Forecasting Day-Ahead Electricity Prices using Technical Prediction Methods

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Abstract — **This paper examines specific features of electricity as a commodity and analyzes the subsequent difficulties arising when accurately forecasting the clearing wholesale electricity price. Statistical methods (different kinds of linear regression), machine learning algorithms (random forest, support vector machines, etc.) and deep learning models (perceptrons, recurrent neural networks) are applied for forecasting the supplier's clearing electricity price for the 2nd price zone of the Russian wholesale electricity and capacity market. The forecasting results are evaluated using statistical error metrics such as R^2, MSE, MAE, and others. The complexities arising from the volatile and nonlinear nature of electricity prices, as well as the challenges in comparing prediction models due to diverse datasets and evaluation metrics are addressed. The need to establish an open platform for exchanging forecasting methods and datasets, including electricity price and auxiliary features, is substantiated. The open platform will also facilitate cooperation among researchers worldwide to evaluate and enhance the accuracy and competitiveness of short-term electricity price forecasting methods.**

Index Terms — **day-ahead, electricity price, forecast, machine learning, and neural networks.**

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I. Introduction

The purpose of this paper is to review the Russian wholesale electricity and capacity market (WECM) and to classify the methods used for short-term forecasting of electricity prices in the day-ahead market (DAM).

Energy resources play a key part in modern society, ensuring its smooth functioning and contributing to economic growth. Since the 1990s, the energy sector in many countries, including Russia, has transitioned from state control to private companies operating under market laws [1]. The WECM in the Russian economy was established in 2003. This market is divided into two sectors: capacity market and electricity market. The latter is subdivided into three parts depending on the contract period: long-term bilateral contracts, balancing market, and day-ahead market. The major volume of energy is traded on the day-ahead market [2].

The clearing price of electricity at the DAM is formed by the interplay of supply and demand, resulting from market competition. The clearing price of electricity is determined by the price bids of suppliers and buyers from the respective price zone and by the need to ensure electricity flows [3].

Generating and consuming companies are interested in high accuracy of short-term forecasting of the wholesale electricity price because it allows them to develop economically feasible plans for energy production and consumption, manage risks, and reduce their financial costs. At the same time, mismatches between actual data and forecasts lead to penalties for market participants and increased electricity costs. Inaccurate forecasts can result in the utilization of emergency power plants, thereby causing a rise in the clearing price of electricity.

This study aims to investigate the problem of accurately forecasting electricity prices and the application of various popular machine learning models and statistical methods to predict future values of wholesale electricity prices.

Section II focuses on the specific properties of electricity as a commodity and classifies existing prediction methods. Section III provides a description of the research methodology and discusses the data used to conduct the experiment. Section IV analyzes and compares the results of the prediction techniques expressed using statistical error metrics. Section V provides an overview of how to achieve greater accuracy in forecasting.

II. Problem description

Electricity possesses specific features that stem from its physical properties. These features should be taken into account when developing price prediction models:

– Necessity to constantly support the equilibrium between electricity production and consumption in order to ensure stable operation of the market [4];

– Impossibility of accurately determining the volumes of electricity production and consumption in advance;

– Inability to determine the exact origin of electricity consumed by different users. This is the main reason why electricity trading takes place in an auction format maintained by the trading system administrator [5];

– Impossibility of accumulating sufficient volumes of electricity for an enterprise power system. This necessitates the development of reserve generating capacities, the expansion of additional capacity for power grids, and the establishment of fuel reserves at power plants. The size of reserves is regulated every operating day, and the costs of their maintenance are included in the cost of electricity. The use of reserves can lead to higher electricity prices [6];

– Dependence of the price on the fuel cost, delivery expenses, and exchange rates;

– Significant autocorrelation of the price time series;

– Nonlinear dependence of price on various weather conditions such as air temperature, wind speed, precipitation, time of year, and daylight hours [7];

– Variability of electricity price depending on the level of business activity, which in turn depends on the duration and type of day (weekday, weekend, holiday, pre-holiday, or post-holiday) [8];

