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Comparative analysis of mathematical models and estimation of errors in computer modeling of the gas consumption process

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Abstract: *The paper considers approaches to mathematical modeling of the gas consumption process based on three models: a model based on a cyclic random process and the classical ARIMA and SARIMA models. The gas consumption process is characterized by the presence of a trend, seasonality, cyclicity, and random disturbances, which necessitates the use of adequate mathematical models for its description and simulation. The paper presents a mathematical model of the gas consumption process in the form of an additive mixture of trend, cyclic, and random components. A comparative analysis of the ARIMA and SARIMA models, which are based on differencing operators and take seasonal features into account, is also provided. The models are compared in terms of adequacy, ability to capture cyclicity and seasonality, interpretability of parameters, and suitability for computer simulation and forecasting. To assess the accuracy of computer simulation of gas consumption process realizations, absolute and relative errors are used. It is shown that the SARIMA model is an effective baseline model for series with stable seasonality, whereas the model based on a cyclic random process is more suitable for describing gas consumption with a pronounced cyclic structure and is better suited for computer simulation tasks.*

Keywords: *modeling; mathematical model; gas consumption; cyclic random process; ARIMA; SARIMA; cyclicity; seasonality; forecast.*

1. INTRODUCTION

Analysis, computer simulation, and forecasting of the gas consumption process are important tasks in energy systems, since the efficiency of resource planning, the stability of system operation, and the quality of control decisions depend on the accuracy of estimating future consumption volumes [5, 6]. In practice, gas consumption time series usually contain a long-term trend, seasonal and cyclic fluctuations, as well as random deviations [5, 7].

Modern studies on natural gas demand forecasting employ both classical time-series models and more sophisticated stochastic, hybrid, and intelligent approaches [6, 7]. Among the most widely used classical approaches are ARIMA and SARIMA models, which allow researchers to account for autocorrelation and seasonality in gas consumption data [7, 8]. Their practical applicability has also been demonstrated for day-ahead and short-term gas demand forecasting tasks [9, 10].

At the same time, the recent literature increasingly explores deep learning, ensemble, and hybrid approaches. These include ARIMA-LSTM combinations, deep neural regression, bagging-based forecasting, and graph-based temporal-spatial architectures [12, 13]. Further developments include federated contrastive learning for mid-term gas demand forecasting and models that integrate weather information, policy-related constraints, and artificial intelligence into natural gas demand prediction [17, 21]. For city-scale and daily forecasting tasks, weather-enhanced artificial intelligence and BiGRU-based methods have also shown promising results [22, 24].

Another line of research is related to grey-system models, fuzzy trees, analog methods, and optimized Grey Bernoulli models for long-term or macro-level demand forecasting [14, 19]. In addition, some studies consider the impact of energy-related policy on national-level gas demand and show that demand forecasting should be linked not only to historical time-series structure but also to institutional and regulatory factors [20, 23].

However, in the case of analysis and computer simulation of the gas consumption process, it is important to take into account not only seasonality in the narrow statistical sense, but also the internal cyclic structure of the process itself [1, 2]. One of the mathematical approaches that allows such structure to be represented is the model based on a cyclic random process in the form of a sum of trend, cyclic, and stochastic components [1, 4]. In practical forecasting, the use of climatic indicators also improves the applicability of such models to real gas consumption data [3].

The purpose of this paper is to perform a comparative analysis of mathematical models of the gas consumption process based on a cyclic random process and the ARIMA and SARIMA models, as well as to compare the results of computer simulation of gas consumption realizations obtained from these models. The study also aims to determine which mathematical model is more suitable for analysis, computer simulation, and forecasting of the gas consumption process.

2. METHODS

2.1. A mathematical model of the gas consumption process based on a cyclic random process

The process of gas consumption belongs to the class of complex stochastic processes, which are characterized by long-term trends in changes in the level of consumption, repeated cyclical fluctuations and random deviations. Seasonal, weekly, and daily rhythms are observed in real gas consumption data, and repeated gas consumption is not constant at different time intervals: they can change in amplitude, duration, and intensity under the influence of various factors: temperature conditions, consumer work modes, calendar, seasonal, and other external disturbances [3, 10, 22].

