An approach to combining forecasts when solving machine learning problems

Peter Bidyuk[1,†], Irina Kalinina[2,†], Aleksandr Gozhyj[2,*,†], Victor Gozhyi[2,†] and Sergii Shiyan[2,†]

[1] *National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", 37, Prospect Beresteiskyi, Solomyanskyi district, Kyiv, 03056, Ukraine*

[2] *Petro Mohyla Black Sea National University, St. 68 Desantnykiv 10, Mykolaiv, 54000, Ukraine*

Abstract

The article investigates an approach to solving forecasting problems based on a combination of forecast solutions. A structural diagram of a forecasting approach using a combination of forecasts is proposed. An information system architecture is developed to improve the efficiency of forecasting based on combined forecasts. The task of forecasting electricity demand in Ukraine is considered as an example. A time series reflecting electricity demand in the period from 2019 to 2024 was studied. A structural diagram of a forecasting approach based on combining forecasts is developed. The scheme considers as basic methods of forecasting time series based on machine learning methods, namely: generalized additive model, exponential smoothing model, ARIMA model and neural network autoregression model. For each method, several models were built, the accuracy of which was evaluated on the training and test samples, then the optimal model was selected, thus 4 independent models were obtained. Several methods of combining forecasts were considered. To solve the forecasting problem, seven forecast combination methods were applied to obtain combined forecasts from the forecasts of individual models. The combination methods demonstrated an improvement in forecast accuracy compared to the best models. Among them, the simple averaging method has the highest accuracy. The proposed approach is effective in solving machine learning problems.

Keywords

combining forecast, forecasting, electricity demand in Ukraine, machine learning, ARIMA, GAM, ETS, NNAR [1]

1. Introduction

Today, forecasting is a powerful tool for predicting resources and resource demand management. A number of companies such as Amazon, Uber, Airbnb and many others use forecasting to predict future economic indicators and identify hidden trends in data, to develop strategies for future activities.

Recently, machine learning methods have been used to solve forecasting problems. Forecasting based on machine learning methods allows you to comprehensively take into account the features of dynamic processes that are reflected in the time series, on the basis of which the forecast will be built. Forecasting based on time series is important for various fields of activity, such as medicine, economics, industry, energy, etc. The complexity of this problem is increased by the presence of nonlinearity and non-stationarity in real data, as well as various types of uncertainty, such as statistical, structural and parametric uncertainties. The problem is solved based on a systematic approach to modeling and forecasting processes. Important features of the system approach are

MoMLeT-2025: 7th International Workshop on Modern Machine Learning Technologies, June, 14, 2025, Lviv-Shatsk, Ukraine

[1*] Corresponding author.

[†] These authors contributed equally.

pbidyke@gmail.com (P. Bidyuk); irina.kalinina1612@gmail.com (I. Kalinina); alex.gozhyj@gmail.com (A. Gozhyj); gozhyi.v@gmail.com (V. Gozhyi); shyiansi@gmail.com (S. Shiyan)

0000–0002–7421–3565 (P. Bidyuk); 0000-0001-8359-2045 (I. Kalinina); 0000-0002-3517-580X (A. Gozhyj); 0000–0002–5341–0973 (V. Gozhyi); 0000-0001-9255-9511 (S. Shiyan)

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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

CEUR-WS.org/Vol-4004/paper2.pdf

comprehensive consideration of features and uncertainties at each stage of solving the problem [1, 2]. But such an approach, although it takes place from the point of view of methodology, does not always provide the necessary forecast accuracy. To increase the accuracy of forecast values, various methods and approaches are used [2, 3]. One of the effective approaches to improving the quality of forecasts on time series is the use of methods for combining forecast values.

Machine learning methods common in forecasting problems based on time series, such as the generalized additive model, the exponential smoothing model, the autoregressive neural network model and the classical ARIMA model, allow obtaining fairly accurate forecasts taking into account different types of trends, seasonal patterns, external disturbances, etc. The classical approach is to fit several forecast models on the training sample and check their accuracy on the test sample with subsequent selection of a high-quality model [4]. However, different models can give quite different predictions because they reflect only some of the features of the real process. Combining predictions obtained from different models allows you to take into account more features of the process and thus improve the accuracy of the resulting forecast.

The authors of the article [5] noted the effectiveness of combined models compared to the approach of selecting the best individual model. The article describes experiments with 3003 data sets, including data taken annually, quarterly, monthly, daily, and others, to test the hypothesis of greater efficiency of combining forecasts compared to choosing the best individual model. The following forecasting methods were considered: various variants of exponential smoothing (simple exponential smoothing, Holt method, damped trend method), ARIMA models, neural network autoregression models. Only simple averaging was used to combine forecasts, but all possible combinations of forecasts were considered. The accuracy of forecast solutions was assessed using sMAPE.

