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Analysis of electricity consumption forecasting methods for the coal industry

***Abstract**. The paper considers a forecast model of electricity consumption of a coal industry enterprise based on three forecast methods, namely the wavelet transform, the vector method, and the recurrent neutral network. A comparative analysis of these methods is performed. For preprocessing the data for forecasting by vector and recurrent methods, the Singular Spectrum Analysis method was chosen. The structure of the model allows taking into account individual features of the operating cycle of the production process and smoothing the noise components and outliers. The results of a short-term hourly forecast for one day ahead are presented with the comparison of the obtained values. The results of short-term electricity consumption forecast were verified based on the actual data of the coal industry enterprise in order to assess the adequacy of the model to the actual values. The proposed models can be applied in automated software systems for predictive control of a production process of a coal mining enterprise.*

Streszczenie.** W pracy uwzględniono model prognozowania zużycia energii elektrycznej przez przedsiębiorstwo przemysłu węglowego w oparciu o trzy metody prognozowania, a mianowicie transformatę falkową, metodę wektorową oraz sieć neutralną rekurencyjną. Przeprowadzana jest analiza porównawcza tych metod. Do wstępnego przetwarzania danych do prognozowania metodami wektorowymi i rekurencyjnymi wybrano metodę Singular Spectrum Analysis. Konstrukcja modelu pozwala na uwzględnienie indywidualnych cech cyklu operacyjnego procesu produkcyjnego oraz wygładzenie składowych i wartości odstających hałasu. Przedstawiono wyniki krótkookresowej prognozy godzinowej na jeden dzień do przodu wraz z porównaniem uzyskanych wartości. Wyniki prognozy krótkookresowego zużycia energii elektrycznej zostały zweryfikowane na podstawie danych rzeczywistych przedsiębiorstwa przemysłu węglowego w celu oceny adekwatności modelu do wartości rzeczywistych. Zaproponowane modele mogą znaleźć zastosowanie w zautomatyzowanych systemach oprogramowania do predykcyjnego sterowania procesem produkcyjnym przedsiębiorstwa górniczego. **Analiza metod przewidywania zużycia energii w przemyśle a)ęglowym.

Keywords: wavelet transform, singular spectrum analysis, power forecasting, power management.
Słowa kluczowe: transformacja falkowa, analiza widma pojedynczego prognozowanie mocy, zarządzanie energią.

Introduction

The operational control of the production process of industrial enterprises is a relevant problem of modern power engineering. It is similar to other problems, such as the need for a complete reconstruction of power equipment, the use of modern methods of analytics and monitoring, and the replacement of power equipment and automation devices that have significantly exceeded their normal operation life. The use of predictive (or forecast) models at industrial enterprises in the fuel and energy sector is one of the directions of the program of power engineering development of the Russian Federation until 2035. This can significantly decrease the influence of the human factor and reduce the risk of emergency situations. In this paper, "predictive control" refers to production process control of an industrial enterprise "by forecast" using forecast values as the basis for decision making [1 – 4].

Electricity consumption forecasting at industrial enterprises allows getting significant financial benefits. This is especially relevant for mining enterprises, where electrical energy is an important component of the technological process, and its interruptions will lead to enormous costs. The damage from the loss of power of one excavator is estimated to be millions of rubles for one hour of downtime, while the losses within the entire enterprise amount to hundreds of millions of rubles. It is practically impossible to predict emergency situations, such as a break in transmission lines, or the loss of a power source from the side of a utility company. However, smart planning of repair time and equipment downtime (according to the necessary features of the technological process), as well as optimization of the electricity consumption schedule during peak hours in the power system, allows minimizing losses. Based on the obtained values of the short-term and long-term electricity consumption forecast, it is possible to optimize the choice of price categories for the consumed electrical energy and change them depending on the forecast trends that results in significant financial benefits. At present, there are methods of electricity consumption forecasting in a great number of variations, the number of which exceeds 400 [4 – 7]. However, there are no more than 20 basic algorithms in these models. Electricity consumption forecasting for coal industry enterprises requires taking into account the individual features of the production process.