Let us consider the mathematical model based on a cyclic random process presented in [4]. The mathematical model of the gas consumption process $\xi'(\omega,t)$, is given by formula (1) in the form of an additive mixture of components: $\xi(\omega,t)$ – cyclic component (cyclic random process), $f_{tr}(t)$ – trend function, $f_{rem}(\omega,t)$ – stochastic residual function.

$$\xi'(\omega,t)=\xi(\omega,t)+f_{tr}(t)+f_{rem}(\omega,t), t\in \boldsymbol{W}, \omega\in \boldsymbol{\Omega} \quad (1)$$

In practice, we process discrete data and therefore present the mathematical model (1) in this form:

$$\xi'_{\omega}(l)=\xi_{\omega}(l)+f_{tr}(l)+f_{rem\omega}(l), l\in \boldsymbol{W}=\boldsymbol{D} \quad (2)$$

where $\xi_{\omega}(l)$ is the implementation of the cyclic component of the gas consumption process, f_{tr} (l) is the trend function, $f_{rem\omega}(l)$ is the stochastic residual function, l is the discrete readings of the gas consumption process, L is the number of readings of the gas consumption process (registered realization).

When applying the caterpillar-SSA method, k – realizations of components $\left\{\overline{f_k}(l), k=\overline{0,K-1}, l=\overline{1,L}\right\}$, are obtained, where $K=10$, l – readings of the gas consumption process, L – the number of discrete readings of the realization.

We will obtain the cyclic component by summing the components obtained based on the caterpillar-SSA method, in particular the components: 0–1, 3–9, cyclic component 2 is the trend component $\overline{f_2}(l)$.

$$\xi_{\omega}(l)=\sum_{k=0}^{1}\overline{f}_{k}(l)+\sum_{k=3}^{9}\overline{f}_{k}(l), l=\overline{1,L} \quad (3)$$

$$f_{tr}(l)=\overline{f}_{2}(l), l=\overline{1,L} \quad (4)$$

We obtain the stochastic residual based on the relation:

$$f_{rem\omega}(l)=\xi'_{\omega}(l)-(\xi_{\omega}(l)+f_{tr}(l)), l=\overline{1,L} \quad (5)$$

Let us focus our attention on considering the cyclic component of the mathematical model (2) ($\xi_{\omega}(l)$, which takes into account information about the gas consumption process:

$$\xi_{\omega}(l)=\sum_{i=1}^{C}f_{i}(l), l\in \boldsymbol{W} \quad (6)$$

where C is the number of segments-cycles of the cyclic gas consumption process. $\mathbf{W}$ is the area of determination of the cyclic process of gas consumption, and the area of its values, for the stochastic approach, is the Hilbert space of random variables set on one probability space ($\xi_{\omega}(l)\in \boldsymbol{\Psi}=\boldsymbol{L}_{2}(\boldsymbol{\Omega},\boldsymbol{P})$). Design (6) takes into account the cyclical structure [4] through segments-cycles $f_{i}(l)$ of the cyclic process of gas consumption, they are determined through indicator functions, i.e.

$$f_{i}(l)=\xi_{\omega}(l)\cdot\alpha_{w_{i}}(l)\cdot I_{w_{i}}(l), i=\overline{1,C}, l\in\boldsymbol{W} \quad (7)$$

This formula takes into account the additional component $\alpha_{w_{i}}(l)$, which reflects the scale coefficients of the amplitude of gas consumption on each segment-cycle of the cyclic process, namely:

$$\alpha_{w_{i}}(l)=\begin{cases}\alpha_{i}, l\in\boldsymbol{W}_{i},\\ 0, l\notin\boldsymbol{W}_{i}.\end{cases}, i=\overline{1,C}, \quad (8)$$

where α_{i} the scale factors of the amplitude of gas consumption on each i-th segment-cycle are determined as follows:

$$\alpha_{i}=\frac{\alpha_{imax}}{\alpha_{aver}}, i=\overline{1,C}, \quad (9)$$

where α_{imax} is the maximum value of the amplitude of gas consumption on the i-th segment-cycle (determined at the segmentation stage of the cyclic gas consumption process), α_{aver} is the average value of the amplitude of gas consumption (the maximum value of the amplitude of the mathematical expectation estimate, determined at the stage of statistical processing of the cyclic gas consumption process).