Various forecast combination methods involve obtaining one combined forecast from a set of several individual forecasts, which, according to many studies, turns out to be more accurate than the best individual forecasts [6]. The paper presents a general overview of scientific works on the use of forecast combination methods. Despite the various proposed approaches to forecast combination, which theoretically should significantly increase the accuracy of the combined forecast, empirical results are ambiguous and often show that the simple averaging method is the most effective, and there is no clear answer to the question of when it is more appropriate to use more complex models and when simple approaches. As a rule, when building several forecast models based on different methods or one method with different parameters for the same time series, one of the most optimal methods is chosen among them. This is a traditional approach, which is based on the assumption that the best method exists and can be found [7].

There are various approaches to forecast combination that demonstrate good results in improving forecast accuracy. In the article [7], forecasts of 10 separate models were studied, including a naive model, a moving average model, several exponential smoothing models and a linear regression model, combined using the minimum variance method. Forecasts were performed for many different time series and with different forecast horizons. As a result, it was shown that the combined forecasts were more accurate than the forecasts of individual models in most cases, except for large forecast horizons.

In the works [8, 9] it is proposed to evaluate the models to compare their effectiveness on test data that were not used to estimate the model parameters, and therefore they can reflect the effectiveness of the forecast model when applied to new data. For evaluation, the model errors are summed up, that is, the deviation of the model predicted value from the real one, in a certain way, obtaining the forecast errors of the model: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), etc. The model that demonstrates the smallest error values on the test data is considered to be more optimal. This approach allows you to choose the optimal method, but the selected model will not be the best and will demonstrate worse results on other data [10]. Choosing only one model from a set of successful models can lead to the loss of valuable information present in alternative models.

The effectiveness of combining forecasts compared to choosing the best individual forecast is presented in [11, 12]. The effectiveness of combining forecasts from different models compared to choosing the best individual model is shown in [11]. The paper compared three separate forecast models (an artificial neural network model, an ARIMA model, and an exponential smoothing model) and three approaches to combining forecasts (simple averaging, minimum variance, and linear regression) on 500 simulated time series of 200 observations each. The MAE, MAPE, RMSE, and Theil's U coefficient were used to evaluate the forecasts. As a result, among the individual models, the artificial neural network model turned out to be the most effective, but it may be inferior to the combined simple averaging and minimum variance models and significantly loses to the regression combined model.

In [12], the effectiveness of combined forecasts in comparison with individual forecasting models was also shown - they were taken as the support vector regression model, the ARIMA model, the exponential smoothing model with multiplicative seasonality (Winters method), as well as naive models. All methods were applied to develop a forecast of the number of tourist trips with different purposes to the United Kingdom. The combination was carried out using the approaches of simple averaging, minimum variance and discounted mean square error.

In [13], forecasts of various economic indicators of several countries were performed, the results of comparing simple models of averaging forecasts or the median with various more complex models (discounted mean square error, calculation of weights based on the AIC and BIC criteria, regression model with determination of coefficients based on the least squares method, etc.) were not in favor of the latter.

Problem statement. To investigate the features of the forecast combination process. To develop an approach for solving time series forecasting problems based on combined forecasts. To experimentally confirm the effectiveness of forecast combination methods for solving machine learning problems.

2. Modeling and forecasting

2.1. Stages of solving forecasting problems

To solve the problems of time series forecasting based on machine learning methods, a structural generalized sequence diagram of the stage [14, 15] was developed, which is presented in Figure 1.

The scheme is presented as a sequence of the following stages: data collection, analysis and preliminary data preparation, modeling (or training models on data), forecasting and determining the quality of forecasts, improving the efficiency of models. At the *first stage*, the input data set is collected and preliminary analyzed. At the same time, procedures for analyzing the data structure, analyzing individual features, visual analysis of data, and possible recoding of individual features are carried out. The result of the first stage is a data set ready for further processing.

The *second stage* is designed to eliminate statistical uncertainty in the data. At this stage, missing values for individual features and observations are identified and processed; anomalous values and noise are identified; data correlation analysis (autocorrelation level) is performed; types of nonlinearity and non-stationarity of the data are identified and determined (if possible, actions are taken to eliminate them); the data set is analyzed for heteroscedasticity and integration.

