A Python Application for Hourly Electricity Prices Forecasting Using Neural Networks

Oleg Yu. Maryasin
Department of Cybernetics
Yaroslavl State Technical University
Yaroslavl, Russia
maryasin2003@list.ru

Andrey I. Lukashov
Yaroslavl State Technical University
Yaroslavl, Russia
lukashovai@ystu.ru

***Abstract*—The paper considers the problem of forecasting hourly market electricity prices using the artificial neural networks. The existing publications are analyzed to determine the most popular methods of electricity prices forecasting, the types of neural networks most commonly used in forecasting, and the existing tools of forecasting algorithms implementation based on neural networks. A Python application has been developed to perform the electricity prices forecasting and analysis, using NeuroLab and Keras libraries for creating neural networks. The paper also presents the results of numerical experiments on electricity prices forecasting using the developed application. The experiments tested the forecast quality dependence on the library used, the structure of neural network, and the training algorithms used.**

Keywords—electricity price, forecasting, artificial neural network, NeuroLab, Keras

I. Introduction

One of the ways to increase the competitiveness of the economy is to develop systems and methods to forecast market conditions. It also relates to those in the markets for the utility sector products, which include the electric power industry. After the state regulation of electricity prices was canceled, the consumer electricity price in the Russian Federation consists of an unregulated wholesale electricity (power) market component, the regulated tariffs for electric power transmission services, sales allowances for guaranteeing suppliers, and fees for other services. Forecasting is primarily concerned with the unregulated part of the price, which generally consists of the wholesale electricity price and the weighted average capacity price in the wholesale market.

The relevance of the electricity prices forecasting topic is based on the business entities' need to have reasonable evaluation of prospective price levels accounting for the existing conditions of price uncertainty and volatility. Thus, they shall be able to mitigate possible risks and improve the quality of operations planning [1]. For instance, knowing the hourly values of electricity prices in the upcoming month, an enterprise could redistribute its needs in such a way as to avoid unnecessary costs, when the prices are high, and, as a result, to save money on energy resources. Reducing price uncertainty, getting ahead of competitors in the price war and the resulting increase in profits are the tasks that a price forecast should solve for an enterprise.

In terms of price volatility, the Russian electricity market can hardly be called highly fluctuating. Over a month the maximum hourly electricity price is rarely more than twice the minimum price. For the retail consumer, these changes are smoothed out due to the regulated component of the price and make up no more than 20-25% within a month. This is a significant difference the Russian market has from the energy markets of the EU and the USA, where the minimum and maximum electricity prices can differ by seven or more times within one day. At the same time, it is important, that for certain groups of Russian consumers, especially large ones, the twofold change in electricity prices is sufficient to make energy consumption schedule decisions as well as to introduce technical solutions, shifting the consumption peaks to the periods falling in the lower price ranges.

This paper focuses on the task of forecasting hourly electricity prices for the month ahead. This is due to the peculiarities of the Russian retail electricity market, in which the information on the actual electricity prices becomes available only a few days after the end of the billing period, that is, the month, when the energy was consumed. This distinguishes the presented research from many other devoted to this topic, where short-term forecasting tasks are considered for a day, several days or weeks in advance.

To date, the Russian market has no ready-made, user-oriented, computer programs capable of forecasting electricity prices. A number of companies are working in this field, including both the immediate members of the wholesale market, and those providing electricity prices forecasting services. However, these companies are not ready to share their own methods and best practices, generating their profit in the competitive market. Therefore, one of the tasks to be solved in this research is the development of a computer program, analyzing and forecasting market electricity prices, which could be used not only by scientists and forecasting methods specialists, as well as the end users.

II. Review of Publications on Electricity Price Forecasting

The topic of electricity market prices forecasting is widely covered in the existing publications worldwide. The paper [2] deserves attention among the early detailed reviews on this topic. This review examined 47 articles published from 1997 to 2006 and analyzed these publications based on the following

978-1-7281-6130-3/20/$31.00 ©2020 IEEE

main characteristics: model type, prediction horizon, input variables used, data preprocessing methods used, and forecasting results. Considering the recent reviews, [3]–[5] can be distinguished. The article [3], being the most extensive of them, reviews scientific publications, indexed in Web of Science (304 publications) and Scopus (497 publications) scientometric databases over the period from 1989 to 2013. The reviews [4], [5], although relatively new, are also based on the work completed before 2014.

