МАТЕМАТИЧНЕ ТА КОМП'ЮТЕРНЕ МОДЕЛЮВАННЯ

MATHEMATICAL AND COMPUTER MODELING

UDC 004.4:004.032.26

COMPARISON OF SHORT-TERM FORECASTING METHODS OF ELECTRICITY CONSUMPTION IN MICROGRIDS

Parfenenko Yu. V. – PhD, Associate Professor of the Information Technology Department, Sumy State University, Sumy, Ukraine.

Shendryk V. V. – PhD, Associate Professor of the Information Technology Department, Sumy State University, Sumy, Ukraine.

Kholiavka Ye. P. – Postgraduate student, Information Technology Department, Sumy State University, Sumy, Ukraine.

Pavlenko P. M. – Doctor of Science, Professor at Air Transportation Management Department, National Aviation University, Kyiv, Ukraine.

ABSTRACT

Context. The current stage of development of the electric power industry is characterized by an intensive process of microgrid development and management. The feasibility of using a microgrid is determined by the fact that it has a number of advantages compared to classical methods of energy generation, transmission, and distribution. It is much easier to ensure the reliability of electricity supply within the microgrid than in large energy systems. Energy consumers in a microgrid can affect the power balancing process by regulating their loads, generating, storing, and releasing electricity. One of the main tasks of the microgrid is to provide consumers with electrical energy in a balance between its generation and consumption. This is achieved thanks to the intelligent management of the microgrid operation, which uses energy consumption forecasting data. This allows to increase the efficiency of energy infrastructure management.

Objective. The purpose of this work is to develop short-term electricity consumption forecasting models for various types of microgrid electricity consumers, which will improve the efficiency of energy infrastructure management and reduce electricity consumption.

Method. The SARIMA autoregressive model and the LSTM machine learning model are used to obtain forecast values of electricity consumption. AIC and BIC information criteria are used to compare autoregressive models. The accuracy of forecasting models is evaluated using MAE, RMSE, MAPE errors.

Results. The experiments that forecast the amount of electricity consumption for the different types of consumers were conducted. Forecasting was carried out for both LSTM and AR models on formed data sets at intervals of 6 hours, 1 day, and 3 days. The forecasting results of the LSTM model met the forecasting requirements, providing better forecasting quality compared to AR models.

Conclusions. The conducted study of electricity consumption forecasting made it possible to find universal forecasting models that meet the requirements of forecasting quality. A comparative analysis of developed time series forecasting models was performed, as a result of which the advantages of ML models over AR models were revealed. The predictive quality of the LSTM model showed the accuracy of the MAPE of forecasting electricity consumption for a private house – 0.1%, a dairy plant – 3.74%, and a gas station – 3.67%. The obtained results will allow to increase the efficiency of microgrid management, the distribution of electricity between electricity consumers to reduce the amount of energy consumption and prevent peak loads on the power grid.

KEYWORDS: Microgrid, machine learning, LSTM model, AR model, forecasting, electricity consumption.

ABBREVIATIONS

AR is an autoregressive;
ARMA is an autoregressive moving average;
ARIMA is an autoregressive integrated moving average;
SARIMAX is a seasonal auto-regressive integrated moving average with exogenous factors;
ML is a machine learning;
LSTM is a long short-term memory;
MAE is a mean absolute error;
RMSE is a root-mean-square error;
MAPE is a mean absolute percentage error.

NOMENCLATURE

y_t is the value of the time series at time t;
$X_{k,t}$ is an exogenous variables;
β_t is aregression parameters;
φ_p is a non-seasonal autoregression;

DOI 10.15588/1607-3274-2023-1-2

Φ_p is a seasonal autoregression;

θ_q is a conditions of non-seasonal moving average;

Θ_q is an average seasonal conditions of movement;

B^s is a lag operator;

z_t is a noise;

x_t is an entrance;

f_t is a forgotten gate;

i_t is an entrance gate;

$\widetilde{C}$ is an updating the cell;

C_t is a state of the cell;

o_t is an output gate;

h_t is an output;

$tanh$ is an activation function;

$\hat{\sigma}^2$ is an expected variance;

n is a number of input data;

$\hat{y}_t$ is a predictive value.

INTRODUCTION

The current stage of the power industry development is characterized by the intensive process of microgrid development and its integration with the big centralized electricity grid. The term microgrid is used to refer to an integrated energy system of small power with distributed generators and energy consumers. Such an energy system, as a rule, is located on a small area [1].

The feasibility of using a microgrid is determined by the fact that it has several advantages compared to classical methods of energy generation, transmission, and distribution. In Microgrid, the energy produced is mainly used by local consumers, which ensures a reduction in losses associated with the transmission and distribution of energy by electric networks [2].

It is much easier to ensure the reliability of electricity supply within the microgrid than in large energy systems. Energy consumers in a microgrid can participate in the power balancing process by regulating their loads, generating, storing, and releasing electricity. One of the main tasks during microgrid management is to forecast electricity consumption to prevent peak loads on the power grid [3, 4].

The electricity consumption forecasting task is quite relevant due to the necessity to correctly load distribution in electrical networks, ensure their reliable operation and uninterrupted power supply to consumers [5].

Efficiency in forecasting electricity consumption, which is evaluated as the correspondence of the required and actual data, can be achieved by solving the task, formulated as follows: with the minimum number of resources, it is necessary to provide consumers with all the necessary electricity [6]. A similar task often arises for power grid organizations and large industrial enterprises. For enterprises, this problem is caused by the fact that organizations of this type must calculate the demand for electricity when it is generated or purchased on the wholesale market [7, 8]. In addition, such an independent calculation can also be used as a factor in detecting commercial losses of electricity, because currently it is one of the rather serious problems at the stage of electricity transmission to end users.

Electricity consumers face the task of calculating the necessary load on the microgrid, which is influenced by various factors, such as climate, geographical location, time of day, socio-economic and other factors [16]. From the available data, it is necessary to select the most significant ones and make a forecast of energy consumption [17].

Energy sources in a microgrid system may be renewable sources of electricity generation from solar panels and wind turbines, as well as energy stored in large-capacity storage batteries. Microgrids can also combine multiple energy sources to provide consumers with uninterrupted access to electricity. The volume of electricity consumption is not a stable value, therefore, for the normal functioning of the microgrid, short-term forecasting is necessary to determine the future volumes of electricity consumption [7].

The electricity consumption forecast allows to reduce risks when making decisions about balancing the operation of the power system and reducing consumption by end users.

