# About Designing an Intelligent System for Forecasting Electric Power Consumption Based on Artificial Neural Networks

Yana Neudakhina[0000-0001-5865-8081] and Vladimir Trofimov[0000-0001-9321-8081]

National University of Science and Technology MISIS, 4, Leninsky Prospekt, Moscow, Russia
yananeu1@gmail.com

**Abstract.** This article examines the problem of forecasting electric power consumption of central heating stations based on the data of a Moscow heating supply company. The features of the proposed neural-network forecasting model include historical data of electricity consumption, and average monthly temperature as a meteorological variable. The intelligent system for forecasting total electricity consumption of central heating supply stations proposed in this work is based on the dual forecasting method. The system consists of three predictor units, which allow to produce several complementary projection variants that can be combined, so the most rational of them can be selected.

**Keywords:** intelligent control of power systems, electricity consumption, neural-network models, time series forecasting, artificial neural networks, machine learning, automated electricity metering systems.

## 1 Introduction

Electricity consumption forecasting is critical for the modern energy industry. Energy enterprises in Russia are interested in an adequate evaluation of electricity consumption for their facilities because the reasonableness of settlements with electricity suppliers is dependent on that evaluation.

Over the last decade, the digital transformation of the Russian fuel and energy complex has stimulated the domestic industrial enterprises to implement automated commercial electricity metering systems, or Automated System for Commercial Accounting of Power Consumption (ASCAPC) for their facilities. ASCAPC smart energy meters collect time series data of electricity consumption that are used for forecasting electric power consumption of production facilities.

To achieve a desired level of forecast accuracy, it is proposed to use artificial neural networks for forecasting time series electricity consumption of central heating supply stations.

## 2 Materials and methods

### 2.1 Description of the automated electricity metering system

The ASCAPC is a two-level system with dedicated distributed functions for each of the levels. Figure 1 shows the structure of the ASCAPC of a Moscow heating supply company.

The data processing complex comprises:

- the existing data collection, processing, and storage servers of the existing district heating stations' ASCAPC of the heating supply company branches;
- a workstation for daily generation of data for dispatching to the System Operator (JSC "SO UPS") and affiliated facilities of the wholesale energy and capacity market (the OREM);
- the existing common timing system of the above-mentioned ASCAPC.

The information-measuring complex comprises:

- multiple-tariff energy meters with load profile storing and event logging functions;
- current transformers and voltage transformers with the defined accuracy class;
- channeling equipment (a GSM module).

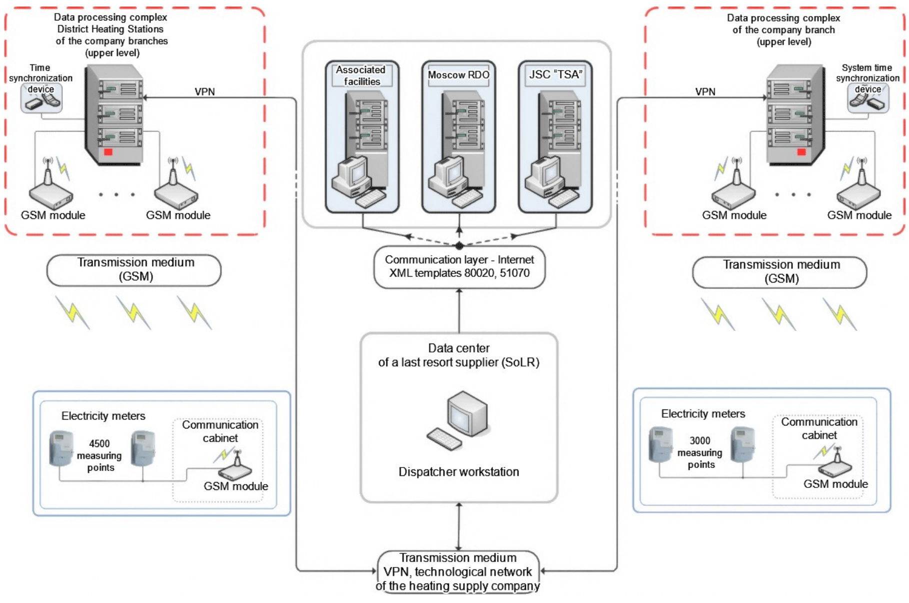


**Fig. 1.** Structure of the ASCAPC of a Moscow heating supply company.

The ASCAPC complies with the technical requirements of the OREM and provides accurate measurements of the amount of consumed electric power and energy.

