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Research article

Forecasting planned electricity consumption for the united power system using machine learning

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Abstract. The paper presents the results of studies of the predictive models development based on retrospective data on planned electricity consumption in the region with a significant share of enterprises in the mineral resource complex. Since the energy intensity of the industry remains quite high, the task of rationalizing the consumption of electricity is relevant. One of the ways to improve control accuracy when planning energy costs is to forecast electrical loads. Despite the large number of scientific papers on the topic of electricity consumption forecasting, this problem remains relevant due to the changing requirements of the wholesale electricity and power market to the accuracy of forecasts. Therefore, the purpose of this study is to support management decisions in the process of planning the volume of electricity consumption. To realize this, it is necessary to create a predictive model and determine the prospective power consumption of the power system. For this purpose, the collection and analysis of initial data, their preprocessing, selection of features, creation of models, and their optimization were carried out. The created models are based on historical data on planned power consumption, power system performance (frequency), as well as meteorological data. The research methods were: ensemble methods of machine learning (random forest, gradient boosting algorithms, such as XGBoost and CatBoost) and a long short-term memory recurrent neural network model (LSTM). The models obtained as a result of the conducted studies allow creating short-term forecasts of power consumption with a fairly high precision (for a period from one day to a week). The use of models based on gradient boosting algorithms and neural network models made it possible to obtain a forecast with an error of less than 1 %, which makes it possible to recommend the models described in the paper for use in forecasting the planned electricity power consumption of united power systems.

Keywords: electricity power consumption; forecasting; gradient boosting; artificial neural network; machine learning

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Introduction. Energy-saving approaches occupy an important place in the modern world. One of the areas of research in the field of energy saving, which has a high practical and scientific significance, is the forecasting of electricity consumption. This is primarily due to the fact that electrical energy is a resource necessary to ensure all spheres of society. Especially large electricity power consumption is observed in industry, in particular, at the enterprises of the mineral resource complex. At the same time, power consumption forecasting is used in solving various problems, each of which is necessarily subject to one goal – the optimal management of power consumption, i.e. minimization of electricity consumption while maintaining the required level of quality of performance of the main functional processes.

In line with the concept of price-dependent electricity consumption, known under the term “demand response” [1, 2], it has become possible to create economically beneficial conditions for the production, distribution, and consumption of electricity for all participants in the electricity market: generating companies, electricity power grid companies, large consumers of electricity, etc. Wholesale electricity and capacity markets (WECM) are currently operating in many countries. In WECM various conditions for the purchase of electricity are offered. The day-ahead market and the balancing market are segments of the WECM. The main condition necessary for participation in them is the availability of a reliable forecast of electricity consumption. In this regard, forecasting is an actual production and scientific problem, which solution determines the economic efficiency for all participants in the WECM and contributes to the development of forecasting methods in general.

The efficiency of energy saving by forecasting of electricity power consumption is represented in many scientific papers [3-5]. At the same time, researchers use various methods for predicting power consumption, such as methods of classical and deep machine learning [6-8], mathematical models with fuzzy logic [9], as well as models that take into account the seasonality of power consumption time series [10] and other approaches [11, 12]. The review [13] presents the results of a comparative analysis of methods for forecasting electricity power consumption in accordance with the classification of the methods used depending on the forecast horizon. It should be noted that despite the wide variety of methods for forecasting electricity power consumption, there are no universal approaches that allow obtaining a reliable forecast of electricity power consumption for each subject area. This is mainly due to changing requirements for forecasting precision, the need to take into account a large number of factors that characterize the specifics of the subject area, for which forecasting is carried out, as well as progress in the field of data mining technologies which makes it more efficient than traditional methods of mathematical statistics (exponential smoothing, moving average, etc.) to process large data arrays, and for other reasons. Therefore, it was decided to conduct an applied research, which consists in forecasting electricity consumption using modern data mining tools for the united energy system with a large share of enterprises of the mineral resource complex. Thus, the purpose of this work is to predict planned electricity consumption, assess the precision of forecasting, and develop recommendations for the practical application of some of the proposed forecasting methods, as well as for the need to take into account the factors that characterize electricity consumption.

