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Energy Consumption Forecasting for Power Supply Companies

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ABSTRACT

The paper investigates an issue of the accuracy of energy consumption forecasts for power supply companies, which are an intermediary between the wholesale energy market and the end user. Therefore, the purchased amount of energy should be equal to the predicted one with the least error. In case of any deviations, there is a problem of unsold amounts of energy or its shortage, which leads to financial losses, as the companies have to purchase or sell excessively the purchased energy at the price that is unprofitable for them in the wholesale market. Planning and monitoring the process of energy distribution are essential to achieving accurate energy consumption forecasting, which is an important component of all measures to optimize energy costs. The application of the statistical methods underlying the mathematical forecast models, which describe the process under study, will allow reducing the time for making managerial decisions and increasing the accuracy of energy consumption forecasts, thereby affecting the cost reduction in the power supply company.

Keywords: Energy Market, Energy Consumption Forecasting, Mathematical Forecast Models, Power Supply Company
JEL Classifications: D24; Q43; M31

1. INTRODUCTION

Electric power industry represents the key driving force behind the growth of world energy and the only sector where all types of primary fuel compete. Analysis of the development of the global energy market for 2017 showed that China ranked first in the world energy production and consumption, accounting for 6015 billion kWh, the USA ranked second - 4327 billion kWh, India ranked third - 1423 billion kWh and Russia ranked fourth - 1049 billion kWh.

Russia became a net electricity exporter in 2016. Energy production exceeded consumption by 21.6 billion kWh. The importers of the Russian energy in the structure of electricity exports by volume are Finland (26%), China (15.3%), Belarus (12.5%), the Ukraine (12.5%) and Lithuania (10.3%) (EY–power–Russia, 2018). Figure 1 shows the structure of the energy market development on a country-by-country basis.

Electric power industry refers to the key industry sectors. Most of the power capacity (67.9%) falls on thermal power stations, 20.2% - hydroelectric power stations, and 11.7% - nuclear power stations. The total capacity of RES is 0.2% of all capacities. In the first half of 2018, the capacity of solar power plants and wind power plants accounted for more than 500 MW and 100 MW respectively.

Energy production in Russia is growing thanks to hydroelectric power stations (from 160.4 bn kWh in 2015 to 188.3 billion kWh in 2017). Next, the energy production of thermal power stations is 673.7 bn kWh and nuclear power stations - 196.4 bn kWh.

In comparison with the energy production forecast, the analysis showed that energy consumption in Russia decreased by 21.6 billion kWh in 2016. The difference in the volume of electricity was redirected to Finland, Belarus, Ukraine, and China. Figure 2 illustrates an analysis of energy production and consumption by year.

The power supply company, as a participant in the wholesale energy market, buys energy on the market and sells it to retail customers. One of the conditions of this kind of activity is equality of the volumes of energy purchased on the wholesale market following the forecasts. The deviations of the actual electricity consumed from the claimed one lead to losses incurred by the power supply company. It has to purchase electricity or sell excessively purchased electricity in the balancing energy market at a less favorable price. Retaliatory measures may be imposed on the company provided that there are significant deviations. Besides, power supply companies are subject to certain risks, financial losses, and an economic decline.

Nowadays, there are a large number of models of time series forecasting, real values, but work on creating new models and improving computing platforms and systems continues. At the same time, the requirements for accuracy of forecasting and economic management are becoming increasingly strict, so time series forecasting is not only being improved but becomes more complicated day by day.

The application of the mathematical forecast models in energy production and consumption will allow increasing the accuracy of forecasting energy consumption, thereby affecting the cost reduction of the power supply company.