## 2.2 Statistics of electric power consumption of the central heating stations

Seasonality is present in electric power consumption of central heating supply stations. As can be seen from the graph in Figure 2, the amount of electric power consumed by heating stations evidently increased in October, with the beginning of the heating season, and decreased in May.

It is evident that electricity consumption trends are influenced by seasonal fluctuations in meteorological factors [1].

The graph in Figure 3 shows data that are not clearly seasonal yet has similar structure.

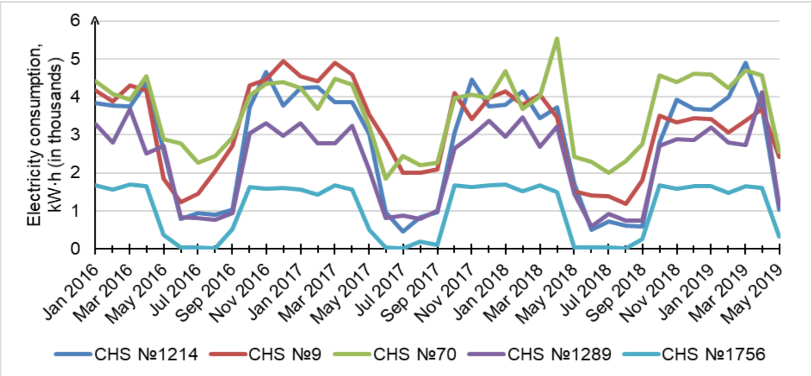


**Fig. 2.** Data with seasonality.

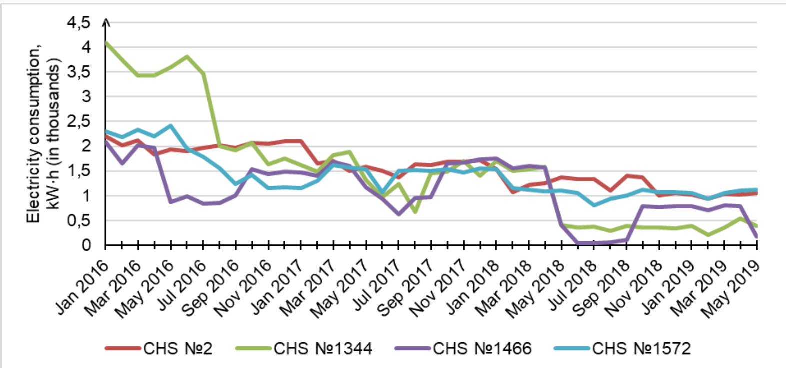


**Fig. 3.** Data with similar structure.

In this work, the meteorological factor, which is average monthly temperature in Moscow, is a feature variable in the forecasting model.

### 2.3 Forecasting using extrapolation

Extrapolation method based on exponential smoothing is one of the widely used statistical methods for time series forecasting. The exponential smoothing is implemented through the exponential filter, which weights past observations with exponentially decreasing weights to forecast future values (1).

$$\widetilde{X}_{smth}(1) = \widetilde{X}_{smth}(i-1) + \alpha \cdot (X_M(i) - \widetilde{X}_{smth}(i-1)\,, \tag{1}$$

Wherein $\tilde{X}_{smth}(i–1)$ is the past value, smoothed by the filter; α is the smoothing parameter; $X_M$ is the initial time series value.

As an example, the time series electricity consumption of CHS No9274 was smoothed by the exponential filter with α set to 0.7. To lower the influence of external disturbances, the three implementations of the exponential filter for the time series from 2016 to 2018 were averaged (Figure 4).

