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Formation of a stable price for energy resources by solving a non-linear dynamic problem as an element of socio-economic stability of the economy

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Annotation
Relevance. The authors note that the formation of a stable price for natural resources and the possibility of smoothing the price during fluctuations not only in demand for them, but also changes in the supply schedule for economic and other reasons require the development of an economic model; they are very relevant.
***The purpose of the study*:** identifying the possibilities of forecasting energy prices in the event of price fluctuations and the formation of various levels of demand in the market and taking into account market and non-market methods for its regulation.
Results of the study. Studying various processes and problems in the field of economics, the authors propose using various types of linear and nonlinear boundary value problems for ordinary differential equations. This paper shows that the theory of boundary value problems for nonlinear differential equations is one of relevant factors in predicting energy prices in the structure of the economic development program. The authors define modeling tasks for the purpose of adjusting energy demand for a long time. This paper notes that the formation of demand for energy resources in addition to the standard time lag, which determines seasonality, also requires adjustment due to the need to formulate the socio-economic task of smoothing demand.
Conclusions. The economic and mathematical models presented in the paper are universal and can be used by business entities, state bodies which form the demand and consumption of energy resources in the country. This will contribute to increasing the efficiency of managing the country's energy complex and ensuring integrated activities focused on making informed and timely decisions in other business facilities.

Keywords: formation of price, smoothing of demand, solution of dynamic problem, economic modeling, level of consumption, linear processes.

Introduction

Energy markets are an important source of information that is unique in speed and quality. Energy prices instantly take into account any new information, both objective and subjective (rumors, expectations and hopes). Thus, an important scientific task is the analysis of information circulating in the markets with the aim of making economic decisions better and more justified.

Among the **variety of methods** that can be used to analyze energy markets (general scientific, economic and logical, economic and mathematical), forecasting is the most problematic and complex. This is due to both the high complexity of the processes taking place in the energy markets and the lack of agreement in the academic community on the fundamental possibility of forecasting in the energy markets. At the same time, forecasting provides a unique opportunity to look into the future. From the perspective of the economic system as a whole, forecasting is a necessary tool for forming a strategy and tactics for its development. When making specific economic decisions, forecasting allows you to get competitive advantages, and therefore provides the opportunity to make the best decision. For participants in energy markets, this means generating additional revenue and even surplus profit. Indeed, investments in an undervalued asset will provide an opportunity not only to generate income equivalent to market income, but also additional income due to its more active dynamics relative to the average market.

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Results and their application

In general, forecasting is a prediction of future events, i.e., in essence, it is a study of an object that does not yet exist. Forecasting is an activity aimed at the formation of a certain judgment regarding unforeknowable future. Forecasting in its narrow sense is the process of making forecasts. Forecast refers to a system of scientifically based ideas about the possible conditions of the object in the future and some alternative ways of its development [1]. We should distinguish between the concepts that stand next to the concepts of "forecast" and "forecasting" when it comes to predicting the future. First of all, it concerns the concepts of "plan" and "hypothesis". The hypothesis that characterizes scientific prediction from the perspective of a general theory is a narrower concept, since it is based only on the qualitative characteristics of the phenomenon [2], while forecasting has a greater level of certainty since it is based on both qualitative and quantitative indicators. As for a plan, the fundamental difference between the plan and the forecast is that the plan is prescriptive in nature while the forecast is probabilistic. At the same time, the forecast acts as the basis for their preparation [3].

The purpose of forecasting is to reduce risk in decision-making by obtaining scientifically based options for trends in the development of certain processes, phenomena. The subject of forecasting is the patterns of development of objects (processes, phenomena) in the past and their state in the future, which must be investigated and known. The main objective of forecasting is to clarify the prospects for the future development of the forecasting object. Forecasts play an important role in the economic system [4]. Their role is in the functions that perform forecasting in the economy. The main ones are:

– scientific analysis of the processes that take place in the economic system, causal relationships that arise in the process of economic activity, assessment of the current economic situation;

– estimation of the object of forecasting;

– assessment of future development trends and prediction of new economic conditions and problems to be addressed;

– identification of possible alternatives to the development of the projected object.

The variety of functions performed determines the presence of a significant number of specific features of the forecast. So, in terms of use, forecasts are divided into economic, financial, social, technological, etc. [5]. There are operational (up to one month), short-term (from a month to one year), medium-term (from one to five years) and long-term (from five or more years) forecasts depending on the forecasting horizon [6]. The scale of the forecast can be:

– macroeconomic;

– branch;

– regional;

– at the level of individual economic entities;

– at the asset level.

Forecasts for objects can be subdivided into a forecast of indicators of the enterprise, industry, macroeconomic indicators, demand and supply for assets and their prices, development of the social sphere, forecasting the number of natural resources, etc. Among the variety of forecasts in this work, we are primarily interested in economic forecasts. Economic forecasting is the process of developing economic forecasts based on scientific methods of cognition of economic phenomena and the use of the totality of methods and methods of economic forecasting [7].

The forecasting methodology assumes the existence of certain principles and methods on which this process is based. The basic provisions for the formation of forecasts (principles) include the following:

– approach of alternativeness – reflects the probabilistic nature of the development of the object and its individual components as a result of the influence of random processes, which leads to the emergence of a number of options for the future;

– systemic approach – provides an integrated approach to forecasting, which includes the creation of a system of methods, models, data arrays that will provide the most coherent picture of the development of a forecasting object;

– approach of focus and priority – the forecast should be subject to a specific goal and be aimed at achieving certain goals;

– integrated approach – a subject of research must be considered in the context of all its possible characteristics, in the totality of its cause-effect relationships with other phenomena and processes;

– optimality approach – as a predicted value, it is appropriate to take the alternative that has the highest probability of implementation, the most effective option [8].

A key element of the forecasting methodology is the choice of forecasting methods [9]. The forecasting method is understood as a set of thinking methods and techniques that derive judgments of certainty regarding the future development of an object (based on the analysis of data and their changes in the considered period of time) [10]. As for forecasting methods in the economy, there are from 150 to 250 despite the fact that no more than 15–20 are used [11]. Based on the significant number of available forecasting methods, we can see that there is pluralism in the theory by their classification. From the standpoint of the goal of our study (forecasting prices in energy markets), we consider it appropriate to use the following classification [12].