According to these sources, all market electricity prices forecasting methods fall into the following main groups:

- methods based on multi-agent and game-theoretic models that simulate the behavior of agents in the electricity market;
- methods based on the models simulating the pricing strategies of market participants and the impact of the most important physical and economic factors on the electricity price;
- methods based on the analysis of time series.

The last group of methods can be divided into the methods that use stochastic models, statistical models, and artificial intelligence models built on the basis of Artificial Neural Networks (ANN).

As far as the forecast horizon, the majority of publications considered in the reviews consider forecasting for a day, a week, or several upcoming weeks. Predicting prices for a month, several months, or a year is much less common. According to [3], statistical methods and methods based on artificial intelligence showed the best results in the short-term forecasting of electricity prices. In [6], it is pointed out that forecasting hourly price values is significantly complicated by the data nonlinear behavior and their rapid changes. Under such conditions, as stated in [6], ANN-based forecasting proves to be a more efficient approach than the statistical methods. The fact that ANNs have better capabilities for modeling unknown laws of changing the time series of market electricity prices is also noted in [7].

The latest information on the use of various types of ANN for forecasting electricity prices can be found in the reviews [8], [9]. In [8], ANN types, such as the Multilayer perceptron (MLP), feed-forward Neural Networks (FFNN), recurrent NNs (RNN), cascaded NNs, probabilistic NNs, fuzzy NNs, are considered along with the hybrid approaches combining ANNs with other well-known technologies such as Kalman filter, chaotic dynamics, and wavelet transformation. In [9], neural networks based on radial bias functions (radial bias function NN) and neural networks using genetic algorithms (genetic algorithm based NN) are also described. The use of currently popular methods of deep machine learning and deep NNs for forecasting electricity prices is considered in [10], [11].

The analysis shows that of all types of traditional ANN architectures, FFNN (including MLP, radial bias function NN and generalized regression NN [12]) and RNN are most often used to forecast the electricity prices. Moreover, of all types of FFNNs, MLP is the most widely used for this. It accounts for most of the publications. Of the deep NNs used to predict electricity prices, convolutional neural networks (CNN) and long short term memory networks (LSTM NN) are of interest.

Based on the result of the existing publications analysis, the authors decided to use the ANN tool to forecast the market electricity prices. This unit has wide forecasting capabilities and provides for the necessary hourly price values forecasting accuracy. If it is necessary to improve forecasting results when using ANN, it is possible to switch to a more complex ANN structure, a more complex ANN architecture, or more complex ANN learning methods.

III. ANN-Based Forecasting Tools

The authors analyzed the available publications, referenced in the reviews listed herein above and on the Internet, seeking for the means their authors used to conduct ANN-based forecasting. Although almost every publication devoted to the practical use of ANN for electricity prices forecasting presents the calculation results, very often, for some reason, the authors provide no description of how these results were obtained. Most of the publications, referring to the ANN implementation tools, feature MATLAB. The MATLAB package includes the Neural Network Toolbox (currently transformed into the Deep Learning Toolbox), which provides powerful tools for ANN. For the examples of using the Neural Network Toolbox MATLAB to predict electricity prices, see [12]–[15]. In addition to MATLAB, [16] mentions the C++ programming language, while the latest works [10], [17], [18] similarly mention the Python language.

The analysis of the publications shows that, the MATLAB package is generally most often used for forecasting electricity prices based on ANN. This is because this package is very common in the academic environment and is used in universities and by scientists around the world. Despite this, the authors do not consider the MATLAB package to be the best existing option for developing ANN-based forecasting applications, primarily because of its high cost. Moreover, to work with ANN in MATLAB, a user needs to master the Deep Learning Toolbox functions and the MATLAB programming language. Learning MATLAB can be avoided by developing GUI applications in MATLAB or stand-alone MATLAB applications. In the first case, the user still needs to purchase MATLAB, and the second option is not always implemented, since the old versions of the Deep Learning Toolbox are not supported, and the new versions have restrictions on the use of some functions [19].