– Cyclical patterns can be observed at various time intervals: daily, weekly, seasonal, and annual;

– Influence of market participants' trading strategies during auction on the final cost of electricity [1];

– Dependence of the price on a wide range of factors, including the characteristics of the generating equipment, fuel types, water levels in hydroelectric power plants, network faults and accidents (including those caused by rare events such as solar storms), electricity consumption levels, the network topology and bandwidth constraints;

– Impact of the reverse leverage and long-term memory effects on the time series of electricity prices [9]. The reverse leverage effect implies that price volatility increases more during positive price changes than during negative ones. Positive price changes indicate an increase in electricity demand, which forces producers to utilize additional high-cost generating capacity. Long-term memory implies that observations are correlated even over large time intervals;

– Values of electricity price do not follow normal distribution [10]. These values follow a heavy-tailed distribution because there are many sharp and unpredictable spikes;

– Time series of hourly electricity price values are non-stationary because the series are non-constant in mean and variance.

All these features combined result in significant price volatility within a day, which motivates researchers to take efforts in order to develop better methods for predicting short-term electricity prices.

Ideally, energy companies need a forecasting algorithm, which, in addition to being accurate, reliable, and able to provide business value [11], is transparent in its operation, i.e. it can explain the primary cause of price fluctuations during the analyzed period compared to the previous one. It should be implemented using an open source code to ensure the reproducibility of the algorithm results [12], i.e. its high performance should be guaranteed to any researcher using it.

Currently, energy companies around the world apply many different forecasting methods to forecast short-term changes in electricity price. Based on the analysis of scientific works on the relevant subject, the methods were classified into the following categories:

A. Econometric (regression, autoregression) methods.

Econometric methods encompass either the use of statistical methods to directly forecast prices or the analysis of data using econometric models within the day-ahead electricity market [13].

Statistical methods of data analysis are used to forecast the current price based on previous prices and other important factors. The accuracy of the forecasts depends on the efficiency of the algorithms and the quality of the data, as well as the ability of the models to account for various factors including demand and consumption, weather, fuel prices, and others.

Statistical analysis techniques include exponential smoothing, linear and multiple regression, and autoregression methods.

Energy market researchers have raised significant objections regarding the limited ability of statistical models to replicate nonlinear relationships in electricity prices [14]. In practice, however, the results of these models are very similar when compared with the results of other nonlinear forecasting methods [15].

B. Computational intelligence methods.

Computational intelligence methods include machine learning algorithms, neural networks, support vector machines, decision trees, ensemble methods, and various types of neural networks, including recurrent and transformer neural networks [16, 17, 18]. They combine elements of training, evolution (additional training), and adaptation to dynamic data [19]. One of the key features of such methods is the ability to make predictions based on complex and nonlinear information. Despite the high adaptability of such models, however, this can be a disadvantage because the ability to adapt to noisy and unstable data does not always lead to improved quality of forecast.

The field of computational intelligence offers a wide array of algorithms, making it challenging to identify an optimal solution at times. In practice, it can be difficult to say which of the various machine learning (ML) and artificial neural network (ANN) methods will perform better.

When analyzing, it is necessary to properly compare the errors of the different models, as this will allow a more accurate determination of their effectiveness. This can only be done when models use the same datasets with the same metrics to measure the accuracy of their predictions [13]. Certain conclusions regarding the accuracy and performance of the models can also be drawn when different initial conditions (hyperparameters) of models are involved.

C. Multi-agent models.

Multi-agent models describe a system in which different agents interact and compete. In the case of the energy market these agents are companies that produce and consume electricity. Such models determine the clearing price in the market by analyzing supply and demand.

Game theory is used to analyze strategies under conditions of uncertainty, which allows modeling the strategic behavior of subjects and predicting the results of their interaction.

Multi-agent models can facilitate the analysis of resource allocation, which provides insight in complex interrelations among market participants in an economically reasonable fashion.