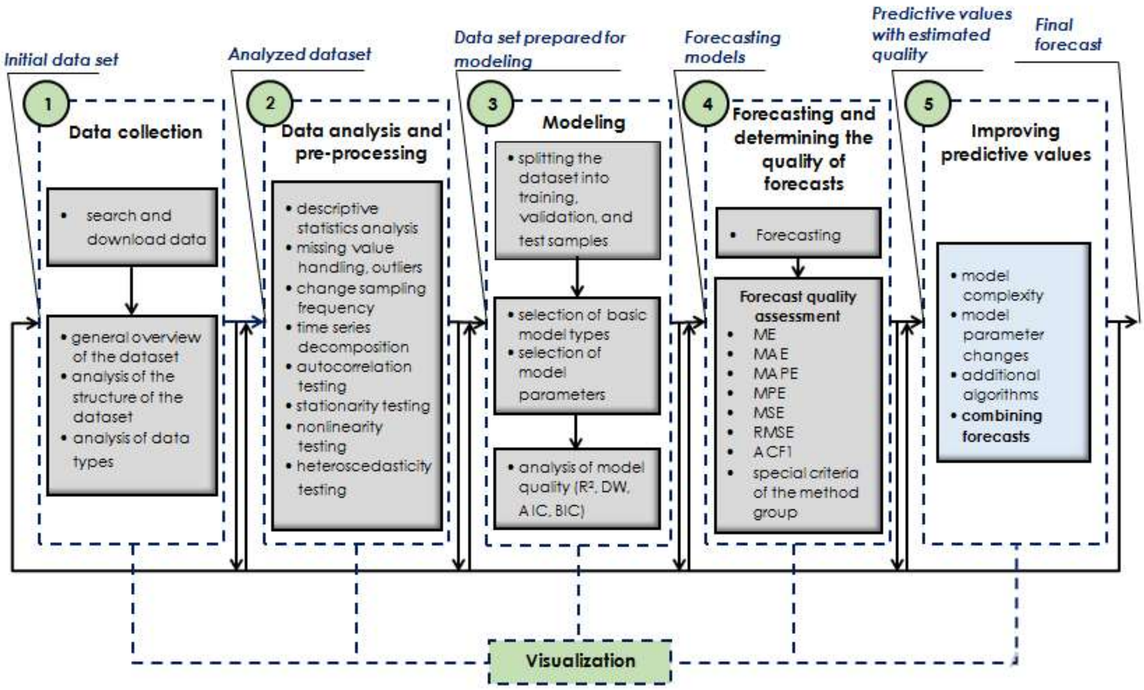

Figure 1: Generalized scheme of the sequence of stages for solving a forecasting problem based on machine learning methods.

The modeling stage (*third stage*) is designed to consistently eliminate structural and parametric uncertainties. It is implemented in three steps: the step of dividing the prepared data set into several samples for training and testing, selecting the structure of the appropriate predictive model, finding the model parameters and training it, checking the adequacy of the model.

Forecasts are built based on the selected models and their quality is assessed at the fourth stage. The *fourth stage* is the stage of building forecasts and assessing their quality. In this case, a system of quality indicators (metrics) is used.

The *fifth stage* is designed to improve the efficiency of basic forecasting models. The following approaches are used for this: changing the model structure, selecting model specifications, refining the model topology, using additional algorithms (ensemble approaches), and using various methods of combining forecast values. Thus, the use of combination methods helps to improve the quality of forecasts.

A necessary part of the generalized scheme for solving the forecasting problem based on machine learning methods is visualization. Visualization helps to adjust the sequence of actions at each stage and quickly identify possible shortcomings. Depending on the specifics of the subject area and the data set, it is possible to re-examine any of the previous stages.

2.2. Stages of solving forecasting problems

The approach to modelling and forecasting based on combination methods, which is developed on the basis of a systematic approach to the modelling process, includes the following basic computational procedures: a procedure for analysing and pre-processing the data set; a procedure for dividing the data set into separate samples (for training, validation, and testing); a modelling and forecasting procedure; a procedure for assessing the quality of modelling and forecasting results; a procedure for combining forecasts using different methods [16, 17]. The result of the presented procedures is a forecast value for the desired horizon value, which has better accuracy and is determined by the analyst or decision maker. The structural diagram of the approach to forecasting based on combining forecasts is presented in Figure 2.

