the factors under consideration.

3. Searching for the Optimal Neural Network Configuration

The next stage of the study was the search for the optimal configuration of a neural network with fixed input data. It was necessary to choose a configuration that provides the best predictive accuracy parameters, taking into account all the factors selected in the previous step while maintaining the minimum possible configuration.

The search was carried out in two directions:

1) increasing the number of layers, increasing the complexity of the network;

2) change the number of neurons on the first LSTM layer.

The study found that increasing the number of layers does not lead to an increase in the accuracy of prediction, and in some cases, on the contrary – worsens due to the complexity of the network configuration and its lack of training.

A significant increase in accuracy was achieved by selecting the number of neurons on the first layer, for this was prepared a platform, similar to that used in selecting factors when automating search for their optimal number. As a result, the network configuration adopted the following structure: the first layer – LSTM layer, 62 neurons, activation function hyperbolic tangent, recurrent activation function of hard sigmoid, the second layer is the Dropout layer with a threshold of 0.15, the third layer is the Dense layer.

To ensure stable prediction accuracy in the long term (accounting for changes in the trend of total energy consumption due to changes in the wholesale market), it was decided to take into account the data for a few days preceding the prediction. It has been experimentally established that three days preceding the prediction are sufficient. The study was conducted on the basis of validation dataset, including data for February 2003 and January 2018.

Thus, a recurrent neural network was obtained. It takes on the input the normalized values of the factors given above, three days before the prediction date. At the output of the network, we have a normalized value of the predicted energy consumption.

4. Testing

The testing was conducted on the test and validation datasets (January 2018) for each federal district. The values of the Mean Absolute Error (MAE) prediction and the Mean Relative Error (MAPE) prediction were used as metrics.

The results of the run on the test dataset are given in Table 2.

Table 2

The results of the run on the test dataset

Federal District	MAE, MW	MAPE, %
Central	10671.7	1.52
Southern	6417.9	2.10
Volga	4049.5	1.25
Siberian	4312.6	0.66
Northwestern	4910.0	1.73
Far Eastern	2020.7	1.73
Ural	8180.8	1.06

Fig. 3, 4 show graphs of the predicted and actual values of energy consumption for two federal districts with the maximum and minimum accuracy of prediction – the Southern Federal District and the Siberian Federal District.

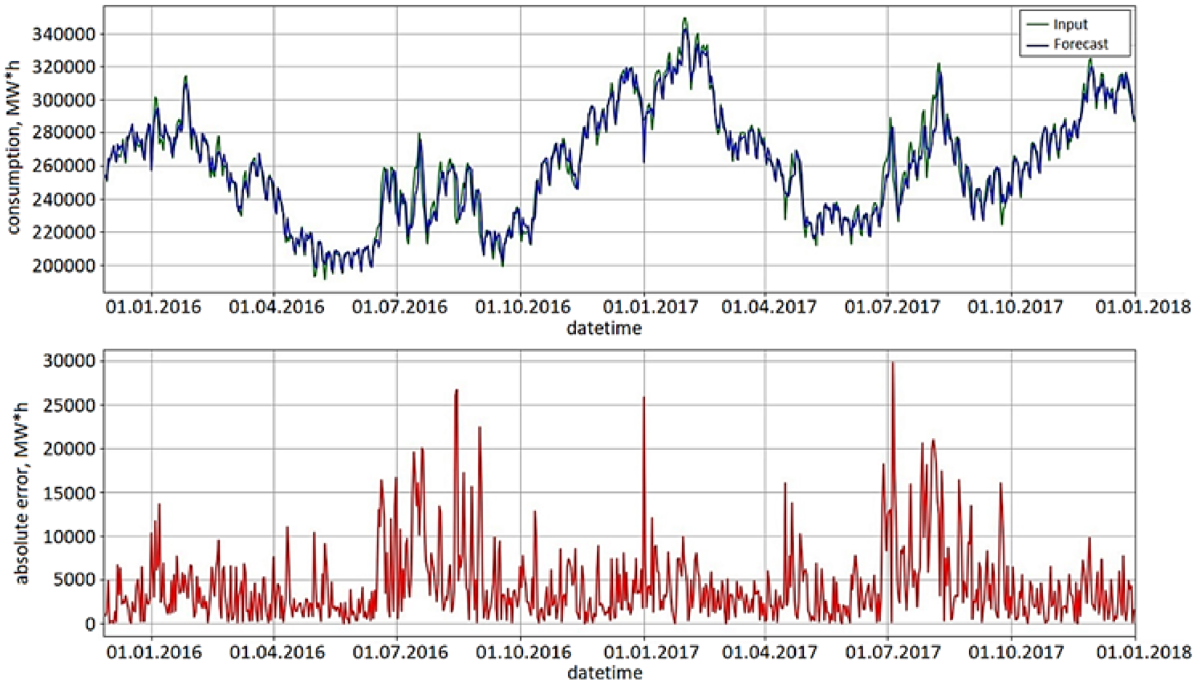

Fig. 3. The results of the run on the test dataset for the Southern Federal District