In works [2,4] it is shown that taking into account component (7) in mathematical model (2) allows to describe the gas consumption process more accurately by taking into account the scale coefficients of the gas consumption amplitude.

In construction (7) indicator functions $I_{w_{i}}(l)$, which distinguish segments-cycles, were defined as follows:

$$I_{w_{i}}(l)=\begin{cases}1, l\in\boldsymbol{W}_{i},\\ 0, l\notin\boldsymbol{W}_{i}.\end{cases}, i=\overline{1,C}, \quad (10)$$

where $\boldsymbol{W}_{i}$ is the definition area of the indicator function, which in the case of a discrete signal, i.e. $\boldsymbol{W}=\boldsymbol{D}$, is equal to a discrete set of readings:

$$\boldsymbol{W}_{i}=\{l_{i,j}, j=\overline{1,J}\}, i=\overline{1,C}, \quad (11)$$

The segmental cyclic structure $\widehat{\boldsymbol{D}}_c$ is taken into account by the set of time counts $\{l_i\}$ or $\{l_{i,j}\}, i = \overline{1, C}, \ j = \overline{1, J}$, where J is the number of discrete counts per cycle. This entry of the mathematical model (2) takes into account the rhythm of the cyclic process of gas consumption through the continuous function of the rhythm, namely:

$$I_{w_i}(l) = I_{w_{i+n}}\big(l + T(l, n)\big), i = \overline{1, C}, n = 1, \in \boldsymbol{W} \quad (12)$$

To evaluate the rhythm function $T(l, n)$, the segmental structure of the gas consumption process [2, 4] (in this case, the segmental cyclical structure) is determined as $\widehat{\boldsymbol{D}}_c = \{l_i, i = \overline{1, C}\}$, which is a set of time points that correspond to the boundaries of segments-cycles of the gas consumption process.

This model (2) is additive, since the overall process of gas consumption is considered as the sum of three components. The trend component $f_{tr}(l)$ – describes the long-term trend of changes in gas consumption, which may be related to an increase or decrease in demand, structural changes in gas consumption, modernization of equipment or network topology, or a change in system operating conditions. The stochastic residual $f_{rem\omega}(l)$ takes into account those fluctuations that are not explained by either the trend or the cyclical component $\xi_\omega(l)$. [1, 2].

The main feature of this model is the cyclic component $\xi_\omega(l)$, which describes the recurring, cyclical fluctuations of the gas consumption process and allows taking into account both the long-term trend of gas consumption changes and its cyclical, rhythmic organization, which creates the basis for adequate computer modeling of gas consumption process implementations [2, 4].

2.2. ARIMA and SARIMA models in the tasks of computer modeling of the gas consumption process

ARIMA and SARIMA class models are widely used for modeling and forecasting the gas consumption process. These models allow us to describe the dependence of the current level of gas consumption on previous data, random disturbances and seasonal fluctuations [7, 8]. Let us consider these models.

Let y_t be the value of gas consumption at time t, and ε_t be a random error, which is white noise with zero mathematical expectation and constant variance.

2.2.1. ARIMA mathematical model

The $ARIMA\,(p, d, q)$ model combines an autoregressive component of order p, an integrated component of order d, and a moving average component of order q.

Let us present a general form of the ARIMA model,

$$\varphi(B)(1 - B)^d y_t = \ c \ + \ \theta(B)\varepsilon_t, \quad (13)$$

where B is a backward shift operator, i.e. $By_t = \ y_{t-1}$ c is a constant, $(1 - B)^d$ is a differentiation operator of order d, $\varphi(B)$ is an autoregression polynomial:

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ ... - \varphi_p B^p, \quad (14)$$

and θ(B) is the moving average polynomial:

$$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ ... + \theta_q B^q \quad (15)$$

After opening, it can be written in the following form:

$$\left(1-\varphi_1 B-\varphi_2 B^2-\ \dots\ -\ \varphi_p B^p\right)(1-B)^d y_t = \\ = c+\left(1+\theta_1 B+\theta_2 B^2+\ \dots\ +\theta_q B^q\right)\varepsilon_t. \quad (16)$$

The ARIMA mathematical model describes autocorrelations and is widely used as one of the basic tools for forecasting time series [8,15].

