ISSN 2070-0482, Mathematical Models and Computer Simulations, 2022, Vol. 14, No. 5, pp. 863–874. © Pleiades Publishing, Ltd., 2022.

Electricity Consumption Forecast Based on Neural Networks

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Received February 21, 2021; revised February 21, 2021; accepted March 3, 2022

Abstract—Load forecasting is an important tool for the operation of power systems. Quality planning of energy consumption leads to lower costs for energy retail companies. In this paper to improve electricity consumption forecasting accuracy, a new model based on an artificial neural network is proposed. A machine-learning-based load prediction model has been developed, implemented on the basis of Matlab simulation modelling. For short-term forecasting, hourly energy consumption data of the city of Nur-Sultan for the period 2018–2019 were used. In the work, the analysis of modern methods for forecasting electricity consumption, the choice of the configuration of the neural network, the determination of the input set of variables were carried out. Testing showed that the best results on the accuracy of the load forecast are achieved by a network with nonlinear autoregression and the Bayesian training principle. As a training algorithm for artificial neural networks, training algorithms for direct distribution networks were used, since they accounted for the greatest spread in forecasting loads. The simulation results illustrated that the proposed model performs well in power consumption forecasting and showed a high accuracy of the forecast.

Keywords: Electricity consumption, load forecasting, artificial neural networks, Matlab

DOI: 10.1134/S2070048222050167

1. INTRODUCTION

The constant growth of energy consumption by the population and industry, an increase in the number of electric power facilities, and an increase in the volume of electricity generation and its costs have all prompted a search for new approaches to solving tasks related to the problems of planning and managing energy supply processes [1].

Some of the ways of improving the efficiency and quality of solving these tasks are the application of modern mathematical apparatus and information technology in the framework of automated dispatch control systems for energy supply.

Under the conditions of continued operation of regional energy systems, taking into account the situation in the wholesale electricity market, the tasks of rational planning of energy supply volumes are of great importance. In addition, to ensure an uninterrupted power supply process in the event of emergency situations, issues of operational regulation of the operation of local energy systems are of particular relevance.

Due to the fact that the processes in power systems are primarily uncertain, it seems appropriate to use mathematical methods of intellectualising processes for predicting the level of energy supply, as well as regulating the operation of local power systems.

Predicting load consumption is a fundamental and vital task in energy generation. Accurate load forecasting helps energy companies minimise energy costs [2]. High accuracy of load forecasting ensures the safe and stable operation of the energy system. Therefore, reliability and accuracy in predicting the consumption of electrical energy should be improved [3, 4].

The forecasting of power consumption in most industrial enterprises is based on the expert assessment method, which in most cases cannot provide the required forecast accuracy. Power consumption forecasting provides initial information for planning normal operation modes in energy management. Based on the forecast, the actual and optimal operating modes of the power systems are calculated, and qualitative parameters, such as reliability, power quality, etc., are estimated. Accurate power prediction ensures optimal load balancing between consumers [5].

In terms of timing, load forecasting is divided into four categories: long-term forecasting with a lead time of more than one year; medium-term forecasting with lead time from one month to one year; short-term load forecasting with lead time from one day to several weeks; operational forecasting, from one to three hours and until the end of the current day [6, 7].

At the first stage, the accounting of meteorological factors affecting the forecast schedule of power consumption is made. The most significant of these factors are air temperature, daylight hours and rainfall. The second stage in the construction of the forecast is to take into account the socio-economic factors in the forecast schedule of power consumption. The third stage in the formation of the forecast is the consideration of market environment factors. It is based on the forecast schedule, with meteorological and socio-economic factors taken into account [8].

The rest of the paper is organised as follows. In Part 2, the literature review is presented. Part 3 is related to the research methodology. In part 4, the experimental results are developed, and part 5 concludes the paper.

2. LITERATURE REVIEW

Currently, there are approximately 150 forecasting techniques, but only about 20–30 basic techniques are used in practice. The classification of forecasting techniques is carried out according to three main characteristics: according to the degree of formalisation of methods; according to the general principle of action; by the method of obtaining predictive information [9, 10]. In recent years, researchers have proposed many models to forecast energy consumption.

Despite such a large number of options, among the classical methods of power consumption, linear regression models and models decomposing the load into basic or regular and weather-dependent components are most widely used. These models are appealing, as they allow us to forecast the load more accurately during the transition from working days to weekends and vice versa, on irregular days, and they are focused on the retrospective information existing in the electric power system.