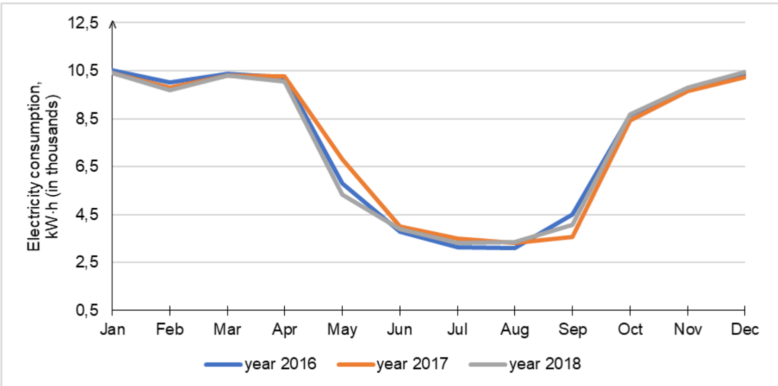


**Fig. 4.** Implementation of the exponential filter for three-year electricity consumption data.

The resulting forecast for CHS No9274 for 2019 is shown in figure 5. As can be seen from the graph (Figure 5), the extrapolation method based on exponential smoothing can produce forecast for data that have seasonality [2].

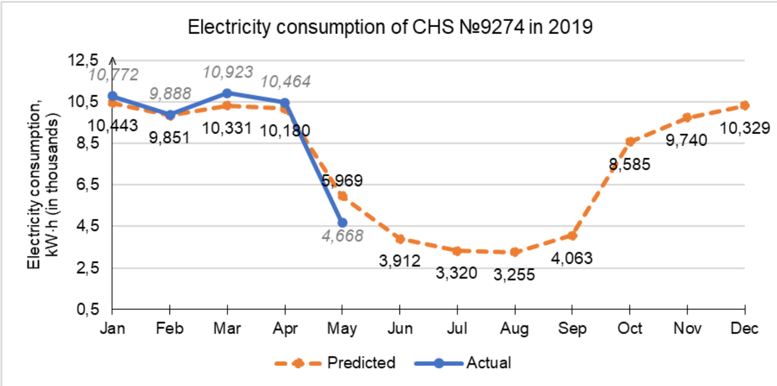


**Fig. 5.** Electricity consumption forecast for a central heating supply station in 2019.

However, unlike neural network approaches, this statistical method does not consider the influence of the external factors. Moreover, to forecast by extrapolation, the process must be monotone and without sharp short-term jumps.

## 2.4 Forecasting using artificial neural networks

Creating the training datasets. For time series with the seasonal component, the training datasets for the "winter" season (October–April) (Figure 6) and the "summer" season (May–September) were created [3]. The input feature variables are data of actual electricity consumption (k), historical data of electricity consumption (in the two previous months, k-1 and k-2), and average temperatures of the corresponding months [4]. Because the forecast is made for the next month, the output variable is the month-ahead electricity consumption (k+1).

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | CHS №9274 | | | | | |
| 2 | *"heating season"* | input | | | | output |
| 3 | Month | Actual electricity consumption, kW·h (in thousands) | | | Average temp. | Forecast |
| 4 | | *k* | *k-1* | *k-2* | | *k+1* |
| 5 | Jan 2016 | 10,504 | | | -11,41 | 9,825 |
| 6 | Feb 2016 | 9,825 | 10,504 | | -1,18 | 10,501 |
| 7 | Mar 2016 | 10,501 | 9,825 | 10,504 | 0,65 | 10,158 |
| 8 | Apr 2016 | 10,158 | 10,501 | 9,825 | 7,54 | 10,429 |
| 9 | Oct 2016 | 10,429 | 10,158 | 10,501 | 4,2 | 10,225 |
| 10 | Nov 2016 | 10,225 | 10,429 | 10,158 | -2,57 | 10,518 |
| 11 | Dec 2016 | 10,518 | 10,225 | 10,429 | -6,24 | 10,461 |
| 12 | Jan 2017 | 10,461 | 10,518 | 10,225 | -8,66 | 9,56 |
| 13 | Feb 2017 | 9,56 | 10,461 | 10,518 | 4,89 | 10,538 |

**Fig. 6.** Training dataset for "winter" season (a fragment).

Training datasets that do not consider the historical data were also created.