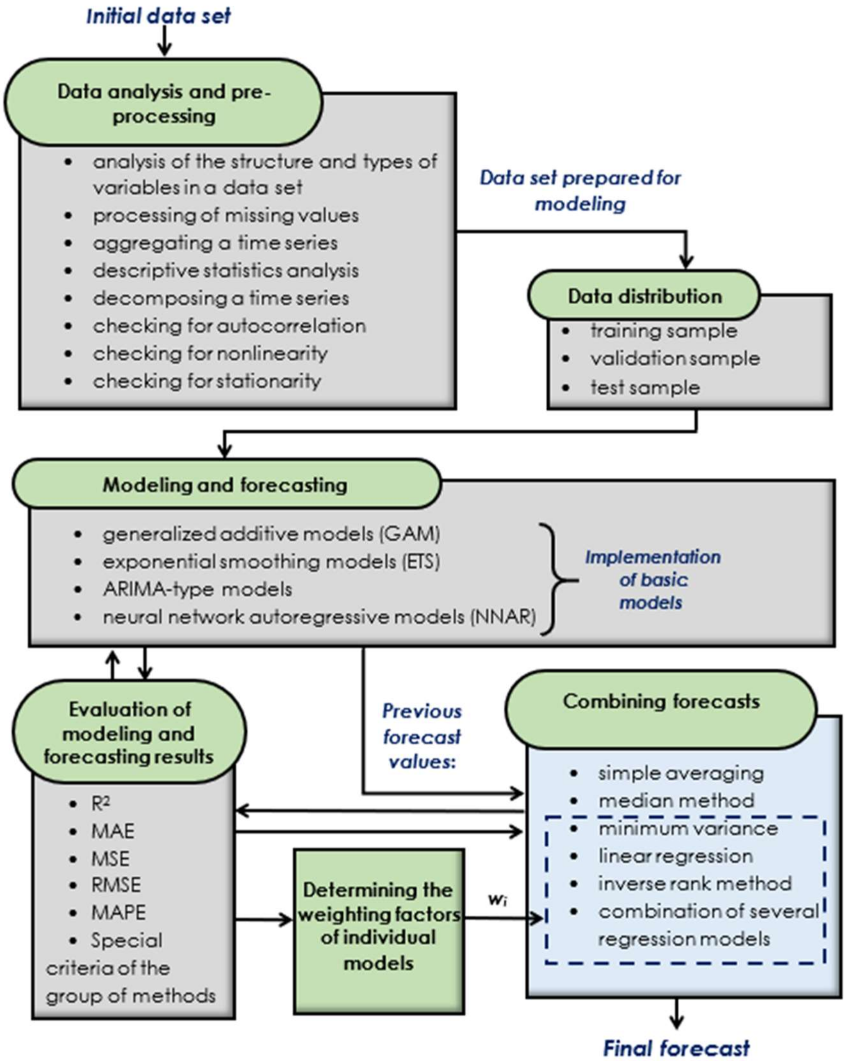

Figure 2: Structural scheme of the forecasting approach based on combining forecasts.

It is important to emphasize that the quality of the results that we have after each computational procedure is reflected in the final result. Therefore, statistical tests are added to each procedure to check the presence of the corresponding properties. The result of the modelling and forecasting procedure is several forecast models (each of a different type), which have the best quality metrics for their type of models. Quality assessments are performed both for individual forecasts and for each type of combined forecasts.

If no increase in forecast accuracy is detected when combining forecasts, it is necessary to return to the stage of forming the basic models or change their number and type of combination.

3. Experimental part

3.1. Data pre-processing

The dataset for combined forecasting studies reflects information on electricity demand in Ukraine from 2019 to 2024. [18, 19]. It contains hourly data on electricity purchase and sale volumes, as well as demand for it in MWh in the Ukrainian electricity grid and the price of electricity starting from July 1, 2019. The dataset has 69,385 observations, each of which is characterized by 10 variables. Among them are the date as a string and the hour represented by an integer, which were converted to the time data format.

As a result of checking for missing values in the dataset, five gaps were found. This number of gaps does not significantly affect the quality of the data, therefore, the LOCF strategy was used to fill in the missing values in the time series, which consists in replacing each missing value with the last previous non-missing value.

The analysis of the time series shows that the load on the Ukrainian power system has changed. Since June 1, 2022, the system has been loaded evenly, therefore, to build forecast models, we separate a part of the time series that reflects electricity demand from June 2022 to October 2024 (Fig. 3).

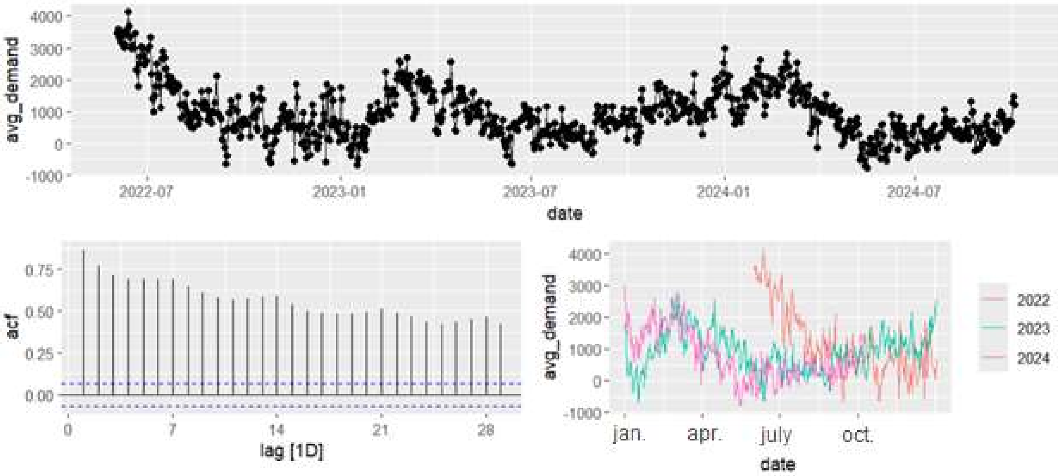

Figure 3: A graph of a fragment of the time series.

After visualization of the time series, its statistical characteristics were analyzed. The decomposition of the time series was performed and a noticeable seasonality with different periods was revealed: annual, weekly, daily. The aggregation of the time series by dates was performed in order to reduce the volume of analyzed data, as well as from the point of view of the feasibility of performing the forecast for a certain number of days ahead, rather than hourly [20, 21]. A noticeable autocorrelation was detected and the number of necessary differentiations was determined. The results of the preliminary analysis confirmed the presence of nonlinearity and non-stationarity in the process under study.

