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To cite this article: A V Peshkov and O K Alsova 2020 *J. Phys.: Conf. Ser.* **1661** 012070

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# Short-term forecasting of the time series of electricity prices with ensemble algorithms

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**Abstract.** This article presents the results of using ensemble algorithms for short-term hourly forecasting of electricity prices. Combining forecasts has proved itself to be the approach that is most useful in the following situations. There is uncertainty in choosing the most accurate forecasting method. There is uncertainty associated with the choice of input data and factors that should be taken into account when forecasting, it is necessary to avoid large forecasting errors, both in the direction of overstatement and in the direction of understatement of the studied indicator. The article describes the author's software implementation of the ensemble model of forecasting the time series (TS) based on the adaptive method in the R environment, as well as the results of a comparative analysis of the accuracy of forecasting TS electricity prices using the single (Holt-Winters, ARIMA) and ensemble models (OPERA, adaptive model). The results obtained allow concluding that the use of ensemble models in solving applied problems of forecasting time series is promising.

## 1. Introduction

Until recently, in the electric power industry, the task of forecasting was to determine future energy consumption. Since the industry is constantly undergoing many changes, such as reforming the industry and creating a wholesale electricity and capacity market (WECM), the task of forecasting is becoming increasingly relevant. In addition, there was a need for short-term forecasting of the free price for electricity of the "day-ahead market" (DAM). This task is new to Russia [1, 2].

The day-ahead market involves a competitive selection of price bids from suppliers and buyers a day before the actual supply of electricity with the determination of prices and supply volumes for each hour of the coming day. The main criterion by which electricity suppliers are selected for the next day is the competitiveness of price bids. Therefore, it is so important for the electricity supplier to predict the price accurately. One of these suppliers is the Novosibirsk department of PJSC «RusHydro» – «Novosibirsk Hydroelectric Power Station». The task of forecasting the price of electricity is solved daily by specialists in the energy market support department. At the moment, for forecasting prices, as a rule, the simplest statistical methods are used (for example, the price is the same as yesterday or in the same period, taking into account the daily and annual cyclical changes in the indicator) and expert knowledge about the subject area (for example, repair of any HPS affects the volume of electricity flows and, as a consequence, its price). The accuracy of such a forecast is not always satisfactory and can lead to significant material losses.



Therefore, it is so important to develop effective algorithms and techniques for predicting the price of DAM. This task is relevant not only for Novosibirsk HPS but also for all Russian suppliers and consumers of electricity.

There are several foreign software projects for forecasting electricity prices (“Energy-Forecast: Prices” from StatSoft [3], “Energy price forecasting” from AleaSoft [4]). However, they have a very limited number of models used and are not possible to build combined forecasts. In addition, these software products have a high cost, are closed and do not take into account the specifics of the Russian electricity market. Therefore, in addition to developing algorithms and methods for forecasting DAM prices, it is also necessary to develop appropriate software aimed at the end user, which will simplify the preparation of forecasts and will increase their accuracy and earliness.

The results of forecasting TS of electricity prices using adaptive resonance theory models are presented in [5].

This article sets the task of studying the effectiveness of the use of ensemble algorithms for short-term hourly forecasting of DAM prices. A description of the implementation of the ensemble adaptive forecasting algorithm in the R environment is given. The time series of the DAM price is investigated using ensemble and single models (Holt-Winters, ARIMA), which are part of the ensemble. A comparative analysis of the statistical characteristics of forecasting accuracy using different methods has also been performed.

## 2. The concept of an ensemble approach

Usually, when forecasting processes in different subject areas, preference is given to a more accurate forecast obtained by using one or another method. However, each forecast obtained using one of the methods contains useful information that is not available in other forecasts, so it is difficult to give preference to one of them [1].

It is assumed that the forecasts obtained by different methods describe only one side of the dynamics of the investigated process, displayed by the studied time series. Therefore, the combination of independently obtained forecasts allows attracting additional information, which can contribute to a more complete and accurate description of the predicted process, and thereby allows obtaining more accurate forecasts [6, 7].