Methods of expert assessment are widely used in the economic sphere and in energy markets forecasting in particular. The methods of this group include a survey of experts (collective or individual) according to a certain algorithm. The result is the formation of a forecast for the phenomenon or process, which is the object of forecasting. The main advantages of this group of methods are the relative simplicity and speed of formation of the predicted value. Moreover, expert estimates can be used in the formation of forecast models, for example, in determining weighting coefficients, indicator values, etc. The disadvantages are a high level of subjectivity in making the forecast, a limited number of experts and an actual lack of responsibility for the forecast values.

The separation of forecasting methods into stochastic and deterministic is due to the need to take into account the specifics of the analyzed data when making the forecast. The question is the characteristics of data behavior – random changes or the presence of a certain kind of relationship between data. Stochastic methods are used to analyze data having a probabilistic nature of communication and forecasting. It is the case that the methods of this group are the most commonly used to predict the processes occurring in the economy, especially in financial markets. Prices in energy markets are influenced by a significant number of multidirectional factors, which can also be different. Ranging from the volumes of supply and demand to political events and force majeure. As a result, prices in energy markets acquire characteristics of random values. For their analysis, methods of analysis of time series and regression analysis can be used. Deterministic methods, in contrast to stochastic ones, presume rigid functional connections between the studied processes and phenomena. Accordingly, the forecasting process is a search for a function that would describe these relationships. The forecast, in this case, is finding a specific productive sign depending on the specific value of the factor sign(s). For example, knowing the amount of dividends, you can determine the price of a share.

Summing up the analysis of scientific and methodological foundations of forecasting, we determine the main stages of this process. It is worth noting that any forecast is probabilistic. In this context, the most important characteristic of forecasting as a process is its accuracy; that is, the generation of information about the future with a minimum probability of error. The question is the difference in the predicted and actual value of the indicator. The smaller the difference, the more accurate and qualitative the forecast is; the less the forecast error. The main options for improving the quality of forecasts are:

– increasing the volume of analyzed information;

– application of more complex and developed methods and technologies;

– forecasting by expanding the set of indicators characterizing the object of forecasting;

– allocation of large resources for the organization and provision of the forecasting process;

– ensuring comparability of data;

– use of forecasting methods and technologies that evaluate existing data sets.

Forecasting in energy markets is a specific area of scientific research and a specific type of forecasting. It should be distinguished from financial forecasting as such. Financial forecasting is a study of specific prospects for the development of finances of business entities and government in the future, a scientifically based assumption about the volumes and directions of the use of financial resources for the future. Financial forecasting reveals the expected future pattern of the state of energy resources, possible options for the implementation of financial activities is a condition for financial planning [13]. Therefore, the main goal of financial forecasting is to assess the future state of financial resources. As you can see, the object and purpose of financial forecasting are different from the goals and objectives that forecasting faces in financial markets. Forecasting objects are primarily asset prices, their future values and trends. The key task of price forecasting in energy markets in this case can be obtaining future values of asset prices or, at least, getting an idea of their trends and direction in the future.

As for the specific features of forecasting prices in financial markets, the following should be included. Unlike classical macroeconomic data that form time-series of dozens of meanings, information on energy markets can contain hundreds of thousands of meanings that significantly increase the ability to formulate a qualitative forecast. The specificity of forecasting in energy markets is the relative availability of data. Current quotes, as well as arrays of historical data, are freely available, which makes it possible to analyze them without additional transaction costs. Ultimately, this makes the forecasting process easier.

The problem that analysts may encounter when forecasting prices in energy markets is the typical nature of data. By typical nature, in this case, we mean that the data should characterize similar processes and meet the same statistical characteristics (for example, random data). If a certain data range is stochastic and the other deterministic, then the use of a specific specialized mathematical apparatus (for example, the law of normal distribution and its rules for the analysis of random variables) can lead to incorrect conclusions, since the accuracy of the forecast directly depends on the choice of method forecasting. Using linear models for a data array of non-linear origin will lead to a false forecast.

The peculiarity of forecasting in energy markets is the diversity of forecasting horizons. These are different data intervals. If classical macroeconomic indicators usually provide information in time horizons – month, quarter, year, then information on financial markets is more diverse. Not only the listed time intervals are available, but some shorter forecast horizons as well. It is about the availability of weekly, daily, hourly, and even minute data intervals. This greatly expands the possibilities of forecasting and expands its range; on the other hand, it makes the process more complex and diverse. The presence of a wide range of time intervals allows you to make more diverse decisions. We mean not just long-term or medium-term, but short-term and extra-long at intervals of day as well (hour or even minute). The current trend is the generation of long-range forecasts when it comes to seconds. The example is high-frequency trading and forecasting future prices online. The specificity of forecasting in energy markets is that the purpose of forecasting can be not only to obtain the future value of price, but also to determine the trends in its movement and the moments when this trend will change. Another feature of forecasting in energy markets is the widespread use of automation. Using mechanical trading systems, trading robots allows you to analyze information and make decisions based on the forecasts received without human intervention. This emphasizes the importance of choosing the best forecasting methodology as the basis for the algorithm of computer systems.

The specificity of forecasting in energy markets is also determined by the used methods. On the one hand, some standard methods are used for forecasting in the financial markets (they were mentioned above); on the other hand, the specificity of pricing in energy markets necessitates the use of a number of specific forecasting methods. In general, there are three scientific and methodological approaches to forecasting financial markets:

1) technical analysis;

2) fundamental analysis;

3) intuitive method [14].

Within the technical analysis, past values of prices are analyzed. Then the conclusion about future prices is made. It uses data extrapolation technologies, time series smoothing, modeling future prices using neural networks, genetic algorithms and other specific methods, and approaches [15]. Fundamental analysis involves determining the fair value of an asset. If it differs from the current market price, we conclude that it is likely to move closer to fair value. For this, a significant array of macroeconomic statistics is studied, and the influence of various economic, political, and force majeure factors are taken into account [16]. Intuitive approach involves the formation of forecasts based on certain expert or personal estimates based on the experience of past decisions or intuitive feelings [17]. Of course, the intuitive approach can hardly be called scientific; therefore more attention should be paid to technical and fundamental analysis.