Forecasting of electricity consumption was carried out on the example of the united energy system of the Ural – a region with a large concentration of enterprises of the mineral resource complex, which are large consumers of electricity in the wholesale electricity and capacity market. Figure 1 shows the structure of electricity consumption for 2021 according to the Unified Interdepartmental Information and Statistical System* for the Ural Federal District (UFD). The largest consumption of electricity falls on the extraction of minerals (70888.4 GW·h) is shown at Fig.1.

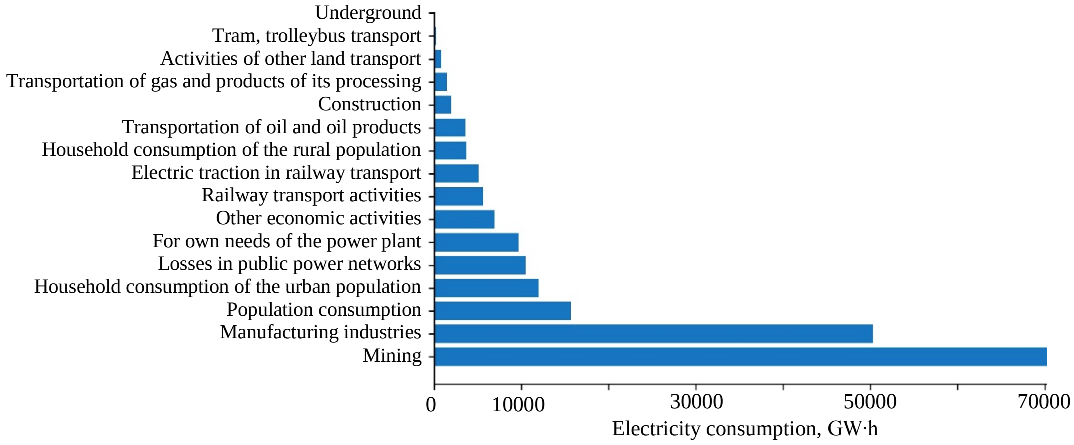

Fig.1. Structure of electricity consumption in the Ural Federal District in 2021

* Unified Interdepartmental Information and Statistical System. URL: https://www.fedstat.ru/indicator/43277 (accessed 12.03.2023).

The deviation of actual values from the planned ones leads to an increase in costs for all participants in the wholesale electricity market [14-16]. Therefore, the purpose of this study is to support management decisions in the process of determining the optimal values of electricity generation and consumption through hourly forecasting of planned consumption and generation of electricity for a period from a day to a week. The goal was achieved in several stages: the previous world experience in applying various approaches to forecasting electricity power consumption was analyzed; retrospective data on planned electricity power consumption, weather data, and data of indicators of the work of the energy system under consideration were obtained, and their analysis was carried out; predictive models were built and their reliability was assessed, and the main conclusions of the study were formulated. The scientific novelty of the work lies in the study of factors affecting the amount of electricity consumption of the integrated energy system, as well as in the creation of predictive models based on modern gradient boosting algorithms and artificial neural networks, and their optimization. The end result of the study, which is of scientific value, is recommendations on the use of economic and meteorological factors in the development of predictive models for large energy systems with consumers – enterprises of the mineral resource complex, as well as the experience of using specific machine learning algorithms and the configuration parameters of the models obtained as a result of the study.

Methods. Before description of the specific methods used in this study, we will note some of the most modern approaches used to forecast electricity power consumption.

For this purpose, a search has been carried out in the database of scientific publications on the websites ScienceDirect.com and ResearchGate.net by the keywords: forecasting, energy power consumption, machine learning, deep learning, modeling, short-term forecasting, mining industry, etc. Search results contain more than 1000 scientific publications. A part of these papers, most corresponding to the objectives of this study, was considered and the table was also compiled with the results of the analysis of some of the existing forecasting methods (Table 1), in which the analyzed studies are grouped according to the forecasting methods used, which also reflects such quantitative and qualitative characteristics of the research results as forecast depth, input and output data, brief description of the object, the forecasting of electricity consumption of which is carried out, the forecast error.