Three forecast models based on the wavelet transform, the recurrent neural network and the vector method are considered in the paper. During electricity consumption forecasting, emergency or forced downtime of power equipment are non-systematic random factors distorting the shape of an electricity consumption curve of the object [8, 9]. Such distortions can significantly reduce the reliability of the results that increases the forecast error. For the vector and recurrent methods, data preprocessing is performed additionally by the Singular Spectrum Analysis method, which has a lot of advantages, as shown in [10, 11]. Wavelet analysis has proven to be efficient in working with data having noise components and outliers [12, 13]. Therefore, it does not require data preprocessing. Using wavelet analysis, it is also possible to identify the trends and periodic components, as well as to evaluate periodicity of power equipment operation, the time of its operation and downtime.

Wavelet Forecasting of Electricity Consumption of a Coal Industry Enterprise

The paper proposes a mathematical model for forecasting electricity consumption of a coal industry enterprise in the Far East region based on the wavelet transform. The electricity consumption schedule of the enterprise for the period from 2010 to 2011 is shown in Fig. 1. As a verification sample, one day of 01.01.2011 is used.

Assume that a retrospective time series describing a random value of energy consumption has constant probabilistic characteristics (i.e. it is stationary) [14]. One of the variants for analyzing stationary and non-stationary time series is based on the Spectro-Temporal method, which has many implementations described in [15]. In this investigation, the wavelet analysis of time series will be used, which is based on the theory of the wavelet transform.

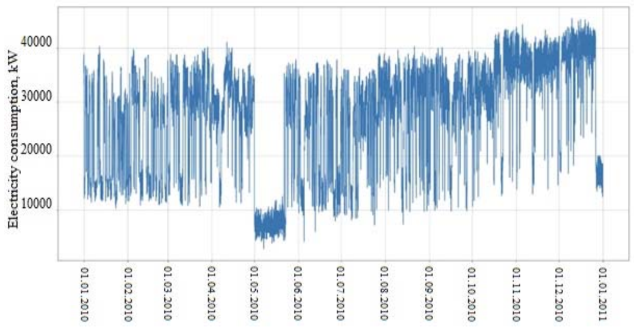

Fig.1. Electricity consumption of the coal enterprise during one year

The wavelet transform decomposes a signal at different time scales. It represents a set of objective functions $\psi_{a,b}(t)$ that can be obtained by scaling and translating a basis wavelet function as follows:

(1) $$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right); a > 0, -\infty < b < \infty$$

where a – the scale parameter, b – the translation parameter, $\psi(t)$ – a basis wavelet function.

The Discrete Wavelet Transform (DWT) is a discrete set of the wavelet scales and translations. It is specially adapted for the sampled value [15]. Actually, the DWT involves a dyadic grid, where the mother wavelet is scaled by a power of two ($a = 2^j$) and translated by an integer ($b = k2^j$), where *k* is a location index varied from 1 to $2^{-j}N$ (*N* is the number of observations) and j varies from 0 to *J* (*J* is the total number of scales). The DWT is expressed by the following equation:

(2) $$\psi_{j,k}(t) = 2^{-j}\psi(2^{-j}t - k)$$

In the present investigation, Daubechies wavelets (“db”), coiflets (“coif”), and biorthogonal wavelets (“bior”) [16] were considered as basis wavelet functions.

Multi-Resolution Analysis (MRA) is determined as a hierarchical representation of the DWT [15]. It is based on decomposing the original signal into m levels by translating and convolving the mother wavelet using low-pass (LP) and high-pass (HP) filters. These filters retain the detail (D) and approximation (A) components.

Therefore, the wavelet transform will be a smoothing function for the original signal (time series).

As a mathematical model for forecasting time series, the ARMA model will be used, which is a combination of an autoregression model (AR) and a moving average model (MA) [16].

Combining the AR and MA models results in developing an autoregressive moving average model (ARMA), which can be used in cases where neither AR nor MA can describe the observed dynamics of the time series with a sufficient accuracy.

The stationary time series $\{X_t\}$ is described by the ARMA model with the parameters specifying the order of the model in the following form:

(3) $$X_t = c + \sum_{i=1}^{p}\alpha_i X_{t-i} + \sum_{i=1}^{q}\beta_i\varepsilon_{t-i} + \varepsilon_t, t = 1,2,...$$

where *c* – the constant, $p, q \in Z^+$ – parameters of the ARMA model, $\alpha_1, ..., \alpha_p$ – autoregressive coefficients, $\beta_1, ..., \beta_q$ – moving average coefficients, ε_t – white noise.

Forecasting will be performed according to the following algorithm:

Input data: time series data $\{X_{train}\}$ for a specific time interval $T_{train} = [0;\, t_i]$.