2.2.2. Mathematical model SARIMA

For the gas consumption process, which has seasonal fluctuations, the SARIMA (p,d,q)(P,D,Q)_s model is used, where p,d,q are the parameters of the non-seasonal part, P,D,Q are the parameters of the seasonal part, and s is the length of the season [7,9].

Let us present the general view of the SARIMA model:

$$\Phi(B^s)\varphi(B)(1-B)^d(1-B^s)^D y_t = c+\Theta(B^s)\theta(B)\varepsilon_t, \quad (17)$$

where $\varphi(B)$ is the non-seasonal autoregression polynomial:

$$\varphi(B)=1-\varphi_1 B-\varphi_2 B^2-\ \dots\ -\varphi_p B^p, \quad (18)$$

$\theta(B)$ is the polynomial of the non-seasonal part of the moving average:

$$(B)=1+\theta_1 B+\theta_2 B^2+\ \dots\ +\theta_q B^q, \quad (19)$$

$\Phi(B^s)$ is a seasonal autoregression polynomial:

$$\Phi(B^s)=1-\Phi_1 B^s-\Phi_2 B^{2s}-\ \dots\ -\ \Phi_P B^{Ps}, \quad (20)$$

$\Theta(B^s)$ is a polynomial of the seasonal component of the moving average:

$$\Theta(B^s)=1+\Theta_1 B^s+\Theta_2 B^{2s}+\ \dots\ +\Theta_Q B^{Qs}, \quad (21)$$

and a $(1-B^s)^D$ is the seasonal differentiation of order D.

Therefore, the complete SARIMA model record has the form:

$$(1-\Phi_1 B^s-\ \dots\ -\Phi_P B^{Ps})\left(1-\varphi_1 B-\ \dots\ -\ \varphi_p B^p\right)(1-B)^d(1-B^s)^D y_t = \\ = c+\left(1+\Theta_1 B^s+\ \dots\ +\Theta_Q B^{Qs}\right)\left(1+\theta_1 B+\ \dots\ +\theta_q B^q\right)\varepsilon_t. \quad (22)$$

In gas consumption analysis tasks, the SARIMA model is appropriate in cases where the time series has pronounced seasonality [7, 9, 11], for example, for monthly data, s = 12, for quarterly data – s = 4, for daily data with a weekly cycle – s = 7.

2.3. Interpretation of mathematical models in gas consumption problems

For gas consumption data, the ARIMA mathematical model allows you to take into account the «inertia» of the consumption process, the dependence of current demand on previous values and random short-term deviations. Unlike the ARIMA model, the SARIMA mathematical model makes it possible to take into account regular seasonal fluctuations in gas demand, repeated cycles of consumption and the interaction of short-term and seasonal dynamics [7, 9, 10].

Thus, mathematically, the ARIMA model is a special case of SARIMA without a seasonal component, and the SARIMA model is more general and better adapted to the description of the gas consumption process taking into account seasonality [7, 9].

3. RESULTS AND DISCUSSION

3.1. Comparative analysis of a mathematical model based on a cyclic random process and ARIMA and SARIMA models

After a brief description of mathematical models: based on a cyclic random process and ARIMA and SARIMA models, we will conduct a more detailed comparative analysis of them. The comparison will be made in terms of the structure of the model, the ability to take into account cyclicality and seasonality, the interpretability of the model parameters, as well as the suitability for computer modeling and forecasting of real gas consumption data.

A mathematical model based on a cyclic random process takes into account the repeated unfolding of gas consumption (in the following i-th segments-cycles,, $i = \overline{1, C,}$) by taking into account the cycles in the component, which acts as a separate structural element $f_i(l)$ and directly describes repeated fluctuations in gas consumption. In contrast, the $ARIMA(p, d, q)$ model has its own p, d, q parameters, such as the autoregressive component, the integrated component, and the moving average component. In contrast, the $SARIMA(p, d, q)(P, D, Q)_s$ model has parameters that allow taking into account non-seasonality and seasonality [7, 9].