The next most popular tool for implementing ANN-based electricity price forecasting is Python. Based on the publications for the last three years only, Python is the undisputed leader. Python is currently one of the most promising programming languages in the field of mathematical calculations, machine learning, and artificial intelligence. Therefore, the authors consider the use of Python and one of its libraries for working with ANN as the most suitable tool to develop an ANN-based forecasting application.

Currently, the most popular Python ANN libraries include TensorFlow, Keras, NeuPy, PyTorch, NeuroLab, Lasagne, Scikit-Neural Network. Keras, NeuPy, Lasagne, and the Scikit-Neural Network are high-level libraries based on renowned deep machine learning platforms. Keras and NeuPy use the TensorFlow library as such platform. Keras can also be connected to Theano, which is the basis for the Lasagne and Scikit-Neural Network libraries. The Scikit-Neural Network also uses the popular Scikit-Learn machine learning library.

The authors decided to use the NeuroLab and Keras libraries in the electricity prices forecasting application. The advantages of the NeuroLab library are its simplicity, compatibility with the Neural Network Toolbox MATLAB in terms of function syntax, many ANN learning algorithms, including using optimization algorithms of the well-known scipy library. NeuroLab supports ANN architectures such as MLP and some types of RNNs. As shown in [20], ANNs implemented using the NeuroLab library showed good results in predicting electricity consumption compared to the Random Forest machine learning algorithm.

The popular Keras library has been included in the application due to the authors' desire to provide the user with a powerful tool for deep machine learning. Keras, in addition to MLP, provides support for many other neural network architectures, including the promising ones like CNN and LSTM NN. In addition, the advantage of the Keras library lies in its high flexibility and the ability to significantly accelerate computations with large data using special graphics processing units (GPUs). The NeuroLab library is distributed under the LGPL license, TensorFlow – under the Apache Software License 2.0, Keras – under the MIT license.

IV. The Application for the Electricity Prices Analysis and Forecasting

A. *Input Data*

The input data used to build up a forecast is the information on market electricity prices in the Yaroslavl region (Russia) for the period from 2013 to 2019 published on the website of TNS energo Yaroslavl [21]. This information is available in the form of Microsoft Word, Microsoft Excel, and PDF files. Conducting analysis and forecasting require performing data sampling operations for a certain period and various conditions. Therefore, for the sake of convenience, a database (DB) of the forecasting system has been created to accommodate the price information from the files. The files-to-DB information transfer had two stages. At the first stage, the information from the source files was saved in .csv format files using the office packages. At the second stage, the data from .csv files was exported to the DB using the developed application. To ensure that there is no dependence on any particular DB, to work with the DB in the application, a high-level Python library that supports SQLite, MySQL, Oracle, PostgreSQL and other DBs was used.

B. *Application Features*

The application developed by the authors is designed to analyze and forecast hourly market electricity prices. The main functions of the application are:

- Reading hourly prices for a certain period (a multiple of a month) from the DB for a specific category, power and voltage level;
- Statistical analysis of the selected data set;
- Plotting price changes with a breakdown into days or hours in absolute or relative values. Construction of graphs of price autocorrelation functions with a breakdown into days or hours;
- Exporting monthly data to Microsoft Excel, highlighting the minimum and maximum rows and columns values;
- Compiling various Data Sets for neural network learning. Saving generated data sets to disk, loading sets from disk, exporting sets to .csv format;
- Performing the functions of preprocessing and preparing data for forecasting;
- Creating an ANN of a given type and structure. Entering the parameters of the ANN learning algorithm. Display the information about ANN learning outcomes;
- Price prediction for a given upcoming month or day. Displaying forecast results in tabular and graphical form. Calculation of standard indicators of forecast accuracy;
- Saving forecast data to a file, loading previously saved results from a file;
- Recording hourly price data for a month from a .csv file in the DB.

The developed application has a simple, intuitive interface. The main application window is shown in Fig. 1.