Zhang et al. [11] proposed to classify electric load prediction models into three main categories: time series models, artificial intelligence models, and hybrid models.

Kaytez et al. [12] implement the least square support vector machines for the prediction of energy consumption in Turkey, where the proposed model proved to be accurate. Another method, based on the least absolute shrinkage and selection operator-quantile regression neural network, is proposed by He et al. [13].

Neural networks can be used to build a power consumption forecast model, since they allow one to set functional dependencies between various parameters set as collection of input and output values of the model, as well as to automatically determine the parameters of these dependencies, and then self-adjust by new input and output values [14].

The following types of neural networks are known: perceptrons, networks on radial basis functions, Kohonen self-organising maps, probabilistic (Bayesian) neural networks, generalised regression neural networks, clustering networks, and linear networks.

Many papers analyze the performance and compare the results achieved by different methods, presenting the advantages and disadvantages of each technique. Recent studies have shown that artificial intelligence methods achieved better performance than traditional methods.

Artificial neural networks with different training algorithms, inspired by the triangle kernel function, are studied in He et al. [15]. Ogcu et al. [16] used ANN models to develop the best model for predicting energy consumption.

To date, there is a fuzzy logic approach to power consumption predicting. Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. A fuzzy set is a set that contains a collection of elements of an arbitrary nature. The fuzzy forecasting approach only imitates the arguments and judgments of experts. They are not only intended to determine the exact mathematical model, but, nonetheless, they are applied in many sectors such as energy, economics, etc. [17].

Hassan et al. [18] proposed a novel design of interval type-2 fuzzy logic systems for electricity load demand forecasting. The authors compared the proposed model with neural networks. Torrini et al. [19] investigated the accuracy of long-term electricity consumption forecasts based on the fuzzy logic approach. They showed that the fuzzy logic model performed better than the Holt two-parameter method.

Several hybrid models are also used. Zhang et al. [11] integrated neural networks with autoregressive integrated moving average. The results show that the hybrid model can capture the different characteristics associated with electricity load. Amina et al. [2] proposed a hybrid intelligent approach for the prediction of electricity consumption. The results show that the novel fuzzy wavelet neural net-work model improved the prediction performance of the power system of the Greek Island of Crete.

As a result, we can conclude that among all forecasting approaches the artificial neural networks technique looks the most promising. Neural networks are widely used for power consumption forecasts. This is due to the number of advantages they have over other techniques, namely:

—high degree of automation of the forecasting process;

—high forecast accuracy;

—a relatively small amount of time required for making a forecast;

—low degree of dependence on the subjective opinion of an expert.

Therefore, in this research we will rely on the neural networks systems and propose a new neural networks model for predicting energy consumption.

3. RESEARCH METHODOLOGY

3.1. Analysis of Factors Affecting the Quality of Forecast Models

When realizing the task of intellectualization of energy system management, the issues of constructing effective parameter models (in particular, the level of consumption load) that make it possible to qualitatively carry out a short-term and long-term forecast of fluctuations of this factor become most urgent [20].

In the process of load fluctuations, regular and random components are present, as noted above. The cyclic (regular) component is determined by the biological rhythm of life, an 8-hour working day, and general trends in the seasons of the year. The random component is determined by a large number of factors, we note the main ones (the unmarked parameters, according to various estimates, account for no more than 1–1.5% of the energy consumed in the system): temperature fluctuations within short (from an hour to several days) periods time; economic mode of operation of enterprises (degree of congestion of main production assets and day of the week); natural illumination of the environment [21].

The load of any power system is variable; distinguish between daily, weekly, and annual load unevenness. The daily change in the load value shows the change in the active and reactive loads in the nodes of the system over a 24 cyclic period. There are 3 characteristic types of load schedule: days following after and before days off; normal working day; weekend.

Figure 1 shows the annual schedule of fluctuations in the consumption of electric power in the city of Nur-Sultan, combined with a schedule for changing the average daily temperature of the ambient air. The period under review covers data from August 2018 to July 2019.

Here, the effect of the average ambient temperature on the amount of electricity consumed in the system is demonstrated. In general terms, it can be noted that with an increase in the average temperature to a certain level, the level of consumption in the energy system decreases.

This is caused by the energy consumption for heating needs of both industrial and residential premises. At the same time, it is necessary to note the inertia of this dependence, expressed in increasing / decreasing energy consumption within a few days after a corresponding (increasing or decreasing) change in ambient air temperature [22, 23].