The total energy consumption of the region depends on internal changes for the enterprise, the sector of household consumers and the social sphere [8]. All the changes that occur in the demand for electric energy pose the task of maintaining the balance between production and consumption, because the energy service provider must fully satisfy the needs of electricity. To forecast energy consumption, a few stages must be completed [11]:

– carry out a graphic or descriptive analysis of the available input information about electricity consumption and factors affecting it;

– study the obtained time series;

– choose forecasting methods and make forecast models taking into account the influence of external factors;

– evaluate the received forecast values and choose the best forecasting model.

There is no standard approach to forecasting electricity consumption, as each consumer has its own specific characteristics [5]. Electricity consumption has cyclical, specific, and random components. Approximately 70–80% of all changes have cyclical trends. Also, one of the researched factors is the regularities of a functional nature [6]. These regularities include deviations explained by relatively well-known factors that are specific to each consumer. The third component of the forecast is random variation. When forecasting, these changes are probabilistic in nature [16].

Microgrid control and operation is carried out using specialized software. It is designed to monitor, control and optimize distributed energy for management and support of local IT infrastructure. For the uninterrupted operation of the Microgrid, the monitoring of current

DOI 10.15588/1607-3274-2023-1-2

electricity consumption and the forecasting for future time periods are required, which ensures the energy systems stability[8].

The object of the study is the process of improving the microgrid efficiency by forecasting electricity consumption for different types of electricity consumers.

The subject of the study are the time series forecasting methods that provide electricity consumption forecasting with high accuracy for various types of consumers.

The purpose of the work is the development of electricity consumption forecast models for various types of microgrid consumers', assessment of the forecast quality of forecasting models.

1 PROBLEM STATEMENT

To calculate the values of a time series at future points in time, it is necessary to define a functional dependence that reflects the relationship between the past and future values of this series [16]:

$$Z(\tau) = \Phi(Z(\tau-1), Z(\tau-2), Z(\tau-3), ...) + \varepsilon_t . \quad (1)$$

Dependency (1) is called the forecasting model. It is necessary to create such a forecasting model for which the average absolute deviation of the true value from the forecast tends to the minimum for a given P [17]:

$$\overline{E} = \frac{1}{P}\sum_{t=T+1}^{T+P} |\varepsilon_t| \to \min . \quad (2)$$

The forecasted amount of electricity consumption depends on the values obtained in the previous time intervals of consumption.

Consumers of electricity in microgrid can be enterprises with a permanent or variable work schedule, household consumers, etc. This necessitates the task to create a universal forecasting model that will ensure high forecasting accuracy for all possible users of microgrid systems.

Short-term forecasting is used for decision support on the microgrid operation to choose the optimal mode of operation of the energy supply system, combining different types of renewable energy sources.

2 REVIEW OF THE LITERATURE

Many domestic and foreign scientists were engaged in solving the problem of electricity consumption forecasting as time series forecasting task including using machine learning methods. To generalize their experience, we studied some theoretical, methodological, and applied publications.

The high-precision data on electricity consumption by households were analysed in [9]. The authors separated the average demand profiles from demand fluctuations based solely on time series data and proposed a stochastic model for quantitative coverage of periodic demand fluctuations. The authors used the empirical mode decomposition (EMD) to decompose the data into a finite number of functions based on the local properties of the data.

The authors of the [10] implemented machine learning (ML) models and described the application of machine learning for the development of energy collection (photovoltaics), storage (batteries), conversion (electrocatalysis), and control (smart grids).

In the study [11], a set of machine learning models of electricity consumption of a shoe store was built. As factors were taken: day of the week, day number, week number, holiday/working day, consumption of the previous day. The following machine learning methods were used in [11]: Linear Regression, Random Forest Regressor, Decision Tree Regressor, KNeighbors Regressor, LinearSVR. The model trained by the Random Forest Regressor method showed the best result.

The article [12] analyses the energy consumption of residential buildings. The model proposed by the authors generates a hidden space for demand peaks from the data fed into the long-short-term memory of a convolutional neural network (CNN-LSTM).

The authors of the article [13] used models based on the integration of seasonal autoregressive integrated moving average, Firefly optimization algorithm and support vector regression (SAMFOR). The comparison results showed that the SAMFOR model was more efficient than others such as Seasonal Autoregressive Integrated Moving Average (SARIMA) and Support Vector Regression (SVR) models, SARIMA-SVR and Random Forest (RF) models.

The authors of the article [20–21], on the basis of the future behavior of the microgrid system, predict the generation of electricity from the supply of energy sources. The authors model a system of microgrid with a large number of interchanges and changes for modeling the technology of generation of electricity and physical characteristics. In the article, there is a dynamic structure with mixed logic, to guarantee the future behavior for the microgrid, and also to protect the hour of the work of the accumulative battery. In order to predict inconsistencies in microgrid, a mechanism of reversal linkage is introduced to eliminate the problem of additional control of the horizon. With the help of model predictive control, the minimization of operating costs is achieved for planning the behavior of microgrid components.

The forecasting using artificial neural networks is widely used in modern research in the forecasting of electricity production and consumption [5]. Neural network models allow consideration of a large amount of data that must be processed in real-time and eliminate the uncertainty factor that further complicates the task of electricity consumption forecasting. Adaptation and constant learning makes the use of ML models the most effective for forecasting electricity consumption.

3 MATERIALS AND METHODS

The main factor that determines the power consumption regimes of the object supplied with

DOI 10.15588/1607-3274-2023-1-2

electricity in the microgrid is the nature of the electrical loads, which are generally divided into three types [3]:

– household – the load consumed by the population (residential buildings, dormitories);

– social – the load consumed by social objects (shops, schools, cinemas, etc.)

– industrial – the load consumed by enterprises with a permanent or variable work schedule.

To take into account all possible consumers, predictive models of electricity consumption are built on three data sets:

– household – a residential house;

– social – a gas station;

– industrial – a dairy plant.

Electricity consumption data was collected automatically every hour and entered into a database. Also, additional data such as ambient temperature, wind speed, and daylight length were used.

After a literature review, autoregressive models and machine learning models for electricity consumption forecasting were chosen. Nowadays they are the most popular time series forecasting models because, in most of the analysed articles, they showed better forecasting quality.