The general formula of a combined forecast made up of two single [8]:

$$f = \omega f_1 + (1 - \omega) f_2 \quad (1)$$

where  $f_1, f_2$  – single forecasts,  
 $\omega$  – weight of the first forecast.

Combined forecast  $\hat{f}(f_1, f_2)$  dominates individual forecasts  $f_1$  and  $f_2$  if

$$E[\ell(f_i, y_{T+r})] > \min_{f(\cdot)} E[\ell(\hat{f}(f_1, f_2), y_{T+r})] \quad (2)$$

Where  $\ell$  – loss function (e.g.,  $MSE = (y - f)^2$ ),

$y_{T+r}$  – outcome  $r$  periods ahead,

$r$  – forecast horizon.

Let the errors of the corresponding forecasts:  $e_1 = y - f_1$ ,  $e_2 = y - f_2$ , average forecast error:  $E[e_i] = 0$ , variances of forecast errors:  $\sigma_i^2$ ,  $i = 1, 2$ , covariance is  $\sigma_{12}$ .

Then the combined forecast error is the weighted average of the individual forecast errors:

$$e(\omega) = y - \omega f_1 - (1 - \omega) f_2 = \omega e_1 + (1 - \omega) e_2 \quad (3)$$

$$E[e(\omega)] = 0 \quad (4)$$

The expression for the variance of the combined forecast error takes the following form:

$$Var(e(\omega)) = \omega^2 \sigma_1^2 + (1 - \omega)^2 \sigma_2^2 + 2\omega(1 - \omega) \sigma_{12} \quad (5)$$

This expression will tend to  $\sigma_1^2$  for  $\omega = 1$ , and for fractional values of  $\omega$  the sum of the expression will be less. This mathematically confirms that the use of an ensemble approach that combines the results of several forecasts will reduce the variance of forecast errors. However, this is true only if the forecast errors are not correlated (single forecasts produce errors of different signs and sizes).

### 3. Description of forecasting models

In this work, we used the method of one-factor forecasting. This is one of the approaches in which only the retrospective time series of electricity prices is used as input. The approach assumes that the influence of external factors is indirectly taken into account in the values of the TS being studied (for example, the influence of air temperature).

To find single forecasts, we use the methods ARIMA (model of autoregression and moving average) and Holt-Winters (triple exponential smoothing), as the most often used, the effectiveness of which has been experimentally confirmed in solving applied forecasting problems from different subject areas.

The ready-made OPERA model from the package R of the same name presents as the first ensemble model, which provides several algorithms for performing reliable online forecasting of time series using expert estimates (single forecasts act as experts) [9].

Opera stands for «Online Prediction by ExpeRt Aggregation». This package contains several models that differ in aggregation (combination) algorithms. Next will be considered a model based on the algorithm "Mlpol", Polynomial potential aggregation, which computes the mixture as a weighted average of experts using polynomial weights and allowing different learning rates on each expert [10, 11]:

$$\hat{f}_T = \frac{\sum_{i=1}^N \left( \sum_{t=1}^{T-1} \left( \ell(\hat{f}_t, y_t) - \ell(f_t^i, y_t) \right)_+^{p-1} \right) f_T^i}{\sum_{i=1}^N \left( \sum_{t=1}^{T-1} \left( \ell(\hat{f}_t, y_t) - \ell(f_t^i, y_t) \right)_+^{p-1} \right)} \quad (6)$$

where  $\hat{f}_T$  – combined forecast at time  $T$ ,

$p$  – polynomial degree,

$\ell$  – loss function,

$f_t^i$  – the predicted value of TS at time  $t$  for the  $i$ -th model,

$y_t$  – the real value of TS at time  $t$ ,

$N$  – number of single forecasts.

The mixture function from the «opera» package computes weights when combining the forecasts based on how well it has done up to that point.

As a second ensemble model, a model based on the adaptive method is presented. A program that implements this model has been developed in the R environment.