In addition, the seasonal temperature change correlates well with the duration of daylight hours: the shorter the daylight hours, the lower the temperature, the winter months and the opposite picture in the summer months.

For this reason, an additional factor in determining the level of energy consumption is the magnitude of the lighting load to some extent correlated with the load on heating needs and, therefore, indirectly dependent on the ambient temperature. Figures 2 and 3 show the monthly cycles of power fluctuations for the typical winter (January) and summer (July) months of 2019.

From the schedule of typical summer and winter months (Figs. 2 and 3), you can notice the following: power consumption for January 2019—509 thousand kWh; July—354 thousand kWh; the absolute maximum of January is 637 thousand kWh; July—471 thousand kWh; the absolute minimum of January is 370 thousand kWh; July—221 thousand kWh.

It is necessary to take a note of the characteristic location of the peak and the position of the peak and half-peak loads for these two characteristic months. So, if in July, during the morning afternoon peak, the power consumption is higher than the corresponding evening readings, then in January the opposite picture is observed—the maximum peak in electricity consumption shifts to the evening load zone. This cir-

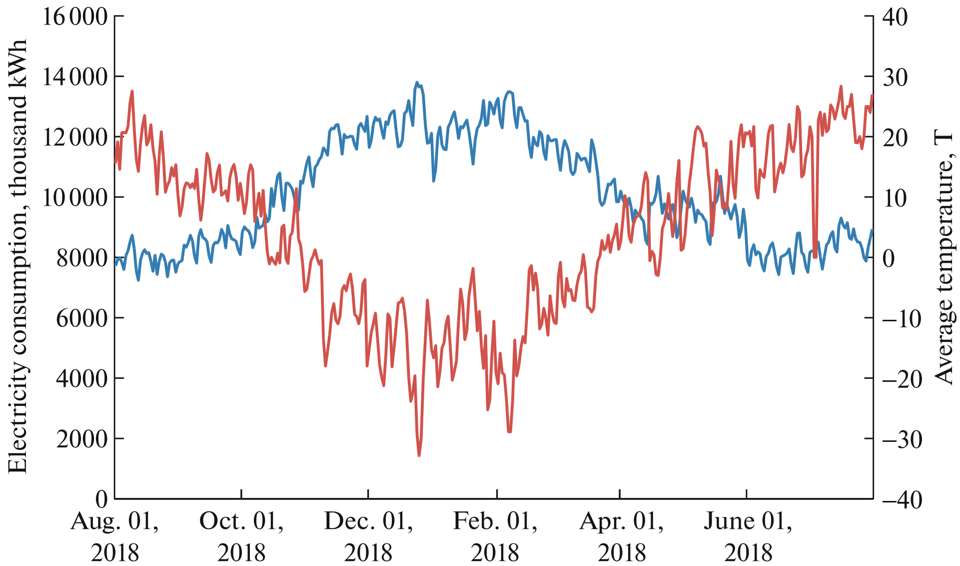

Fig. 1. Power consumption and temperature schedule in the city of Nur-Sultan city for 2018–2019.

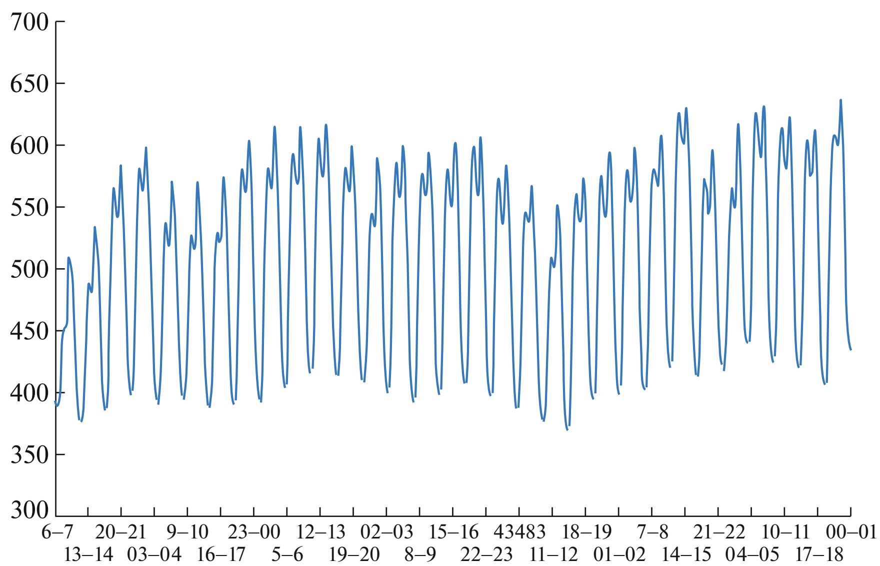

Fig. 2. Fluctuations in power consumption in January 2019.

cumstance is caused, first of all, by the nature of the distribution of heat and lighting load for the months considered.