Currently, there is an increased interest in complex discrete systems, most of which are non-linear. For their adequate description, new modeling methods are needed in comparison with well-developed linear analysis methods [18]. Nonlinear dynamics (nonlinear science) focuses on new types of behavior in nonlinear systems, namely dynamic chaos – the occurrence of irregular movements in deterministic systems in which complex sources of unbalanced motion are possible without random noise; it can hurt prices for energy resources. Nonlinear difference equations are often found in the study and when modeling of various applied problems in economics and in other disciplines. In economics, nonlinear difference equations appear, in particular, when analyzing the convergence of various iterative processes, such as ensuring a single price for energy commodities combined with social tasks, such as maintaining the selling price for the population [19]. In the theory of difference equations, it is assumed that the indicators of economic process are investigative; they are determined at discrete points in time. The feasibility of such a consideration is determined by the initial data on the economic process, which are often measured at discrete points in time (official statistics, periodic surveys, censuses, etc.). The time interval can be a five-year period, a year, a quarter, a month, a week, etc. If the interval becomes infinitely small, then the process is considered as continuous and it is studied using the theory of differential equations. In this regard, it is necessary to adjust the maximum level of the impact of time on the behavior of the economic system of energy commodities. The behavior of the system in discrete time is determined using the difference equation, which connects the value of the economic indicator studied at the neighboring moments of time [20]. When modeling economic processes one can often use an equation.

$$x_i = F\left(x_{i-1}, x_{i-2}, \ldots, x_{i-n}\right), \tag{1}$$

where the value of x_i at any point in time $t_i = i\ddot{A}t, i = n+1,\ n+2,\ldots$ depends on its values in the previous n points in time $t_{i-1}, t_{i-2}, \ldots, t_{i-n}$. This equation is a difference, or recurrent equation of n-th order.

The solution to the difference equation is a sequence $x_k\left(k = 0,1,2,\ldots\right)$, that turns it into an identity. The solution of the equation (1) can be found if you specify n so-called initial conditions, for example, $x_0, x_1, \ldots, x_{n-1}$. Substituting the initial conditions in the right part of the equation (1), we find x_n, then using values we find x_{n+1}, x_{n+2}. Equation

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_n x_{t-n} + \alpha_0\left(t\right), \tag{2}$$

where α_1, α_2, ..., α_n are the coefficients of the equation, it is an n-th order linear difference equation with stable coefficients. The equation is called homogeneous if $\alpha_0\left(t\right) \equiv 0$, and heterogeneous otherwise.

In the theory of difference equations, it is proved that the general solution of equation (2) is equal to the sum of the general solution of the corresponding homogeneous equation

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \ldots + \alpha_n x_{t-1}$$

and any specific solution of the heterogeneous equation (2).

Equation

$$x_t = \alpha x_{t-1} + \alpha_0\left(t\right), t = 1,2,\ldots$$

is called a linear difference equation of the first order.

The general solution of the homogeneous equation

$$x_t = \alpha x_{t-1}$$

is a geometric progression $x_t = C\alpha^t$, where C is an arbitrary constant. The following options are available:

$0 < \alpha < 1, -x_t$ monotonously falls;

$\alpha > 1, -x_t$ monotonously increases;

$-1 < \alpha < 0, -x_t$ alternately changes the sign, $|x_t|$ monotonously falls;

$\alpha < -1, -x_t$ alternately changes the sign, $|x_t|$ monotonously increases;

$\alpha < -1, -x_t$

$\alpha - 1 - x_t$ has the form of oscillatory movements,

$$x_t \begin{cases} C, t = 0,2,\ldots,2n,\ldots \\ -C, t = 1,3,\ldots,2n+1,\ldots \end{cases}$$

Here is the solution of an inhomogeneous equation. Let us consider two characteristic options.

1. If $\alpha_0 = \text{const}$ and $\alpha \neq 1$, then the specific solution of the inhomogeneous equation

$$x_t = \alpha x_{t-1} + \alpha_0$$

we search in the form of a constant $x_{nh} = C_0$.

After substituting in the equation, we get $C_0 = \alpha C_0 + \alpha_0$, or

$$C_0 = \frac{\alpha_0}{1-\alpha}; x_{nh} = \frac{\alpha_0}{1-\alpha}.$$

If $\alpha = 1$, then the specific solution of the $\alpha < -1, -x_t$ inhomogeneous equation is as follows:

$$x_{tnh} = C_0 t.$$

After substituting in the equation, we get

$$C_0 t = C_0 (t-1) + \alpha_0; C_0 = \alpha_0; x_{nh} = \alpha_0 t.$$

2. If the difference equation is as follows:

$$x_t = \alpha x_{t-1} + \alpha_0 d^t,$$

then in case the $\alpha \neq d$, specific solution of the inhomogeneous equation is sought as follows:

$$x_{nh} = C_0 d^t.$$

After substituting in the equation, we get

$$C_0 d^t = \alpha C_0 d^{t-1} + \alpha_0 d^t; C_0 = \frac{\alpha_0 d}{d-\alpha}; x_{nh} = \frac{\alpha_0}{d-\alpha} d^{t+1}.$$

The linear difference equation of the second order with constant coefficients is written as follows:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \alpha_0, t = 2, 3, \ldots.$$

Solution of a homogeneous equation

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} \tag{3}$$

we search in the form of $x_t = \lambda^t$. Substitution $x_t = \lambda^t, x_{t-1} = \lambda^{t-1}, x_{t-2} = \lambda^{t-2}$ in the equation (3) give the so-called characteristic equation to determine λ:

$$\lambda^2 - \alpha_1 \lambda - \alpha_2 = 0. \tag{4}$$

Let us indicate its roots λ_1, λ_2, where

$$\lambda_{1,2} = \frac{\alpha_1 \pm \sqrt{D}}{2}; D = \alpha_1^2 + 4\lambda_2.$$

In the theory of difference equations, we prove that the general solution of equation (3) is as follows:

$$x_t = A_1 \lambda_1^t + A_2 \lambda_2^t; \lambda_1 \neq \lambda_2; x_t = (A_1 + A_2 t)\lambda^t; \lambda_1 = \lambda_2,$$

where A_1, A_2 are arbitrary constants.

The solution of equation (4) λ_1, λ_2 depends on discriminant D.