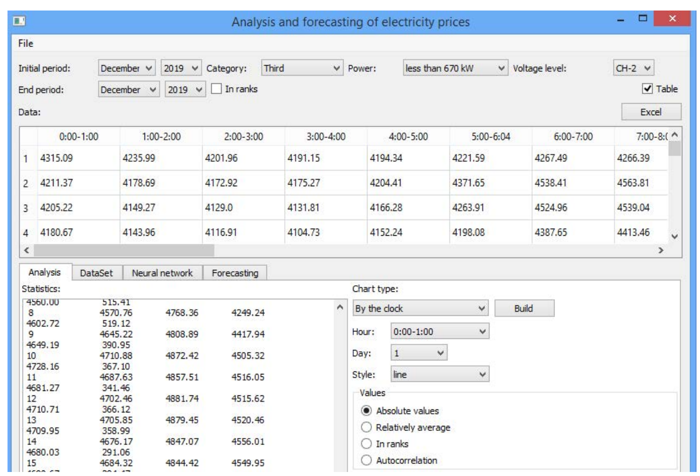

Fig. 1. The application main window

C. *Data Analysis*

The analysis of the source data enables the users to determine the statistical characteristics of the time series of the electricity prices changes, to identify patterns or features of pricing at a certain time interval. The developed application performs automatic calculations and displays of the average, maximum, minimum values and other indicators for rows, columns and for the entire loaded data set. The extensive capabilities of the numpy, scipy, pandas, matpotlib, statsmodels Python libraries are used to conduct various data manipulations, statistical analysis and data visualization. Users can plot price changes with breakdown into days or hours in absolute terms, relative to the average value or in ranks (relative to the minimum and maximum values); graphs of the prices autocorrelation functions with breakdown into days or hours. An example of a daily price change chart for three months from September to November, 2019, for a time interval from 10 to 11 hours, is shown in Fig. 2. All graphs presented in this paper were obtained using the developed application.