It is worth noting a clear trend in the magnitude of the load of electricity on Saturday and Sunday.

A similar trend is observed when considering holidays that fall on any day—the nature of electricity consumption in them is similar to Saturday and Sunday. This circumstance is shown in Figs. 4 and 5.

Analysis of the data on the consumption of electric energy in the city of Nur-Sultan allows us to conclude on the influence of the temperature factor on the process of electricity consumption in the region. As evidenced by the averaged sample data for 2018 and 2019.

In a separate way, when assessing factors affecting the consumption of electricity in the region, one should take into account the natural illumination of industrial and domestic premises, since this indicator directly affects the fluctuations caused by the mass switching on/off of the lighting load.

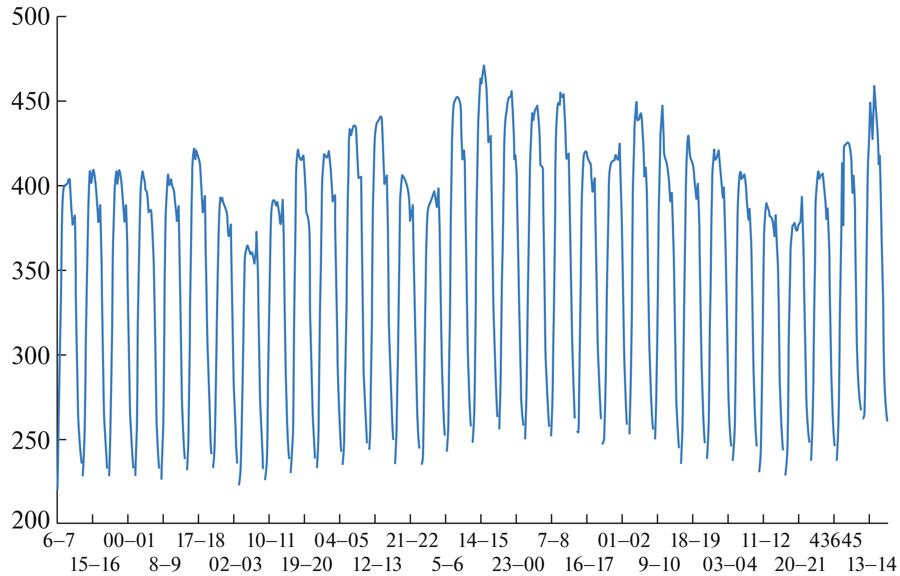

Fig. 3. Fluctuations in power consumption in July 2019.

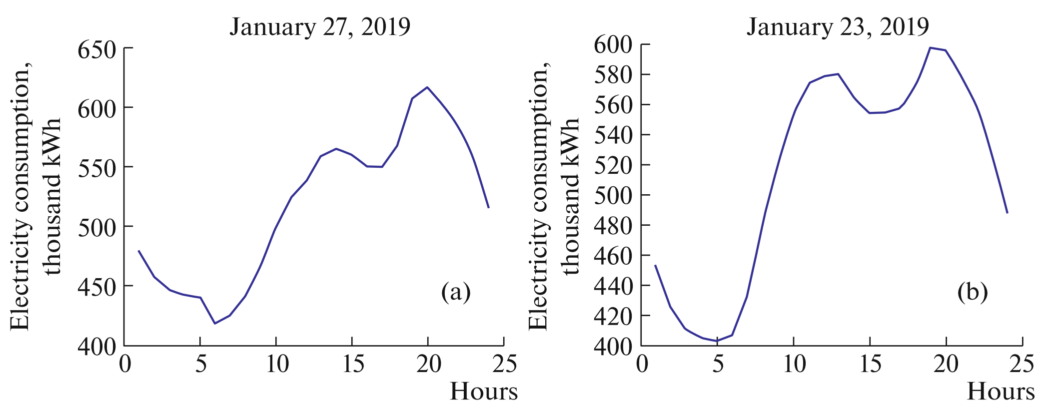

Fig. 4. Dynamics of power consumption in the city of Nur-Sultan city in January: (a) weekends (holidays) and (b) working days.