However, such models require a detailed description of all assumptions included in the system as well as possible strategies, types of interaction, and rewards for market participants. Interpreting the predictions of such models is challenging, which can reduce the credibility of both predictions and models themselves [13]. Multi-agent models usually focus on analyzing qualitative aspects, such as the probability of price fluctuations, rather than making quantitative predictions.

D. Hybrid methods.

Hybrid methods combine different methods and approaches to improve the accuracy of forecasting results. Typically, hybrid models include a decomposition method to divide the prediction problem into several steps, a method to select the most important features, various prediction models to make a forecast (including statistical, regression, and computational intelligence-based algorithms). In some cases, heuristic algorithms are used to optimize the models such as finding optimal hyperparameters, ultimately enhancing the forecasting accuracy [20].

At the same time, the advantage of combining forecasting approaches is not that the best possible combinations outperform the best individual forecasts but that in practice combining forecasts is less risky compared to relying solely on one forecasting method for decision-making [21].

III. METHODOLOGY

This study involves analyzing and forecasting hourly clearing electricity prices of suppliers in the 2nd price zone of the Russian wholesale electricity day-ahead market. The analysis covers the period from 27.05.19 to 27.05.24, resulting in a dataset of 43,872 time series values. During this period, there were events that had, or continue to have, an impact on the Russian energy market to varying degrees. These were the start of the COVID-19 pandemic (March, 2020), the end of the pandemic (May, 2023), and sanctions of various magnitudes imposed on the Russian economy (2022-2024). These factors influence the volumes and the prices of electricity on the day-ahead market. It is

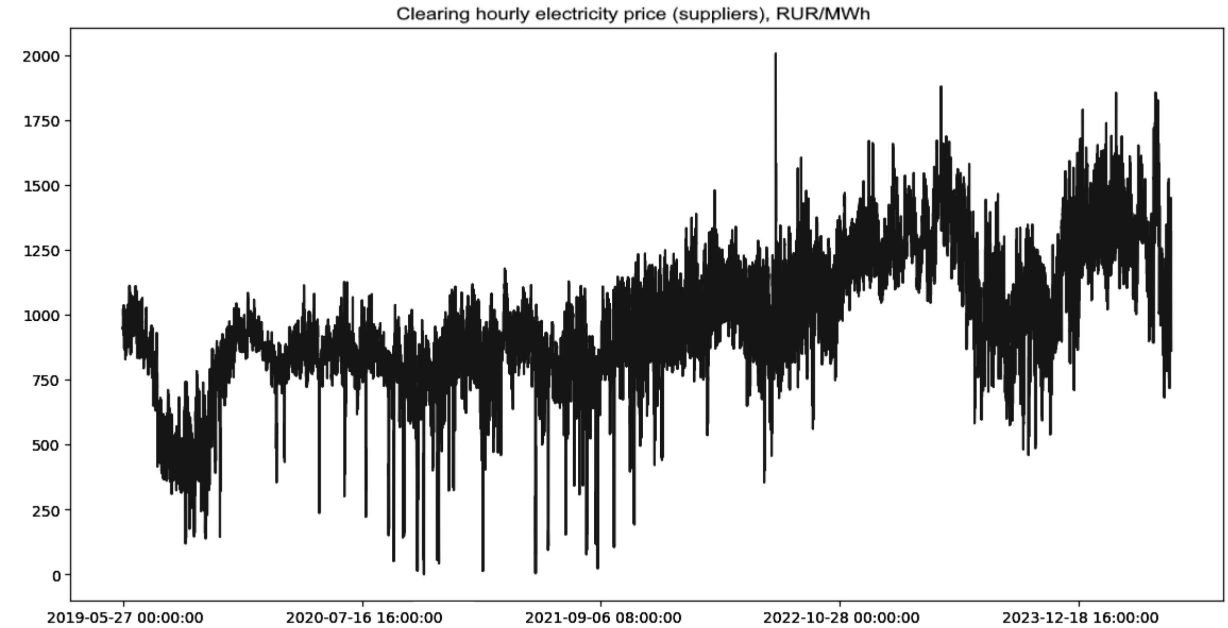

Fig. 1. The graph of hourly clearing electricity prices of suppliers, 27.05.19–27.05.24. The sharp fluctuations in the graph reflect the high volatility of the price.

important to note that all the forecasting techniques used to conduct the experiment can produce good forecasts only when trained on a sufficient amount of data, preferably unaffected by any unpredictable large-scale changes such as geopolitical events. Statistical methods, machine learning models, and deep learning models can often significantly overestimate or underestimate the target value (electricity price in this case) due to insufficient data.

