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Industrial Power Consumption Forecasting Methods Comparison

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Abstract—The article is devoted to the analysis of methods for forecasting electricity consumption. Forecasting consumption is highly relevant for the subjects of the wholesale electricity market. The article considered the following forecasting methods: Long short-term memory (LSTM) artificial neural networks (ANN), support vector machine (SVM) regression based on radial basis functions (RBF), SVM Regression linear and Autoregressive integrated moving average. To implement the forecasting methods, Python 3.6 and various libraries were used. For each method, configuring, forecasting, and error evaluation were performed. As a result of the work the SVM regression method based on RBF has a lower maximal absolute percentage error (MaxAPE) of 21% and has better accuracy in the power consumption forecasting problem.

Keywords—energy consumption, forecasting, ANN, SVM Regression, ARIMA

I. Introduction

The question of forecasting plays an important role for the electrical grid industry. The subject of forecasting in the electrical grid industry is the future power consumption for objects with different consumption from small power centers and enterprises to large energy districts, regions and power systems in general.

Since 2009, the Federal Law of the Russian Federation No. 261 “On Energy Saving and Improving Energy Efficiency and Amending Certain Legislative Acts of the Russian Federation” go into effect [1]. The purpose of the law is to promote energy conservation and increase energy efficiency.

There are two ways to reduce energy consumption:

- The first way is to replace power engineering equipment and heat systems. This decision will lead to significant financial expenses and, ultimately, to the rise in the cost of the final product.
- An alternative way to improve energy efficiency is to forecast future energy consumption. This method uses a maximum of useful statistical information from all parameters of the production process both external factors and internal factors are taken into account.

This law concerns primarily the main sectors of the economy. According to Russian Federal State Statistics Service, 42% of the total energy consumed is accounted for by the production sector [2]. Enterprises are interested in efficient energy consumption, as they seek to reduce costs.

From the quality of forecasting at the enterprise level depends on the value of production costs, and hence the performance indicators.

The importance of electricity consumption forecasting increased when the wholesale electricity market (WEM) was created [3]. The WEM was established in 2003 as part of the reform of Russian Joint Stock Company Unified Energy System of Russia with the goal of uniting large producers and consumers of electricity in one place.

In the electricity market, planned consumption is formed on the basis of bilateral agreements. In fact, the actual amounts of electricity consumption in practice differ from the planned ones. Deviations from planned targets are sold on the balancing market. At the same time, the system operator of the Unified Energy System of Russia regularly conducts additional competitive selection of suppliers ’applications. Selection of applications are carried out taking into account the consumption of electricity, which was forecasted. Deviations of actual consumption from the forecasted imposes financial costs on market entities.

Understating of the forecast leads to the need to use expensive emergency electric generating stations. Overestimation of the forecast increases the cost of maintaining in excess idle capacity.

The task of forecasting is highly relevant for a large number of entities operating in the wholesale electricity market. Forecast accuracy is important for both generation companies and consumers. In the balancing market, generation companies that have reduced production on their own initiative, and consumers who have increased their workload, will be charged an additional fee [4]. The accuracy of electricity consumption forecasting has a great influence on the financial gain of market entities. Thus, the task of forecasting the consumption of electric energy by the consumer is very relevant.

There are a large number of methods for forecasting time series reports based on existing data. The purpose of this work is to conduct a comparative analysis of various methods of forecasting data in the task of forecasting the consumption of electrical energy.

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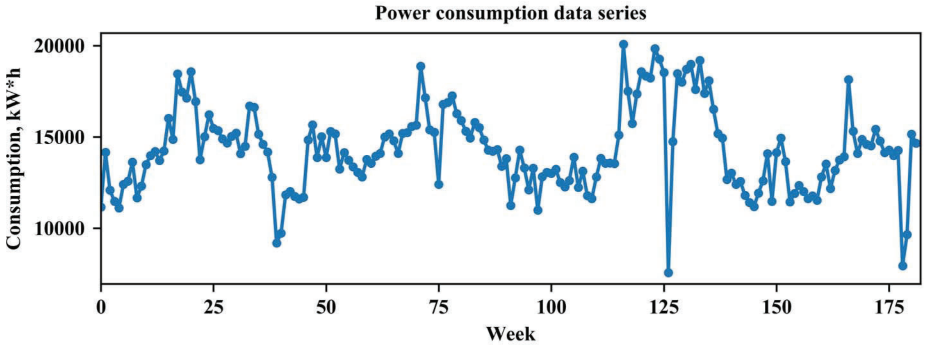

Fig. 1. Power consumption per week data series

II. MATERIALS AND METHODS

This study was conducted on the basis of consumption data engineering company in the city of Yekaterinburg, Sverdlovsk region of Russia. Total for the study was used testimony automated energy metering point for the period from July 2012 to January 2016.

The data were provided in a *.csv file and contained information in a timestamp format - hour-meter reading per kW * h. The period for receiving the next data report was 30 minutes. The data obtained had no missing values, so no interpolation or filtering of missing values was performed. The data was down sampled up to one sample rate per week, as shown on Fig. 1.

From a business point of view, the forecasting of the consumption of electrical energy for the four weeks based on historical information obtained in 24 weeks is optimal. The forecasting for 4 weeks allows us to develop a strategy for concluding contracts with electrical energy consumers for the next reporting period. On the other hand, when using weeks as data samples in the presence of a six month history, it allows us to have 24 data samples, which contains a large amount of information for new customers.