Table 1

Analysis of methods for forecasting power consumption

Forecast method	Object of study	Forecast depth	Forecast quality	Input/output data	Reference
Long Short Term Memory Model (LSTM)	Port of Busan, South Korea	1 month	R^2 = 0.973 RMSE = 107105	Input data: forecast of the monthly throughput of the port. Forecast value: electricity consumption	[17]
Hybrid: seasonal and trend decomposition using locally weighted regression, XGBoost gradient boosting and support vector regression	Australian Wholesale Electricity Market Operator	12 h 24 h	sMAPE = 0.75-3.18 % sMAPE = 1.56-7.72 %	Input data: electrical load time series. Predicted value: electrical load	[18]
Ensemble model: LSTM, GRU and TCN	Data from Bejaia Electricity Company, Algeria	1 month	$MAPE_{min}$ = 0.64 % $MAPE_{max}$ = 10.16 %	Input data: power consumption data for the previous 12 months. Output data: electricity consumption	[19]

Various forecasting methods were used in the papers presented in Table 1. In papers [18, 19], retrospective data on electricity consumption were used as predictors, in article [17], a factor that significantly affects the amount of electricity consumption was studied. However, these works do not present a study of exogenous factors that nonlinearly affect the amount of electricity consumption, such as meteorological, social, economic, etc.

The paper [20] presents the results of electricity sales forecasting based on a Deep Spatio-Temporal Residual Network (ST-ResNet). Sales forecasting is directly related to the planning of power generation, so this actual problem was effectively solved. The use of the artificial neural network ST-ResNet made it possible to reduce the value of the mean absolute percentage error of prediction by more than 2.5 % compared to the use of various forecasting models (recurrent neural networks, moving average, exponential smoothing, etc.) in the short-term (1 day) and medium-term forecasting (1 week). When forecasting, the authors used weather data, a binary sign of the type of the day of the week (workday/day off), data on sales of electricity consumption 1 hour ago.

Forecasting allows you to optimally control the operating modes of electricity storage devices, which contributes to a more rational use of electricity. In research paper [21] presents the results of forecasting electricity power consumption by means of a decision tree model using exogenous variables. The results of forecasting are used in the decision support system in the process of determining the optimal capacity of an electric power storage device on an industrial scale.

The results of a comparative analysis of machine learning methods and traditional methods for forecasting electricity power consumption, carried out in paper [22], confirm the significant superiority of machine learning methods in terms of forecast accuracy, which, in turn, indicates the relevance of developing predictive models based on neural networks and algorithms of classical machine learning. However, as noted in paper [23], the main disadvantage of using these methods is computational complexity, which makes the task of improving the efficiency of data mining algorithms especially relevant.

In research paper [24], machine learning models were built to predict the power consumption of a small industrial facility. The model based on the gradient boosting algorithm of the CatBoost library turned out to be the best model.

In study [25], a hybrid model was developed that combines the use of singular spectrum analysis for partitioning the time series of power consumption and a fully connected neural network. The model described in paper [25] made it possible to improve the results of forecasting the electricity power consumption of a mining and metallurgical plant compared to using a neural network (without singular spectrum analysis) for forecasting. The application of data mining methods and best practices for their implementation are given in paper [26]. A promising direction is the use of hybrid forecasting models using a combination of several mining methods [27-29]. However, even when using the most modern approaches for forecasting power consumption [30] scientists note limitations in the application of some methods [31]. This only confirms the need for research to modernize and expand the methodological arsenal used in solving the problem of forecasting electricity power consumption. As applied to mining enterprises, the research results are given in papers [32, 33].

Therefore, it is advisable to conduct systematic reviews, such as in papers [13, 34], reflecting the current state of research in the field of electricity power consumption forecasting. Taking into account the undying interest of the scientific community in the issues of energy saving, the progress of means and methods of intelligent data processing, and the high practical significance of the development of energy-saving technologies, it is necessary to conduct applied research in order to develop recommendations on the possibility of using various forecasting methods.

The study was carried out in the Python programming language (v. 3.10.0) in the Jupyter Notebook programming environment. The NumPy and Pandas libraries were used for calculations and data manipulation, Matplotlib, Seaborn (for data visualization), SKLearn, XGBoost and CatBoost – for data preprocessing and loading regression model instances, tensorFlow.keras – for creating artificial neural networks . The choice of algorithms is justified by the recommendations in the literature [8, 19, 24] and the need to conduct a comparative analysis of the application of different algorithms in the same conditions. The advantages of ensemble approaches and neural networks are high generalizing ability, low overfitting of models. Linear regression and *k*-nearest neighbors algorithms were chosen to validate the non-linearity of the original data and compare the results with more sophisticated methods.