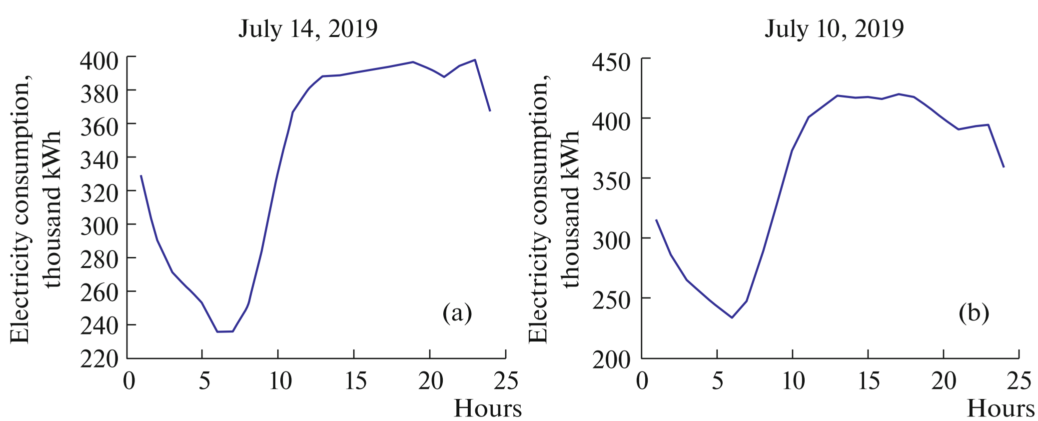

Fig. 5. Dynamics of power consumption in the city of Nur-Sultan city in July: (a) weekends (holidays) and (b) working days.

In addition, the most important factor in assessing power consumption in the system is the consideration of economic indicators, such as: stock market activity, raw materials and production assets, macro and microeconomic components [24]. In the framework of this work, issues of assessing and the impact of the importance of economic parameters on the degree of energy consumption in the region are not considered and are a separate topic for further research.

However, three groups of zones of belonging of the noted factor are conditionally allocated: the most loaded production; medium and low degrees of activity. Difficulties in the quantitative description of the influence of illumination parameters and economic factors consist mainly in the difficult formalization of these indicators and the establishment of the degree of influence on the processes of power and electricity consumption in systems.

It should be noted that the final result of neural network modeling is a refinement coefficient, which, together with a database of previous periods (hourly and daily values of electricity consumption in the regional energy system), allows obtaining the absolute values for the process under consideration.

3.2. The Choice of Neural Network Learning Algorithm

To create a forecasting model based on ANN, the software product MATLAB was selected. This choice is due to the availability of experience in MATLAB and its availability, as well as the great computing capabilities of this software package.

To train a neural network, it is necessary first of all to form a training sample. It is known that the larger the training sample, the more accurate the model. At the same time, an excessive increase in sample size leads to a delay in the process of training ANNs. To date, there is no universal rule according to which a sufficient sample size can be established. In most studies, it is proposed to use the number of samples that exceeds the number of adjustable ANN parameters (w_{ij}, w_{jk}) at least twice. In other works, on the contrary, they argue that the number of weights w_{ij}, w_{jk} must be greater than the dimension of the sample. Therefore, it is more expedient to solve this problem experimentally [25–27].

In the work for training ANNs, two algorithms were chosen that are most often used in forecasting time series. The first to use is the Levenberg–Marquardt algorithm, which is based on the achievement of the least mean square error. Network training is interrupted at the moment when its reduction stops. The advantages of this artificial neural network learning algorithm include the speed of training and a fairly low standard error. However, when using this algorithm, we revealed that the error on the test sample was higher than on the training one. Therefore, this artificial neural network training algorithm was not chosen to solve the problem.

The second algorithm for training ANNs is an algorithm based on Bayes regularization. The essence of this algorithm is that the change in the weights of synaptic functions ceases when the smallest mean square error is reached. Training on this algorithm takes longer than the Levenberg–Marquardt algorithm, but, at the same time, the minimum standard error is achieved. Also, when predicting time series, the error in the test sample becomes smaller than in the training [28].

In this paper, Bayesian regularization is selected as an algorithm for training a neural network.

3.3. Development of a Forecast Model for Power Consumption

To increase the accuracy of the process of short-term forecasting of energy consumption, a neural network based on Matlab simulation was implemented. The influence of the following factors on the accuracy of the process was studied in detail: selection of input terms of membership in the formation of the architecture of the neural network; selection of an optimization algorithm for the model used; preparation of a preliminary training sample; variation of the structure of the neural network and the number of epochs of learning [29].

