https://www.proconference.org/index.php/usc/article/view/usc35-00-003
DOI: 10.30888/2709-2267.2026-35-00-003

**UDC 004.9**

# ENSEMBLING OF TIME SERIES FORECASTING MODELS

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***Abstract.*** *This study presents the results of an analysis of the effectiveness of ensemble time series modeling in forecasting electricity supply. The voting method turned out to be the most effective among the ensemble methods considered. Ensemble allowed combining the strengths of each individual model, which led to an improvement in the overall forecasting result.*

***Key words:*** *machine learning, model, neural networks, forecasting, time series, ensembling*

## Introduction.

Recently, the problem of improving the quality of forecasting future events in such areas as industrial technologies, economics, and medicine has become particularly important. Forecasting methods usually involve the analysis of the necessary data using statistical and neural network models [1].

The most effective forecasting models include, in particular, the SARIMA, SARIMAX, and Prophet models. SARIMA and SARIMAX are classic models that have already proven their effectiveness in forecasting time series. They are well suited for modeling and forecasting time series with various seasonal and trend components. Both methods have a fairly wide range of applications and can be successfully used in many situations. Prophet is a more modern model developed by the Facebook team for forecasting time series. It is distinguished by its ability to automatically take into account seasonality, holidays, trend changes, and possible changes in the forecasted processes. Given the success of these three methods individually, we will choose them for further investigation with ensembles, as it can be expected that their combination can lead to improved accuracy and reliability of forecasts. In addition, each of these models has its own unique features that can complement each other in an ensemble, making them attractive choices for research.

**Main text**.

Ensembling the considered types of time series forecasting models can be an effective way to obtain accurate and stable forecasts in situations where a single model may not be sufficient in a specific time series forecasting context [2].

For further analysis, we will use a dataset containing data on electricity consumption in Portugal. The dataset consists of measurements of total consumption every 15 minutes during the day (in kilowatt-hours, kW). The dataset does not contain missing values, which allows us to avoid additional data processing and focus directly on modeling and forecasting.

*Model assembly by voting*. The voting method involves combining the predictions of several base models and determining the final prediction based on the majority vote of each model. This can be especially effective when different models have different strengths and weaknesses, and can complement each other in different ways. The voting method allows you to use any base models that have proven effective in previous studies. This allows you to experiment with different models and determine the optimal set for a particular task.

The initial stage of the method is training the models. Let $M_1$, $M_2$, …, $M_k$ be the models that will be included in the ensemble. Each model is trained independently on the training data set.

In the next stage of the method, each model $M_j$ makes a prediction $y_{t,j}$ for each time point $t$.

In the third stage, voting is implemented to obtain the final forecast. The final forecast $y_t$ at time point $t$ is obtained using one of the known voting method algorithms (simple average, weighted average or median voting.

In particular, the weighted average of the forecast is defined as follows:

$$y_t = \frac{1}{\sum_{j=1}^{k} w_j} \sum_{j=1}^{k} w_j \, y_{t,j}, \tag{1}$$

where $w_j$ is the weight of the $M_j$ model, which can be determined based on some measure of the quality of each model.

Voting is used to smooth out differences in forecasts using individual models and reduce the impact of individual model errors on the overall result. In the context of time series, this can help effectively adapt the model to changes in data over time.

Figure 1 shows the results of comparing the forecasts of the SARIMA, SARIMAX, and Prophet ensemble models with actual data for the voting method.

The voting method allows combining the forecasts of several models using their weights or majority decisions to obtain a more accurate forecast.