The initial data for the study were hourly data for the period from 04.03.2020 to 04.03.2023: on the planned electricity consumption of the united power system of the Ural; the power system operation indicator (frequency); production calendar data on the type of day (workday/day off/a day before holiday); data on the heating period. All data are taken from open sources. Since the study [35] analyzed the influence of climatic factors, confirming their significant impact on the magnitude of power consumption, it was decided to add the actual meteorological data of the administrative center – Ekaterinburg, as the initial ones.

The following assumptions were made when creating forecast models: the actual meteorological factors of the administrative center were used, despite the fact that the district occupies a vast territory belonging to various climatic zones; the data on the frequency in the power system were also taken actual.

A schedule of the planned electricity consumption is shown on Fig.2 and Fig.3 shows an example of a weekly schedule of planned electricity power consumption. On Fig.3, the index (serial number) of the time interval is plotted along the abscissa axis, the magnitude of the planned power consumption is plotted along the ordinate axis. Analysis of the graphs allows us to conclude that the amount of electricity power consumption depends on the time of day and the season.

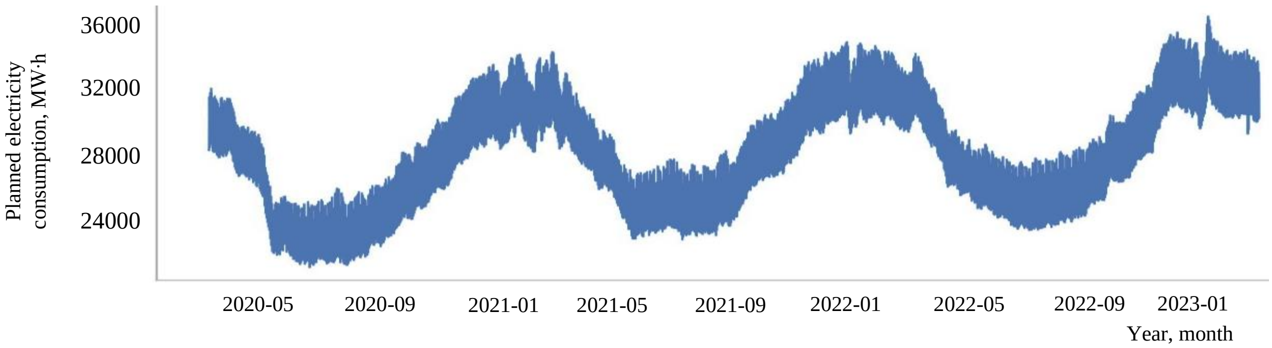

Fig.2. Schedule of planned electricity power consumption

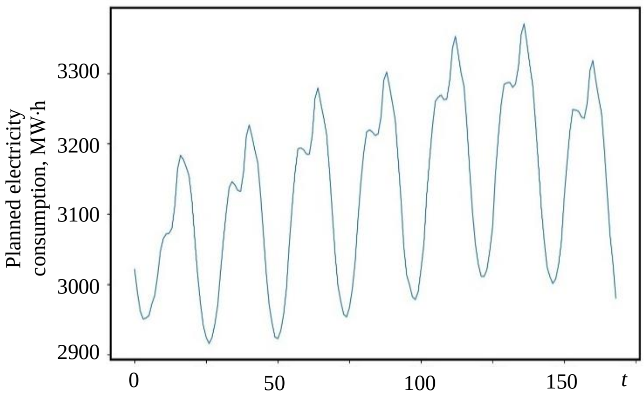

Fig.3. Weekly schedule of planned electricity power consumption

A correlation analysis was carried out in order to assess the influence of meteorological factors and the possibility of their further use in creating forecasting models. According to the Pearson paired correlation coefficient, the correlation coefficients between the features and the target variable were calculated. The notation and description of the factors and the target variable is shown in Table 2, correlation matrix is shown in Fig.4:

$$r_{xy} = \frac{\overline{xy} - \overline{x}\overline{y}}{\sigma(x)\sigma(y)},$$

where x and y are pairwise enumerated features and the target variable.