The graph of the time interval mentioned above is presented in Figure 1.

Before developing complex and highly specialized forecasting algorithms, it was necessary to verify that widely used machine learning and deep learning algorithms are not precise enough and much more sophisticated models are required to accurately forecast electricity prices.

Price forecasts were made using a wide range of machine learning algorithms, including linear regression, Bayesian linear regression, ridge linear regression, and passive-aggressive regressions. Additional methods employed were stochastic gradient descent (SGD) method, support vector machine (SVM), K-nearest neighbor algorithm, decision tree, random forest and its modifications (AdaBoost, CatBoost, XGBoost).

Various deep learning models were also used such as those based on fully connected layers, using Rectified Linear Unit (ReLU) as the layer activation function and those based on recurrent layers of two types: long-short term memory (LSTM) and gated recurrent units (GRU), both using hyperbolic tangent as the layer activation function. For simplicity, neural networks were divided into three categories based on the type of layer they use: fully connected, LSTM, and GRU respectively. Neural networks with diverse number of layers and neurons in each layer were tested. The neural networks employed in our experiment had the following configurations, reflecting the layers and the number of neurons in them: 10-1, 10-5-1, 10-5-2-1, 20-10-5-1, and 20-10-5-2-1. All the neural networks used Mean Square Error (MSE) as the loss function and the Adam algorithm as the optimizer.

The forecasting accuracy was expressed using statistical metrics such as R^2 (coefficient of determination), MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error), and SMAPE (symmetrical mean absolute percentage error). The results were then compared with the prediction accuracy of a series of baseline predictors: naive predictor that simply returns the first value from the test sample, drift predictor that describes the fluctuations of the target variable over analyzed period of time and average predictor that returns average value of the time series.

The implementations of all machine-learning algorithms are provided by Scikit-learn library. Deep learning models are implemented using the Keras framework, which is a

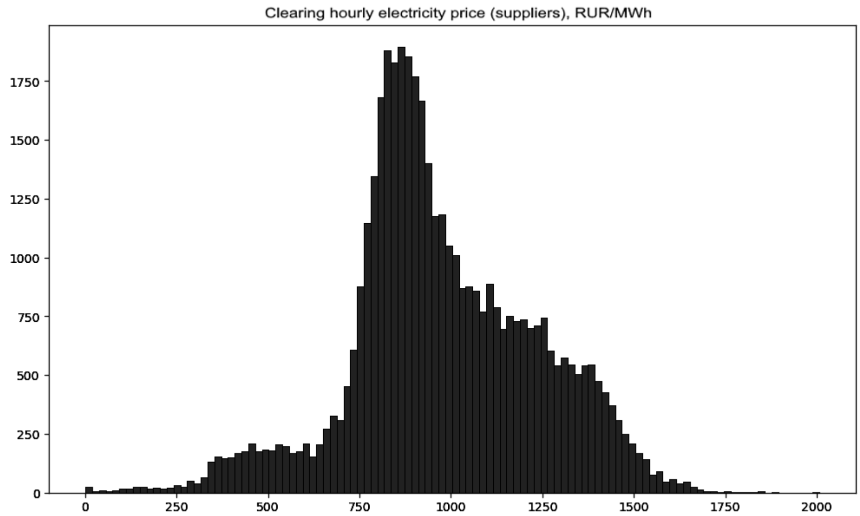

Fig. 2. Histogram of clearing electricity price distribution. It shows that distribution is not normal but there are not many outliers either.

high-level API for TensorFlow, an open-source software library for artificial intelligence. Both of these libraries are implemented in the Python programming language.