3. If the equation $x_t = \alpha x_{t-1} + \alpha_0 d^t$, then in the case $\alpha = d$, the specific solution of the inhomogeneous equation is as follows:

$$x_{nh} = C_0 a^t.$$

After substituting in the equation, we get

$$C_0 d^t = \alpha C_0 d^{t-1} + \alpha_0 d^t; C_0 = \frac{\alpha_0 d}{d-\alpha}; x_{nh} = \frac{\alpha_0}{d-\alpha} d^{t+1}.$$

Three options are available:

1) $D \leq 0, \lambda_1 \lambda_2$ — valid and different, general solution is found by the formula

$$x_t = A_1 \lambda_1^t + A_2 \lambda_2^t;$$

2) $D = 0$ – characteristic equation has the same roots $\lambda_1 = \lambda_2$, then

$$x_t = (A_1 + A_2 t)\lambda^t x_t = (A_1 + A_2 t)\lambda^t;$$

3) $D > 0, \lambda_1 \lambda_2$ — complex conjugate

$$\lambda_{1,2} = \alpha \pm i\beta,$$

where

$$\alpha = \frac{\alpha_1}{2}, \beta = \sqrt{-D}, i^2 = -1,$$

or using the trigonometric form of a complex number, we find

$$\lambda_{1,2} = \rho(\cos\omega \pm i \sin\omega); \rho = \sqrt{\alpha^2 + \beta^2} = \sqrt{-a_2}; \operatorname{tg}\omega = \beta/\alpha.$$

The solution of equation (3) is based on the formula

$$x_t = \rho^t (B_1 \cos \omega t \pm B_2 \sin \omega t),$$

where B_1, B_2 – became arbitrary constants.

Thus, if $D > 0$, the solution is about oscillations whose amplitude increases, if $\rho > 1$ or decreases, if $\rho < 1$. If $\rho = 1$ we will have an oscillatory mode of behavior of solutions.

If

$$\lambda_1 \neq 1, \lambda_2 \neq 1,$$

then the specific solution of the heterogeneous equation

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \alpha_0$$

we find in the form of stable $x_{nh} = C_0$. After substitution in the equation we get

$$C_0 = \frac{\alpha_0}{1 - \alpha_1 - \alpha_2}.$$

If just one of the roots of the characteristic equation is equal to one

$$\lambda_1 = 1, \lambda_2 = 1,$$

(in this case, obviously, $1 - \alpha_1 - \alpha_2 = 0$), the specific solution of the inhomogeneous equation is as follows:

$$x_{nh} = C_0 t.$$

After substituting in the equation, we get

$$C_0 = \frac{\alpha_0}{\alpha_1 + 2\alpha_2}.$$

In this way,

$$x_{tnt} = \frac{\alpha_0}{\alpha_1 + 2\alpha_2} t.$$

An example is the fluctuation of prices for energy futures during their production under contracting conditions. Let us solve the equation

$$x_t = 2x_{t-1} - 0,99 x_{t-2} + 1, x_0 = 1, x_1 = 2.$$

Here is the solution. The roots of the characteristic equation $\lambda^2 - 2\lambda + 0,99 = 0$ are calculated as follows: $\lambda_1 = 0,9, \lambda_2 = 1,1$. Therefore, the overall solution of a homogeneous equation is as follows:

$$x_{Gt} = C_1 (0,9)^t + C_2 + (1,1)^t.$$

We seek the specific solution to the inhomogeneous equation in the form of a stable $x_t = \bar{x}$. Substituting $x_t = \bar{x}$ into the original equation, we obtain

$$\bar{x} = 2\bar{x} + 1, \bar{x} = -100.$$

Constant C_1, C_2 are determined from the initial conditions $x_0 = 1 x_1 = 2.$ Then

$$\begin{cases} C_1 + C_2 = 101; \\ 0,9\,C_1 + 1,1\,C_2 = 102; \end{cases} \quad C_1 = \frac{91}{2}; C_2 = \frac{111}{2}.$$

In mathematical terms, the problems of formation of energy reserves can also be solved by these types of equations. Let us try to solve the equation

Here is the solution. The roots of characteristic equation are $\lambda^2 + 2\lambda + 2 = 0$ complex:

$$x_t = -2x_{t-1} - 2x_{t-2} + 5; x_0 = 1; x_1 = 2.$$

$$\lambda - 1 \pm i = \sqrt{2}\left(\cos\frac{3\pi}{4} \pm i\sin\frac{3\pi}{4}\right).$$

Therefore, the overall solution of the homogeneous equation

$$x_{Gt} = 2^{t/2}\left(C_1\cos\frac{3\pi}{4}t + C_2\sin\frac{3\pi}{4}t\right).$$

We find the specific solution to the inhomogeneous equation in the form of a stable $\bar{x}_t = \bar{x}$. Substituting this expression into our equation, we obtain $\bar{x} = 1$. General solution of the equation:

$$x_t = 2^{t/2}\left(C_1\cos\frac{3\pi}{4}t + C_2\sin\frac{3\pi}{4}t\right) + 1.$$

Constants C_1, C_2 are determined from the initial conditions $x_0 = 1, x_1 = 2$:

$$\begin{cases} C_1 + C_2 + 1 = 1; \\ \sqrt{2}\left(C_1\cos\frac{3\pi}{4} + C_2\sin\frac{3\pi}{4}\right) + 1. \end{cases}$$

Result $C_1 = 0, C_2 = 1, x_t = 2^{t/2}\sin\frac{3\pi}{4}t + 1.$

In the tasks of energy management there is always a probability factor for the early termination of supplies of this type of resources. Let us form and solve this task with the help of an equation

$$x_t = -2x_{t-1} - x_{t-2} + 4, x_0 = 1, x_1 = 2.$$

Here is the solution. The characteristic equation $\lambda^2 + 2\lambda + 1 = 0$ has a multiple root $\lambda_1 = \lambda_2 = -1.$ Therefore, the general solution of the homogeneous equation is written as follows:

$$x_{Gt} = (-1)^t (C_1 + C_2 t).$$

We find the specific solution of the inhomogeneous equation in the form of stable $\bar{x}_t = \bar{x}$. Substituting $\bar{x}_t = \bar{x}$ into the original equation, $\bar{x} = 1.$ The general solution of the equation will be as follows:

$$x_t = (-1)^{t+1} t + 1.$$

The difference equation is written as follows:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \alpha_0 d^t,$$

then if the roots of the characteristic equation do not converge with *d*, that is the $\lambda_1 \neq d, \lambda_2 \neq d,$ specific solution of the inhomogeneous equation is as follows:

$$x_{tnh} = C_0 d^t.$$

After substituting in the equation, we get

$$C_0 = \frac{\alpha_0 d^2}{d^2 - \alpha_1 d - \alpha_2}; x_{tnh} = \frac{\alpha_0 d^{t+2}}{d^2 - \alpha_1 d - \alpha_2}.$$

The system of linear difference equations of the second order with constant coefficients is as follows:

$$x_t = \alpha_{11}x_{t-1} + \alpha_{12}y_{t-1} + b_1;$$
$$y_t = \alpha_{21}x_{t-1} + \alpha_{22}y_{t-1} + b_2,$$

where x_t, y_t are unknown sequences; $\alpha_{11}, \alpha_{12}, b_1, \alpha_{21}, \alpha_{22}, b_2$ — constants. $t = 1, 2, \ldots$ Such a system is called homogeneous, if $b_1 = b_2 = 0$, heterogeneous – in another variant.