Thus, in the mathematical models ARIMA and SARIMA, the current value of the time series is determined through the dependencies between the previous values and random disturbances, while in the model based on a cyclic random process, the cycle is considered as an independent component of the model [2, 3].

From the point of view of the model structure, the approach based on a cyclic random process is more subject-oriented, it immediately assumes in the model that gas consumption is a process with pronounced cyclicity, which can vary in amplitude and shape in different segments-cycles of observation and has a complete rhythm due to the consideration of the rhythm function. In contrast, ARIMA and SARIMA belong to universal time series models. Their advantage lies in mathematical rigor, a formalized procedure for parameter estimation, and wide practical applicability [12, 15, 16].

The fundamental difference between these approaches is that in the cyclic random process model, cyclicality is a primary property of the process, embedded in the mathematical construction itself. In the SARIMA model, seasonality is described indirectly - through seasonal biases, seasonal differentiation and seasonal autoregressive or moving average components. Therefore, the SARIMA model works well for relatively regular seasonality, but less naturally describes the variable structure of cycles, when the amplitude or shape of oscillations changes from cycle to cycle [7, 9].

Another important difference is how transparent and understandable the parameters of the models are. In the model based on a cyclic random process, the trend, cycle and stochastic residual are analyzed separately, which allows you to directly link the components of the model with the real nature of gas consumption. In the ARIMA and SARIMA models, the parameters p, d, q, P, D, Q have primarily statistical meaning and characterize the order of time delays and differentiation operations, but do not provide the same natural division of the process into physically meaningful components [7, 9].

The mathematical models ARIMA and SARIMA have a strong practical side: they are convenient for evaluation, testing and use as reference statistical models [7, 9]. The SARIMA model is especially useful because it allows you to take into account seasonality, for example, annual for monthly data or weekly for daily data. At the same time, in cases where gas consumption has a complex internal cyclical structure, a model based on a cyclic random process is more adequate, since it allows for flexible description of the variability of cycle characteristics over time [1–3]. Table 1 summarizes the comparative characteristics of the analyzed mathematical models.

Therefore, if the main goal is to build a universal mathematical model for short- or medium-term forecasting, it is advisable to use SARIMA as a classic proven tool [7, 9]. If the goal is a deeper mathematical description of gas consumption as a process with a cyclical structure that takes into account seasonality, then a mathematical model based on a cyclical random process is more adequate [2–4].

Table 1. General comparative characteristics of gas consumption models.

Criterion	The model is based on the CVP	ARIMA	SARIMA
Consideration of cyclicality	Obviously, as a separate component	Implicit	Implicit, through seasonal operators
Taking into account the trend	A separate component of the model	Through differentiation	Through differentiation
Taking seasonality into account	Due to the cyclic structure of the process	Limited	Limited
Interpretability of parameters	High	average	average
Flexibility with regard to changes in the amplitude of cycles	High	Lower	Lower
Ease of practical implementation	average	High	High
Suitability for modeling seasonal gas consumption	High	average	High only for regular seasonality
Predictability	High	low	Average for a short- or medium-term forecast

3.2. Results of computer modeling of the gas consumption process and comparison of their accuracy

Let us proceed to a comparative analysis of the results of computer modeling of the gas consumption process based on the consideration of mathematical models. To assess the accuracy of computer modeling of the mathematical model of the gas consumption process based on a cyclic random process and ARIMA and SARIMA models, it is advisable to use computer modeling errors that characterize the accuracy of computer modeling. For this purpose, we use the root-mean-square absolute and relative errors. Which were determined by the formulas:

$$\Delta_q(k) = \sqrt{\frac{1}{L}\sum_{l=1}^{L}(\xi'_{\omega}(l) - \xi_{modq}(l))^2}\,;\ \delta_q(k) = \frac{\Delta_q(k)}{\sqrt{\frac{1}{L}\sum_{l=1}^{L}\xi_{modq}(l)^2}}, \qquad (23)$$