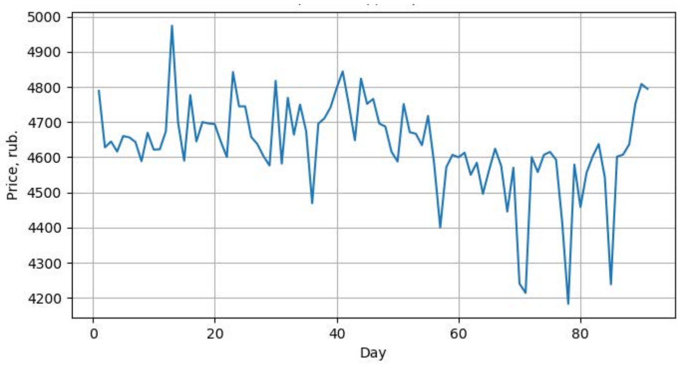

Fig. 2. Three month price change chart

The table of prices, in which the weekends and holidays, as well as the corresponding minimums and maximums are highlighted in certain colors, is very instrumental to obtain the information about the location of minimums and maximums of prices by days of the week and hours within a month. An example of such Microsoft Excel table for December 2019 is shown in Fig. 3.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Month	Decembe	Year	2019	Category	Third	Power	less than (	Voltage	CH-2		
2		0:00-1:00	1:00-2:00	2:00-3:00	3:00-4:00	4:00-5:00	5:00-6:04	6:00-7:00	7:00-8:00	8:00-9:00	9:00-10:00	10:00-11:0
3	1	4315,09	4235,99	4201,96	4191,15	4194,34	4221,59	4267,49	4266,39	4384,01	4525,27	4560
4	2	4211,37	4178,69	4172,92	4175,27	4204,41	4371,65	4538,41	4563,81	4573,89	4602,08	4728,38
5	3	4205,22	4149,27	4129	4131,81	4166,28	4263,91	4524,96	4539,04	4569,61	4604,44	4722,92
6	4	4180,67	4143,96	4116,91	4104,73	4152,24	4198,08	4387,65	4413,46	4529,26	4584,45	4592,98
7	5	4174,38	4154,8	4127,15	4116,01	4160,44	4226,43	4525,36	4557,51	4607,89	4633,66	4744,49
8	6	4226,63	4181,64	4162,59	4156,01	4210,45	4384,49	4533,44	4583,01	4623,26	4712,34	4805,34
9	7	4504,25	4388,76	4313,03	4282,98	4297,64	4443,53	4535,68	4565,24	4622,57	4677,15	4728,16
10	8	4504,61	4284,62	4236,66	4220,72	4227,43	4282,02	4393,38	4411,7	4531,66	4562,19	4587,55
11	9	4468,23	4280,93	4203,34	4203,03	4242,2	4431	4585,32	4665,48	4722,37	4762,84	4804,39
12	10	4422,26	4296,58	4252,72	4252,67	4303,28	4420,84	4581,19	4712,96	4768,36	4808,89	4869,96
13	11	4435,77	4296,04	4292,33	4285,85	4345,27	4548,08	4674,51	4727,81	4760,21	4798,54	4872,42
14	12	4395,05	4273,27	4233,72	4232,94	4281,29	4397,8	4535,71	4566,6	4602,72	4685,48	4763,64
15	13	4419,43	4294,8	4237,04	4224,09	4263,32	4399,84	4523,63	4568,04	4623,87	4733,04	4812,9
16	14	4555,1	4518,4	4511,52	4393,58	4473,61	4516,62	4542,8	4566,44	4676,16	4805,6	4852,61
17	15	4339,59	4210,38	4169,28	4170,77	4177,48	4187,23	4184,08	4267,14	4429,96	4546,26	4589,26
18	16	4340,59	4274,96	4231,28	4220,5	4290,42	4370,01	4543,01	4570,83	4609,6	4773,61	4866,51
19	17	4283,96	4204,64	4186,43	4182,77	4207,89	4265,28	4554,39	4585,15	4618,53	4759,09	4848,51
20	18	4221,89	4195,94	4178,93	4178,15	4188,78	4313,04	4521,7	4560	4606,81	4702,32	4814,64
21	19	4271,08	4201,75	4192,98	4193,24	4201,7	4339,76	4543,57	4574,22	4642,95	4707,39	4790,19
22	20	4216,87	4171,94	4146,59	4137,81	4180,74	4229,99	4452,19	4538,67	4581,46	4602,64	4664,89

Fig. 3. Price table with highlighting highs and lows

D. Network Training

The developed application allows preparing various Data Sets for ANN training and testing, as well as downloading previously prepared sets stored on a disk. The datasets differ in the number and composition of attributes. They include the following main features: hour, day, day of the week, month, year, price data at past points in time. The values of delays in hours (lags), used to set prices, have been selected according to the results of correlation analysis and reference data [12], [22]. As a result, the lag values $l \in L = \{1, 2, 3, 24, 48, 168\}$ have been chosen.

As stated earlier, MLP is the most popular type of ANN used to predict electricity prices. As [23] shows, the accuracy of the MLP electricity prices forecast is relatively the same as that provided by such advanced deep ANNs as CNN and LSTM NN. Therefore, MLP has been chosen as the main type of ANN used for electricity prices forecasting in the developed application. At the same time, two hidden layers are enough to obtain the permissible accuracy of forecasting [22]. Based on this, ANN in the form of MLP with two hidden layers and a single neuron in the output layer has been used for the forecast.

The developed application allows users to determine the structure of ANN by setting the number of hidden layers and the number of neurons in each hidden layer. Users can also choose the search algorithm, the number of epochs and accuracy (goal) of the training process. The NeuroLab library supports optimization algorithms such as gradient descent, gradient inertia descent, gradient inertia descent and adaptation of the learning rate coefficient, the Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS), the conjugate gradient algorithm, and others. Keras also supports various versions of the gradient descent algorithm, as well as RMSProp, Adagrad, Adam, Nadam, Adamax and others.

E. Forecasting Results

Using the developed application, the authors have conducted multiple numerical experiments to forecast the electricity prices. During the experiments, the quality of the forecast has been studied depending on the selected input data sets, the library used to create the ANN, the ANN structure, the learning algorithms used, the number of learning epochs, and other factors. The forecasting results have been checked both on the existing data and against the next-month real prices data obtained later. The forecasting with Keras library has been done without using the GPU.