We will consider the case $\det A = \alpha_{11}\alpha_{22} - \alpha_{12}\alpha_{21} \neq 0.$ of replacing unknown variables

$$x_t = u_t + x_*, y_t = v_t + y_*,$$

where x_*, y_* — solutions of the system of linear algebraic equations

$$\alpha_{11}x_* + \alpha_{12}y_* + b_1 = 0;$$
$$\alpha_{21}x_* + \alpha_{22}y_* + b_2 = 0,$$

it comes down to a homogeneous

$$u_t = \alpha_{11}u_{t-1} + \alpha_{12}v_{t-1};$$
$$v_t = \alpha_{21}u_{t-1} + \alpha_{22}v_{t-1}.$$

It can be reduced to a linear difference equation of the second order with constant coefficients, for example, in this way: we can write the first equation (1) for the moment $t + 1$:

$$u_{t+1} = \alpha_{11}u_t + \alpha_{12}v_t = \alpha_{11}u_t + \alpha_{12}\left(\alpha_{21}u_{t-1} + \alpha_{22}v_{t-1}\right) = \alpha_{11}u_t + \alpha_{12}\alpha_{21}u_{t-1} + \alpha_{22}\left[u_t - \alpha_{11}u_t\right],$$

or

$$u_{t+1} - \left(\alpha_{11} + \alpha_{22}\right)u_t + \det A u_{t-1} = 0.$$

This equation can be solved in the way described earlier and we get u_t, as $u_t = A_1\lambda_1^t + A_2\lambda_2^t$, and then v_t. However, it is more convenient to do in this way:

Let us write the system (2) in matrix form

(5) $$z_t = \begin{pmatrix} u_t \\ v_t \end{pmatrix} = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}\begin{pmatrix} u_{t-1} \\ v_{t-1} \end{pmatrix} \equiv Az_{t-1}.$$

Substitution

$$z_t = \begin{pmatrix} U \\ V \end{pmatrix}\lambda^t = e\lambda^t$$

reduces equation (5) to the task by eigenvalues

$$e\lambda^t = \lambda^{e-1}Ae; Ae = \lambda e; \begin{pmatrix} \alpha_{11}-\lambda & \alpha_{12} \\ \alpha_{21} & \alpha_{22}-\lambda \end{pmatrix}\begin{pmatrix} U \\ V \end{pmatrix} = 0,$$

where λ, e – eigenvalues and corresponding vectors, or

(6) $$\begin{cases} \left(\lambda - \alpha_{11}\right)U - \alpha_{12}V = 0; \\ -\alpha_{21}U + \left(\lambda - \alpha_{22}\right)V = 0. \end{cases}$$

The eigenvalues λ_1, λ_2 are determined from the characteristic equation

$$\begin{vmatrix} (\lambda - \alpha_{11}) - \alpha_{12} \\ -\lambda_{21}(\lambda - \alpha_2) \end{vmatrix} = \lambda^2 - \left(\alpha_{11} + \alpha_{22}\right)\lambda + \alpha_{11}\alpha_{22} - \alpha_{12}\alpha_{21} = 0.$$

Let the roots λ_1, λ_2 different. Substituting $\lambda = \lambda_1, \lambda = \lambda_2$ in any of the equations of the system (6), we define eigenvectors

$$e_1 = \begin{pmatrix} U_1 \\ V_1 \end{pmatrix}; e_2 = \begin{pmatrix} U_2 \\ V_2 \end{pmatrix}.$$

The overall solution of the system is found by the formula

$$z_t = C_1\lambda_1^t e_1 + C_2\lambda_2^t e_2$$

or

$$u_t = C_1U_1\lambda_1^t + C_2U_2\lambda_2^t; v_t = C_1U_1\lambda_1^t + C_2U_2\lambda_2^t, \quad (7)$$

where C_1, C_2 are arbitrary constants.

The formula (7) is convenient to use when λ_1, λ_2 are real numbers. If λ_1, λ_2 — complex conjugate

$$\lambda_{1,2} = \alpha \pm i\beta\, \lambda_{1,2} = \rho\left(\cos\vartheta \pm i\sin\vartheta\right),$$

and $e_{1,2} = e_{\mathrm{Re}} \pm ie_{\mathrm{Im}} \equiv \begin{pmatrix} U_R \\ 0 \end{pmatrix} \pm i\begin{pmatrix} 0 \\ U_{\mathrm{Im}} \end{pmatrix}$,

then the overall solution of the system can be found using the formula

$$z_t = \rho^t\left[\left(C_1\cos t\,\vartheta + C_2\sin t\,\vartheta\right)e_{\mathrm{Re}} + \left(-C_1\sin t\,\vartheta + C_2\cos t\,\vartheta\right)e_{\mathrm{Im}}\right]$$

or

$$u_t = \rho^t U_{\mathrm{Re}}\left(C_1\cos t\,\vartheta + C_2\sin t\,\vartheta\right); v_t = \rho^t U_{\mathrm{Im}}\left(-C_1\sin t\,\vartheta + C_2\cos t\,\vartheta\right), \quad (8)$$

where C_1, C_2 are arbitrary constants. $\rho = \sqrt{\alpha^2 + \beta^2}$, $\cos\vartheta = \frac{\alpha}{\rho}$, $\vartheta = \frac{\beta}{\rho}$.