Output data: forecast time series $\{X_{for}\}$ for the time interval $T_{pred} = [t_{i+1}, ..., t_{i+j}]$.

The following steps are carried out:

Step 1. Determine approximation A_2 and detail D_1, D_2 coefficients using the MRA diagram.

Step 2. Determine the ARMA model coefficients *p,q* for each decomposition level of the MRA.

Step 3. Make a forecast for the next k time instants using the developed ARMA models of each level and reconstruct the time series $\{X_{for}\}$ according to the MRA diagram.

To take into account all possible changes in the analyzed value of electricity consumption, it is recommended to select the training data for at least one calendar year of the enterprise's operation, i.e. to use $i = 24 * 365$.

After determining the forecast values, their verification and accuracy assessment are required according to the following algorithm:

Input data: the basis wavelet function $\psi(t)$ and the time series data set $\{X_{train_l}\}\ l = \overline{0,29}$ for time intervals $T_{train_l} = [t_{24*l}; t_{i+24*l}]$, where $i = 24 * 365$. For each basis model, 30 iterations of calculations were carried out on a one-year time interval to average the error, where each cycle of iterations, starting from the second, is a shift of the previous one by a day ahead relative to its beginning and the end.

Output data: the values of the l-average relative error of electricity consumption values of each hour with the day-ahead forecasting in regard to the sample for the specified basis wavelet function $\psi(t)$.

The following steps are carried out:

Step 1. Determine the shift value $l = 0$.

Step 2. Make a forecast for the values $\{X_{for}\}$ according to the forecasting algorithm described above at time instants $T_{for} = [t_{i+24*l+1};\, t_{i+24*l+24}]$ (i.e. 24 hours ahead) using the sample $\{X_{train_l}\}$.

Step 3. Determine a relative error Δ_{lm}, $m = \overline{1,24}$ of the result for each forecast value of $\{X_{for}\}$ according to equation (4).

Step 4. If $l < 29$, then $l = l + 1$ and go back to Step 2.

Step 5. Average the value of the relative forecast error from l calculated values for each hour using equation (5).

The relative forecast error can be found by the following equation:

(4) $$\Delta_{lm} = \frac{|x_{lm}^* - \hat{x}_{lm}|}{x_{lm}^*} * 100\%$$

where *l* – the value of the selected shift relative to the beginning of the year, *m* – the hour for which the forecast is made, x_{lm}^* – the actual value of the considered parameter, $\hat{x}_{lm}$ – the forecast of the considered parameter.

The average value of relative forecast error for each hour of the model can be found as:

(5) $$\bar{\Delta}_m = \sum_{k=1}^{30}\Delta_{lm},\ m = \overline{1,24}$$

Using the values of the average relative error calculated for each basis function, it is possible to identify the best basis function for forecasting the considered parameter.

The coiflet of the 4th order (“coif4”) was determined as the best basis function, since it gave the maximum forecasts with the minimum average error. The maximum average value of relative forecast error for the selected basis wavelet is 18.65%. The results were obtained by computational experiments using the Python programming language with the help of the open source library PyWavelets (providing an interface for working with wavelet functions) and Statmodels (providing an interface for working with the ARMA model). Table 1 shows the values of the average relative forecast error of the model for each hour with a step of 4 in combination with the results of forecasting by vector and recurrent methods for visual comparison.

The forecast value is represented by the decomposition components in Figures 2-4 using the selected basis wavelet function.