A well-known MAPE (Mean Absolute Percentage Error) indicator has been used to evaluate the forecasting results. The authors faced the fact that in different works MAPE is defined differently, that is, there are several options for MAPE. In this work, MAPE has been calculated in the same way as in [14], [22].

Market electricity prices are clearly seasonal in nature and are strongly tied to the current calendar month. Price analysis showed that the nature of price changes within a month, the position of its lows and highs, are more likely to resemble the price behavior in the same month of the last year than in the previous month of the same year. Fig. 4 shows the results of the hourly price forecasting for December 2019 by days, for the time interval from 10 to 11 hours, using the data on prices in November 2019. Prediction was performed using NeuroLab. The solid line in Fig. 4 shows the real values of the price, and the dashed line shows the predicted values. The MAPE value for this forecast was 6.004.

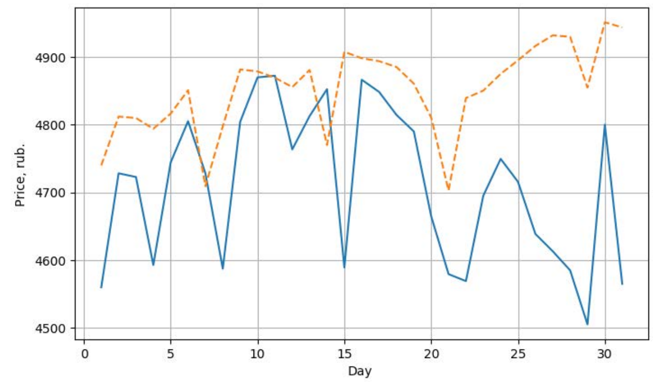

Fig. 4. Price forecast for December 2019 based on price data for November 2019 (NeuroLab)

Fig. 5 shows the results of the hourly price forecasting for December 2019 (obtained via NeuroLab), for the same time interval, with the data set enriched with the price information for December 2018. The MAPE value for this case was 1.76. Consequently, the use of information on last year's prices has significantly improved the forecasting results. For comparison, Fig. 6 shows the results of forecasting hourly prices, performed for the same conditions as in the previous case, but obtained using Keras. The MAPE value in this case was 1.61.

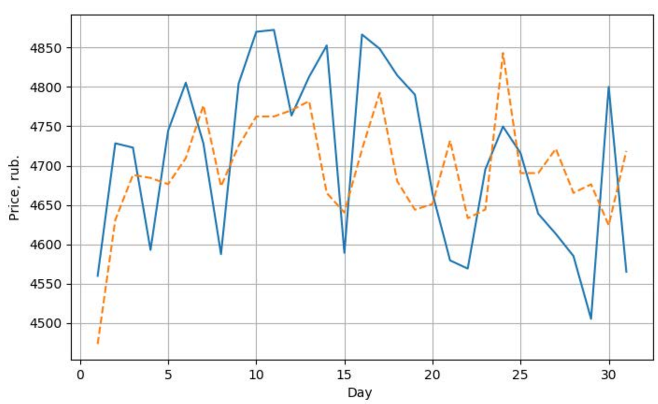

Fig. 5. Price forecast for December 2019 with the addition of price information for December 2018 (NeuroLab)

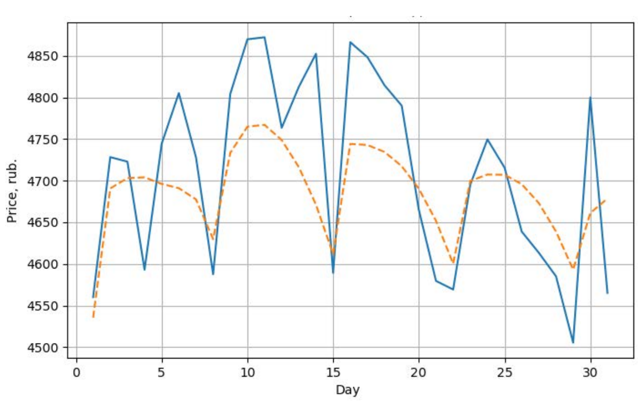

Fig. 6. Price forecast for December 2019 with the addition of price information for December 2018 (Keras)

Table I shows the MAPE values obtained by forecasting using the NeuroLab and Keras libraries for MLP with two hidden layers at different numbers of neurons in the hidden layers. MAPE values have been determined by averaging over the results of ten forecasting runs for each variant of the structure. It has also been found that the greatest accuracy of forecasts is achieved when BFGS algorithm for the NeuroLab library and Nadam algorithm for Keras are used in ANN training.