3.2. Selection of basic forecasting models

Generalized additive model. The first among the basic predictive models to describe the process under study is the generalized additive model (GAM). Five alternative models were considered to select the best model parameters. Analysis of the quality metrics of the predictive values on the test sample showed that the best quality is model No. 2 with a larger number of trend nodes (Table 1).

Figure 4 shows the forecasting results based on the best GAM model against the test data.

Exponential smoothing model. The exponential smoothing model was chosen as the next basic forecast model. Taking into account additional components of the time series (trend, seasonality) in the model structure made it possible to consider four alternative types of exponential smoothing models. Table 2 summarizes the results of forecast quality assessments for different ETS models. The best forecast quality assessments were received by model No. 4, the Holt-Winters model with additive errors.

Table 1
Result of checking the accuracy of GAM models on the test data sample

No.	Type of GAM model	MSE	RMSE	MAE
1	Model with default parameters	628387.8	792.709	724.517
2	**Model with more trend nodes**	**157228.5**	**396.521**	**324.326**
3	Model with fewer trend nodes	500017.0	707.119	638.502
4	Model with greater influence of seasonal components	892512.7	769.749	700.469
5	Model with multiplicative seasonality	308917.3	555.803	447.977

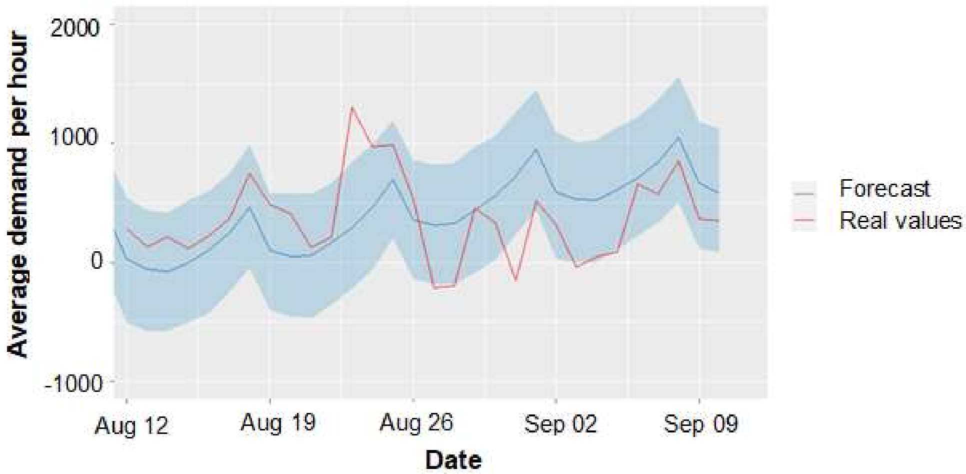

Figure 4: Graph of forecast values using the best of the GAM models and actual electricity demand.

Table 2
Result of checking the accuracy of ETS models on the test data sample

No.	Type of ETS model	MSE	RMSE	MAE
1	Simple Exponential Smoothing Model	125493.7	354.251	277.452
2	Holt Model	127238.3	356.705	279.093
3	Holt-Winters model	135878.5	368.617	290.161
4	**Holt-Winters model with additive errors**	**127475.5**	**357.037**	**276.293**

Figure 5 visualizes the forecast values obtained based on the best ETS model against the background of the test data sample.

ARIMA model. The third basic forecasting model was the ARIMA model, taking into account the seasonal component of the time series. Varying the values of the model parameters made it possible to obtain five alternative types of ARIMA models. Table 3 shows the quality metrics of forecasts for these models. The best quality indicators are given by model No. 4 (ARIMA(2,1,2)(1,0,2)[7]). Figure 6 presents the forecast values, which are constructed based on the ARIMA(2,1,2)(1,0,2)[7] model against the background of the test sample.

Neural network models. The fourth type of basic models is the neural network autoregression model. The model parameters allow us to set the number of inputs to the non-seasonal and seasonal components of the model, so we will obtain four alternative neural network autoregression models. The resulting forecasts for these models are the average of the forecast values of several models. Increasing the parameter values leads to a significant increase in the model training time. Table 4 presents the results of the quality assessments of the forecasts obtained on the test data. The best values for all quality metrics were demonstrated by model No. 4 (NNAR(100,100,k)[7], Max_it=20000).