Autoregressive models are a statistical method of time series analysis. They use the linear dependence of the future value of the forecast on some number of previous values of the time series [3]. One of the main disadvantages of autoregressive models (AR, ARMA) is the inability to work with non-stationary data [10], therefore, the SARIMAX model was chosen. The SARIMAX model is a seasonal autoregressive integrated moving average model that considers exogenous variables that influence the determination of the forecast value.

$$y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \dots + \beta_k X_{k,t} + \\ + \frac{(1-\theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)(1-\Theta_1 B^S - \Theta_2 B^{2S} - \dots - \Theta_Q B^{QS})}{(1-\varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p)(1-\Phi_1 B^S - \Phi_2 B^{2S} - \dots - \Phi_P B^{PS})} Z_t, \quad (3)$$

A machine learning model such as long-short-term memory (LSTM) network was also chosen for short-term electricity consumption from microgrid (Figure 1). LSTM is a recurrent neural network (RNN) [15] for forecasting time series under conditions where peak values have uncertain periodicity. An advantage over other time series forecasting methods is the insensitivity to noise and outliers.

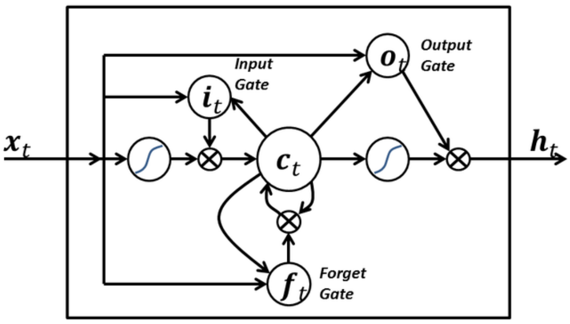

Figure 1 – LSTM Neural Network Architecture [22]

The principle of the model is as follows: first, the level of the forgetting filter determines what information can be forgotten or retained:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f). \quad (4)$$

Then the new information in the state of the cell is selected. In the next step, the input filter layer (sigmoid layer) updates the data. The tanh layer then creates a vector of new candidate values $\widetilde{C}_t$, that can be added to the state of the cell:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad (5)$$

$$\widetilde{C}_t = than(W_c \cdot [h_{t-1}, x_t] + b_c), \quad (6)$$

The next step is to replace the old state of the cell with a new one:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C}_t, \quad (7)$$

The last step is to select the source information.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + o), \quad (8)$$

$$h_t = o_t \cdot than(C_t). \quad (9)$$

Information criteria are used to select the best parameters for the autoregression model. They allow you to compare models with each other and cannot test models in the sense of statistical hypotheses checking.

Akaike (AIC) – the criterion for assessing the quality of statistical models, that is defined as follows:

$$AIC = \ln(\hat{\sigma}^2) + \frac{2(p+q+1)}{n}. \quad (10)$$

The Bayesian Information Criterion (BIC) is based on finding the maximum of the likelihood function. BIC is defined as follows:

$$BIC = \ln(\hat{\sigma}^2) + \frac{(p+q+1)\ln(n)}{n}. \quad (11)$$

To compare various forecasting models forecasting accuracy estimates are used.

Mean absolute error (MAE) is the arithmetic mean of absolute errors, calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_l\right|. \quad (12)$$

The root mean square error (RMSE) is the square root of the root mean square error, calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_l\right|}. \quad (13)$$

DOI 10.15588/1607-3274-2023-1-2

The mean absolute percentage error (MAPE) is the mean absolute percentage deviation calculated as follows:

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_l}{y_i}\right|, \% \tag{14}$$

Forecasting errors are used to evaluate the quality of the developed forecasting models. Checking the accuracy of the built models allows to change the input parameters of the models to increase the forecasting accuracy. The forecasting model meets the accepted requirements if the value of the MAPE parameter is less than 5%.

4 EXPERIMENTS

The study was carried out in several stages. First, several types of consumers with various sources of electricity consumption were selected, then different forecasting time intervals were considered. A microgrid system with renewable sources of electricity has been installed at all these consumers. Solar panels have been installed for a residential house and a gas station, and a wind generator for a dairy plant. Renewable sources partially cover the need for electricity.

A data set containing information on electricity consumption in a two-story private house was selected as a household consumer (Table 1).

Table 1 – An example of a data set for a residential house

Date	Value (kWh)	Day of week	notes	Hour	Month	Length of day
01.01.2018 0:00	1.057	2	weekday	0	June	49834
01.01.2018 1:00	1.171	2	weekday	1	June	49834
01.01.2018 2:00	0.560	2	weekday	2	June	49834
01.01.2018 3:00	0.828	2	weekday	3	June	49834
01.01.2018 4:00	0.932	2	weekday	4	June	49834

The level of electricity consumption in the house increases at night and during the hot season (Fig. 2).

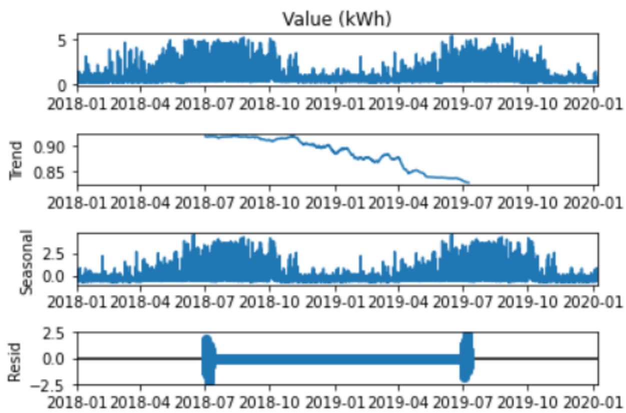

Figure 2 – Time series decomposition for residential consumer

The social electricity consumer is a gas station (Table 2).

Table 2 – An example of a data set for a gas station

Date	Value (kWh)	Indication	Length of day	Month	Week	Hour
01.01.2020 0:00	29.0	68.0	36190	11	44	0
01.01.2020 1:00	60.0	136.0	36190	11	44	1
01.01.2020 2:00	61.0	136.0	36190	11	44	2
01.01.2020 3:00	61.0	136.0	36190	11	44	3
01.01.2020 4:00	61.0	138.0	36190	11	44	4

The volume of electricity consumption at the gas station increases at night and in the cold season (Fig. 3).