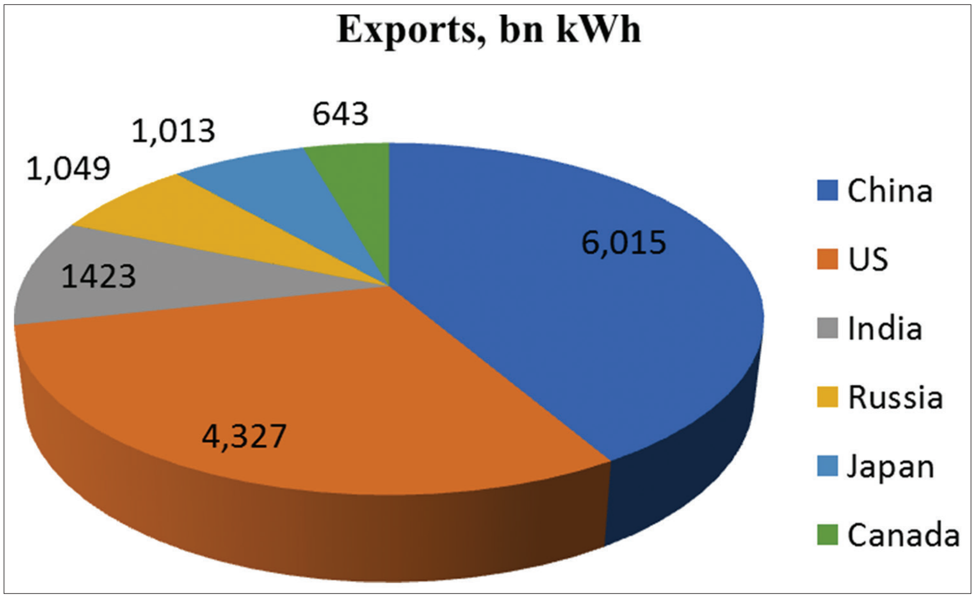
This paper is organized as follows. Section 2 gives a brief review of the literature. Section 3 provides a brief analysis of the energy characteristics of major energy consumers. Section 4 considers energy forecasting methods for the power industry and an algorithm for selecting initial factors that affect the process of energy consumption is proposed. Section 5 proposes recommendations on the criteria and requirements for the model.

2. LITERATURE REVIEW

A growing body of literature by Russian and foreign scholars has investigated the issue of energy consumption forecasting. Modeling and forecasting energy consumption in the market economy were examined by Val and Popov (2011), Polyakhov et al. (2013), Zahan (2013), Apolonsky and Orlov (2014), Ozturk and Ozturk (2018).

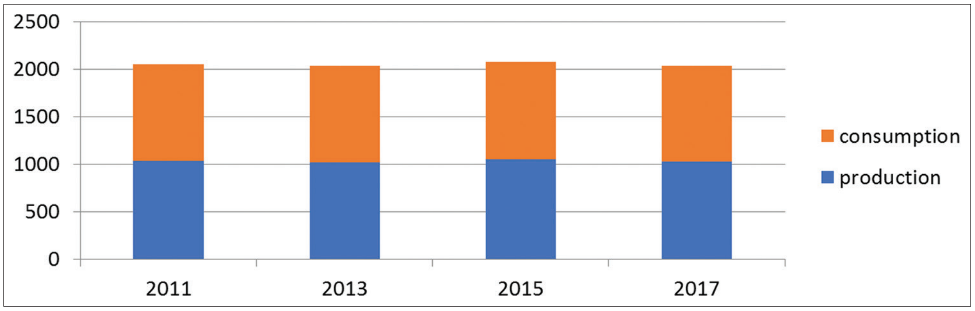
The use of modern approaches and methods for forecasting energy consumption has been widely addressed by Gofman (2010),

Figure 1: Structure of the energy market development on a country-by-country basis



Source: Review of the Russian electric power industry for 2017

Figure 2: Energy production and consumption in Russia



Source: System operator of the united power system, Russian statistics agency

Kaytez et al. (2015), Gwaivangmin (2016) Several studies, for example, Apergis and Payne (2009) and Philippov (2010), have been conducted on forecasting extrapolation as a method of short-term forecasting. The authors note that this method makes it possible to calculate the predicted characteristics of electrical loads under various energy consumption regimes. The method of electric load forecasting using artificial neural networks was proposed by Galperova (2011), Bubnov et al. (2013), Fazelpour et al. (2016). A number of studies (Philippov, 2010) have found that an adaptive forecasting method (the method of exponential smoothing) is reliable and effective in the opinion of such authors as it allows to make calculations and estimate the work parameters, which characterize the trend developed by the time of the last observation rather than an average level of the process. Forecasting using hybrid systems was studied by Philippov (2010), Capuno et al. (2017). The method has a cluster basis and allows performing an analysis on days of the week, decades, months and forming trends of values corresponding to the periods.

The considered methods allow creating mathematical models of energy consumption at an industrial enterprise and developing forecast models with input parameters. Energy forecast methods using neural networks are becoming increasingly popular because of their high accuracy in comparison with other statistical forecasting models, for example, regression models (Tamizharasi et al., 2014; Khajeh et al., 2018).