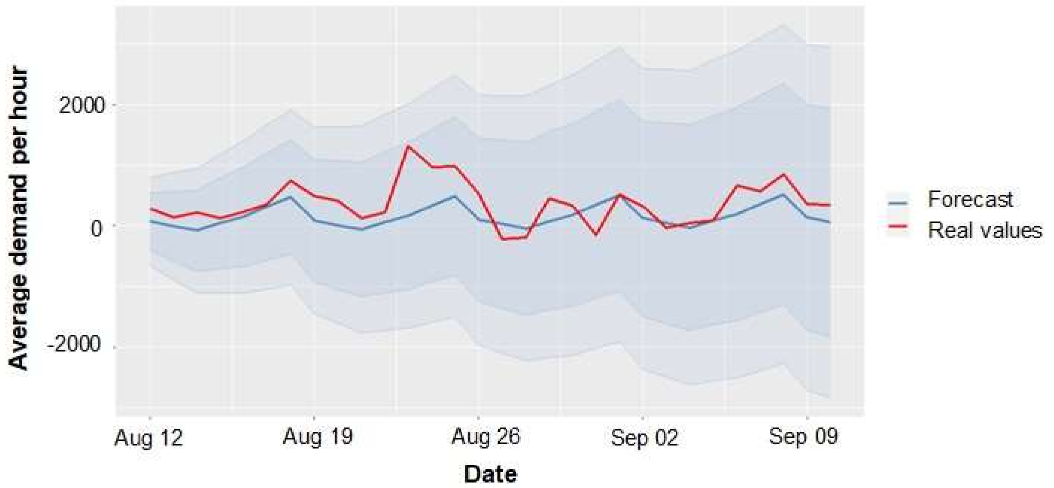

Figure 5: Graph of forecast values using the best of the ETS models and actual electricity demand.

Table 3
Result of checking the accuracy of ARIMA models on the test data sample

No.	Type of ARIMA model	MSE	RMSE	MAE
1	ARIMA(1,1,2)(0,0,2)[7]	134552.86	366.815	291.900
2	ARIMA(2,1,2)(0,0,2)[7]	134702.54	367.018	292.186
3	ARIMA(1,1,2)(2,0,2)[7]	96497.25	310.640	231.007
4	**ARIMA(2,1,2)(1,0,2)[7]**	**93986.56**	**306.572**	**228.721**
5	ARIMA(2,1,2)(2,1,2)[7]	97004.87	311.456	228.864

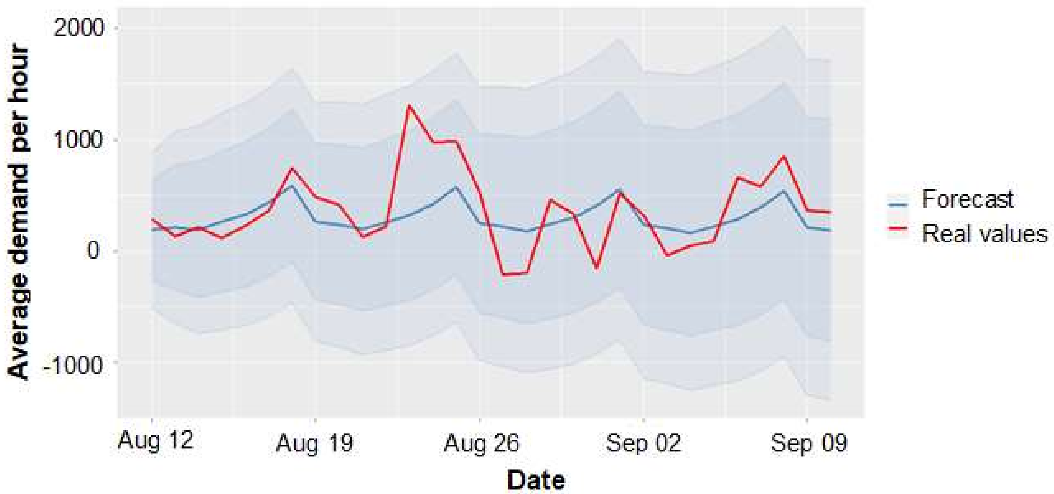

Figure 6: Graph of forecast values using the best ARIMA model and actual electricity demand.

Table 4
Result of checking the accuracy of NNAR models on the test data sample

No.	Type of NNAR model	MSE	RMSE	MAE
1	NNAR with default number of lags	283759.35	532.691	443.085
2	NNAR(25,25,k)[7], Max_it=1500	417616.99	646.233	487.792
3	NNAR(50,50,k)[7], Max_it=5000	431768.49	657.091	533.003
4	**NNAR(100,100,k)[7], Max_it=20000**	**110804.56**	**332.873**	**256.034**

Figure 7 presents the forecast values obtained based on the best of the NNAR models.