TABLE I. MAPE VALUES FOR VARIOUS ANN STRUCTURE

ANN	**Number of neurons in the hidden layer 1**	**Number of neurons in the hidden layer 2**	**MAPE (NeuroLab)**	**MAPE (Keras)**
1	12	3	2.35	1.66
2	16	4	1.86	1.72
3	20	5	1.765	1.61
4	25	5	1.803	1.53
5	24	6	1.815	1.57
6	36	6	1.911	1.61
7	49	7	1.95	1.65
8	64	8	2.152	1.77

Table II shows the MAPE values obtained when forecasting electricity prices for the last six months of 2019. The forecast is based on MLP with two hidden layers with 20 neurons in the first layer and 5 neurons in the second layer. As before, the MAPE values have been averaged over the results of ten forecasting runs for each month. As can be seen from the above data, the use of the Keras library for forecasting generally allows for slightly better results on the MAPE indicator.

TABLE II. FORECASTING RESULTS FOR THE VARIOUS MONTHS OF 2019

Month	**MAPE (NeuroLab)**	**MAPE (Keras)**
July	3.559	3.308
August	2.484	1.708
September	2.726	2.066
October	2.091	1.682
November	3.602	2.439
December	1.765	1.614

The developed application allows forecasting not only for a month ahead, but also for any day ahead within a month. However, in order to carry out operational forecasting for the day ahead, it is necessary that information on hourly prices the next day be available daily.

V. CONCLUSIONS AND PROSPECTS

The work considers the problem of predicting hourly market electricity prices using the ANN tool. The authors analyzed reference sources to identify the most popular methods for forecasting electricity prices, the most commonly used in forecasting ANN types, and existing tools for implementing forecasting algorithms based on ANN. To perform the functions of electricity prices analyzing and forecasting, the authors have developed an application in Python using popular libraries to create ANN NeuroLab and Keras. The paper presents the results of numerical experiments on forecasting electricity prices using the developed application, during which the forecast quality has been studied depending on the library used, the ANN structure and the learning algorithms used.

The prospects for the application presented in this article to be used to forecast market electricity prices are associated with the need to improve the quality, availability and efficiency of price forecasts. In the future, it is planned to expand the Keras library support, since deep NNs such as CNN and LSTM NN are just beginning to be used to predict electricity prices, and their potential is still to be revealed. The extensive possibilities of the Python language, its machine learning libraries, deep machine learning and data visualization open up new prospects for improving the quality of market electricity prices analysis and forecasting.

References

[1] I. Yu. Zolotova and V. V. Dvorkin, “Short-term forecasting of prices in the Russian wholesale electricity market based on neural networks,” Forecasting Problems, no. 6, pp. 47–57, 2017.

[2] S. K. Aggarwal, L. M. Saini, and A. Kumar, “Electricity price forecasting in deregulated markets: A review and evaluation,” Electrical Power and Energy Systems, 31, pp. 13–22, 2009.

[3] R. Weron, “Electricity price forecasting: A review of the state-of-the-art with a look into the future,” Int. Journal of Forecasting, 30(4), pp. 1030–1081, 2014.

[4] N. Singh and S. R. Mohanty, “A Review of Price Forecasting Problem and Techniques in Deregulated Electricity Markets,” Journal of Power and Energy Engineering, 3, pp. 1–19, 2015.

[5] N. Singh, S. R. Mohanty, K. K. Mishra, and F. Neri, “A Review of Electricity Price Forecasting Problem and Techniques in Deregulated Markets,” Int. Journal of Economics and Statistics, 5, pp. 101–112, 2017.