IV. Results

The analysis of data representing the clearing electricity price in the 2nd price zone of the Russian day-ahead electricity market reveals that the average price for the analyzed period is RUR 975.60 per MWh. The standard deviation is RUR 257.65 per MWh, while the minimum and maximum prices are RUR 0.45 and RUR 2,005.86 per MWh respectively. A significant level of Pearson correlation coefficient noticed between the supplier's price and consumption volume is 0.54. The electricity price time series also exhibits a high degree of autocorrelation. The distribution does not correspond to the normal distribution as revealed by the Kolmogorov-Smirnov test. The p value stands at 0.0619 for $\alpha = 0.05$. The histogram of price distribution is shown in Figure 2. Prices fluctuate seasonally throughout the year and cyclically throughout the day, varying by month and by hour. There are few outliers in the series: 878, which accounts for 2% of the total number when using the 1st and 99th quantiles to determine the outliers, and 190 or 0.433% when using the Z-score. This contrasts with the data on a significant number of outliers and long tails from paper [10].

Forecasts were made for a single variable, specifically for the clearing electricity price of suppliers. The aim was to eliminate the forecasting error caused by auxiliary features in the final forecast and to be able to make forecasts of upcoming price changes not only for a short term, but for any future timeframe. Dummy variables used to capture the effect of time were year, quarter, month, week number, week day, month day, year day, and hour.

The accuracy of the forecasting was assessed through cross-validation. This involved dividing the observed interval into 10 segments (or folds), using both the current and previous segments to train the model, and then estimating the model error on the next segment, following an expanding window approach. The average results of the models' predictive abilities obtained by cross-validation are shown in Table 1. The best values of the models' accuracy metrics are indicated in a bold font.

The results shown for different predictive models indicate their poor performance on average when it comes to forecasting clearing prices of electricity. In addition, the distribution of residuals, i.e. the difference between the true and predicted values of each model does not follow the normal distribution as shown by the Kolmogorov-Smirnov test. This suggests that the models do not extract all valuable information from the dataset.

In general, the results of regression and machine learning models do not differ significantly those of the baseline predictors. Neural networks often outperform baselines in predicting future values, but their forecasts still lack the desired level of accuracy. Despite being an appropriate choice when working with sequenced data, recurrent neural networks (RNNs) did not show any increase in forecasting accuracy. Multilayered perceptron with configuration of 10-5-2-1 proved to be the most accurate model. However, it is evident that this model is not suitable for functioning in a competitive energy market due to its high error rate. This clearly indicates the need to improve prediction algorithms and/or enhance the range of useful features.

It is necessary to explain why all the prediction methods listed above yield R^2 scores below 0. Normally, the range of R^2 is between 0 and 1, and it might seem strange at first to encounter negative values of the coefficient of determination. A common way to interpret R^2 is as the fraction of variability in the dependent variable that the model accounts for. This interpretation only makes sense for values between 0, which means the model accounts for none of the variability, and 1, which means the model accounts for all of it. However, time series data often exhibit non-stationary behavior, with their statistical properties changing over time. Therefore, evaluation of a time-series model is based on how well it predicts future values rather than on how well it fits past values. The R^2 mainly reflects the latter, not the former. It is also often used as an in-sample measure of performance, meaning it measures how well a model predicts values of the training data and not the future values. This is where the computational definition of R^2 diverges from both the notation and its common interpretation. Apart from the special case of a linear regression model with an intercept term, R^2 is not actually equal to the square of any specific quantity. Its calculation involves taking the mean of the squared errors, dividing by the variance of the dependent variable, and subtracting this ratio from 1. Given that there is no limit on how bad a model's predictions can be and how large the errors can grow, it is possible for this ratio to become arbitrarily large, which would result in a negative value when extracted from 1. To summarize, we should expect R^2 to be constrained within the range of 0 to 1 only when a linear regression model is fitted and evaluated on the same data. Otherwise, the determination of R^2 can lead to negative values that exceed 1 in absolute value.