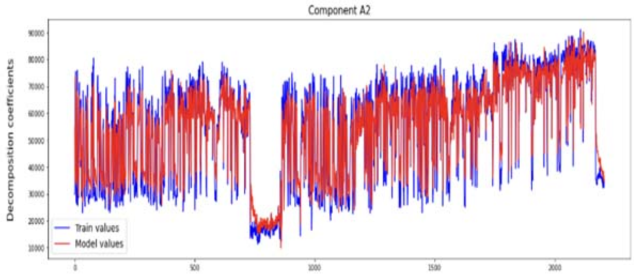

Fig.2. Decomposition coefficients of the A2 component

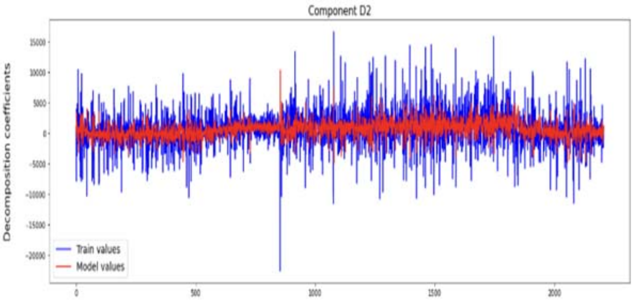

Fig.3. Decomposition coefficients of the D2 component

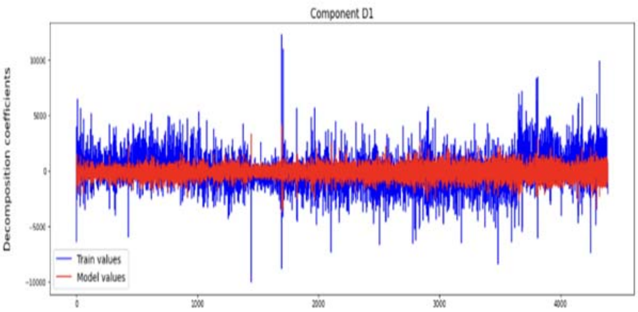

Fig.4. Decomposition coefficients of the D1 component

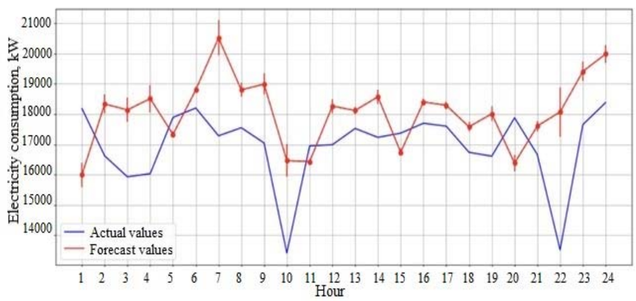

Fig.5. Comparison of actual and forecast values by the wavelet transform

Figure 5 shows the actual and forecast values of the considered electricity consumption for the period of 01.01.2011 01:00 - 02.01.2011 00:00 obtained using the developed forecast model with the selected training data for the period of 01.01.2010 00:00 - 01.01.2011 00:00. Forecast values are marked in red, and actual values are marked in blue.

Forecast Model Based on Singular Spectrum Analysis

Singular Spectrum Analysis (SSA) is a method for processing time series data based on the principal component analysis, which is sometimes called as the “Caterpillar” method. The method is quite simple and includes the advantages of regression analysis and Fourier analysis that makes it relevant for forecasting electricity consumption. Earlier, the SSA method was used only for linear data series [17-19]. The result of applying the SSA method is the analysis and identification of anomalous values (outliers) from the initial data series and a decrease of their influence on the forecast quality, as well as the determination of systematic components (trends).

Then, the SSA method is applied to analyze the initial data on electricity consumption, identify systematic components, trends, as well as noise and outliers reducing the quality of the forecast. The Singular Spectrum Analysis method is detailed in [20 – 25]. Data preprocessing is performed to remove noise components and outliers, and to identify individual features of the production process of the coal enterprise. Preprocessing is carried out for electricity consumption data of the enterprise presented in Figure 1.

In the SSA method, the following stages can be conventionally distinguished:

1. Processing and analysis of the initial electricity consumption data of the enterprise
2. Determining the optimal length for an electricity consumption data segment of retrospective time series of electricity consumption
3. Constructing the trajectory matrix
4. Application of principal component analysis

At the stage of using the principal component analysis, the search for systematic and non-systematic components is carried out, “anomalous” data is sifted out, and the data array is decomposed into principal components. Then, using the matrix of indices developed at the first stage, the order of data processing is reconstructed.

Forecasting Electricity Consumption of the Mining Enterprise

The matrix of approximated electricity consumption data is the basis for further forecasting the electricity consumption of the enterprise. The main criteria are the forecast accuracy and the adaptivity of the model to insignificant changes in the electricity consumption of end consumers. The forecast models based on the recurrent neural network and the vector method are presented below.

The forecast model based on the recurrent neural network

The structure of the model of a recurrent neural network allows forecasting even highly noisy data. The algorithm of the method sequentially processes each element of the entire data array, maintaining the internal condition obtained when processing the previous elements [26, 27]. The recurrent neural network model is a classical perceptron model consisting of three layers, one of which is hidden, and a set of additional input and output neurons. At each iteration, the input data is propagated over the neurons in the forward direction, after that a training rule is applied to them. There are feedbacks between the inputs, outputs and the hidden layer, each of which has a fixed weight, that allows storing the information about the previous iteration. This improves the trainability of the model and increases the quality of the forecast.