For short-term forecasting, hourly energy consumption data of the Nur-Sultan city were used during the characteristic days of January, March, April, May, June, and July, 2019.

As a training algorithm for artificial neural networks, training algorithms for direct distribution networks were used, since they accounted for the greatest spread in forecasting loads.

Figure 6 shows a two-layer network with a direct connection, a hidden layer of sigmoidal type neurons and linear output neurons. This type of network may be suitable for multidimensional imaging tasks, given consistent data and a sufficient number of neurons in a hidden layer [30].

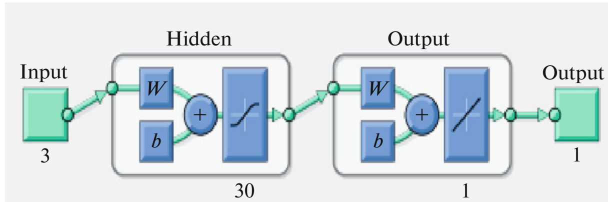

Fig. 6. Network structure.

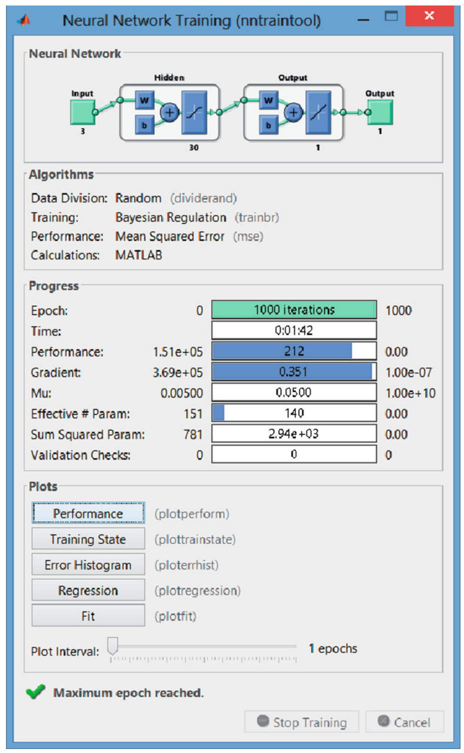

Fig. 7. Neural network training.

Graphical interfaces for working with neural networks, which allow you to automate the training of neural network for the task of approximating input and output data, monitor training progress, as well as calculate statistical results and display training quality estimates, are presented in Fig. 7.

4. EXPERIMENTAL RESULTS

4.1. Evaluation of Forecasting Effectiveness of the Developed Neural Network Model

Let us consider the post-processing schedule of the results for network quality analysis, including the standard error on the validation data set for successive training eras (Fig. 8) and error histograms (Fig. 9) for the training, validation, and testing stages.

The network training schedule shows the behavior of learning errors on the training and test sets. In this case, cross entropy is used as the error functional.

From the network training graph (Fig. 8), it is seen that over 1000 epochs, the root mean square error of 211.53 has been achieved. The training function uses early stopping training as a means of combating overtraining. The graph shows that training is stopped when the error on the test set has ceased to decrease.

The error histogram, constructed for 20 columns, shows that the errors are small and distributed in a narrow interval. The histogram of errors shows on which number of examples (instances) the network

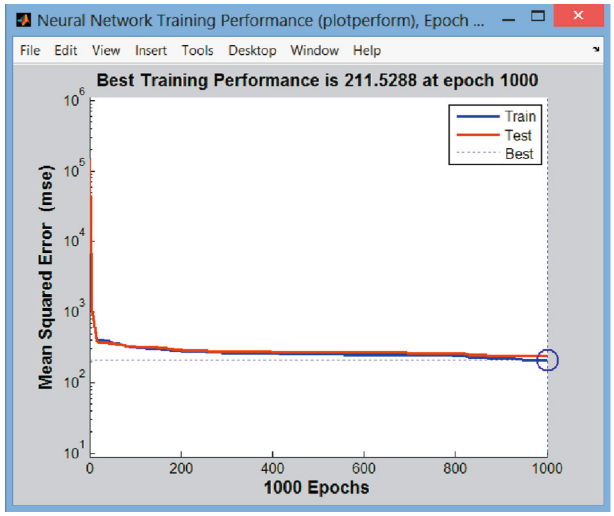

Fig. 8. Network training graph.