V. DISCUSSION

Currently, when forecasting time series data, there is no way to accurately determine in advance which model should be used. Furthermore, there are no formal attributes to aid in this determination. There is no undeniable evidence of superiority of any single model over the others in terms of forecasting accuracy beyond statistical

Table 1. Results of the Forecasting Methods

Model	R^2	MSE	RMSE	MAE	MAPE	SMAPE
Naive	-0.92	36,379.80	190.49	145.65	21.20%	16.23%
Drift	-0.79	40,376.44	200.94	158.67	17.67%	16.94%
Average	-1.68	48,839.86	220.69	197.71	25.85%	21.53%
Linear regression	-0.70	40,398.34	200.65	160.15	17.18%	15.85%
Bayesian ridge regression	-0.70	40,328.98	200.45	159.63	17.15%	15.83%
Passive-aggressive regression	-1.24	71,105.71	265.98	215.28	25.73%	21.01%
SGD	-0.70	51,528.24	226.97	191.70	21.67%	19.34%
SVR	-3.57	90,574.71	300.96	279.92	26.31%	30.81%
K-nearest neighbors	-1.11	42,300.70	205.67	162.02	19.00%	17.75%
Decision tree	-0.41	35,415.63	187.67	149.25	16.05%	14.79%
Random forest	-0.38	34,702.17	185.90	141.05	**15.06%**	14.79%
AdaBoost	-1.40	43,874.93	209.33	173.63	22.39%	19.57%
XGBoost	-0.39	35,128.82	186.80	141.97	15.38%	15.45%
CatBoost	-0.27	33,857.59	183.99	147.26	16.83%	14.39%
FFNN (10-1)	-0.29	28,124.03	167.56	135.76	15.17%	13.86%
FFNN (10-5-1)	-0.15	27,991.95	166.95	131.42	17.12%	13.67%
FFNN (10-5-2-1)	**-0.04**	**27,312.74**	**165.22**	**124.74**	16.64%	**12.74%**
FFNN (20-10-5-1)	-0.25	29,011.47	170.33	133.97	15.58%	13.33%
FFNN (20-10-5-2-1)	-0.65	35,094.21	187.31	153.17	19.53%	15.55%
GRU (10-1)	-0.56	41,355.91	202.45	163.84	20.61%	16.79%
GRU (10-5-1)	-0.77	39,729.84	199.31	160.93	20.70%	17.71%
GRU (10-5-2-1)	-0.69	38,373.30	194.97	148.35	20.90%	16.12%
GRU (20-10-5-1)	-0.68	34,497.70	185.72	147.36	21.28%	16.78%
GRU (20-10-5-2-1)	-0.34	32,394.15	179.96	148.89	17.40%	14.76%
LSTM (10-1)	-0.46	32,271.73	179.57	144.55	17.06%	14.80%
LSTM (10-5-1)	-0.73	35,610.38	188.63	156.18	17.52%	16.28%
LSTM (10-5-2-1)	-0.45	32,449.90	180.04	143.02	17.02%	14.72%
LSTM (20-10-5-1)	-0.48	33,089.81	181.85	148.40	17.75%	14.62%
LSTM (20-10-5-2-1)	-0.48	31,876.00	178.49	141.88	20.00%	14.36%

comparison of the effectiveness of the models [22].

It is evident that every model has advantages and disadvantages. Each model produces different results based on different forecasting horizons, forecasting steps, and volumes of statistical data.

Comparing the models' results presented in the papers by other authors is challenging because of the use of different error metrics. The quality of forecasting depends not only directly on the model but also on the data available for the energy market studied, its specific features (technological, meteorological, regulatory), and largely on hyperparameters, i.e. fine-tuning of the models' settings. The absence of source code for the conducted experiments does not help improve this situation either.