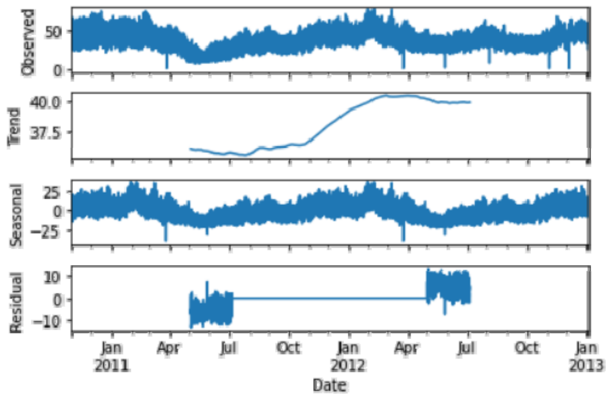

Figure 3 – Time series decomposition for gas station

Industrial electricity consumption data was provided by the dairy plant (Table 3).

Table 3 – An example of a data set for a dairy plant

Date	Value (kWh)	Length of day	T°	Week	Day of week	Hour
01.01.2013 0:00	223	42449	17	39	6	0
01.01.2013 1:00	215	42449	16	39	6	1
01.01.2013 2:00	218	42449	16	39	6	2
01.01.2013 3:00	210	42449	14	39	6	3
01.01.2013 4:00	214	42449	14	39	6	4

The amount of electricity used at the dairy plant increases during the day and during the hot season (Fig. 4).

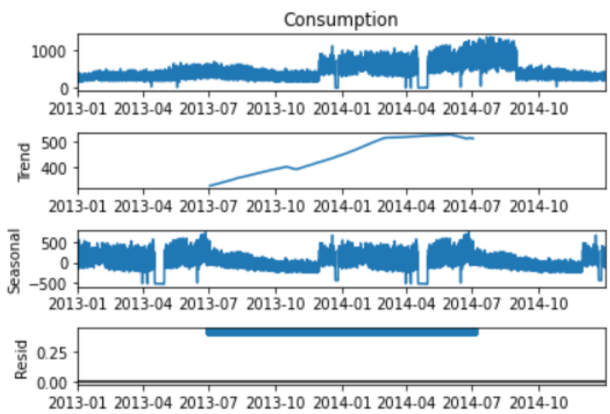

Figure 4 – Time series decomposition for dairy plant

Data from the above sources contained gaps that were filled with the average value of neighbouring indicators. The decomposition of the time series showed a seasonal

DOI 10.15588/1607-3274-2023-1-2

component, a large number of residuals, and the absence of a trend. Weather indicators of the environment, duration of a sunny day were taken as additional data.

The Python programming language and the Google Colab development environment were used to forecast the time series. The SARIMAX model was built for a residential house with the following parameters: p = 0, d = 1, q = 3, P = 1, D = 2, Q = 1, m = 12. The day of the week and the current time are chosen as exogenous parameters. The parameters which are shown in Table 4, provided the best values of the information criteria for a residential house.

Table 4 – Coefficients of the SARIMAX model for a residential house

	coef	std err	z	[0.025	0.975]
Day of week	0.0039	0.004	0.907	–0.004	0.012
Hour	0.0165	0.002	10.606	0.013	0.020
ar.L1	0.6891	0.004	162.102	0.681	0.697
ma.L1	–0.9856	0.001	–836.893	–0.988	–0.983
ar.S.L12	–0.2341	0.006	–40.045	–0.246	–0.223
ma.S.L12	–0.9450	0.002	–568.840	–0.948	–0.942
sigma2	0.2242	0.001	221.779	0.222	0.226

For the gas station, the SARIMAX model was built with the following parameters: p = 1, d = 1, q = 3, P = 1, D = 1, Q = 1, m = 12. The length of the day and the current time are additional data (Table 5).

Table 5 – Coefficients of the SARIMAX model for a gas station

	coef	std err	z	[0.025	0.975]
Length of day	0.0033	0.002	1.365	–0.001	0.008
Hour	0.0285	0.020	1.429	–0.011	0.068
ar.L1	0.7650	0.004	187.115	0.757	0.773
ma.L1	–1.0199	0.002	–616.789	–1.023	–1.017
ar.S.L12	–0.5938	0.004	–132.943	–0.603	–0.585
ma.S.L12	–1.2057	0.005	–251.137	–1.215	–1.196
sigma2	8.4633	0.083	102.044	8.301	8.626

For the dairy factory, the SARIMAX model was built with the following parameters: p = 1, d = 0, q = 1, P = 1, D = 1, Q = 1, m = 12. The length of the day and the ambient temperature serve as auxiliary data (Table 6).

Table 6 – Coefficients of the SARIMAX model for a dairy plant

	coef	std err	z	[0.025	0.975]
Length of day	0.0010	0.003	0.366	–0.004	0.006
T	2.2368	0.156	14.346	1.931	2.542
ar.L1	0.8849	0.004	246.114	0.878	0.892
ma.L1	–1.0000	0.022	–46.128	–1.042	–0.958
ar.S.L12	–0.4206	0.008	–55.627	–0.435	–0.406
ma.S.L12	–0.8688	0.004	–214.637	–0.877	–0.861
sigma2	860.8387	19.769	43.545	822.092	899.585

Another model for forecasting was the LSTM machine learning model. The model was built using the Keras library for Python. The model is built on four layers. First the Sequential class is instantiated, then the LSTM layers and the Dropout and Dense auxiliary layers are added. The number of neurons in the LSTM layer is indicated. Return_sequences parameter is set to "true" to add the following data. The parameter Input_shape indicates the number of time steps, and output_shape shows the number of indicators. A dropout layer is added to avoid retraining. To ensure the reliability of the prediction, a Dense layer with the number of neurons 1 is added. The model for training uses 20 epochs, the data batch size is 100 (Table 7).

Table 7 – Coefficients of the LSTM model

Layer	Shape	Param
LSTM	100	52400
Dropout	100	0
Dense	1	101
Total params	52.501	
Trainable params	52.501	
Epochs	20	
Batch size	100	

Input values of the LSTM model for all types of consumers are indicators of hourly electricity consumption, the length of the day is used as an additional value. The coefficients of the LSTM model were selected in such a way that when the type of electricity consumers changed, the forecasted accuracy remained at a high level.

5 RESULTS

Experiments on forecasting volumes of electricity consumption for selected data sets were conducted. The predictive quality of the models was checked on test data. The selected models forecast hourly electricity consumption for 6 hours, 1 day, 3 days ahead.

The results of testing the forecasting accuracy of the SARIMAX model are in Table 8.