Let us consider the option when the delay in the receipt of energy resources is nonlinear (chaotic). We solve the task at which the delay in the receipt of resources is possible

$$u_t = -u_{t-1} - 2v_{t-1}, v_t = 3u_{t-1} + 4v_{t-1}.$$

The system in this version is as follows:

$$\begin{cases} \left(\lambda + 1\right)U + 2V = 0; \\ -3U + \left(\lambda - 4\right)V = 0. \end{cases}$$

The roots of the characteristic equation

$$\begin{vmatrix} \lambda + 1 & 2 \\ -3 & \lambda - 4 \end{vmatrix} = \lambda^2 - 3\lambda + 2 = 0$$

are valid: $\lambda_1 = 1, \lambda_2 = 2$. Substituting $\lambda_1 = 1$ into the system, we get

$$\begin{cases} 2U_1 + 2V_1 = 0; \\ -3U_1 - 3V_1 = 0. \end{cases}$$

The second equation is a consequence of the first, and the solution is determined with precision to the stable multiplier $V_1 = -U_1$. For example, $U_1 = 1$. Then $V_1 = -1$ and $e_1 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$. Then we put in the system $\lambda = 2$ and we get $e_2 = \begin{pmatrix} 1 \\ -\frac{3}{2} \end{pmatrix}$. Therefore the overall solution of the system would be like this:

$$u_t = C_1 + C_2 2^t; v_t = -C_1 - \frac{3}{2}C_2 2^t.$$

We solve the system in case of complete non-fulfillment of the contract for the supply of energy resources

$$u_t = u_{t-1} - \sqrt{3}v_{t-1};\, v_t = \sqrt{3}u_{t-1} + v_{t-1}.$$

The system in this variant will be written as follows:

$$\begin{cases} (\lambda - 1)U - \sqrt{3}V = 0; \\ \sqrt{3}U + (\lambda - 1)V = 0. \end{cases}$$

The roots of the characteristic equation are $\lambda^2 - 2\lambda + 4 = 0$ complex: $\lambda_{1,2} = 1 \pm \sqrt{3}i$.
Using the trigonometric form of a complex number $\lambda_{1,2} = \rho(\cos\vartheta \pm i\sin\vartheta)$, we get

$$\rho = \sqrt{1+3} = 2; \cos\vartheta = \frac{1}{2}, \sin\vartheta = \frac{\sqrt{3}}{2}; \vartheta = \frac{\pi}{2}, \lambda_{1,2} = 2\left(\cos\frac{\pi}{3} \pm i\sin\frac{\pi}{3}\right).$$

Substituting $\lambda = 1 + \sqrt{3}i$ into the system, we get $V_1 = U_1 i$,

$$e_1 = \begin{pmatrix} 1 \\ i \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} + i\begin{pmatrix} 0 \\ 1 \end{pmatrix},$$

therefore

$$e_{\mathrm{Re}} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, e_{\mathrm{Im}} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}.$$

Similarly, substituting $\lambda = 1 - \sqrt{3}i$ in the system, we get $V_2 = -U_2 i$, that gives the opportunity to get the equation $e_2 = e_1^* = \begin{pmatrix} 1 \\ -i \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \end{pmatrix} - i\begin{pmatrix} 0 \\ 1 \end{pmatrix}$. So, according to the formula (8), the overall solution of the system is as follows.

$$u_t = 2^t\left[C_1\cos\frac{\pi t}{3} + C_2\sin\frac{\pi t}{3}\right], v_t = 2^t\left[-C_1\sin\frac{\pi t}{3} + C_2\cos\frac{\pi t}{3}\right].$$

Conclusion

Summarizing the analysis of the forecasting methodology in the energy markets we note that forecasting is an activity that is aimed at determining the patterns of development of certain processes and phenomena, as well as identifying their future conditions. Despite the wide scope of forecasting, a significant number of species features are distinguished according to which forecasts are divided. The type of forecasts that is of particular interest from the perspective of this work is the economic forecast. In turn, it is also divided into various subspecies depending on the object of study and the scope of economic activity. Economic forecasting is based on a whole complex of methods and scientific and methodological approaches. The main groups of forecasting methods are expert, deterministic and stochastic, which in turn contain dozens of varieties of specific methods for generating forecasts. The analysis of peculiarities of forecasting in energy markets revealed that it is a process of determining future asset prices and trends in their changes. Taking into account the specificity of this type of forecasting, a specific methodology is used for it (along with generally accepted). Technical and fundamental analyses from the point of view of the theory of differential equations are specific methods that are typical for forecasting prices in the energy markets. It allows you to adjust the maximum level of time impact on the behavior of the economic energy system.

REFERENCES

1. Abbasi Z., Pore M., Gupta S. K. S. 2013, Impact of Workload and Renewable Prediction on the Value of Geographical Workload Management. Energy-Efficient Data Centers: Second International Workshop. Berkeley, CA, USA, May 21. pp. 1–15. https://doi.org/10.1007/978-3-642-55149-9_1
2. Zhu B., Chevallier J. 2017, An Adaptive Multiscale Ensemble Learning Paradigm for Carbon Price Forecasting. Pricing and Forecasting Carbon Markets: Models and Empirical Analyses. Cham: Springer International Publishing, pp. 145–165. https://doi.org/10.1007/978-3-319-57618-3_9
3. McHugh C., Coleman S., Kerr D., McGlynn D. 2019, Daily Energy Price Forecasting Using a Polynomial NARMAX Model. A. Lotfi, H. Bouchachia, A. Gegov, C. Langensiepen, M. McGinnity (Eds). Advances in Computational Intelligence Systems. Cham: Springer International Publishing, pp. 71–82.