Based on the analysis of literary sources [5]–[9] was decided to analyze the following data forecasting methods:

- Long short-term memory (LSTM) artificial neural networks (ANN);
- Support vector machine (SVM) regression based on radial basis functions (RBF);
- Linear SVM regression;
- Autoregressive integrated moving average (ARIMA).

A. LSTM ANN method

LSTM network is a subspecies of the recurrent architecture of neural networks based on LSTM modules. Each module has three ports: input, output and forgetting port. Each LSTM module is capable of storing values for both short and long periods of time. The storage time of values in memory is determined at the forgetting port.

LSTM networks with multiple inputs and single output investigated during this research. The number of LSTM modules of neural network varied to achieve the smallest forecasting error at the training sample. The optimal number of LSTM blocks for the task of forecasting the consumption of electrical energy was 12.

The method of stochastic optimization was used as a method for teaching a neural network. Adam algorithm was used as optimization algorithm. The learning process was completed after 100 iterations of optimization.

B. SVM Regression linear and based on RBF method

The support vector machine regression method based on the support vector machine method. The main idea of the method is to search for a regression function based on data samples that are no more than a certain distance from the function.

The regression method based on RBF, in contrast to the linear regression method, translates data samples into a high dimension space, and only at the second step of the algorithm in the high dimension space does a linear regression model are built. The SVM based regression methods were not customized during this study.

The penalty parameter for the SVM methods was obtained empirically equal to 1000. The gamma parameter for the RBF SVM was obtained empirically equal to 0.1.

C. ARIMA method

The ARIMA model belongs to the class of statistical models for analyzing and forecasting time series.

ARIMA models are generally denoted ARIMA (p, d, q), where parameters are non-negative integers that characterize the order for parts of the model.

Model parameters mean:

- p is the order of delayed observations;
- d is the order of the time series difference;
- q is the order of the moving-average model.

The ARIMA model building methodology has an iterative method, which consists of 4 steps.

In the first step, a stationary time series should be obtained. If the time series is not stationary, the first difference operator is applied to the time series until the time series becomes stationary.

In the second step, the ARMA model parameters for the data are identified.

In the third step, an estimate of the selected parameters is carried out using numerical methods in order to minimize losses or errors.

In the fourth step, occurs diagnostic check each test model adequacy [10].

Empirically on 125 experiments were received optimal parameter values for forecasting the consumption of electric energy were p = 3, d = 1, q = 0.

To calculate the power consumption forecasting, a Python 3.6 program was written with keras, scikit-learn, statsmodels libraries containing the implementations of the forecasting algorithms used.

The algorithm consists of the following steps:

- Data aggregation. At this step, down sampling of electrical energy consumption data is carried out to the value of one consumption sample per week. Thus, a time series of 182 samples was obtained.
- Data separation. At this step, the data were divided into training and test samples in the ratio of 2 to 1. The first 66% of the data or 120 samples were included in the training sample. The remaining 34% of the data or 62 samples were included in the test sample. Training and forecast were conducted on the basis of a sliding window that includes information on consumption consistently over 24 weeks. The window step was 1 week.
- Then, for each of the forecasting methods that were considered, the following steps were performed:
  - Configuring a method or its training. At this step, neural networks were trained using the previously received training sample. For non-learning methods, such as SVM-regression and ARIMA, parameter settings were made.
  - Forecasting. At this step, the test sample was divided into test data sets. Then the forecasting was carried out on them.
  - Error evaluation. At this stage, the estimation of data forecasting error was carried out. Two methods were used to estimate the magnitude of the error: mean absolute percentage error (MAPE) and maximal absolute percentage error (MaxAPE).

III. RESULTS

The values of MAPE for various forecasting methods is presented in Table 1.

TABLE I. VALUES OF MAPE

Method	**MAPE**			
	1 week	**2 weeks**	**3 weeks**	**4 weeks**
LSTM	0.54	0.56	0.57	0.59
SVM RBF	0.12	0.12	0.12	0.12
SVM linear	0.14	0.14	0.15	0.15
ARIMA	0.11	0.12	0.12	0.12

The minimum values of MAPE in the problem of electric energy forecasting are possessed by SVM based on RBF and ARIMA methods. These methods show an mean average forecasting error of 12% in the forecasting range from 1 to 4 weeks. The SVM regression method based on RBF has a lower MaxAPE of 21% compared to ARIMA for an interval forecasting of 4 weeks. SVM regression method based on RBF has better accuracy in the power consumption forecasting problem.

The values of MaxAPE for various forecasting methods is presented in Table 2.

TABLE II. VALUES OF MAXAPE

Method	**MaxAPE**			
	1 week	**2 weeks**	**3 weeks**	**4 weeks**
LSTM	0.71	0.75	0.79	0.77
SVM RBF	0.12	0.17	0.19	0.21
SVM linear	0.14	0.19	0.23	0.26
ARIMA	0.11	0.17	0.20	0.28

IV. CONCLUSION

This article presents a comparative analysis of time series forecasting methods: linear SVM, SVM based on RBF, ARIMA and LSTM ANN. As data, observations of consumption of electric energy by an industrial consumer in the Sverdlovsk Region were taken. The minimum values of MaxAPE equal to 21% were obtained using SVM RBF with a penalty parameter equal to 1000 and gamma equal to 0.1.

The results obtained in the work can be used in the design of electrical energy forecasting systems by industrial consumers.

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