Choosing the artificial neural network architecture. Multilayer perceptron (MLP) is one of the most widely used neural-network models in neural network approaches. MLP consists of artificial neurons located parallelly in one or multiple hidden layers and an output layer. For building our neural-network model (Figure 7), we used Statistica Neural Networks software.

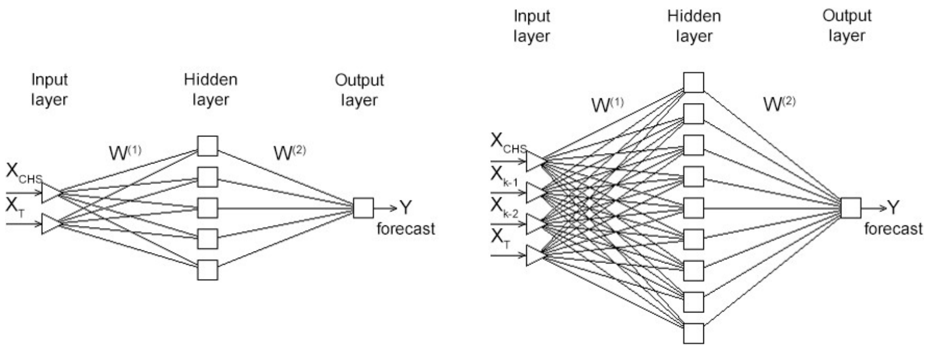


**Fig. 7.** MLP structure.

The proposed neural-network model comprises:

- *N* input neurons. *N*=2 for the model that takes the actual electricity consumption of the central heating station and the meteorological factor as feature variables (Figure 7, left), and *N*=4 for the model that additionally takes historical data as feature variable (Figure 7, right);
- 2*N*+1 neurons in the hidden layer that processes the inputs;
- one output neuron that produces the forecast.

To avoid the saturation behavior, the logistic, or sigmoid, function was chosen as the activation function for the hidden layer in the MLP.

### 2.5 Multivariant forecasting

ANNs can function as the tool for multivariant forecasting [5]. In this work, we develop a multivariant forecast for the estimator, which is the total electricity consumption for several central heating stations.

Forecasting by the dual forecasting method (Figure 8) [6] can be executed using the two methodological "branches", which are:

- $A^{I}$ – forecasting the behavior of the initial values, calculating the estimate by the forecasted values;
- $A^{II}$ – calculating the estimator by the actual initial values data, with forecasting the behavior of the estimator.

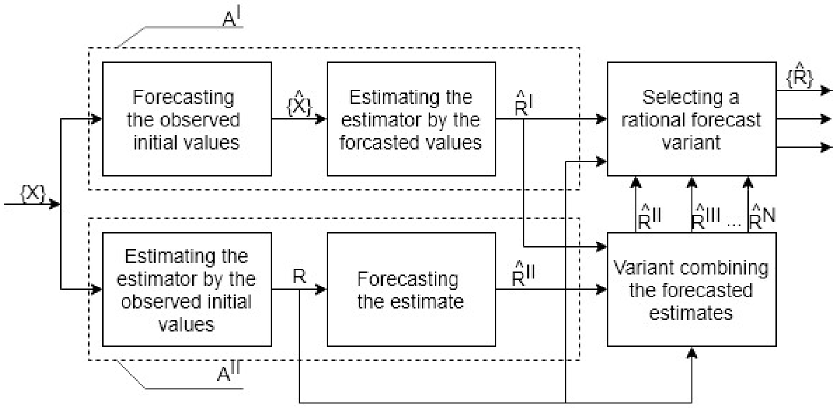


**Fig. 8.** Schema of the multivariant multistructural algorithmic block based on the dual forecasting method.

## 3 Results

The structure of the proposed intelligent system for forecasting the total electricity consumption for several central heating stations is shown in Figure 9.