Table 8 – Forecasting accuracy of the SARIMAX model

Forecast period/ Assessment of accuracy		6 hours	1 day	3 days
Dairy Plant	**MAE**	36.6893	49.8139	64.2426
	RMSE	50.7658	110.2718	118.1284
	MAPE (%)	11.4544	13.1783	17.6610
Residential house	**MAE**	0.1145	0.2226	0.2393
	RMSE	0.1066	0.0043	0.3135
	MAPE (%)	0.0021	0.0070	0.0647
Gas Station	**MAE**	4.3309	4.6415	5.1155
	RMSE	11.5534	12.9961	5.9725
	MAPE (%)	5.6638	9.0617	11.5512

DOI 10.15588/1607-3274-2023-1-2

Forecasted by the SARIMAX model and the actual values of electricity consumption by the dairy plant are shown in Fig. 5.

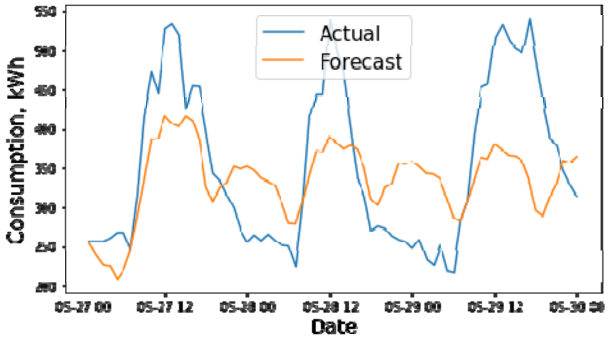

Figure 5 – Actual and forecasted values of electricity consumption by the dairy plant using the SARIMAX model

As a result of using the LSTM model built on parameters (Table 7), forecasting results (Table 9) were obtained for three types of electricity consumers.

Table 9 – LSTM model forecasting quality

Forecast period/ Assessment of accuracy		6 hours	1 day	3 days
Dairy Plant	MAE	15.4205	26.3461	24.5023
	RMSE	20.5534	35.6533	32.5615
	MAPE (%)	3.7420	6.7309	6.6436
Residential house	MAE	0.0902	0.0596	0.0908
	RMSE	0.1048	0.0784	0.2396
	MAPE (%)	0.1586	0.1631	0.1243
Gas Station	MAE	2.2020	3.0619	2.2143
	RMSE	2.4266	3.8967	2.9812
	MAPE (%)	3.6706	6.0989	4.6605

Forecasted by the LSTM model and the actual values of electricity consumption by the dairy plant are shown in Fig. 6.

The loss function (Fig. 7) was used to adjust the model, it is used to adjust the weights during the next evaluation of the model.

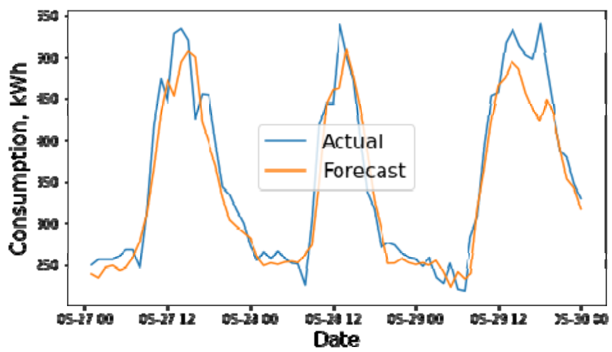

Figure 6 – Actual and forecasted values of electricity consumption by the dairy plant using the LSTM model

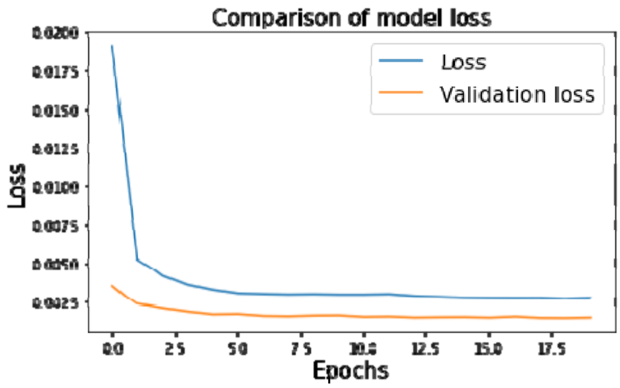

Figure 7 – Dependence of LSTM network loss on the number of training epochs on the dairy plant data set

6 DISCUSSION

The following conclusions can be drawn from the analysis of the results of the forecasting of electric energy in Microgrids. The SARIMAX model does not meet the requirement for forecasting electricity consumption. This model can only be used for short-term forecasting (from 1 hour to 6 hours). Only the prediction of electricity consumption for a private house using the SARIMAX model showed a slight advantage in predictive quality.

The forecasting results of the LSTM model met the forecasting requirements, providing better forecasting quality compared to AR models.

Compared to existing electricity forecasting works [7–12], forecasting results for the private sector have been significantly improved. The quality of forecasting of the LSTM model with the proposed parameters showed better results and forecasts than in the reviewed works. The proposed universal model showed high forecasting results for the considered types of consumers, compared to articles [10] where model parameters need to be constantly adjusted to obtain competitive forecasting results.

CONCLUSIONS

A study of the forecasting of electricity consumption by various types of consumers was conducted, which made it possible to develop universal consumption forecasting models that meet the requirements of forecast quality.

Autoregressive models for selected data sets are built with different values of input parameters. Since the SARIMAX model is sensitive to the input data, there is a need for a large number of values (6–10 seasons) unlike the LTSM model. The parameters of the forecasting models were selected experimentally. The forecasting quality of each model was compared by conducting a series of experiments for each data set and for each time interval.

The comparative analysis of the developed time series forecasting models made it possible to draw a conclusion about the advantages of ML models over AR models. The forecasted quality of the LSTM model showed the accuracy of the MAPE of electricity consumption forecasting: for a residential house – 0.1%, a dairy – 3.74%, and a gas station – 3.67%.

DOI 10.15588/1607-3274-2023-1-2

The scientific novelty consists in building a universal forecasting model that provides high forecasting accuracy for different types of microgrid consumers.

The practical significance is that the developed forecasting models are used in decision support system for microgrid real-time operation. It allows effectively implement microgrid technology to increase the efficiency of energy infrastructure management and reduce electricity consumption.

Prospects for further research include the development of intelligent information technology to support decision-making and a set of software tools for energy infrastructure management, which will increase the efficiency of decision-making at various levels of energy infrastructure management.

ACKNOWLEDGEMENTS

The work was carried out with the support of the state budget research project of the Sumy State University “Intelligent Information-analytical Technologies and Means of Presentation, Assessment, and Management of the Country’s Energy Infrastructure” (state registration number 0121U109558).