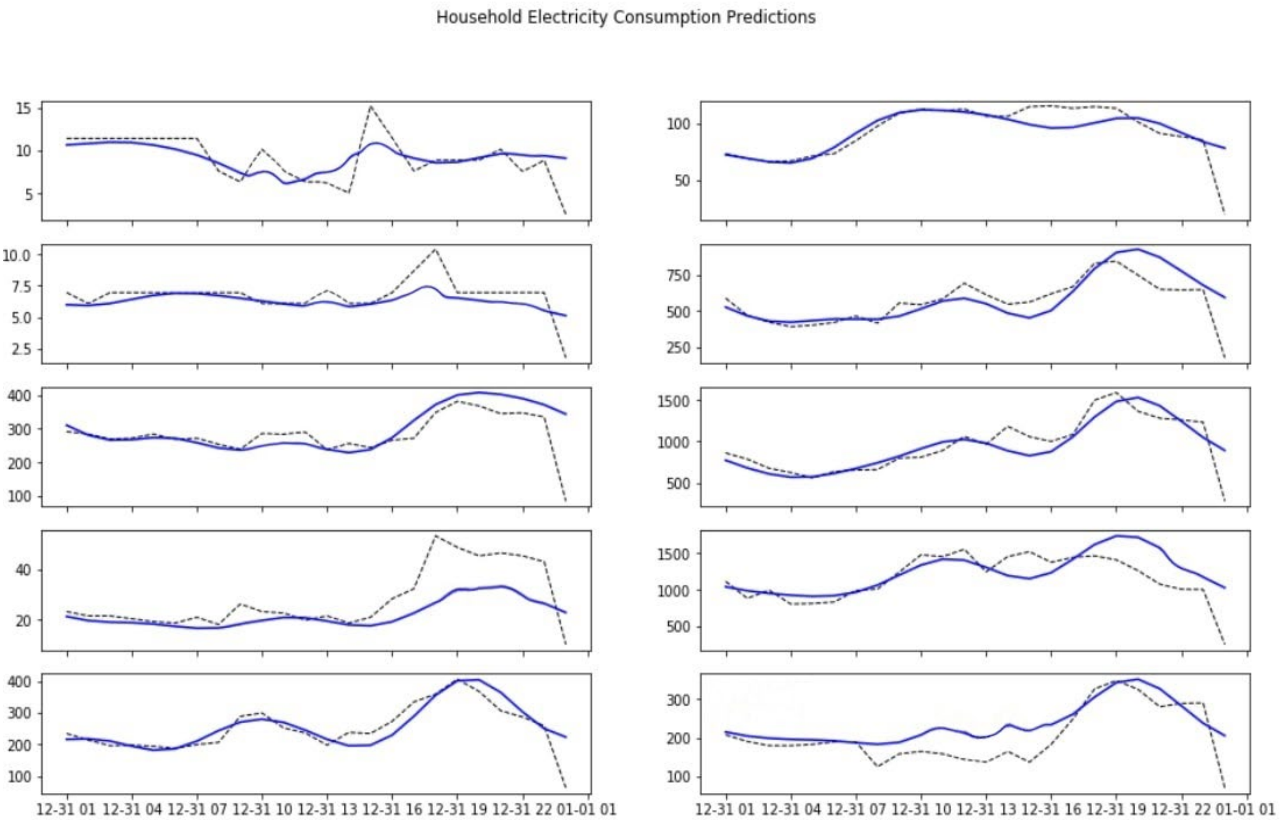


**Figure 1 – Comparison of forecasts after ensemble of SARIMA, SARIMAX, Prophet models with actual data for the voting method**

According to the graphs in Fig. 1, ensemble helped to reduce the variance of the forecasts and bring the predicted data closer to the real ones. In addition, the results showed smoother and more balanced dynamics, reflecting the better ability of the ensemble model to generalize and adapt to variations in the input data.

*Ensembling models using the bagging method*. The bagging method is used to create several base models that are trained on random subsamples of the training data with repetition. Each of these models is independent, and their forecasts are combined using the average or majority vote to obtain the final forecast.

It should be noted that the bagging method does not sufficiently take into account the time dependences in the data. In the case of a random selection of data for training each model, the forecasts obtained from individual models can be quite different. This can lead to less stable forecasts or heterogeneity of results.

Let us consider the basic algorithm for implementing the bagging method. Let the total data set $D$ contain $n$ elements. In the first step of the algorithm, $B$ bootstrap samples $D_1, D_2, \ldots, D_B$ are created, each of which contains n elements selected from $D$ with replacement. Each sample may contain repetitions of some elements.

In the next step, models are trained on each sample. On each bootstrap sample $D_b$, the model $M_b$ is trained (models can be implemented as regression trees or neural networks).

Next, the forecasts of all models are aggregated. Each model $M_b$ makes a forecast $y_{t,b}$ for each time point $t$. The final forecast $y_t$ is calculated as the arithmetic mean of the forecasts of all models at time $t$.

The aggregation of model forecasts is carried out as follows:

$$y_t = \frac{1}{B}\sum_{b=1}^{B} y_{t,b}, \qquad (2)$$

where $y_t$ is the aggregated forecast for time point $t$; $y_{t,b}$ is the forecast from the $b$-th model for time point $t$; $B$ is the number of models in the ensemble.

This method is particularly useful for reducing overfitting, as different models are trained on partially different datasets, which allows smoothing out random noise and outliers in the original data.

Figure 2 shows the results of comparing the ensemble predictions of the SARIMA, SARIMAX, and Prophet models with the actual data for the bagging method.