The system consists of the three predictor units, each representing the respective forecasting model. This allows to produce several complementary forecast variants that can be combined, so the most rational of them can be selected.

The first variant of the forecasted estimate $\hat{R}^I$ is calculated by the formula (2).

$$\hat{R}^I = \hat{X}_{CHS9} + \hat{X}_{CHS9274} + \hat{X}_{CHS70} + \hat{X}_{CHS1214} + \hat{X}_{CHS1289} + \hat{X}_{CHS1756}\,, \tag{2}$$

Wherein $\hat{X}_{CHSn} = \alpha_1 \hat{X}_{\exp smthCHSn} + \alpha_2 \hat{X}_{ANNnohistoryCHSn} + \alpha_3 \hat{X}_{ANNhistoryCHSn}$ is the forecasted initial value; $\alpha_1+\alpha_2+\alpha_3=1$.

The estimates, $R$, are calculated by the formula (3).

$$R = X_{CHS9} + X_{CHS9274} + X_{CHS70} + X_{CHS1214} + X_{CHS1289} + X_{CHS1756}\,, \tag{3}$$

Wherein $X_{CHSn}$ is the measured initial values.

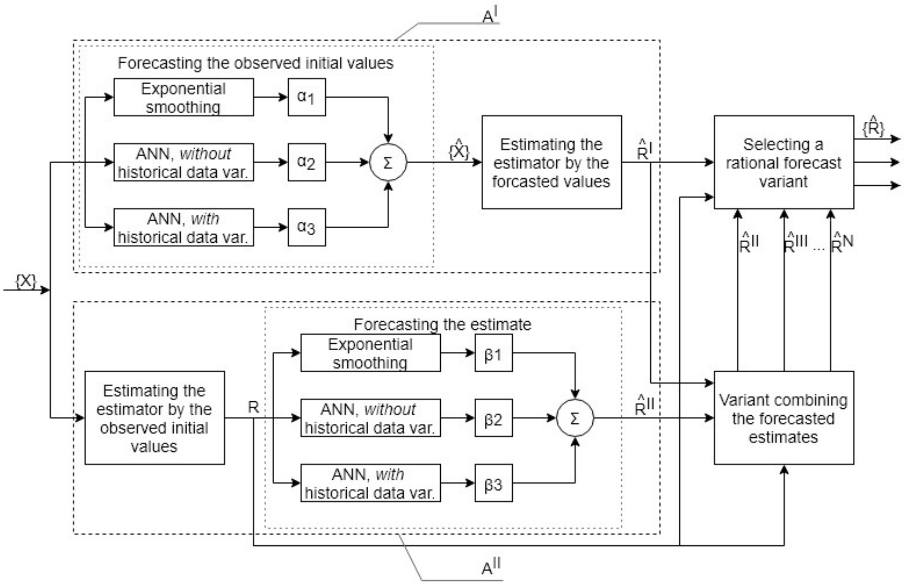


**Fig. 9.** Structure of the intelligent system for forecasting total electricity consumption.

The second variant of the forecasted estimate $\hat{R}^{II}$ is calculated by the formula (4).

$$\hat{R}^{II} = \beta_1 \hat{R}_{\exp smth} + \beta_2 \hat{R}_{ANNnohistory} + \beta_3 \hat{R}_{ANNhistory}, \tag{4}$$

Wherein $\hat{R}$ is the forecasted estimate that was predicted by the respective forecasting model; $\beta_1+\beta_2+\beta_3=1$.

For ANN-based forecasting model, the MLP was tuned with the data from the training dataset and trained using the backpropagation algorithm. The quality of the resulting neural-network model was evaluated by its scatter diagram (Figure 10). As can be seen from figure 10, almost all deviations of the predicted values are inside the confidence interval.

Forecasted and measured values of electricity consumption are shown in Figure 11. As indicated in the graph (Figure 11), the resulting neural-network model has high approximation capabilities. The values of the initial time series have a high correlation with the forecasted time series.