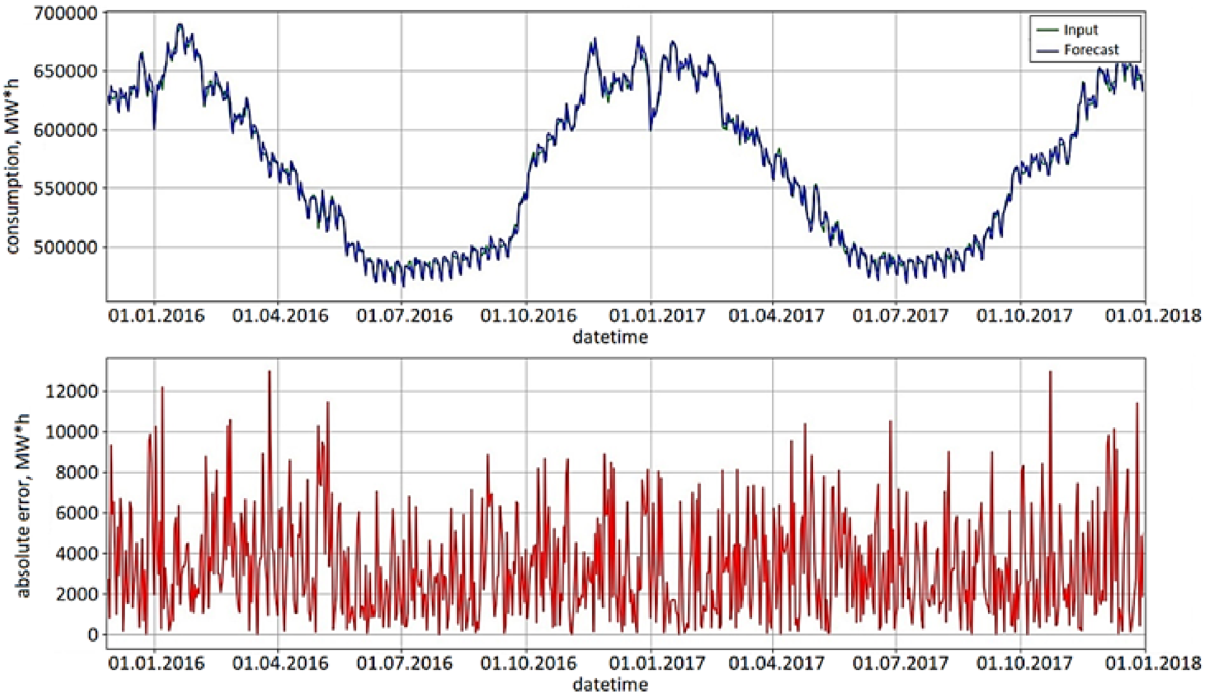

Fig. 4. The results of the run on the test dataset for the Siberian Federal District

From the presented graphs it is evident that the greatest values of the absolute error fall on the New Year holidays. For the Southern Federal District increasing the prediction error in the summer season is characterized, which is due to the specifics of the industry in this region and the need to entry additional prediction factors.

To assess the stability of the obtained results, runs were performed on the validation dataset. The difference between the validation dataset and the test dataset is that its values were not used in calculating the thresholds for normalization. In order to obtain more objective results, we select a section on which the average prediction error has the greatest value in all districts for the first half of January. The results of the run are shown in Table 3.

Table 3

The results of the run

Federal District	MAE, MW	MAPE, %
Central	11079.2	1.73
Southern	4271.1	1.66
Volga	5839.8	2.02
Siberian	3290.8	0.58
Northwestern	2590.5	1.01
Far Eastern	1350.1	1.52
Ural	6401.6	0.91

Fig. 5, 6 show graphs of the predicted values for two federal districts with a minimum and maximum prediction accuracy.