The forecast using the recurrent neural network is based on the following expression:

$$g_i = \begin{cases} y_i, \ i = 1, \dots, N; \\ \sum_{j=1}^{L-1} a_j g_{1-j}, \quad i = N+1, \dots, N+M \end{cases} \tag{6}$$

where y_i – the i-th value of the time series; a_j – the j-th value of the linear recurrence formula coefficient; L – dimension of the function; N – the length of the time series y; M – the depth of the forecast horizon.

The matrix of approximated data is a deterministic system, in which chaotic data is identified and eliminated using the SSA method. The system condition is determined by the parameter x. Using this parameter, the evolution of the system can be described in the following way:

$$\frac{dx}{dt} = f(x,t) \tag{7}$$

where *f (x, t)* is an unknown function.

To solve this equation, the Euler method is used with the corresponding sample spacing for the time series of

$$\frac{x_{n+1} - x_n}{\Delta t} = f(x_n, t_n) \tag{8}$$

or

$$x_{n+1} = \Delta t * f(x_n, t_n) + x_n \tag{9}$$

Expressions (8) and (9) are recurrent expressions that determine the value of x_{n+1} through a previous x_n. It is possible to obtain forecast values using the presented method with a monotonic increase or decrease of time series values. For these purposes, at the software level, a matrix of indices is composed, which is necessary for the subsequent ordering of the forecast values, and the vectors are formed:

$$\begin{cases} X_1 = \{x_1, x_2, \dots, x_{n-k}\} \\ X_2 = \{x_2, x_3, \dots, x_{n-k+1}\} \\ X_k = \{x_k, x_{k+1}, \dots, x_{n-1}\} \\ Y = \{x_{k+1}, x_{k+2}, \dots, x_n\} \end{cases} \tag{10}$$

The resulting forecast values are determined according to the following expressions:

$$x_{n+1} = g(x_{n-k}, \dots, x_n); \ x_{n+2} = g(x_{n-k+1}, \dots, x_{n+1}), etc. \tag{11}$$

The results of forecasting by the recurrent neural network method are presented in Figure 6 together with the results obtained by the vector method for comparative analysis of the methods.

The vector forecast model

The vector forecast model is a modification of the recurrent method, which is directly related to linear recurrence formulas. The procedure for obtaining the forecast values is iterative. During each iteration, it is possible to obtain only one forecast value [28 – 31]. All forecast values are determined on the basis of the trajectory matrix reconstructed in a lower dimension. The vector method in some cases surpasses the recurrent method in the accuracy of the given forecast. The data matrix processed earlier by the SSA method is taken as the initial data.

The application of the vector method can be conventionally divided into several stages.

In the beginning, the first forecast value is determined. Determination of the forecast value is carried out step by step as presented below.

Step 1. Calculation of the ordinates of the integral vector (P_1^{N-2}, P_2^{N-2}) using the recurrence formula:

$$P_i^n = \frac{P_i^{n-1} + P_{i+1}^{n-1}}{2}, \tag{12}$$

where n – the number of the averaging stage, $n = 1, \overline{(N-2)}$; i – the ordinal number of the point corresponding to the value of the volumetric characteristic at the n-th stage of averaging, $i = 1, \overline{(N-n)}$.

Step 2. Calculation of the average duration of the analyzed period:

$$t_c = \frac{\sum_{i=1}^{N} t_i}{N-1} \tag{13}$$

Step 3. Calculation of the center of the analyzed period:

$$t_ц = \frac{\sum_{i=2}^{N} t_i}{2} \tag{14}$$

Step 4. Calculation of the time period ta, for which the behavior of the system is forecasted when counting from the first point of the integral vector $(P_1^{(N-2)})$:

$$t_a = t_ц + \frac{t_c}{2} + t_{N+1} \tag{15}$$

Step 5. Calculation of the change in the system behavior in relation to the analyzed period of the average length Δp:

$$\Delta p = P_2^{N-2} - P_1^{N-2} \tag{16}$$

Step 6. Calculation of the change in the system behavior in the first forecast period:

$$\Delta P = \frac{\Delta p \times t_a}{t_c} \tag{17}$$

Step 7. Determination of the system behavior in the first forecast period:

$$P_{N+1} = P_1^{N-2} + \Delta P \tag{18}$$

At the next stages, the rest of the forecast values are determined similarly to the algorithm of the first stage. At the second and subsequent stages, information about the forecast value obtained during the previous iteration is used for training the model. The dimension of the data array does not change throughout the iterations. The calculations are completed after obtaining all the forecast values for a given time interval.