However, the literature review showed that the applied methods could not take into account all the features of the customer in the forecast values for electricity consumption and production. So one issue that needs to be raised is the search for new models and forecast methods, which are considered in the paper.

3. DESCRIPTION OF DATA

As practice shows, there are no uniform methods in applying approaches for forecasting energy consumption, since power supply companies have special technological cycles that form temporary processes that are unique for each enterprise. And so it only makes sense that the production cycles of energy consumption have similar trends, which allows them to be taken into account to improve the accuracy of forecasts.

When forecasting, cyclical, factorial and random patterns are taken into account. Cyclic trends account for about 70-80% of all changes in energy consumption, such as time, the day of the week and daytime length. The regularities of a functional aspect make up about 10-15% of the total deviations, depending on the customer: Air temperature or the coolant used, raw materials supply, gas pressure, overall production, etc. Random patterns are usually separately studied. The unreliability of the initial data leads to a forecast uncertainty of energy consumption.

Let's consider the relationship between electricity tariffs (g) and energy consumption level (j) as an example of the regression equation. In this study, we have developed the models of the pairwise linear (L), hyperbolic (D) and exponential (E) regressions. The criterion for assessing the quality of the model is the mean absolute percentage error (MAPE):

$$mare = \frac{1}{n}\sum_{i=1}^{n}\frac{j_{i-}\hat{j}}{j_i}\times 100\% \qquad (1)$$

The average coefficient of elasticity reflects the average value of the projected deviation from the real one and is calculated by the formula (2):

$$\dot{H} = f(g)_i \ \frac{g}{j} \qquad (2)$$

Where g_i - real value,
j - projected value.

Formula 3 is used to determine the correlation coefficient in the range -1≤R ≥1. The closer the coefficient is to 1, the better the linear dependence conforms to the observations. If the coefficient is equal to 1, then the connection becomes functional for the whole range of observations.

$$R = \frac{n\sum g_i j_i - \left(\sum g_i\right)\left(\sum j_i\right)}{\sqrt{\left[n\sum g_i^2 - \left(\sum g_i\right)^2\right]\left[n\sum j_i^2 - \left(\sum j_i\right)^2\right]}} \qquad (3)$$

To assess the quality and accuracy of the mathematical regression model, we used the coefficient of determination (5):

$$R^2 = 1 - \frac{\sum e_i^2}{\sum\left(j_i - \bar{j}\right)^2} \qquad (4)$$

Next, we made the Fisher hypothesis, where the number of degrees of freedom k is determined from the tables, where k_1=k, k_2=n-k-1, etc. The Fisher criterion is calculated by the formula (5):

$$F = (n-2)\frac{R^2}{1-R^2} \qquad (5)$$

The significance of the coefficients of the paired regression equation was determined by the estimation of the standard deviations of the probability density function of the coefficient (6):

$$W_a = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{J}_i - j_i\right)^2 \sum_{i=1}^{n} g_i^2}{(n-2)n\sum_{i=1}^{n}\left(g_i - \bar{g}\right)^2}}\ ; \qquad (6)$$

$$W_b = \sqrt{\frac{\sum_{i=1}^{n}\left(\hat{J}_i - j_i\right)^2}{(n-2)\sum_{i=1}^{n}\left(g_i - \bar{g}\right)^2}}$$

The standard errors of the regression coefficient can be determined through the formulas (7):

$$t_a = \frac{a}{W_a};\ t_b = \frac{b}{W_b} \qquad (7)$$

With a standardly distributed error, t_a and t_b are random variables with a degree of freedom according to Student's test (n-2). If $t_a \geq t_{crit}$, then t is determined by the Student's tables regarding the number of degrees of freedom. Figure 3 shows the summary results of the calculated indicators for 2015 and 2016.

2015 results. In the course of the research, the coefficients of correlation, determination, and elasticity of the energy consumption were calculated, which for all models turned out to be close to zero, which explains the low functional relationship between the indicators, and the absence of a significant dependence of the volume of consumption on the tariff. According to the results of the Fisher's F-criterion, only the equation of exponential regression is significant, which reflects the absence of a functional relationship between the indicators.

2016 Results. During the research, the dependence between the amount of energy consumption and the tariff was determined. The 2016 indicators are very close to those of 2015, but the elasticity increases to -0.33, which indicates that there is an inverse relationship between the amount of energy consumption and the tariff. The error of approximation for all equations is satisfactory and is within the permissible range.