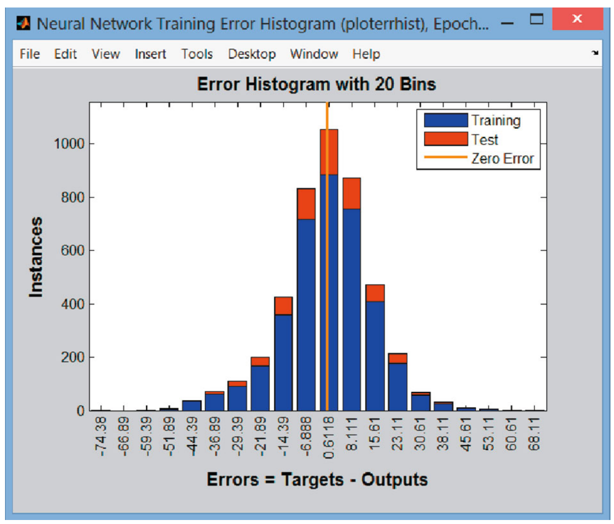

Fig. 9. Error Histogram.

gives this or that error. The error is calculated as the difference between the target value and the network output. The graph displays the errors for the training, validation, and test sets (Fig. 9).

The histogram in Fig. 9 shows that most errors lie in the range from –36.89 to 30.61. There are a small number of errors in excess of these values.

Graphs of the training state (Fig. 10) show the change in the gradient of the error functional and the magnitude of the error on the test set in the learning process.

The val fail graph shows the change in error on the control set. The gradient graph shows the change in the gradient of the learning error functional by network weights. The mu graph reflects the change in the learning parameter [30].

The regression graph (Fig. 11) shows a linear regression of the learning results of the network on the three considered subsets and on all sets. For each result, the correlation coefficient R is calculated, a graph is built, and the regression equation is derived in the form $Output = a \times Target + b$ (Fig. 11). When the network outputs completely coincide with the target values $R = 1$, $a = 1$, and $b = 0$.

From Fig. 11 it can be seen that the network almost perfectly approximates the function.

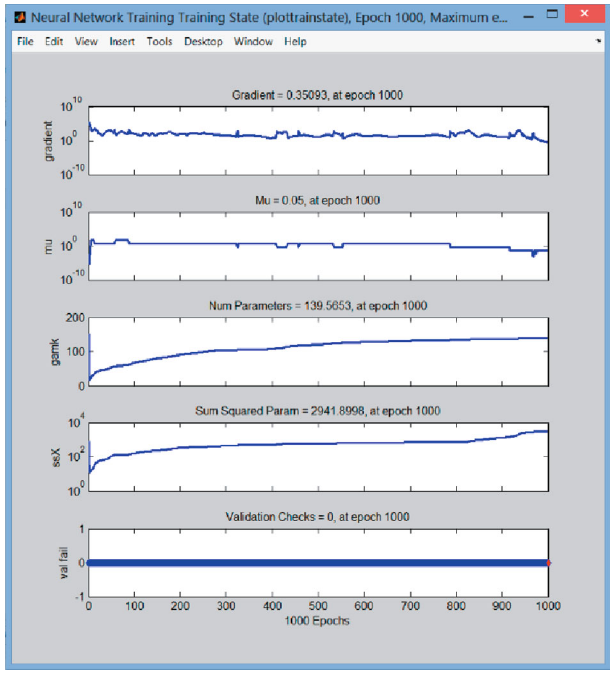

Fig. 10. Training state.

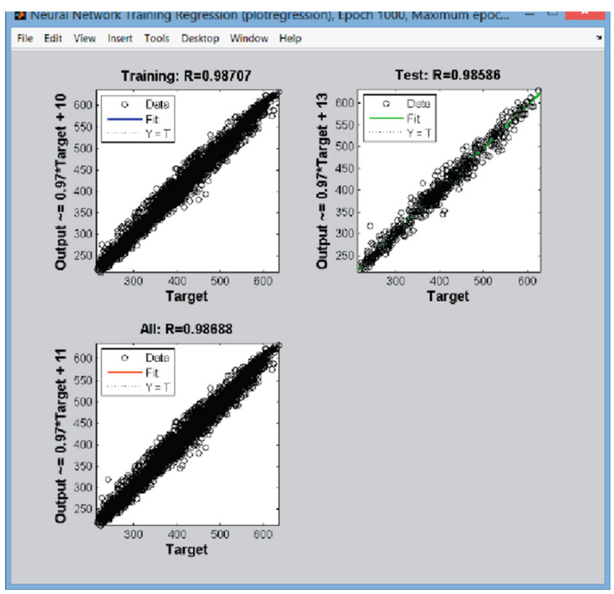

Fig. 11. Regression.