4. Yamaguchi N., Hori M., Ideguchi Y. 2018, Minimising the expectation value of the procurement cost in electricity markets based on the prediction error of energy consumption. *Pacific Journal of Mathematics for Industry*, vol. 10(1). https://doi.org/10.1186/s40736-018-0038-7

5. Aksanli B., Venkatesh J., Monga I., Rosing T. S. 2016, Renewable Energy Prediction for Improved Utilization and Efficiency in Datacenters and Backbone Networks. J. Lässig, K. Kersting, K. Morik (Eds). Computational Sustainability. Cham: Springer International Publishing, pp. 47–74. https://doi.org/10.1007/978-3-319-31858-5_4

6. Nowotarski J., Weron R. 2015, Computing electricity spot price prediction intervals using quantile regression and forecast averaging. *Computational Statistics*, vol. 30(3), pp. 791–803. https://doi.org/10.1007/s00180-014-0523-0

7. Xu J., Christie R. D. 2001, Decentralized Unit Commitment in Competitive Energy Markets. B. F. Hobbs, M. H. Rothkopf, R. P. O'Neill, H. Chao (Eds). The Next Generation of Electric Power Unit Commitment Models. Boston, MA: Springer US, pp. 293–313. https://doi.org/10.1007/0-306-47663-0_16

8. Ge Y., Wu, H. 2019, Prediction of corn price fluctuation based on multiple linear regression analysis model under big data. *Neural Computing and Applications*, pp. 1–13. https://doi.org/10.1007/s00521-018-03970-4

9. Barbato A., Capone A., Carello G., Delfanti M., Falabretti D., Merlo M. 2014, A framework for home energy management and its experimental validation. *Energy Efficiency*, vol. 7(6), pp. 1013–1052. https://doi.org/10.1007/s12053-014-9269-3

10. Sun X., Wang X., Wu J., Liu Y. 2014, Prediction-based manufacturing center self-adaptive demand side energy optimization in cyber physical systems. *Chinese Journal of Mechanical Engineering*, vol. 27(3), pp. 488–495. https://doi.org/10.3901/CJME.2014.03.488

11. Vineeth N., Ayyappa M., Bharathi B. 2018, House Price Prediction Using Machine Learning Algorithms. I. Zelinka, R. Senkerik, G. Panda, P. S. Lekshmi Kanthan (Eds). Soft Computing Systems. Singapore: Springer Singapore, pp. 425–433.

12. Prediction on the Value of Geographical Workload Management. S. Klingert, X. Hesselbach-Serra, M. P. Ortega, G. Giuliani (Eds). Energy-Efficient Data Centers. Berlin; Heidelberg: Springer Berlin Heidelberg, pp. 1–15.

13. Gabralla L. A., Mahersia H., Abraham A. 2015, Ensemble Neurocomputing Based Oil Price Prediction. A. Abraham, P. Krömer, V. Snasel (Eds). Afro-European Conference for Industrial Advancement. Cham: Springer International Publishing, pp. 293–302.

14. Pan H., Haidar I., Kulkarni, S. 2009, Daily prediction of short-term trends of crude oil prices using neural networks exploiting multimarket dynamics. *Frontiers of Computer Science in China*, vol. 3(2), pp. 177–191. https://doi.org/10.1007/s11704-009-0025-3

15. De Cauwer M., O'Sullivan B. 2013, A Study of Electricity Price Features on Distributed Internet Data Centers. J. Altmann, K. Vanmechelen, O. F. Rana (Eds). Economics of Grids, Clouds, Systems, and Services. Cham: Springer International Publishing, pp. 60–73.

16. Belitskaya M. 2018, Ecologically adaptive receptions control the number of pests in the ecosystems of transformed at the forest reclamation. *World Ecology Journal*, vol. 8(2), pp. 1–10. https://doi.org/https://doi.org/10.25726/NM.2018.2.2.001

17. Semenyutina A., Lazarev S., Melnik K. 2019, Assessment of reproductive capacity of representatives of ancestral complexes and especially their selection of seed in dry conditions. *World Ecology Journal*, vol. 9(1), pp. 1–23. https://doi.org/https://doi.org/10.25726/NM.2019.66.65.001

18. Ifrim G., O'Sullivan B., Simonis H. 2012, Properties of Energy-Price Forecasts for Scheduling. M. Milano (Ed.). Principles and Practice of Constraint Programming. Berlin; Heidelberg: Springer Berlin Heidelberg, pp. 957–972.

19. Niño-Peña J. H., Hernández-Pérez G. J. 2016, Price Direction Prediction on High Frequency Data Using Deep Belief Networks. J. C. Figueroa-García, E. R. López-Santana, R. Ferro-Escobar (Eds). Applied Computer Sciences in Engineering. Cham: Springer International Publishing, pp. 74–83.

20. Chiroma H., Abdul-Kareem S., Abdullahi Muaz S., Khan A., Sari E. N., Herawan T. 2014, Neural Network Intelligent Learning Algorithm for Inter-related Energy Products Applications. Y. Tan, Y. Shi, C. A. C. Coello (Eds). Advances in Swarm Intelligence. Cham: Springer International Publishing, pp. 284–293.

21. Semenyutina V., Svintsov I. 2019, Indicator signs of the adaptation of subtropical wood plants based on complex researches. *World Ecology Journal*, vol. 9(1), pp. 70–104. https://doi.org/https://doi.org/10.25726/NM.2019.60.66.005

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Формирование устойчивой цены на энергоресурсы путем решения нелинейной динамической задачи как элемента социально-экономической устойчивости экономики

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Аннотация

Актуальность. Авторами отмечается, что формирование устойчивой цены на природные ресурсы и возможность сглаживания цены при колебаниях не только спроса на них, но также и изменения графика поставок по экономическим и иным причинам требуют разработки экономической модели и являются весьма актуальными.

***Цель исследования*:** выявление возможностей прогнозирования цены на энергоресурсы при колебаниях цен и формировании различного уровня спроса на рынке и учета рыночных и нерыночных методов его регулирования.

Результатыисследования.Исследуяразличныепроцессыипроблемывобластиэкономики,авторыпредлагают использовать различные типы линейных и нелинейных краевых задач для обыкновенных дифференциальных уравнений. В статье отражено, что теория краевых задач для нелинейных дифференциальных уравнений является одним из актуальных факторов прогнозирования цены на энергоресурсы в структуре программы экономического развития. Авторы определяют задачи моделирования для целей корректировки спроса на энергоресурсы в течение длительного времени. В статье отмечается, что формирование спроса на энергоресурсы помимо стандартного временного лага, который определяет сезонность, также требует корректировки в связи с необходимостью формирования социально-экономической задачи сглаживания спроса.

Выводы. Экономико-математические модели, представленные в статье, являются универсальными и могут быть использованы в практической работе субъектов хозяйствования, государственных органах, формирующих спрос и потребление энергоресурсов на территории страны. Это будет способствовать повышению эффективности управления энергокомплексом страны и обеспечению комплексной целенаправленной деятельности, ориентированной на принятие обоснованных и своевременных решений в иных объектах хозяйствования.

***Ключевые слова*:** формирование цены, сглаживание спроса, решение динамической задачи, экономическое моделирование, уровень потребления, линейные процессы.