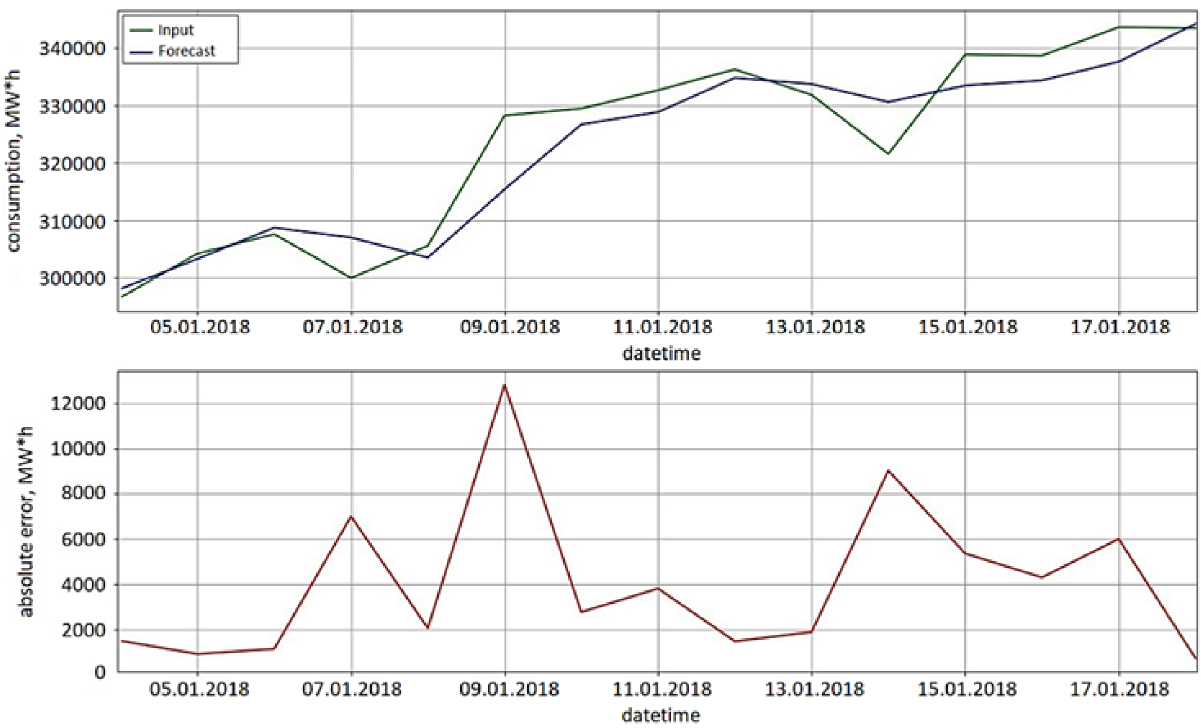

Fig. 5. The results of the run on the validation dataset for the Volga Federal District