To study the created forecasting model, the neural network was tuned with the data from training dataset and verified with verification dataset. Both datasets with and without historical data as feature variable were used for the MLP training.

To produce a multivariate forecast [7–8], three copies of the MLP were made. Each copy was trained with different starting conditions, i.e., the initial weights were generated randomly. Multivariant forecast for central heating station No 9274 for April 2019 is shown in figure 12 (left), and averaged forecast is in figure 12 (right).

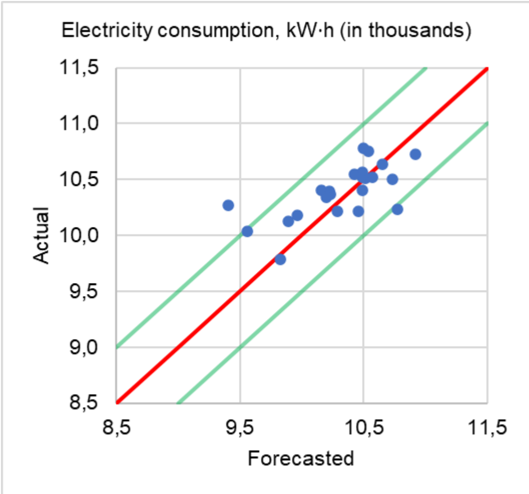


**Fig. 10.** Scatter plot of the trained ANN.

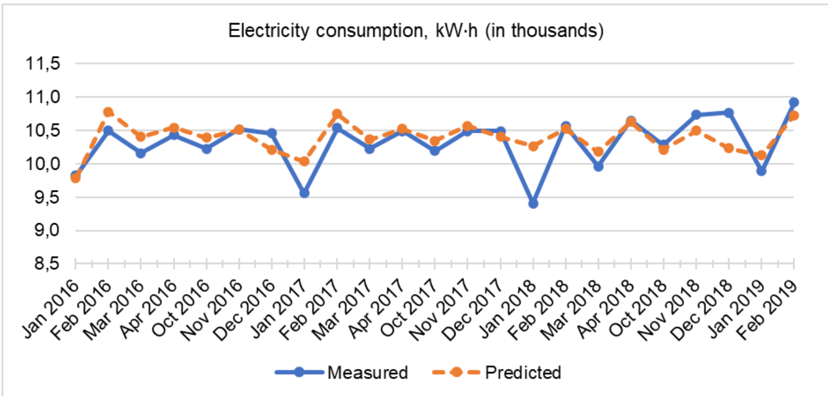


**Fig. 11.** Forecasted and measured values of electricity consumption.

To achieve a desired level of forecast accuracy, it is recommended to consider historical data as feature variable.

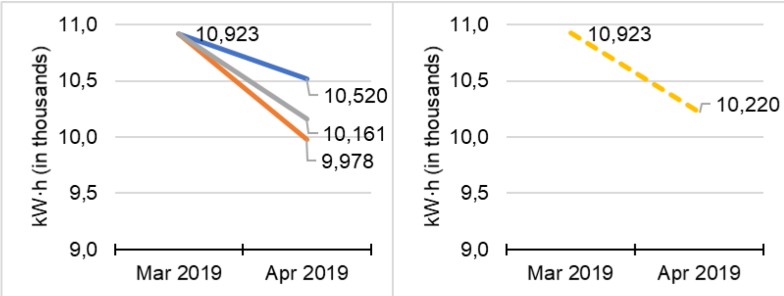


**Fig. 12.** Multivariant forecast (left) and averaged forecast (right).

Forecasted estimates for data with seasonality were calculated separately for each of the seasons ("winter" and "summer"). The graphs in Figure 13 and Figure 14 compare the changes in measured values and forecasted total electricity consumption values for "winter" and "summer" season, respectively.

The graphs (Figures 13 and 14) indicate that both variants of the forecasted estimate can take the data seasonality into consideration and confirm one another, which allows to develop a more accurate forecast of the estimator, i.e., total electricity consumption.