ЛИТЕРАТУРА

1. Abbasi Z., Pore M., Gupta S. K. S. Impact of Workload and Renewable Prediction on the Value of Geographical Workload Management. // Energy-Efficient Data Centers: Second International Workshop. Berkeley, CA, USA, May 21, 2013. P. 1–15.
1. Zhu B., Chevallier J. An Adaptive Multiscale Ensemble Learning Paradigm for Carbon Price Forecasting // Pricing and Forecasting Carbon Markets: Models and Empirical Analyses. Cham: Springer International Publishing, 2017. P. 145–165. https://doi.org/10.1007/978-3-319-57618-3_9
2. McHugh C., Coleman S., Kerr D., McGlynn D. Daily Energy Price Forecasting Using a Polynomial NARMAX Model / A. Lotfi, H. Bouchachia, A. Gegov, C. Langensiepen, M. McGinnity (Eds) // Advances in Computational Intelligence Systems. Cham: Springer International Publishing, 2019. P. 71–82.
3. Yamaguchi N., Hori M., Ideguchi Y. Minimising the expectation value of the procurement cost in electricity markets based on the prediction error of energy consumption // Pacific Journal of Mathematics for Industry. 2018. Vol. 10(1). https://doi.org/10.1186/s40736-018-0038-7
4. Aksanli B., Venkatesh J., Monga I., Rosing T. S. Renewable Energy Prediction for Improved Utilization and Efficiency in Datacenters and Backbone Networks / J. Lässig, K. Kersting, K. Morik (Eds) // Computational Sustainability. Cham: Springer International Publishing, 2016. P. 47–74. https://doi.org/10.1007/978-3-319-31858-5_4
5. Nowotarski J., Weron R. Computing electricity spot price prediction intervals using quantile regression and forecast averaging // Computational Statistics. 2015. Vol. 30(3). P. 791–803. https://doi.org/10.1007/s00180-014-0523-0
6. Xu J., Christie R. D. Decentralized Unit Commitment in Competitive Energy Markets / B. F. Hobbs, M. H. Rothkopf, R. P. O'Neill, H. Chao (Eds) // The Next Generation of Electric Power Unit Commitment Models. Boston, MA: Springer US, 2001. P. 293–313. https://doi.org/10.1007/0-306-47663-0_16

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7. Ge Y., Wu, H. Prediction of corn price fluctuation based on multiple linear regression analysis model under big data // Neural Computing and Applications. 2019. P. 1–13. https://doi.org/10.1007/s00521-018-03970-4
8. Barbato A., Capone A., Carello G., Delfanti M., Falabretti D., Merlo M. A framework for home energy management and its experimental validation // Energy Efficiency. 2014. Vol. 7(6). P. 1013–1052. https://doi.org/10.1007/s12053-014-9269-3
9. Sun X., Wang X., Wu J., Liu Y. Prediction-based manufacturing center self-adaptive demand side energy optimization in cyber physical systems // Chinese Journal of Mechanical Engineering. 2014. Vol. 27(3). P. 488–495. https://doi.org/10.3901/CJME.2014.03.488
10. Vineeth N., Ayyappa M., Bharathi B. House Price Prediction Using Machine Learning Algorithms / I. Zelinka, R. Senkerik, G. Panda, P. S. Lekshmi Kanthan (Eds) // Soft Computing Systems. Singapore: Springer Singapore, 2018. P. 425–433.
11. Prediction on the Value of Geographical Workload Management / S. Klingert, X. Hesselbach-Serra, M. P. Ortega, G. Giuliani (Eds) // Energy-Efficient Data Centers. Berlin; Heidelberg: Springer Berlin Heidelberg. P. 1–15.
12. Gabralla L. A., Mahersia H., Abraham A. Ensemble Neurocomputing Based Oil Price Prediction / A. Abraham, P. Krömer, V. Snasel (Eds) // Afro-European Conference for Industrial Advancement. Cham: Springer International Publishing, 2015. P. 293–302.
13. Pan H., Haidar I., Kulkarni, S. Daily prediction of short-term trends of crude oil prices using neural networks exploiting multimarket dynamics // Frontiers of Computer Science in China. 2009. Vol. 3(2). P. 177–191. https://doi.org/10.1007/s11704-009-0025-3
14. De Cauwer M., O'Sullivan B. A Study of Electricity Price Features on Distributed Internet Data Centers / J. Altmann, K. Vanmechelen, O. F. Rana (Eds) // Economics of Grids, Clouds, Systems, and Services. Cham: Springer International Publishing, 2013. P. 60–73.
15. Belitskaya M. Ecologically adaptive receptions control the number of pests in the ecosystems of transformed at the forest reclamation // World Ecology Journal. 2018. Vol. 8(2). P. 1–10. https://doi.org/https://doi.org/10.25726/NM.2018.2.2.001
16. Semenyutina A., Lazarev S., Melnik K. Assessment of reproductive capacity of representatives of ancestral complexes and especially their selection of seed in dry conditions // World Ecology Journal. 2019. Vol. 9(1). P. 1–23. https://doi.org/https://doi.org/10.25726/NM.2019.66.65.001
17. Ifrim G., O'Sullivan B., Simonis H. Properties of Energy-Price Forecasts for Scheduling / M. Milano (Ed.) // Principles and Practice of Constraint Programming. Berlin; Heidelberg: Springer Berlin Heidelberg, 2012. P. 957–972.
18. Niño-Peña J. H., Hernández-Pérez G. J. Price Direction Prediction on High Frequency Data Using Deep Belief Networks / J. C. Figueroa-García, E. R. López-Santana, R. Ferro-Escobar (Eds) // Applied Computer Sciences in Engineering. Cham: Springer International Publishing, 2016. P. 74–83.
19. Chiroma H., Abdul-Kareem S., Abdullahi Muaz S., Khan A., Sari E. N., Herawan T. Neural Network Intelligent Learning Algorithm for Inter-related Energy Products Applications / Y. Tan, Y. Shi, C. A. C. Coello (Eds) // Advances in Swarm Intelligence. Cham: Springer International Publishing, 2014. P. 284–293.
20. Semenyutina V., Svintsov I. Indicator signs of the adaptation of subtropical wood plants based on complex researches // World Ecology Journal. 2019. Vol. 9(1). P. 70–104. https://doi.org/https://doi.org/10.25726/NM.2019.60.66.005

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