4. METHODS AND MODELS

Formal approaches and adaptive methods are used for forecasting the energy consumption market. Formal approaches are divided into extrapolation and modeling methods. The most common formal approaches to forecasting are as follows (Val and Popov, 2011):

- Predictive extrapolation
- ARIMA models
- Hybrid systems.

Recently, methods of forecasting the energy market using neural networks (regression analysis) have also been used to a greater degree due to their high accuracy. The regression analysis is carried out in several stages: At the first stage initial data preprocessing is implemented; at the second stage the form of the regression equation is determined, the coefficients of the regression equation are calculated; at the third stage the adequacy of the constructed model is tested according to the results of observations (Ibiraimov, 2002). Artificial neural networks act as a combination of two types of elements: The first type is neurons, the second type is the synapses. The neuron model is described through the mathematical expression (8):

$$N = \sum_{i=1}^{m} wx,\ y = \varphi\left(w+b\right) \tag{8}$$

Where x_n - The incoming signals,
w_n – The synoptic weight of a neuron,
N – The combination of input influences,
Y – The input signal of the neuron.

ARIMA models proposed by Box and Jenkins make it possible to accurately describe the seasonal time series, which can be attributed to the energy consumption of an industrial enterprise.

One of the most frequently used methods of obtaining energy consumption forecasts is the least square method of the multiple regression model (Tikhonov, 2006). For the linear case, the multiple regression model is written as (9):

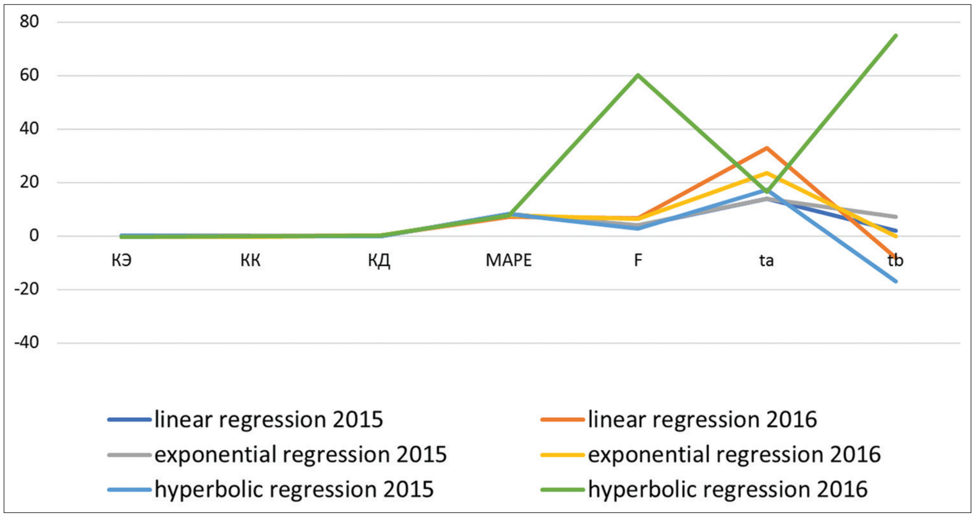
$$y_n = \sum_{i=1}^{n} \propto_i\ x_{ij} +_{\varepsilon_j} \tag{9}$$

Where $\propto$ - The coefficients of the regression model
x, y - The predictor and regressor
ε_j – The random error
n - The number of independent variables in the model.

The methods of predictive extrapolation are based on the representation of the time series in the following form (10):

$$y_i = f(t) + \varepsilon \tag{10}$$

Figure 3: Dynamics of elasticity coefficients



Where *f(t)* - The nonrandom function of time
ε - The random value.

The most common forecast method is the multiple regression method, which allows determining the regression coefficients based on the available data about the forecast object and the factors affecting it. For the linear case, the multiple regression model is written as:

$$y = \sum_{i=1}^{n} ax + \varepsilon \tag{11}$$

Where a - The regression coefficients
y, x - The values - f-dependent variable, f-independent variable.

Adaptive methods include the Brown’s, Holt’s and Holt-Winters’ methods.