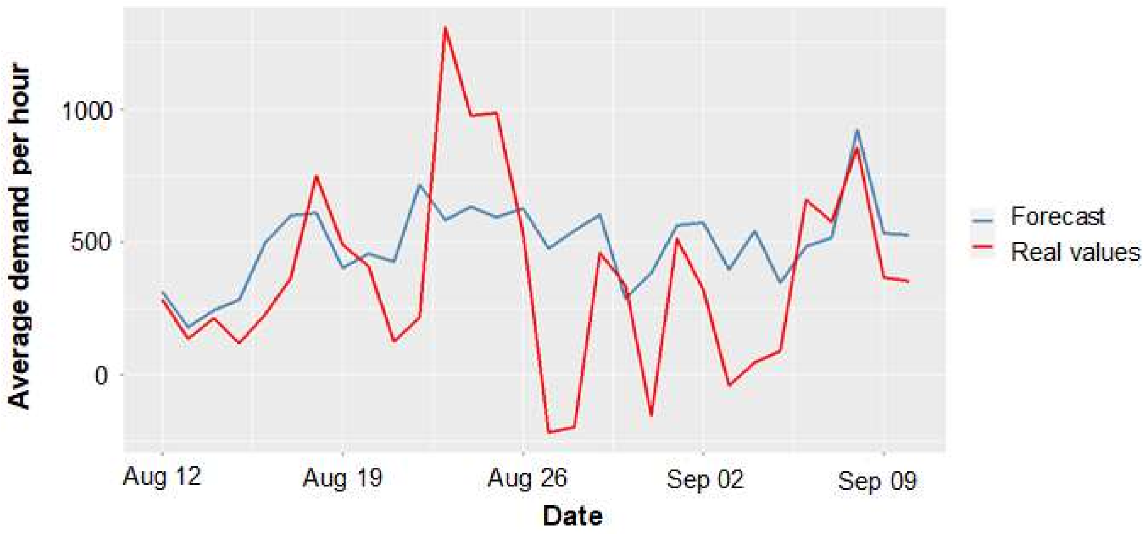

Figure 7: Graph of forecast values using the best NNAR model and actual electricity demand.

3.3. Combining forecasts

Based on the analysis of the forecast values obtained using the best baseline models (Fig. 8), it is obvious that no model takes into account all the features of the dynamic process under study. Therefore, to increase the accuracy of the forecasts, the approach of combining forecast values was used [22-24].

Seven different forecast combination methods were selected and implemented in the work: the simple averaging method; the median method; the minimum variance method; the method based on the regression model with coefficients fitted by the least squares method; the method based on the regression model with coefficients fitted by the least absolute deviation method; the inverse rank method and the combination of multiple regression models [25-27].

Table 5 presents a comparison of the indicators for three forecast quality metrics for all forecast combination methods. The best quality values were shown by models based on methods No. 1 and No. 6, which are the simple averaging method and the inverse rank method. The best quality model based on the simple averaging method is presented in Figure 9 against the background of forecasts obtained using the best basic forecast models.

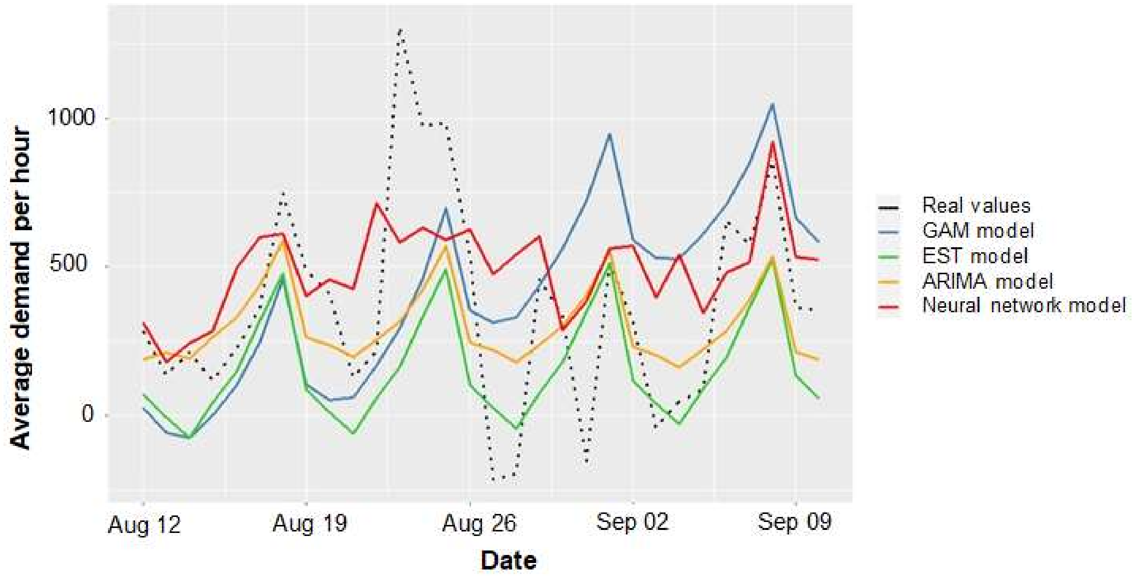

Figure 8: Graph of actual electricity demand values and forecasts using the best forecasting models.