$$k = \overline{1,L}, q = \overline{1,3}$$

Where $\xi_{modq}(l)$ is the value of the simulated implementation of the gas consumption process based on three mathematical models, $q = \overline{1,3}$; $\xi'_{\omega}(l)$ – the value of the actual implementation of the gas consumption process; L is the number of realization counts, $l = \overline{1,L}$; k is the calculation for absolute and relative errors, respectively, $k = \overline{1,L}$. The results of the obtained absolute and relative errors are shown in Figures 5–7. Figure 1 shows a fragment of the implementation of the gas consumption process for 2008–2012. Figures 2–4 show the results of computer-simulated realizations of the gas consumption process.

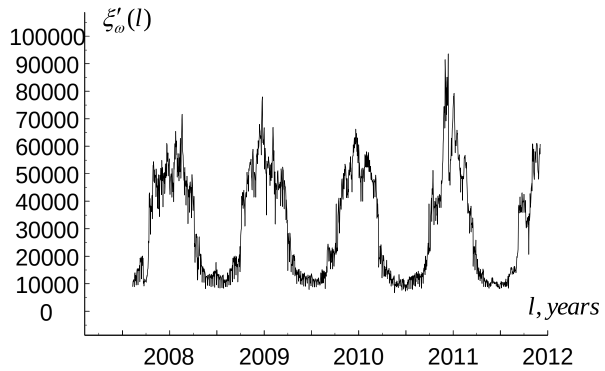

Figure 1. Fragment of the input process of gas consumption for 2008–2012.

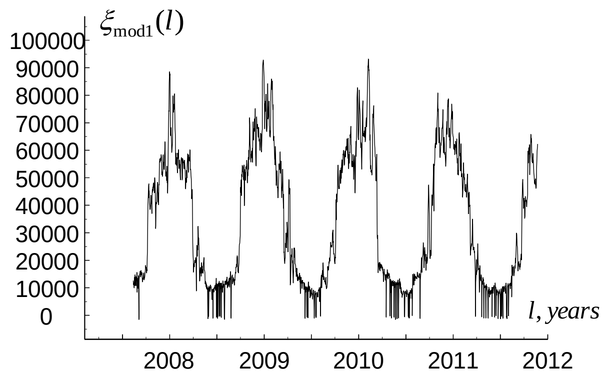

Figure 2. A fragment of the gas consumption process is modeled on the basis of the ARIMA mathematical model.

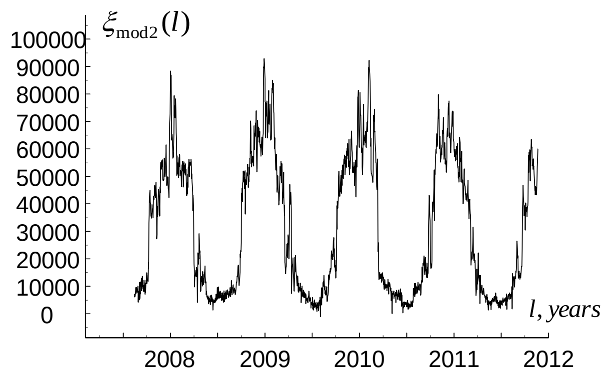

Figure 3. A fragment of the gas consumption process is modeled on the basis of the SARIMA mathematical model.

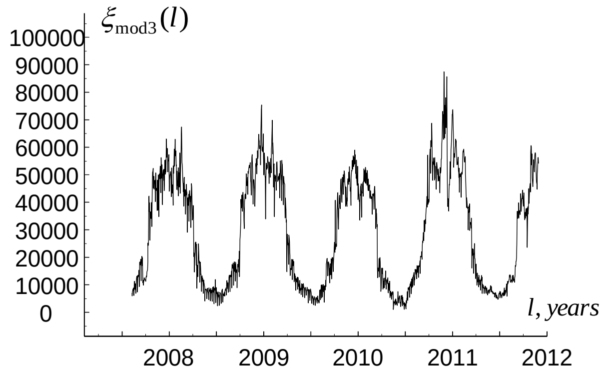

Figure 4. A fragment of the gas consumption process is modeled on the basis of a mathematical model of a cyclic random process.