The idea of the adaptive method is to exponentially smooth the squared errors of single forecasts [6]:

$$S_t^i = (1 - \alpha) S_{t-1}^i + \alpha (e_t^i)^2 \quad (7)$$

where  $S_t^i$  – exponentially smoothed squared errors obtained by the  $i$ -th model ( $i = 1, 2, \dots, m$ ),

$\alpha = \text{const}$  – adaptation parameter ( $0 < \alpha < 1$ ),

$(e_t^i)^2$  – the square of the error obtained in predicting the  $i$ -th model at time  $t$ .

Exponential smoothing allows taking into account the accuracy and weight of the forecast results obtained in the last steps of forecasting, and take into account the change in the dynamics of forecasting.

In this case, the weights for the partial forecasts are calculated one forecast period ahead using the expression:

$$W_i(t) = \frac{P_t}{S_t^i} \quad (8)$$

where  $W_i(t)$  – single forecast weights, and the expression for  $P_t$  determined taking into account the value  $m$  – number of single forecasts.

So, for two particular models, the expression for  $P_t$  has the form:

$$P_t = \frac{s_t^1 s_t^2}{s_t^1 + s_t^2} \quad (9)$$

Therefore, the weight coefficient of the  $i$ -th model at time  $t$  will be determined as:

$$W_i(t) = \frac{s_t^1 s_t^2}{s_t^1 (s_t^1 + s_t^2)} \quad (10)$$

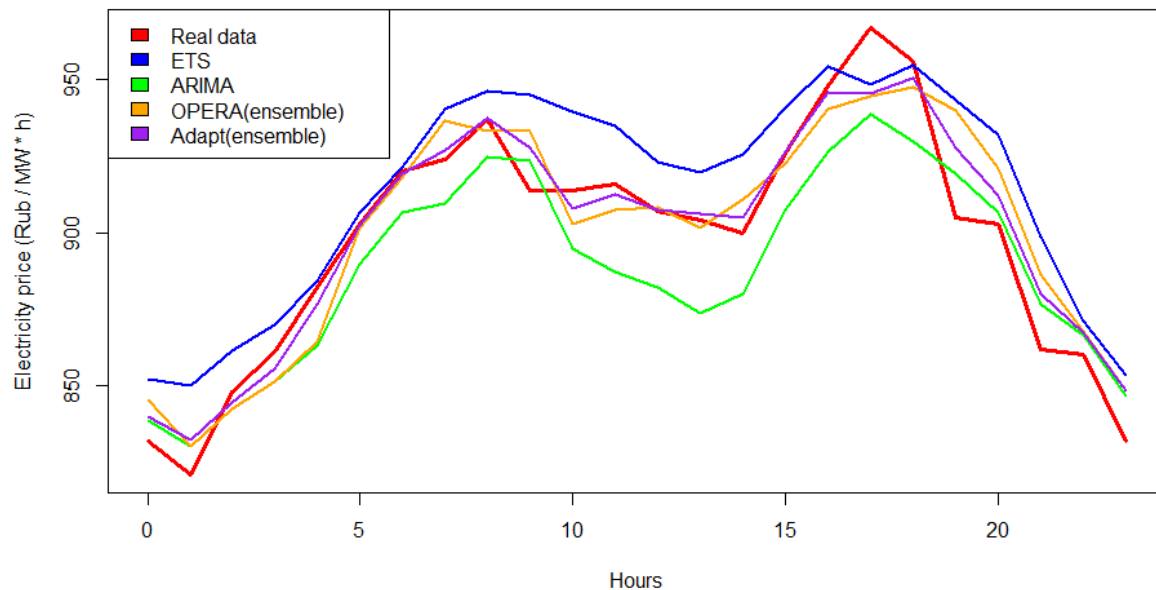
The following is the pseudocode of the developed function for calculating the forecast based on the adaptive method described above:

```
Adapt_forecast (tsData, forecast1, forecast2, a)
{
    ▷ tsData – an array of real data
    ▷ forecast1 – an array of forecast data of the first single model
    ▷ forecast2 – an array of forecast data of the second single model
    ▷ a – smoothing factor
    ▷ array length
    l := length(tsData);
    ▷ calculation of squared errors of partial forecasts
    for i := 1 to l do
        sqr1[i] := (tsData - forecast1)2;
        sqr2[i] := (tsData - forecast2)2;
    ▷ calculation of exponentially smoothed squared errors
    S1[1] := sqr1[1];
    S2[1] := sqr2[1];
    for i := 2 to l do
        S1[i] := (1 - a) * S1[i - 1] + a * sqr1[i];
        S2[i] := (1 - a) * S2[i - 1] + a * sqr2[i];
    ▷ calculation of weights and the resulting forecast
    for i := 1 to l do
        w1[i] := S2[i] / (S1[i] + S2[i]);
        w2[i] := S1[i] / (S1[i] + S2[i]);
        resultForecast[i] := w1[i] * forecast1[i] + w2[i] * forecast2[i];
    return resultForecast;
}
```