REFERENCES

1. Issa Walid, Al-naemi Faris, Konstantopoulos George Stability analysis and control of a microgrid against circulating power between parallel inverters [Electronic resource], *Energy procedia*, 2019, Volume 157, pp. 1061–1070. – Mode of access: https://doi.org/10.1016/j.egypro.2018.11.273. (date of access: 24.11.2022).
2. Sonam Parashar [et al.] Multiobjective optimal sizing of battery energy storage in grid-connected microgrid [Electronic resource], *The journal of engineering,* 2019, Vol. 2019, No. 18, pp. 5280–5283. Mode of access: https://doi.org/10.1049/joe.2018.9237 (date of access: 24.11.2022).
3. Barzegarkhoo Reza, Farhangi Majid, Sze Lee Sing Nine-Level Nine-Switch Common-Ground Switched-Capacitor Inverter Suitable for High-Frequency AC-Microgrid Applications [Electronic resource], *IEEE transactions on power electronics*, 2022, Vol. 37, No. 5, pp. 6132–6143. Mode of Access: https://doi.org/10.1109/TPEL.2021.3131847 (date of access: 24.11.2022).
4. Shendryk Vira [et al.] Modeling techniques of electricity consumption forecasting [Electronic resource], *AIP conference proceedings*, 2022, No. 2570, 030004. Mode of access: https://doi.org/10.1063/5.0100123 (date of access: 24.11.2022).
5. Dhabi Abu Electricity storage valuation framework. [Electronic resource]. IRENA, 2020. Mode of access: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Mar/IRENA_storage_valuation_2020.pdf (date of access: 24.11.2022).
6. Lianyong Qi, Wanchun Dou, Wenping Wang Dynamic mobile crowdsourcing selection for electricity load forecasting [Electronic resource], *IEEE access*, 2018, pp. 256–263. Mode of access: https://doi.org/10.1109/ACCESS.2018.2866641 (date of access: 24.11.2022).
7. Stanislaw Czapp, Hanan Tariq, Seweryn Szultka Electrical safety in low-voltage DC microgrids with B-type residual current devices [Electronic resource], *Eksploatacja i niezawodnosc – maintenance and reliability,* 2022, pp. 346–358. Mode of access: https://doi.org/10.17531/ein.2022.2.16 (date of access: 24.11.2022).
8. Potapov Viktor, Khamitov Rustam, Makarov Vladimir Short-Term Forecast of Electricity Load for LLC “Omsk Energy Retail Company” Using Neural Network [Electronic resource], *Dynamics of Systems, Mechanisms and Machines,* 2018, pp. 1–5. Mode of access: https://doi.org/10.1109/Dynamics.2018.8601430 (date of access: 24.11.2022).
9. Brancucci Carlo, Martinez-Anido Brancucci, Botor Benjamin, Florita Anthony The value of day-ahead solar power forecasting improvement [Electronic resource] / // Solar Energy, 2016. pp. 192–203. Access mode: https://doi.org/10.1016/j.solener.2016.01.049 (date of access: 24.11.2022).
10. Mehrnaz Anvari, Elisavet Proedrou, Benjamin Schäfer Data-driven load profiles and the dynamics of residential electricity consumption, *Nature Communications*, 2022, pp. 1711–1723. Access mode: https://doi.org/10.1038/s41467-022-31942-9 (date of access: 24.11.2022).
11. Yao Zhenpeng, Lum Yanwei, Johnston Andrew Machine learning for a sustainable energy future [Electronic resource], *Nature reviews. Materials*, 2022, pp. 1–14. Access mode: https://doi.org/10.1038/s41578-022-00490-5 (date of access: 24.11.2022).
12. Guillermo Hernández, Juan M. Corchado, Sigeru Omatu Machine Learning Models for Electricity Consumption Forecasting: A Review [Electronic resource], *International Conference on Computer Applications & Information Security,* 2019, pp. 1–6. Access mode: https://doi.org/10.1109/CAIS.2019.8769508. (date of access: 24.11.2022).
13. Hyung-Jun Moon, Seok-Jun Bu, Sung-Bae Cho Learning Disentangled Representation of Residential Power Demand Peak via Convolutional-Recurrent Triplet Network [Electronic resource], *International Conference on Data Mining Workshops (ICDMW),* 2020, pp. 757–761. Access mode: https://doi.org/10.1109/ICDMW51313.2020.00110 (date of access: 24.11.2022).
14. Ngoc-Tri Ngo, Anh-Duc Pham, Thi Thu Truong Developing a hybrid time-series artificial intelligence model to forecast energy use in buildings [Electronic resource], *Scientific Reports*, 2022, Vol. 12, No. 1, pp. 2045–2053. Access mode: https://doi.org/10.1038/s41598-022-19935-6 (date of access: 24.11.2022).
15. Gers Felix, Cummins Fred Understanding LSTM Networks [Electronic resource]. https://colah.github.io/. Mode of access: https://colah.github.io/posts/2015-08-Understanding-LSTMs/ (date of access: 24.11.2022).
16. Robert H. Shumway, David S. Stoffer Time series analysis and its applications (springer texts in statistics). [S. l.]. Springer, 2005, 562 p.
17. John Lu Z. Q. The elements of statistical learning: data mining, inference, and prediction [Electronic resource], *Journal of the royal statistical society: series A (statistics in society),* 2010, Vol. 173, No. 3, pp. 693–694. Mode of access: https://doi.org/10.1111/j.1467-985x.2010.00646_6.x (date of access: 24.11.2022).
18. Asterios Papageorgiou [et al.] Climate change impact of integrating a solar microgrid system into the Swedish electricity grid [Electronic resource], *Applied energy,* 2020.