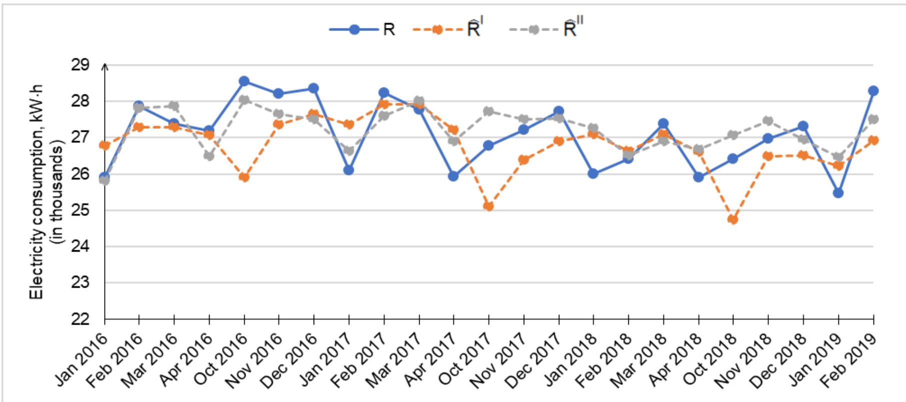


**Fig. 13.** Changes in the observed and the variant forecasted values of total electricity consumption ("winter").

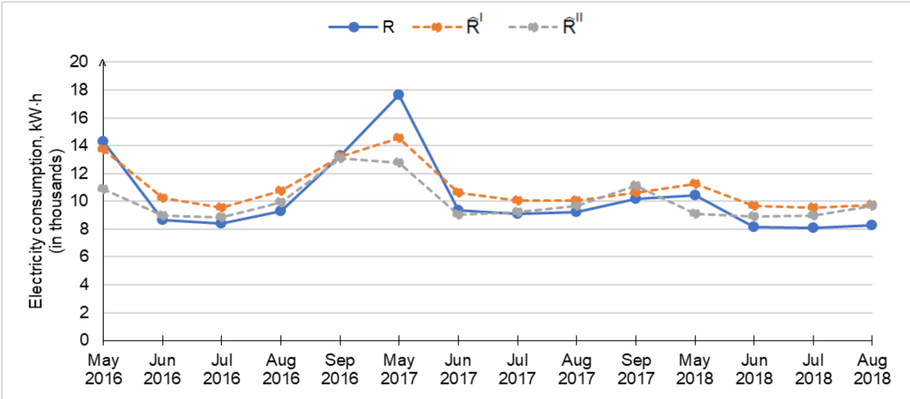


**Fig. 14.** Changes in the observed and the variant forecasted values of total electricity consumption ("summer").

To achieve a desired level of forecast accuracy, it is recommended to take both variants of the forecasted estimate into consideration.

## 4 Discussion

The digitalization rate of the Russian energy sector and the economy in general dictates the requirements for the quality of forecasts. This, in return, causes the transition to modern intelligent technologies in forecasting, and wide implementation of the AI methods in intelligent control systems [9], including time-dependent forecasting systems.

Due to the characteristics of the analyzed electricity consumption time series of central heating stations, it is recommended to combine both statistical and intelligent forecasting methods for developing intelligent systems for forecasting. In the core of such systems are several predictor units that can produce multiple forecast variants.

In one paper [10] formulated were the principles and application of predictive analytics methods in intelligent systems. Because one or few dozens of cases is not enough to achieve high forecasting accuracy, for correct application of predictive analytics methods and identification of future trends, it is recommended to create databases and knowledge bases that contain a great number of incidents [11].

## 5 Conclusion

The efficiency of the multivariant approach for forecasting is evident; it allows to produce several complementary forecast variants that can be combined, so the most rational of them can be selected.

The proposed intelligent system for forecasting electricity consumption of the facilities connected to the ASCAPC can be also applied in forecasting for other industrial facilities as well as for housing and utilities infrastructure objects.

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