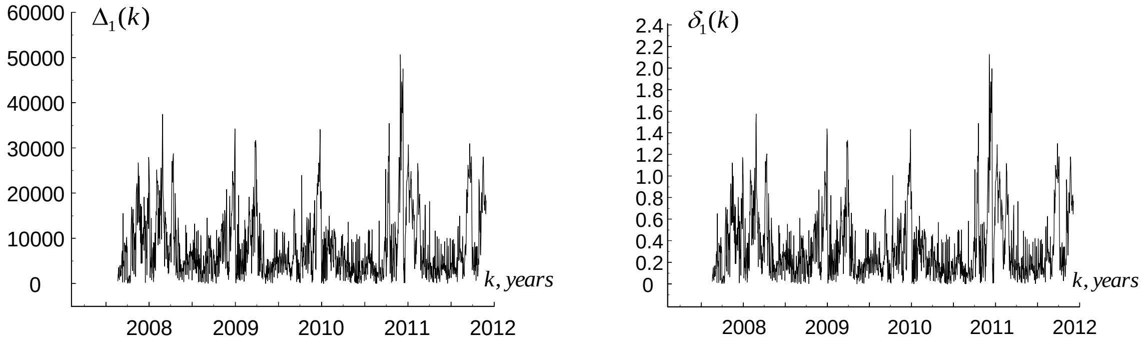

Figure 5. Absolute and relative error of computer modeling of the implementation of the gas consumption process based on the ARIMA mathematical model.

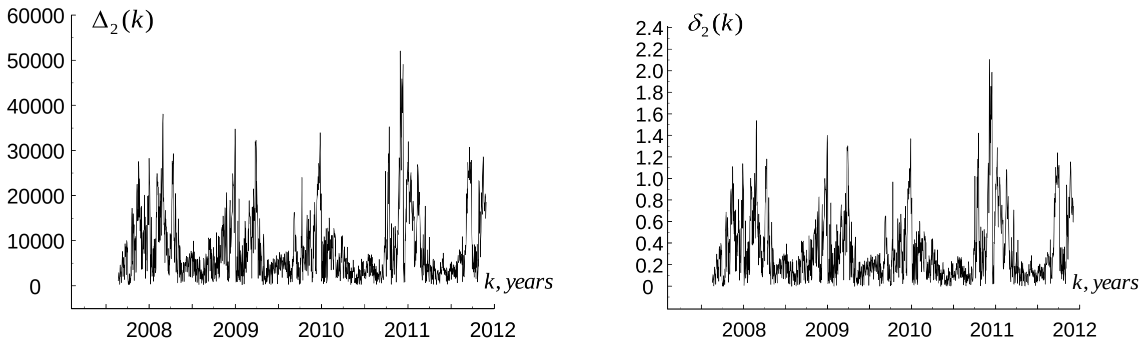

Figure 6. Absolute and relative error of computer modeling of the implementation of the gas consumption process based on the SARIMA mathematical model.

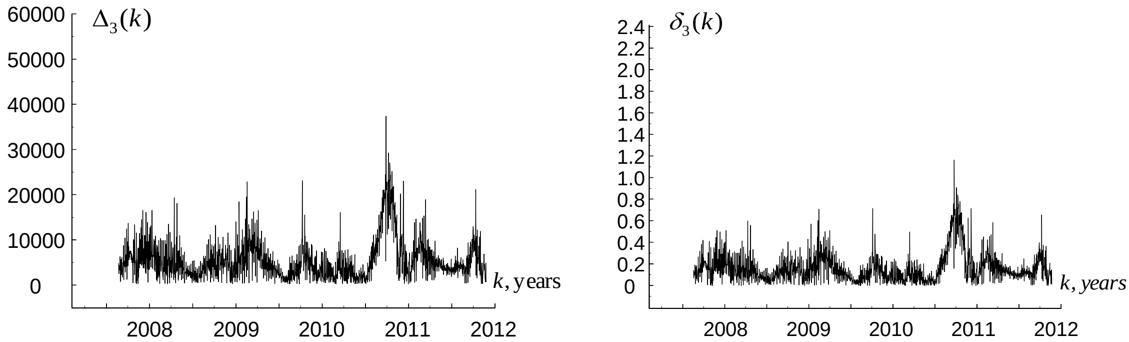

Figure 7. Absolute and relative error of the computer simulation of the implementation of the gas consumption process based on a mathematical model based on a cyclic random process.