4.2. Testing the Developed Neural Network Model

To verify the correctness of building the network, it was necessary to conduct tests on various types of graphs. Since at different times of the year, power consumption schedules differ significantly, such a check will show how true the artificial neural network recognizes patterns in the data series and is able to rebuild in accordance with the changing nature of the data.

Figure 12 shows the forecast and actual power consumption graphs of the energy for June 2019. As a percentage of total daily power consumption, the error for July was 2.35%. In absolute terms, the forecasting error was 7168 kWh.

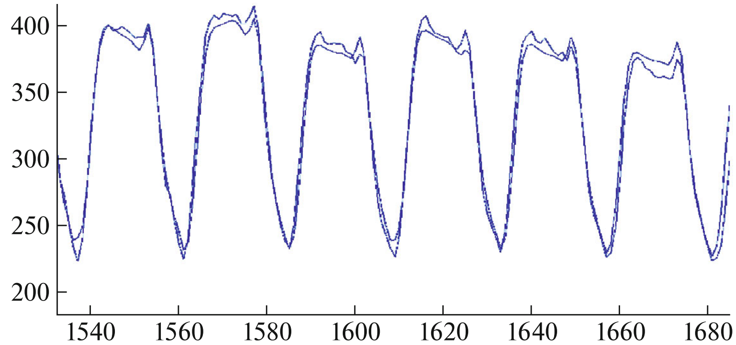

Fig. 12. Forecasted and actual power consumption graphs for July 2019.

The data obtained indicate that the introduction of the possibility of accounting for meteorological factors in the forecast model of power consumption increases the efficiency of the artificial neural network. As for the results themselves, in general, they can be described as positive. In particular, the forecast schedule for June 1, 2019 has deviations from the actual, the value of which is satisfactory for the efficient operation of the energy retail company in the wholesale electricity market. This criterion, established by the management of the company, is 5%. It is also necessary to say that such indicators of forecasting accuracy allow this model to compete with the accuracy indicators obtained in the course of forecasts by expert analysts. A priori, it is believed that this method is the most accurate and effective in making forecasts of this kind. In comparison with the accuracy indicators obtained using other software systems, a forecast error of 2.35% is a very good result, given that the bulk of automated software systems give an error of 5–6%. Table 1 shows some input data for network training.

5. CONCLUSIONS

The proposed paper highlights issues related to the use of machine learning, in particular, artificial neural networks, to solve the problem of predicting electrical loads. This approach is widely discussed and applied abroad. In the CIS countries, there is also work on forecasting loads using artificial neural networks, but there are not so many.

High requirements of the electricity market for the quality indicators of forecast calculations, ensuring the reliability of energy systems, make us look for new approaches to forecasting loads. The research results presented in the paper lead to conclusion that the neural network models for predicting electrical loads give quite acceptable forecast accuracy. The results include analysis of modern methods for forecast-

Table 1. Input data

Date	Hour	Temperature	Load
01.06.2019	6	20	226.0
02.06.2019	7	21	221.6
03.06.2019	8	18	276.2
04.06.2019	9	22	322.8
05.06.2019	10	11	361.9
06.06.2019	11	10	389.9
07.06.2019	12	15	392.9
08.06.2019	13	14	376.1
09.06.2019	14	13	357.8
10.06.2019	15	17	383.7
11.06.2019	16	20	399.4
12.06.2019	17	22	405.3
13.06.2019	18	22	415.5

ing power consumption, the choice of the configuration of the neural network, the determination of the input set of variables, the analysis of factors affecting the quality of forecast models, etc.

Bayesian regularization was chosen as an algorithm for training a neural network, so, when using this training algorithm, the minimum standard error is achieved.

As a training algorithm for artificial neural networks, training algorithms for direct distribution networks were used, since they accounted for the greatest spread in forecasting loads.

A machine-learning-based power prediction model has been developed, implemented on the basis of Matlab simulation modeling. The choice was due to the availability of experience in MATLAB and its availability, as well as the great computing capabilities of this software package.

For short-term forecasting, hourly energy consumption data of the Nur-Sultan city for the period 2018–2019 were used.

Testing showed that the best results on the accuracy of the forecast are achieved by a network with nonlinear autoregression and the Bayesian training principle. An analysis of the effectiveness of the developed model of short-term forecasting of energy consumption based on machine learning showed a high accuracy of the forecast.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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