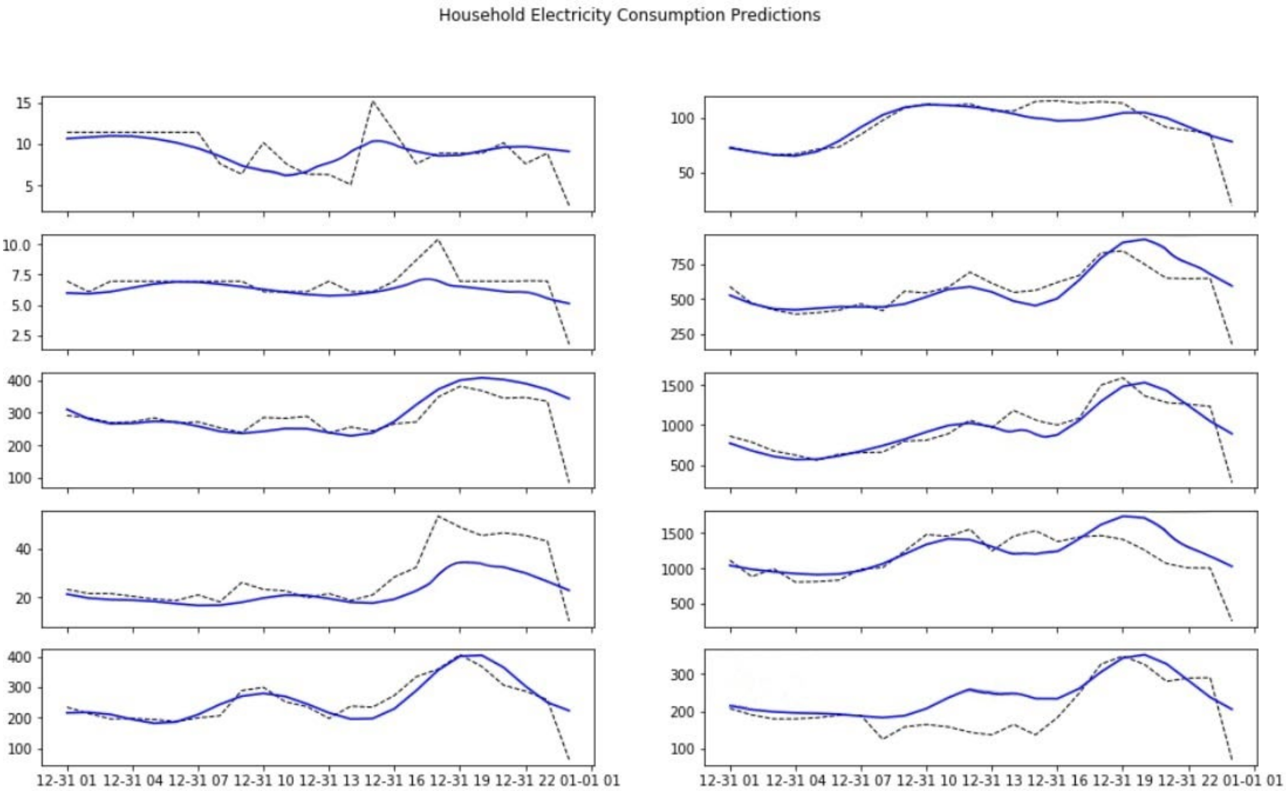


**Figure 2 – Comparison of forecasts after ensemble of SARIMA, SARIMAX, Prophet models with actual data for the bagging method**

**Summary and conclusions**.

In this study, we analyzed the effectiveness of ensemble modeling of SARIMA, SARIMAX, and Prophet using voting and bagging methods in forecasting electricity supply. The voting method turned out to be the most effective among the considered ensemble methods. The use of voting allowed to combine the strengths of each individual model, which led to an improvement in the overall forecasting result.

Therefore, based on the study, it can be concluded that the best ensemble method for forecasting electricity supply is the voting method, which provides the highest accuracy of the results.

In the context of electricity forecasting, the use of ensemble modeling of SARIMA, SARIMAX, and Prophet can significantly improve the forecasting results by combining the strengths of individual models and reducing the impact of their shortcomings.

**References:**

1. Zhang Y.,Wei, W. Decentralized coordination control of PV generators, storage battery, hydrogen production unit and fuel cell in islanded DC microgrid. International Journal of Hydrogen Energy. 2020. Vol. 4., no. 15. pp. 8243–8256.

2. Udovenko S.G., Zatkhey V.A., Teslenko O.V. Modular system of decentralized processing of richly connected processes for the detection of structural problems // Automation control system and equipment. 2024. No. 180. P. 88-103. DOI: 10.30837/0135-1710.2024.180.088

sent: 20.12.2025