When comparing gas consumption models, it is important to consider that ARIMA and SARIMA models are primarily focused on reproducing the structure of the time series through lag dependencies and seasonal operators [7, 9]. In contrast, the model based on a cyclic random process directly takes into account the cyclical nature of the gas consumption process, which is a significant advantage for data containing random amplitude values and a variable shape of cycles [1, 2].

Table 2. Comparison of the accuracy of computer modeling of gas consumption models

Model	Absolute error, no more than	Relative error, no more than	Overall score
ARIMA	55000	2,2	Lower accuracy when taking seasonality into account
SARIMA	55000	2,2	Higher accuracy when taking into account seasonality
The model is based on the CVP	40000	1,2	It is most adequate to take into account the cyclicality and seasonality of the gas consumption process

According to the results of the comparative analysis, it can be stated that for time series with a clearly expressed, but relatively stable seasonality, the SARIMA model will demonstrate an accuracy that does not exceed the ARIMA model, however, it allows taking into account seasonality (this affects the reduction of fluctuations in the troughs of cycles during computer modeling of the implementation of the gas consumption process Fig. 2). This is explained by the fact that SARIMA specifically takes into account seasonal dependencies and recurring fluctuations [7–9]. In turn, the ARIMA model is less suitable for describing gas consumption in cases where the seasonal or cyclical component is significant [1, 2] the error of computer modeling at the troughs of cycles increases significantly compared to SARIMA. At the same time, for gas consumption data, in which the cyclicality has a more complex structure, the model based on a cyclical random process is more adequate. The errors of computer modeling of the implementation of the gas consumption process are significantly smaller compared to the errors of simulated implementations based on the SARIMA and ARIMA models. The advantage of the mathematical model based on the CVP is that it allows you to separately take into account the trend, the cyclical component and the stochastic residue, as well as to take into account the variability of the characteristics of the cycles in time and the rhythm of such a process [1, 2]. That is why in problems where it is necessary not only to carry out computer modeling of implementations, but also to obtain a forecast, the model based on the cyclic random process has a higher analytical value [3, 22, 23].

4. CONCLUSIONS

Three mathematical models of the gas consumption process were considered in the work: a model based on a cyclic random process and classical ARIMA and SARIMA mathematical models. It is shown that both approaches to computer modeling can be used in practice to simulate the implementation of the gas consumption process, however, they are based on different principles of formalization of process dynamics and not all models allow taking into account the cyclical structure of the development of the gas consumption phenomenon.

The ARIMA model is appropriate for data in which there is no pronounced seasonality and cyclicality or with a weak seasonal component. The SARIMA model is an extension of it and allows you to effectively take into account regular seasonal fluctuations, which makes it a convenient tool for short- and medium-term forecasting of gas consumption, however, it has a higher computer simulation error compared to a model based on a cyclic random process.

Unlike the ARIMA and SARIMA models, the model based on a cyclic random process directly takes into account the cyclic nature of gas consumption, presenting it as the sum of trend, cyclic and random components. This allows not only to obtain the results of computer modeling with a much smaller error compared to the ARIMA and SARIMA models and, in the future, to build a more accurate forecast, in addition, to more fully describe the internal structure of the studied gas consumption process.

Thus, in the tasks of computer modeling and forecasting of the gas consumption process, it is advisable to consider the SARIMA model as a simple basic model, and the model based on a cyclic random process as a more promising mathematical tool for describing processes with a pronounced cyclic nature.

The question of researching these mathematical models based on a cyclic random process and the SARIMA model for forecasting problems will be considered in further research, where we will compare forecast results based on them.

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