DOI 10.15588/1607-3274-2023-1-2

Vol. 268, pp. 164–181. Mode of access: https://doi.org/10.1016/j.apenergy.2020.114981 (date of access: 24.11.2022).
19. Pramode K. Verma, Mayssaa El Rifai, Kam Wai Clifford Chan Application of the multi-stage protocol in IEEE 802.11i [Electronic resource], *Multi-photon quantum secure communication*. Singapore, 2018, pp. 143–159. Mode of access: https://doi.org/10.1007/978-981-10-8618-2_9 (date of access: 24.11.2022).
20. Sherin A. Helal [et al.] Energy management system for smart hybrid AC/DC microgrids in remote communities [Electronic resource], *Electric power components and systems,* 2019, Vol. 47, No. 11–12, pp. 1012–1024. Mode of access: https://doi.org/10.1080/15325008.2019.1629512 (date of access: 24.11.2022)
21. Changbin Hu [et al.] Coordinative optimization control of microgrid based on model predictive control [Electronic resource], *Research anthology on smart grid and microgrid development,* [S. l.], 2022, pp. 233–252. Mode of access: https://doi.org/10.4018/978-1-6684-3666-0.ch012 (date of access: 24.11.2022)
22. Kosarev V. S. Neural network approach to the electricity market forecasting with different-frequency data among the explanatory variables [Electronic resource], *2022 III international conference on neural networks and neurotechnologies (neuront)*. Saint Petersburg, Russian Federation, 16 June 2022, [S. l.], 2022. Mode of access: https://doi.org/10.1109/neuront55429.2022.9805538 (date of access: 24.11.2022).
23. Kinanti Hanugera Gusti, Irhamah Irhamah, Heri Kuswanto Hybrid double seasonal ARIMA and support vector regression in short-term electricity load forecasting [Electronic resource], *IPTEK journal of proceedings series*, 2021, No. 6, pp. 322–341. Mode of access: https://doi.org/10.12962/j23546026.y2020i6.11117 (date of access: 24.11.2022).

Received 10.11.2022.
Accepted 23.12.2022.

УДК 004.4:004.032.26

ПОРІВНЯННЯ МЕТОДІВ КОРОТКОСТРОКОВОГО ПРОГНОЗУВАННЯ СПОЖИВАННЯ ЕЛЕКТРОЕНЕРГІЇ ДЛЯ МІКРОМЕРІЖ

Парфененко Ю. В. – канд. техн. наук, доцент кафедри інформаційних технологій, Сумський державний університет, Суми, Україна.
Шендрик В. В. – канд. техн. наук, доцент кафедри інформаційних технологій, Сумський державний університет, Суми, Україна.
Холявка Є. П. – аспірант, кафедра інформаційних технологій, Сумський державний університет, Суми, Україна.
Павленко П. М. – д-р техн. наук, професор, професор кафедри організації авіаційних перевезень, Національний авіаційний університет, Київ, Україна.

АНОТАЦІЯ

Актуальність. Сучасний етап розвитку електроенергетики характеризується інтенсивним процесом розвитку та управління мікромережею. Доцільність використання мікромережі визначається тим, що вона має низку переваг порівняно з класичними методами генерації, передачі та розподілу енергії. Забезпечити надійність електропостачання в мікромережі набагато легше, ніж у великих центролізованих енергосистемах. Споживачі енергії в мікромережі можуть впливати на процес балансування електроенергії, регулюючи свої навантаження, генеруючи, накопичуючи та відпускаючи електроенергію. Одним із головних завдань Microgrid є забезпечення споживачів електричною енергією в балансі між її генерацією та споживанням. Це досягається завдяки інтелектуальному управлінню роботою Microgrid, яке використовує дані прогнозування енергоспоживання. Це дозволяє підвищити ефективність управління енергетичною інфраструктурою, робить її більш стійкою.

Мета. Метою даної роботи є розробка моделей короткострокового прогнозування споживання електроенергії для різних типів споживачів електроенергії у Microgrid, що дозволить підвищити ефективність управління енергетичною інфраструктурою та загалом зменшити споживання електроенергії.

Метод. Для отримання прогнозних значень споживання електроенергії використовуються авторегресійна модель (AR) SARIMA та модель машинного навчання (ML) LSTM. Інформаційні критерії AIC і BIC використовуються для порівняння авторегресійних моделей. Точність моделей прогнозування оцінюється за допомогою помилок MAE, RMSE, MAPE.

Результати. Проведено експерименти з прогнозування обсягів споживання електроенергії для різних типів споживачів. Прогнозування проводилося як з використанням моделей LSTM, так і моделей AR на сформованих наборах даних з інтервалами кожну годину протягом 6 годин, 1 день і 3 дні. Результати прогнозування з використанням моделі LSTM відповідали вимогам, забезпечуючи кращу якість прогнозування порівняно з авторегресійними моделями.

Висновки. Проведене дослідження прогнозування споживання електроенергії дозволило знайти універсальні моделі прогнозування, які відповідають вимогам якості прогнозування. Проведено порівняльний аналіз розроблених моделей прогнозування часових рядів, у результаті якого виявлено переваги моделей ML перед моделями AR. Прогностична якість моделі LSTM показала точність MAPE прогнозування споживання електроенергії для приватного будинку – 0,1%, молокозаводу – 3,74%, АЗС – 3,67%. Отримані результати дозволять підвищити ефективність управління мікромережею, розподілу електроенергії між споживачами для зменшення загальних обсягів споживання енергії та запобігання виникнення пікових навантажень.

КЛЮЧОВІ СЛОВА: мікромережа, машинне навчання, модель LSTM, модель AR, прогнозування, споживання електроенергії.

ЛІТЕРАТУРА

1. Issa W. Stability analysis and control of a microgrid against circulating power between parallel inverters [Electronic resource] / Walid Issa, Faris Al-naemi, George Konstantopoulos // Energy procedia. – 2019. – Vol. 157. – P. 1061–1070. Mode of access: https://doi.org/10.1016/j.egypro.2018.11.273. (date of access: 24.11.2022).
2. Multiobjective optimal sizing of battery energy storage in grid-connected microgrid [Electronic resource] / Sonam Parashar [et al.] // The journal of engineering. – 2019. – Vol. 2019, No. 18. – P. 5280–5283. – Mode of access: https://doi.org/10.1049/joe.2018.9237 (date of access: 24.11.2022).
3. Barzegarkhoo R. Nine-Level Nine-Switch Common-Ground Switched-Capacitor Inverter Suitable for High-Frequency

DOI 10.15588/1607-3274-2023-1-2

AC-Microgrid Applications [Electronic resource] / Reza Barzegarkhoo, Majid Farhangi, Lee Sze Sing // IEEE transactions on power electronics. – 2022. – Vol. 37, No. 5. – P. 6132–6143. – Mode of access: https://doi.org/10.1109/TPEL.2021.3131847 (date of access: 24.11.2022).