[6] N. Amjady and M. Hemmati, “Energy price forecasting problems and proposals for such predictions,” IEEE Power and Energy Magazine, 4(2), pp. 20–29, 2006.

[7] J. Zhang, Z. Tan, and S. Yang “Day-ahead electricity price forecasting by a new hybrid method,” Computers and Industrial Engineering, 63, pp. 695–701, 2012.

[8] S. Vijayalakshmi and G. P. Girish, “Artificial Neural Networks for Spot Electricity Price Forecasting: A Review,” Int. Journal of Energy Economics and Policy, 5 (4), pp. 1092–1097, 2015.

[9] K. Sarada and S. S. Tulasi Ram, “Different ANN Models for Short Term Electricity Price Forecasting,” Int. Journal of Recent Technology and Engineering, vol. 8(3), pp. 6706–6712, 2019.

[10] J. Lago, F. De Ridder, and B. De Schutter, “Forecasting spot electricity prices: deep learning approaches and empirical comparison of traditional algorithms,” Applied Energy, 221, pp. 386–405, 2018.

[11] A. Naz, M. U. Javed, N. Javaid, and T. Saba, “Short-Term Electric Load and Price Forecasting Using Enhanced Extreme Learning Machine Optimization in Smart Grids,” Energies, 12, pp. 1–30, 2019.

[12] S. Anbazhagan and N. Kumarappan, “Day-ahead price forecasting in Asia's first liberalized electricity market using artificial neural networks,” Int. Journal of Computational Intelligence Systems, vol. 4, no. 4, pp. 476–485, 2011.

[13] J. P. S. Catalao, S. J. P. S. Mariano, V. M. F. Mendesb, and L. A. F. M. Ferreira, “Short-term electricity prices forecasting in a competitive market: A neural network approach,” Electric Power Systems Research, 77, pp. 1297–1304, 2007.

[14] S. Anbazhagan, N. Kumarappan, and S. Neelan, “Electricity Price Forecasting in an Ontario Power Market Using Artificial Neural Network,” First Int. Conf. on Computation of Power, Energy, Information and Communication, pp. 1–4, 2012.

[15] H. Y. Yamina, S. M. Shahidehpourb, and Z. Lic, “Adaptive short-term electricity price forecasting using artificial neural networks in the restructured power markets,” Electrical Power and Energy Systems, 26, pp. 571–581, 2004.

[16] Li Zhang, P. B. Luh, and K. Kasiviswanathan, “Energy Clearing Price Prediction and Confidence Interval Estimation With Cascaded Neural Networks,” IEEE Transactions on Power Systems, vol. 18, no. 1, pp. 99–105, 2003.

[17] D. McGlynn, S. Coleman, D. Kerr, and C. McHugh, “Day-Ahead Price Forecasting in Great Britain’s BETTA Electricity Market,” IEEE Symposium on Computational Intelligence for Financial Engineering and Economics, pp. 1–5, 2018.

[18] M. Zahid, F. Ahmed, N. Javaid, and R. A. Abbasi, “Electricity Price and Load Forecasting using Enhanced Convolutional Neural Network and Enhanced Support Vector Regression in Smart Grids,” Electronics, 8, 122, pp. 1–32, 2019.

[19] MATLAB Compiler and Simulink Compiler-Support for MATLAB, Simulink, and Toolboxes, 2020. [Online]. Available: https://www.mathworks.com/products/ compiler/compiler_support.html

[20] M. W. Ahmad, M. Mourshed, and Y. Rezgui, “Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption,” Energy and Buildings, vol. 147, pp. 77–89, 2017.

[21] Electricity prices TNS energo Yaroslavl, 2020. [Online]. Available: https://yar.tns-e.ru/legal-entities/prices/

[22] M. Ranjbar, S. Soleymani, M. Sadati, and A. M. Ranjbar, “Electricity Price Forecasting Using Artificial Neural Network,” Int. Conf. on Power Electronics, Drives and Energy Systems, pp. 1–6, 2006.

[23] P. Kuo and C. Huang, “An Electricity Price Forecasting Model by Hybrid Structured Deep Neural Networks,” Sustainability, 10, pp. 1–17, 2018.