Table 2

Description of the target variable and factors

Name	Units	Designation
Volume of planned electricity consumption	MW·h	y
Frequency	Hz	X1
Index of equilibrium prices for the purchase of electricity	rub./MW·h	X2
Index of equilibrium prices for the sale of electricity	rub./MW·h	X3
Maximum equilibrium price index	rub./MW·h	X4
Minimum equilibrium price index	rub./MW·h	X5
Heating season in Ekaterinburg (yes 1/no 0)	–	X6
Type of day (working 0 / non-working 1 / pre-holiday 2)	–	X7
Temperature	°C	X8
Relative humidity	%	X9
Direction of the wind	rhumbs	X10
Wind speed	m/s	X11
General cloudiness	%	X12
Horizontal line of sight	km	X13
Dew point temperature	°C	X14
Day	–	X15
Month	–	X16
Year	–	X17
Hour	–	X18

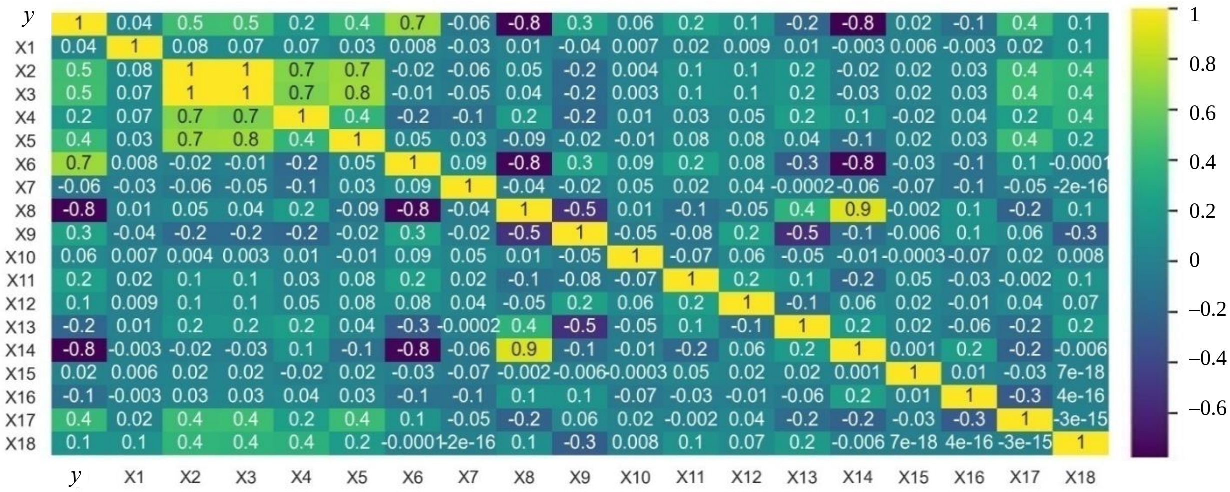

Fig.4. Correlation matrix of features and target variable

As a result of the analysis of the correlation matrix, it was decided to exclude the factors X3-X6, X14 from further research due to the presence of multicollinearity of features. All the other factors were used as input features in forecast models.

The next step was the normalization of features using the MinMaxScaler function of the SKLearn library. Using normalization, the values of all features were brought to the same scale

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}},$$

where x is the actual value of the attribute; $x_{\min}$ and $x_{\max}$ are the minimum and maximum values.

The following algorithms of the SKLearn library were used to create forecast models: Linear Regression (LR), k-nearest neighbors KNeighborsRegressor (KNN), random forest Random-ForestRegressor (RFR). Ensemble methods were also applied (XGBRegressor extreme gradient boosting and CatBoostRegressor gradient boosting) and a Long short-term memory (LSTM) recurrent neural network model was created in tensorFlow.keras. The algorithms of various complexity were used: from linear regression to ensemble methods and neural networks. The choice of these machine learning algorithms is due to the need to conduct a comparative analysis of algorithms applied in the same conditions. The reliability of some of the methods used is confirmed in some works, such as [12, 24, 36].

The neural network model was created by performing a series of experiments on the selection of parameters and the choice of the optimal network structure. The best-fitted network configuration is as follows: two LSTM layers of 30 and 25 neurons, respectively, with an activation function of hyperbolic tangent (tanh), one linear layer, including 25 neurons, the output layer. The Adam optimization algorithm was used as an optimizer, and the root mean square error was used as a loss function. The training of the neural network model took place with partitioning into batches, the optimal batch size turned out to be 5, the convergence of the result is observed at 1000 iterations.