Let’s consider an algorithm for selecting the initial factors that have an obvious effect on the energy consumption studied. The set of factors that are used to make forecasts is individual for each enterprise. The first stage assumes that all data must be unified and converted to a single format, Excel. The second stage is associated with the choice of methods of data representation. For example, if the “weekend and holidays” factor is selected, then it is necessary to determine the way of its formalization. The accessibility of factors is very important. It should be noted that some of the data (readily-accessible) are extracted from existing information systems, some (hard-to-get) are studied in the dynamics of process changes. It is important to understand that if the process is characterized by seasonality/cyclicity, cyclic data with the possibility of variation of intervals is taken into account. The third stage involves the selection of data, which also has its own structure:

- The formation of a list of factors, which may have an impact on the investigated value of energy consumption according to various data sources
- Development of a descriptive model
- Determination of the significance of the value of each factor
- Cutting off factors with unsatisfactory low significance cutting off factors with the unsatisfactory low significance
- Expert selection of significant factors
- Correlation factor analysis
- Energy consumption forecast.

For example, the values of the initial time series Q(t) are available at discrete instants of time t = 1,2,…, T. It is assumed that Q (t) is influenced by a set of external factors, such as:

- Humidity
- Day of the week
- Seasonality
- Air temperature
- Daytime length
- Energy consumption in kWh.

The first external factor $b_1(t_1)$ is accessible at discrete instants of time $t_1 = 1,2.,T_1$, the second external factor $b_2(t_2)$ is available at the instants of time $t_2 = 1,2.,T_{2,}$ etc. In the case of different discreteness indicators of the initial time series and external factors, as well as the values of $T,T_1.,T_n$, the time series of external factors $b_1(t1).,b_n(t_n)$ should be reduced to a single time scale t. When forecasting, it is necessary to determine the future values of the initial process Q(t) at the instants of time T+1., T+P, taking into account the influence of external factors $b_1(t).,b_n(t)$. The values of external factors at the instants of time $b_1(T+1).,b_1(T+P).,b_n(T+1).,b_n(T+P)$ are recognized as being accessible.

It should be noted that the most effective model is obtained by splitting the initial data by the days of the week. This is because a large proportion of energy consumption falls on enterprises, including very large: Plans, factories, various industries. The main peak of energy consumption for them is in the middle of the week. Machines and shops consume very little electricity at the weekend, but at the beginning of the week the production machines and furnaces are warmed up, and the consumption of energy grows. Conversely, the factor of seasonality is most important for the energy consumption among the general public: In summer the energy consumption increases in gardeners’ partnerships, recreation centers, cottages and so on.

5. RESULTS AND DISCUSSIONS

The forecast mathematical model of energy consumption is a set of equations with coefficients that are formed during the development of the model at the stage of qualitative modeling. The forecast is known to be an enterprise itself when forecasting energy consumption by the enterprise, which is a set of processes of energy consumption by all electric receivers of the enterprise. The output parameters in the forecast model are those to be chosen, to a greater or lesser degree, affecting the amount of energy consumption. In fact, when developing a forecast model of energy consumption, the regularities of the change in the output parameter (the amount of energy consumption) are determined depending on the parameters chosen as input ones. Let’s consider the requirements for the forecast model of energy consumption, which are optimal:

1. The model must meet the requirements of adaptability and evolution. It should provide the ability to include a sufficiently wide range of changes and additions, which contributes to the accuracy of forecast results.
2. The model should be sufficiently abstract to allow working with a large number of input parameters, but not so much that there are doubts about the reliability and practical usefulness of the forecast results.
3. The forecast model should ensure the forecast is made by the specified date.
4. The model should be adapted to the use of modern technologies.
5. The model should provide for the possibility of verifying the truth, matching it with the original one.

It is necessary to choose the following forecasting factors for the optimal choice of methods for developing a forecasted energy consumption model for an industrial enterprise: Forecast accuracy, adaptability of the forecast model, its speed, etc. The accuracy of the forecast is determined according to such characteristics of the enterprise as: The share of electricity costs in the final product cost, potential financial losses in case of deviations of the real values of energy consumption from the claimed (predicted) ones, emergency, failures in the work of technological chains, the volume of output, start/stop of technological chains and environmental parameters. The optimal forecast model should take into account as many factors as possible.

6. CONCLUSION

The problem of the mathematical forecast models of energy consumption is of much importance under market conditions. Large energy consumers are interested in making accurate forecasts of the planned amount of energy consumption. Energy producers are interested in forecasts of energy consumption to respond quickly to fluctuations in demand and optimal development of the infrastructure. The efficiency of energy management solutions, the possibility of energy conservation and the efficiency of the operating modes of the entire power system largely depend on the reliability of the energy consumption forecasts.

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