Under conditions of high uncertainty and unpredictability of the energy market, the price forecasting models that do not rely on forecasting exogenous variables (external factors) will be in demand [2]. This is explained by the fact that the forecast error rate for the associated variables eventually leads to an increase in the forecast error rate for electricity prices. Exogenous variables, on the other hand, can provide useful information for prediction models, thereby enhancing the accuracy of forecasting.

The openness of algorithms and data is needed to achieve a breakthrough in electricity price forecasting. For example, this approach has contributed to the rapid development of software technologies such as the Linux operating system. Such openness, however, comes at the cost of risking the research stagnation in the field. Why invest money and effort in developing a new forecasting method when you can simply take and use the existing ones? Companies are often reluctant to share their proprietary forecasting methods that grant them a competitive advantage in the market. Nevertheless, there is a need to systematize various methods for the benefit of all.

The overview of related papers highlights the importance of conducting unbiased comparative studies. These studies should analyze different forecasting methods using identical datasets, identical forecasting horizons, identical procedures for error rate estimation, and statistical tests. One of the solutions to this problem is the establishment of an open competition platform for forecasting short-term changes in electricity prices, which will allow objective evaluation of forecast accuracy [13]. The platform like this can be designed in a manner similar to Kaggle, which is an open web platform that organizes competitions among data analysts and scientists.

VI. Conclusions

This paper provides an overview of short-term electricity price forecasting problems. Some of them are related to the nature of electricity as a commodity, which creates forecasting challenges such as: rapid price movements and non-linear dependence on numerous factors. Another part of the problems is related to the approaches researchers take when addressing short-term price forecasting. Various models are proposed using different time series of electricity prices and diverse metrics are applied to estimate the prediction error rates. These facts make comparing the models' accuracy highly complicated and almost impossible.

One possible solution to enhance the quality of research on day-ahead electricity price forecasting is to establish an open platform for sharing the forecasting algorithms and datasets. This platform would enable the researchers from around the world to assess and compare the accuracy of different methods, fostering the development of more accurate, efficient, and competitive approaches to short-term electricity price forecasting.

To summarize, our experiment aimed to predict hourly electricity prices in the 2nd price zone of the Russian day-ahead electricity market, featuring 43,872 price values, covering the period from 27.05.19 to 27.05.24. Ten-fold cross-validation and comparison of error metrics reveal that, on average, feed-forward neural networks (multi-layer perceptrons) are more precise than linear regressions, support vector machines, ensemble methods, recurrent neural networks, and naive baseline models. It is also important to note that the most accurate perceptron was the one with the correct number of layers and neurons in each layer, and this "correct" number can be calculated only empirically when working with a specific dataset. This is why it is so important to compare the results of neural networks with different configurations in order to empirically prove the advantage of one configuration over the others.

After each prediction procedure, the residuals were plotted on a histogram to visualize their distributions. Moreover, autocorrelation plots were generated to identify the relationship between the current and past values of the target variable's residuals. As a result, there was always non-normal distribution of residuals suggesting that there was additional useful information not accounted for by the prediction models [23]. There was also significant autocorrelation in the residuals, indicating the presence of trends and seasonality that were not captured by the models. This means the forecasting models should be enhanced by incorporating additional features and/or technical indicators into the dataset.

It is worth noting that MAE and RMSE are the most useful error metrics for time series prediction because their outputs have the same (or roughly the same in the case of the latter) scale as the target variable, making them easy to interpret. These metrics reflect linear and nonlinear differences between real and predicted values respectively. Although percentage errors such as MAPE and SMAPE are easier to understand for non-technical people, they can be misleading by both exaggerating some errors and disguising others because of bias towards smaller targets and outliers. SMAPE is brought to address the issue of the bias towards smaller values but in the end both metrics are recognized for assigning unequal weights to overestimated and underestimated predicted values. Furthermore, the coefficient of determination (R^2) does not necessarily indicate the goodness of fit because there can be a low R^2 value for a good model and a high R^2 value can be found with a model that does not fit the data. Moreover, R^2 fails to offer any business value because its result does not provide any concrete information about the quality of the forecast. This lack of tangible characteristics proves to be unhelpful in the highly competitive energy market.

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