The mean absolute error in percent (MAPE) and the coefficient of determination (R^2) were chosen as forecast quality metrics:

$$\mathrm{MAPE}(y,\hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}\frac{|y_i-\hat{y}_i|}{y_i}\cdot 100\ \%;$$

$$\mathrm{R}^2(y,\hat{y}) = 1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2},$$

where y and $\hat{y}$ are the actual and forecast values of the volume of planned electricity power consumption, n is the length of the time series.

The training and test data (datasets) were divided in a ratio of 80:20. The corresponding values of the quality of predictive models are shown in Table 3. Selection of parameters for RFR, KNN, XGBoost, and CatBoost models was performed using the cross-validation tool GridSearchCV.

Table 3

Assessment of the predictive models quality

Model	Forecast quality metrics										
	Training dataset		Test dataset		MAPE of forecast for n days, % ($n = \overline{1.7}$)						
	MAPE, %	R^2	MAPE, %	R^2	n = 1	n = 2	n = 3	n = 4	n = 5	n = 6	n = 7
LR	3.37	0.86	3.39	0.86	2.08	2.09	1.93	1.79	1.89	2.16	2.22
KNN	1.26	0.97	1.66	0.96	1.10	1.25	1.50	1.55	1.79	1.93	1.84
RFR	0.41	0.99	0.78	0.99	1.39	1.31	1.41	1.37	1.59	1.64	1.59
XGBoost	0.73	0.99	0.82	0.99	0.47	0.63	0.71	0.74	1.07	1.20	1.17
CatBoost	0.17	0.99	0.36	0.99	0.42	0.86	0.75	0.71	0.71	0.68	0.64
LSTM	0.36	0.99	0.40	0.99	0.36	0.74	0.64	0.62	0.59	0.59	0.55

For these models the forecasting was carried out for a period from one day to a week. The values of forecast errors for each period (n) of forecasting are shown in Table 3. So, with n = 1 24 forecast values (1 day) were obtained, with n = 2, the forecast was made for 48 points (2 days), etc. up to 7 days. As can be seen from Table 3, with an increase in the forecasting horizon, the accuracy of the forecast decreases, but the error does not exceed 1-2 %. The best forecast was shown by the LSTM recurrent neural network model, the mean absolute percentage error (MAPE) of which is less than 1 % for a weekly lead period. The results obtained allow us to consider the model reliable.

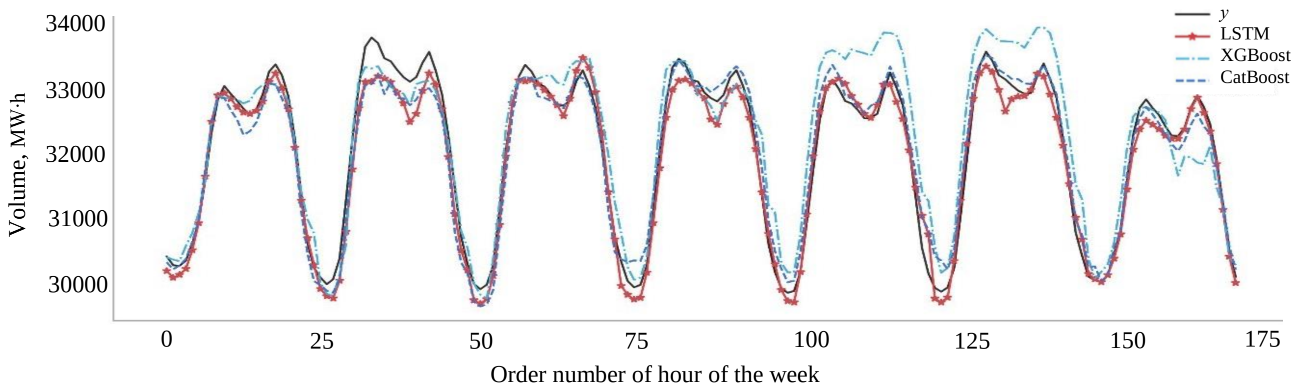

Fig.5. Actual and forecast values

Graphs of volumes of planned electricity power consumption (y) and its forecasted values obtained by different models for the week ahead are shown on Fig.5. As can be seen from Fig.5, the largest deviations of the forecasted values from the actual ones are observed in the XGBoost model with a forecast for a period of 4 to 7 days. With a forecast horizon of up to 4 days, the error is comparable to other methods. Therefore, it can be assumed that for a weekly period it is better to use LSTM neural network models and the CatBoost ensemble algorithm. It is possible that combining the analyzed models using the stacking technology will make it possible to obtain the smallest forecast error.