4. Modeling techniques of electricity consumption forecasting [Electronic resource] / Vira Shendryk [et al.] // AIP conference proceedings. – 2022. – No. 2570. – 030004. – Mode of access: https://doi.org/10.1063/5.0100123 (date of access: 24.11.2022).
5. Electricity storage valuation framework. [Electronic resource]. – Abu Dhabi : IRENA, 2020. – Mode of access: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2020/Mar/IRENA_storage_valuation_2020.pdf (date of access: 24.11.2022).
6. Lianyong Q. Dynamic mobile crowdsourcing selection for electricity load forecasting [Electronic resource] / Qi Lianyong, Dou Wanchun, Wang Wenping // IEEE access. – 2018. – P. 256–263. – Mode of access: https://doi.org/10.1109/ACCESS.2018.2866641 (date of access: 24.11.2022).
7. Stanislaw C. Electrical safety in low-voltage DC microgrids with B-type residual current devices [Electronic resource] / Czapp Stanislaw, Tariq Hanan, Szultka Seweryn // Eksploatacja i niezawodnosc – maintenance and reliability. – 2022. – P. 346–358. – Mode of access: https://doi.org/10.17531/ein.2022.2.16 (date of access: 24.11.2022).
8. Potapov V. Short-Term Forecast of Electricity Load for LLC “Omsk Energy Retail Company” Using Neural Network [Electronic resource] / Viktor Potapov, Rustam Khamitov, Vladimir Makarov // Dynamics of Systems, Mechanisms and Machines. – 2018. – P. 1–5. – Mode of access: https://doi.org/10.1109/Dynamics.2018.8601430 (date of access: 24.11.2022).
9. Brancucci C. The value of day-ahead solar power forecasting improvement [Electronic resource] / Carlo Brancucci Martinez-Anido, Benjamin Botor, Anthony Florita // Solar Energy. – 2016. – P. 192–203 – Access mode: https://doi.org/10.1016/j.solener.2016.01.049 (date of access: 24.11.2022).
10. Anvari, M. Data-driven load profiles and the dynamics of residential electricity consumption / Anvari Mehrnaz, Proedrou Elisavet, Schäfer Benjamin // Nature Communications. – 2022. – P. 1711–1723. – Access mode: https://doi.org/10.1038/s41467-022-31942-9 (date of access: 24.11.2022).
11. Yao Z. Machine learning for a sustainable energy future [Electronic resource] / Zhenpeng Yao, Yanwei Lum, Andrew Johnston // Nature reviews. Materials. – 2022. – P. 1–14. – Access mode: https://doi.org/10.1038/s41578-022-00490-5 (date of access: 24.11.2022).
12. Hernández G. Machine Learning Models for Electricity Consumption Forecasting: A Review [Electronic resource] / Hernández Guillermo, Corchado Juan M., Omatu Sigeru // International Conference on Computer Applications & Information Security. – 2019. – P. 1–6. – Access mode: https://doi.org/10.1109/CAIS.2019.8769508. (date of access: 24.11.2022).
13. Moon H. Learning Disentangled Representation of Residential Power Demand Peak via Convolutional-Recurrent Triplet Network [Electronic resource] / Moon Hyung-Jun, Bu Seok-Jun, Cho Sung-Bae // International Conference on Data Mining Workshops (ICDMW). – 2020. – P. 757–761. – Access mode: https://doi.org/10.1109/ICDMW51313.2020.00110 (date of access: 24.11.2022).
14. Ngo, NT. Developing a hybrid time-series artificial intelligence model to forecast energy use in buildings [Electronic resource] / Ngo Ngoc-Tri, Pham Anh-Duc, Truong Thi Thu // Scientific Reports. – 2022. – Vol. 12, No. 1. – P. 2045–2053. – Access mode: https://doi.org/10.1038/s41598-022-19935-6 (date of access: 24.11.2022).
15. Gers F. Understanding LSTM Networks [Electronic resource] / Felix Gers, Fred Cummins // https://colah.github.io/. – Mode of access: https://colah.github.io/posts/2015-08-Understanding-LSTMs/ (date of access: 24.11.2022).
16. Shumway R. H. Time series analysis and its applications (springer texts in statistics) / Robert H. Shumway, David S. Stoffer. – [S. l.] : Springer, 2005. – 562 p.
17. John Lu Z. Q. The elements of statistical learning: data mining, inference, and prediction [Electronic resource] / Z. Q. John Lu // Journal of the royal statistical society: series A (statistics in society). – 2010. – Vol. 173, No. 3. – P. 693–694. – Mode of access: https://doi.org/10.1111/j.1467-985x.2010.00646_6.x (date of access: 24.11.2022).
18. Climate change impact of integrating a solar microgrid system into the Swedish electricity grid [Electronic resource] / Asterios Papageorgiou [et al.] // Applied energy. – 2020. – Vol. 268. – P. 164–181. – Mode of access: https://doi.org/10.1016/j.apenergy.2020.114981 (date of access: 24.11.2022).
19. Verma P. K. Application of the multi-stage protocol in IEEE 802.11i [Electronic resource] / Pramode K. Verma, Mayssaa El Rifai, Kam Wai Clifford Chan // Multi-photon quantum secure communication. – Singapore. – 2018. – P. 143–159. – Mode of access: https://doi.org/10.1007/978-981-10-8618-2_9 (date of access: 24.11.2022).
20. Energy management system for smart hybrid AC/DC microgrids in remote communities [Electronic resource] / Sherin A. Helal [et al.] // Electric power components and systems. – 2019. – Vol. 47, No. 11–12. – P. 1012–1024. – Mode of access: https://doi.org/10.1080/15325008.2019.1629512 (date of access: 24.11.2022)
21. Coordinative optimization control of microgrid based on model predictive control [Electronic resource] / Changbin Hu [et al.] // Research anthology on smart grid and microgrid development. – [S. l.], 2022. – P. 233–252. – Mode of access: https://doi.org/10.4018/978-1-6684-3666-0.ch012 (date of access: 24.11.2022)
22. Kosarev V. S. Neural network approach to the electricity market forecasting with different-frequency data among the explanatory variables [Electronic resource] / Vladimir S. Kosarev // 2022 III international conference on neural networks and neurotechnologies (neuront), Saint Petersburg, Russian Federation, 16 June 2022. – [S. l.], 2022. – Mode of access: https://doi.org/10.1109/neuront55429.2022.9805538 (date of access: 24.11.2022).
23. Gusti K. H. Hybrid double seasonal ARIMA and support vector regression in short-term electricity load forecasting [Electronic resource] / Kinanti Hanugera Gusti, Irhamah Irhamah, Heri Kuswanto // IPTEK journal of proceedings series. – 2021. – No. 6. – P. 322. – Mode of access: https://doi.org/10.12962/j23546026.y2020i6.11117 (date of access: 24.11.2022).

DOI 10.15588/1607-3274-2023-1-2