Figure 6 presents a comparative analysis of forecast values with actual data for the recurrent neural network and the vector method.

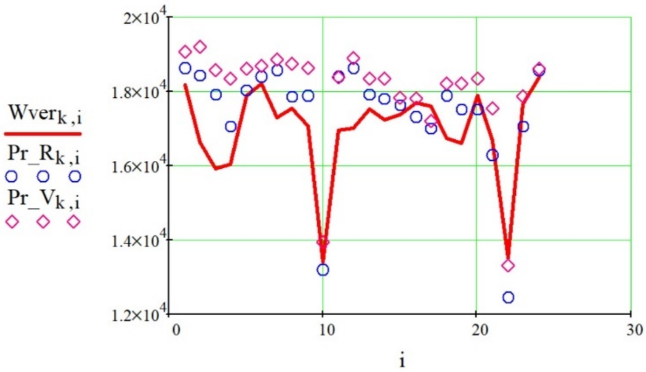

Fig.6. Comparison of forecast and actual values for the recurrent neural network and the vector method,
where the solid line is actual data, dots are the forecast values of the recurrent neural network, and the diamonds are the forecast values of the vector method. The abscissa is hours, and the ordinate is electricity consumption, kW*h.

The maximum deviation for the recurrent neural network is 12.491%, for the vector method – 16.568%, and for the wavelet transform – 18.650%. Table 1 shows the deviations of the forecast values by three forecast methods from the actual data for selected control hours.

Table 1. Average relative forecast errors for selected control hours

Recurrent neural network		Vector method		Wavelet transform	
Hour	Deviation, %	Hour	Deviation, %	Hour	Deviation, %
4	6.313	4	14.374	4	10.080
8	1.747	8	6.785	8	12.210
12	9.571	12	11.121	12	13.230
16	2.120	16	0.611	16	15.650
20	2.021	20	2.605	20	17.740
24	1.107	24	1.183	24	18.650

Discussion of Results

It is shown that the best result was shown by the recurrent neural network with the largest average forecast error of 12.491%, the vector method with the largest average forecast error of 16.568% was in the second place, and the wavelet transform method with the largest average forecast error of 18.650% was in the third place.

The highest forecast error of the wavelet transform method is probably caused by the insufficient degree of data processing within the method and the need for additional data preprocessing.

The adequate results were obtained for the recurrent neural network and the vector method after application of the methodologies. The quality of the forecast depends on the optimal parameter settings of the Singular Spectrum Analysis method.

The disadvantage of the SSA method is the need to select the optimal length of the “caterpillar” that requires higher computation capacity for a large time series of electricity consumption data of an enterprise. However, the obtained forecast data and a low average daily forecast error indicate the successful implementation of the method and great prospects for its application in the future. Optimizing the choice of a data fragment length is a promising direction for further investigations.

The structure of the models allows taking into account the individual features of the operating cycle of the production process, as well as identifying and smoothing the “noise” components of this production process. The results of short-term electricity consumption forecast were verified in order to assess the adequacy of the models to the actual values.

Conclusions

1. A new conception of predictive control of the production process of an enterprise based on the forecast by the wavelet transform, the recurrent neural network and the vector method is proposed. This corresponds to international energy conceptions for the modernization and development of the power engineering industry. Based on the results of applying three mathematical models, it can be seen that the recurrent neural network gave more accurate forecast values in comparison with wavelet analysis and the vector method.

2. The structure of the models allows taking into account the individual features of the production process of the enterprise, identifying the trends and systematic components. The proposed models can be applied in automated systems for predictive control of the technological process of an industrial enterprise.

3. Data preprocessing by the Singular Spectrum Analysis method has a significant positive effect on the quality of the forecast. At the same time, the structure of the method allows identifying systematic components and trends, eliminating noise components and outliers. The adaptivity of the model to insignificant changes in electricity consumption directly depends on the correct selection of the “caterpillar” length that is, in turn, a separate element of the further investigation.

4. Short-term forecasting of electricity consumption will allow increasing the efficiency of power supply system operation for a mining enterprise by controlling consumption during peak hours and reducing a load peak and optimizing the selection of price categories.

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