#### 4. The study of electricity prices based on application ensemble algorithms

For studying the models, the hourly range of DAM prices for electricity for the first two weeks of March 2017 was used. This time series was divided into two parts: the period from March 1, 2017, to March 13, 2017, was used as a training part, data for March 14, 2017 (by hours) was used as a test part.

Figure 1 shows a graph of changes in electricity prices of the test part with the imposition of forecast models of the time series.



**Figure 1.**TS of electricity prices with the imposition of forecast models

The figure above clearly shows how in the central part of the single chart forecasts (ETS and ARIMA) are mistaken in different directions. At the same time, ensemble forecasts (OPERA and Adaptive) come close to real data.

For assessing the accuracy of the forecasts, the following statistical characteristics of the residuals were used:

- *MAE* – mean absolute error;
- *MPE* – mean percentage error;
- *MAPE* – mean absolute percentage error;
- *RMSE* – square root of the mean square error;

and coefficient of determination (*DETERM*), which estimates how much of the variance of the investigated TS the model explains.

The obtained indicators of forecasting accuracy when using various models on the training and test parts are presented in table 1.

**Table 1.**Statistical characteristics of prediction accuracy

Statistical characteristic	Train part				Test part			
	<i>ETS</i>	<i>ARIMA</i>	<i>OPERA</i>	<i>Adaptive</i>	<i>ETS</i>	<i>ARIMA</i>	<i>OPERA</i>	<i>Adaptive</i>
<i>MAE</i>	10.84	12.88	10.39	9.57	17.24	16.02	11.32	7.16
<i>MPE</i>	-0.03	0.01	0.02	0.003	-1.77	1.01	-0.32	-0.32
<i>MAPE</i>	1.20	1.42	1.15	1.06	1.94	1.77	1.27	0.81
<i>RMSE</i>	15.65	18.52	14.93	14.27	20.24	17.72	13.95	9.73
<i>DETERM</i>	0.942	0.919	0.947	0.952	0.891	0.853	0.877	0.943

The analysis of the results indicates the high accuracy of ensemble forecast models both on the training and on the test part of TS. This fact is confirmed by the coefficient of determination, which is 0.877 on the test part for the OPERA model and 0.943 for the adaptive model. The total forecast error can be estimated using the RMSE indicator, which on the test part is 14.12 for the OPERA model and 10.22 for the adaptive model, which is a good result. Also, the adaptive model has an average absolute percentage error of less than 1 per cent.

## 5. Result and Discussion

Based on the above results, the following conclusions can be drawn:

1. Ensemble prediction models are superior in accuracy to single models in almost all accuracy characteristics.
2. Own software implementation of the adaptive model shows the forecasting results better than the OPERA model from a specialized package.
3. The use of ensemble methods in predicting the time series of electricity prices is a promising approach.

One of the advantages of the ensemble approach is that the combination of forecasts cannot lead to less accurate results than the use of particular models included in the ensemble for forecasting.

The disadvantages of the ensemble method include the need to fulfill the conditions for the uncorrelated forecast errors, that is, it is necessary to select single forecast models in such a way that they produce errors of different signs and sizes.

## 6. Conclusion

In this paper, using the example of a fragment of the time series of electricity prices, we show the advantage of using the ensemble approach to form a short-term forecast. The obtained results are a good prerequisite for its use not only for predicting TS of electricity prices, but also in solving applied problems of researching TS from different subject areas.

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