Table 5
Result of checking the accuracy of combined models

No.	Methods for combining forecasts	MSE	RMSE	MAE
1	**Simple averaging method**	**91834,74**	**303,04**	**214,02**
2	Median method	95734,16	309,41	217,29
3	Minimum variance method	97225,87	311,81	219,14
4	Regression model with coefficients fitted by the least square's method	101700,17	318,91	233,06
5	Regression model with coefficients selected by the least absolute deviation method	103181,16	321,22	239,18
6	**Inverse rank method**	**92097,26**	**303,48**	**216,40**
7	Combination of multiple regression models	97019,76	311,48	219,29

Table 6 presents the forecast quality metrics for the best baseline forecast models and the best forecast combination model. The forecast combination model shows improvements in various quality metrics ranging from 1% to 2,5%.

Table 6
Estimates of forecast accuracy for the best baseline models and the combined forecast sample

No.	Types of models	MSE	RMSE	MAE
1	GAM models with an increased number of trend nodes	157228,52	396,5205	324,3262
2	ETS (A, A, A)	127475,51	357,0371	276,2925
3	ARIMA(2,1,2)(1,0,2)[7]	93986,56	306,5723	228,7214
4	NNAR(100,100,k)[7], Max_it=20000	110804,56	332,8732	256,0339
5	**Combining forecasts using the "Simple Averaging" method»**	**91834,74**	**303,04**	**214,02**

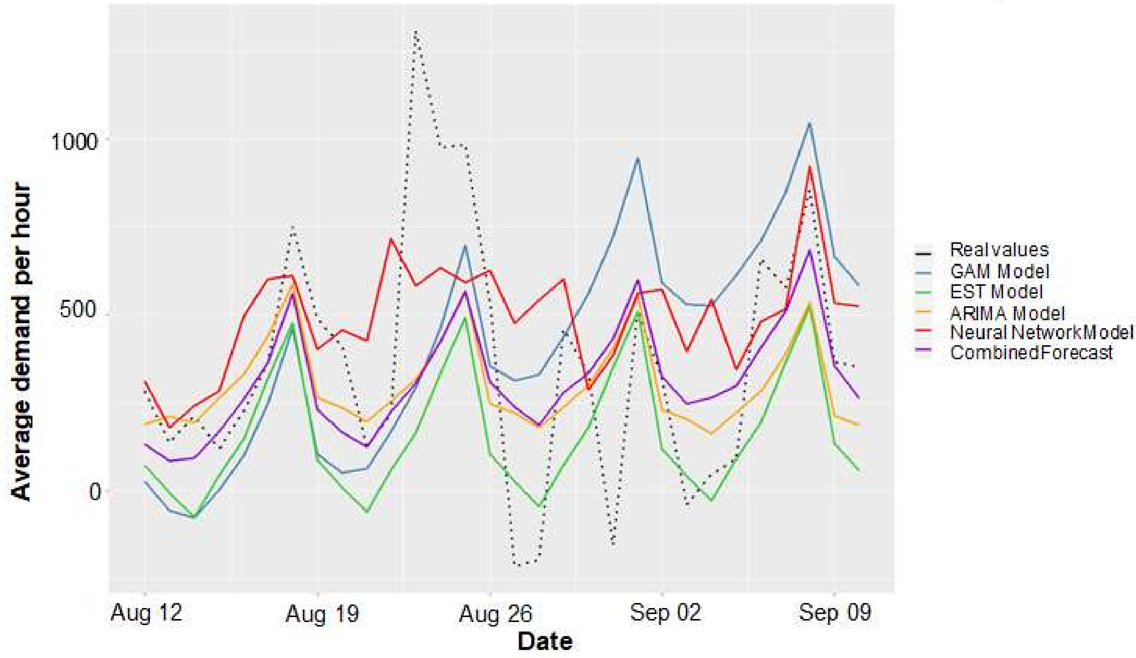

Figure 9: Graph of actual electricity demand values and forecasts using the best forecasting models.

The presented approach to improving forecast accuracy based on combining forecast values from the best basic forecast models demonstrates an increase in forecasting efficiency in machine learning tasks.

4. Conclusions

The article considered an approach to improving the accuracy of time series forecasting by using forecast combination methods to solve machine learning problems. The problem of forecasting electricity demand in the Ukrainian power grid was considered as a machine learning problem. A structural diagram of the forecasting approach using a combination of forecasts was proposed. In the developed approach, the basic methods of time series forecasting based on machine learning were used, namely: a generalized additive model, an exponential smoothing model, an ARIMA model, and a neural network autoregression model. For each method, several alternative models with different parameters were constructed, the accuracy of which was evaluated on training and test samples, as a result, the optimal model was selected for each type of model.

Seven different methods of combining forecast values were considered. To solve the forecasting problem, forecast combination methods were used to obtain combined forecasts based on the forecasts of the best models. Two of the considered combination methods (simple averaging and inverse rank method) demonstrated improved forecast accuracy compared to the best baseline models across all quality metrics. Among the combination methods, the simple averaging method has the highest accuracy. The proposed approach is effective for obtaining point forecasts on time series.

Declaration on Generative AI

The authors did not use any generative AI tools.

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