The results of forecasting electricity power consumption using the Holt – Winters method for two days ahead are presented in paper [33]. At the same time, MAPE was 1.08 %. In the mathematical modeling of power consumption based on the maximum likelihood sample, described in [14], the forecast error was 2.19 %. In addition, when forecasting electricity consumption using a multifactorial regression model, the forecasting error turned out to be 3.32 % [37].

Using the models reviewed in this study, it is possible to reduce the forecast error (when forecasting two days ahead, using the XGBoost model, the MAPE value was 0.63 %, when using the model based on the CatBoost algorithm, 0.86 %, when using the neural model LSTM network 0.74 %). All of this confirms the effectiveness of ensemble methods and deep learning methods for forecasting electricity power consumption.

The discussion of the results. During the study, the machine learning models were created that made it possible to obtain a short-term forecast of planned electricity power consumption (from a day to a week) with an error of 0.63 %. The results obtained will make it possible to take into account the forecast data obtained using the models described in this study in the process of making managerial decisions when forming applications for the production and consumption of electricity, which will allow making more in-formed decisions when planning the volume of electricity consumption. Thus, the presence of a reliable forecast should help to reduce the deviation of actual volumes of electricity consumption from the planned ones due to the intellectual analysis of retrospective data and taking into account a large number of weather (X8-X13), technical (X1, X7), economic (X2) factors, etc. It should be noted that without the assumption made in this study regarding weather factors, the forecast error may change. On the one hand, when using more detailed climatic data, for example, several settlements with different climatic conditions, the forecast error should probably decrease. On the other hand, the study used actual climate data rather than predictive ones. Therefore, in the presence of forecast data, the magnitude of the error in the forecast of electricity consumption will increase due to the error in the weather forecast. In this reason, one of the promising areas is the further study of meteorological factors and their influence on the target result.

Economic factors are subject to the influence of macro- and microeconomic indicators. In particular, it is worth assessing the risks of unforeseen situations related to the concept of the so-called "black swan" (accidents, sanctions, etc.). The forecasting of electricity consumption is based on past events and established correlations between factors, new events can be taken into account based on the detection of a large mismatch error at the moment when the "black swan" appears. In this case, the error will occur immediately, and by detecting it, it is possible to investigate the influence of a new factor caused by an unforeseen situation and evaluate its relationship to the forecast of power consumption directly. Then, taking into account the new factor, the model is reset. If there is a sharp change in the economic factor (X2) or any other factor already existing in the model, caused by sharp changes in the economic situation, then it is necessary to update the weights in the models, select the optimal hyperparameters and retrain the models.

Since one of the problems in forecasting electricity consumption is the lack of the universal models suitable for all subject areas and different forecast lead times, a promising direction of research is the search for universal approaches to creating predictive models. Thus, the results of this study, in particular, the structure of input forecast features, can be used in similar researches. In addition, the recommendations obtained in this study include the effectiveness of using gradient boosting models and neural networks in forecasting electricity consumption.

Conclusion. The conclusions of a practical and theoretical nature were obtained as a result of the study. Prognostic models were developed, their comparative analysis was carried out according to the quality metrics of predictive values. It can be argued that the use of ensemble (gradient boosting algo-rithms CatBoost and XGBoost) and the LSTM neural network model showed close results. However, with a better generalizing ability of the neural network and, as a result, more precise results, the disadvantage of this method compared to the ensemble ones is the high computational complexity and the time spent on training the model. The direction of future research is to increase the forecasting horizon, compare forecasting methods in terms of the forecast execution time, and optimize model parameters. The practical significance of the study lies in the use of forecasting results in making managerial decisions in the process of drawing up applications for the WECM. The models developed in this study can be implemented in the decision support system for participants in the whole-sale electricity markets, in particular, JSC "Administrator of the Trading System", who are involved in the calculation of the volume of the total planned electricity consumption. In addition, the results of this study can be used in the development of decision support subsystems for generating companies when forecasting demand for electricity and for large industrial enterprises when calculating planned electricity consumption.

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