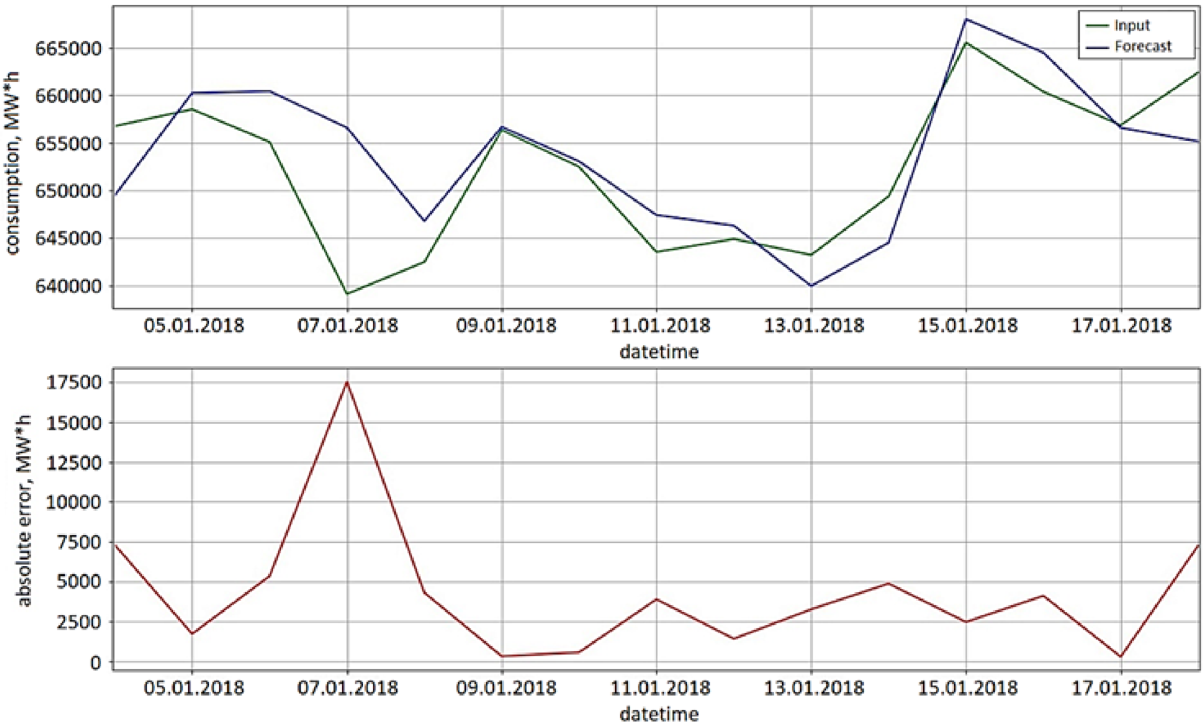

Fig. 6. The results of the run on the validation dataset for the Siberian Federal District

The obtained results testify to the correct operation of the trained neural network.

5. Assessment of Performance

The application of machine learning algorithms allowed to achieve better results in comparison with mathematical models based on linear regressions due to the complexity of implementing multifactor systems. As benchmarks for comparison, the results of [19] and [28] were used. In these works, regression prediction models based on maximum likeness dataset were used. Despite the high quality of prediction with this method, the value of the average relative error of prediction was 3.30 %, while the use of a neural network allowed to reduce the error value to 2.10 %. Further development of machine learning algorithms will improve the quality of prediction when solving problems of this type.

Conclusion

The world scientific community is searching for methods for prediction the main parameters of the electric power market, which most adequately reflect the volatility of the market and give more accurate prediction results. In the last decade, among the diversity of methods used, researchers place special emphasis on prediction based on neural network models.

The authors made an attempt to contribute to the study of the basic parameters of the wholesale electricity energy in Russia. To predict the amount of energy consumption, a recurrent neural network was built and trained. Its use is due to the better adaptability of this type of network to the processing tasks of time sequences in comparison with other types of neural networks.

Testing of the constructed model was carried out on the test and validation datasets (January 2018) in 7 major federal districts of Russia. The received results testify to the correct operation of the trained neural network. The use of neural network allowed to reduce the average relative error of the prediction to 2.10 %. The obtained scientific result will help reduce costs and increase the energy efficiency of the electric power engineering entities when operating in the wholesale electricity and power market of Russia.

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ПРОГНОЗИРОВАНИЕ ЭЛЕКТРОПОТРЕБЛЕНИЯ ФЕДЕРАЛЬНОГО ОКРУГА РОССИИ НА ОСНОВЕ РЕКУРРЕНТНОЙ НЕЙРОННОЙ СЕТИ

В. Г. Мохов, В. И. Цимбол

В статье рассмотрено прогнозирование потребления электрической энергии с использованием рекуррентной нейронной сети. Нейронная сеть построена на данных энергопотребления крупных федеральных округов России за последние 13 лет. При построении модели были учтены доминантные факторы: данные об энергопотреблении за предшествующий прогнозу промежуток времени; метеорологические факторы (температура воздуха, облачность, количество осадков, скорость ветра, длина светового дня и т.д.); дата (день, месяц); данные производственных календарей (информация о дне недели: будний/выходной/праздничный/сокращенный); специфика промышленности рассматриваемого округа (объединение статистической информации по крупным центрам федеральных округов), отбор которых проводился на основе тестовых прогонов через нейронную сеть фиксированной конфигурации. Актуальность исследования объясняется практической значимостью поисков наиболее точных методов прогнозирования основных параметров энергетического рынка, проводимых учеными в большинстве развитых стран мира. Построенная рекуррентная нейронная сеть дала более точные результаты прогнозирования, чем широко используемые математические модели прогнозирования на основе регрессионных зависимостей. Полученный научный результат будет способствовать снижению издержек и повышению энергоэффективности субъектов электроэнергетики при работе на оптовом рынке электрической энергии и мощности России.

Ключевые слова: модель; прогнозирование; рекуррентная нейронная сеть; электроэнергетика.

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