RUDN Journal of Economics
Вестник Российского университета дружбы народов. Серия: Экономика
ISSN 2313-2329 (Print); ISSN 2408-8986 (Online)
2025 Vol. 33 No. 3 495–504
http://journals.rudn.ru/economics

DOI: 10.22363/2313-2329-2025-33-3-495-504
EDN: FAMWNA
UDC 338.45

Research article / Научная статья

Econometric model of energy: Russia's response to the challenges of the global economy

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Abstract. The relevance of the study is due to both the high degree of importance of energy for the economic development of Russia and the insufficient use of econometric models in modern energy research. The purpose of the study is to develop and propose an econometric model of the country's fuel and energy resources. In line with this objective, the research provides a detailed examination of the methodological framework and key stages involved in developing an econometric model using autoregressive analysis for the purpose of studying the Russian energy sector. This is both the scientific and applied, as well as the scientific and methodological significance of the presented publication. To achieve this goal, statistical materials from Rostat "Consumption of fuel and energy resources per person employed in the country's economy" have been used since 2012. Econometric analysis and statistics are used as a methodology, in particular, an autoregressive analysis model is used. The methodological advantage of the autoregressive model is its flexibility when working with a wide range of different time series patterns. Data Science methods were used to develop the model in particular, cMLE (conditional maximum likelihood method). The autoregressive model itself is written in the high-level Python language. Pandas, Numpy, Statsmodels, Sklearn.metrics, and Matplotlib libraries and modules were used. The study describes in detail the main stages of building an autoregressive model: data selection, visualization and verification for stationarity, data separation into test and training samples, training of an autoregressive model, RMSE analysis. The data obtained are characterized by the absence of an obvious trend: there have been periods of a decrease in the consumption of fuel and energy resources per person employed in the country's economy since 2012, as well as periods of an increase in the corresponding consumption in tons of conventional fuel. The study concludes that the autoregressive model is applicable to the analysis of the Russian energy sector. Although the time series of data is limited, the autoregressive model has high predictive characteristics. The "conservatism" of the autoregressive model towards underestimating the forecast values is emphasized. It is indicated that as new energy statistics accumulate, the autoregressive qualities of the model will improve.

Keywords: electric power industry of Russia, econometric analysis, autoregressive analysis, energy industry of Russia, fuel and energy resources

Authors' contribution. Borodin A.E. — research concept and design, data collection, data analysis, text writing; Chernyaev M.V. — research concept, supervision, correction of results. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest. The authors declare that there is no conflict of interest.

Article history: received 15 February 2025; revised 26 March 2025; accepted 10 April 2025.

For citation: Borodin, A.E., & Chernyaev, M.V. (2025). Econometric model of energy: Russia's response to the challenges of the global economy. *RUDN Journal of Economics*, *33*(3), 495–504. https://doi.org/10.22363/2313-2329-2025-33-3-495-504

Эконометрическая модель энергетики: ответ России на вызовы глобальной экономики

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Аннотация. Актуальность исследования обусловлена как высокой степенью значимости энергетики для экономического развития России, так и недостаточным использованием эконометрических моделей в современных энергетических исследованих. В соответствии с поставленной целью, в исследовании детально рассмотрены методологические основы и этапы разработки эконометрической модели на базе авторегрессионного анализа для изучения российского энергетического сектора. Использованы статистические материалы Росстата «Потребление топливно-энергетических ресурсов на одного занятого в экономике страны» с 2012 г. Подробно рассмотрены основные методические и методологические аспекты, показаны ключевые этапы разработки эконометрической модели в виде авторегрессионного анализа. Авторегрессионные модели (АМ) отличаются методической гибкостью в обработке временных данных с разными характеристиками. АМ для анализа энергосферы России разработана методами Data Science, в частности, cMLE (условный метод максимального правдоподобия) и написана на высокоуровневом языке Python. Использовались библиотеки и модули Pandas, Numpy, Statsmodels, Sklearn.metrics, Matplotlib. Представлены основные этапы построения АМ: отбор данных, их визуализация и проверка на стационарность, разделение данных на тестовую и обучающую выборки, обучение авторегрессионной модели, анализ RMSE. Полученные данные характеризуются отсутствием очевидного тренда: с 2012 г. наблюдаются как периоды снижения потребления топливно-энергетических ресурсов на одного занятого в экономике страны, так и периоды роста соответствующего потребления в тоннах условного топлива. Сделан вывод о применимости АМ для анализа энергетики России. Хотя временной ряд данных является ограниченным, АМ обладает высокими прогностическими характеристиками. Подчеркнута «консервативность» АМ в сторону занижения прогнозных значений. Указано, что по мере накопления новой энергетической статистики авторегрессионные качества модели будут улучшаться.

Ключевые слова: электроэнергетика России, эконометрический анализ, авторегрессионный анализ, энергетика России, топливно-энергетические ресурсы

Вклад авторов. Бородин А.Е. — концепция и дизайн исследования, сбор данных, анализ данных, написание статьи; Черняев М.В. — концепция исследования, руководство, коррекция результатов. Все авторы одобрили окончателбную версию рукописи.

Заявление о конфликте интересов. Авторы заявляют об отсутствии конфликта интересов.

История статьи: поступила в редакцию 15 февраля 2025 г., доработана после рецензирования 26 марта 2025 г., принята к печати 10 апреля 2025 г.

Для цитирования: *Borodin A.E., Chernyaev M.V.* Econometric model of energy: Russia's response to the challenges of the global economy // Вестник Российского университета дружбы народов. Серия: Экономика. 2025. Т. 33. № 3. С. 495–504. https://doi.org/10.22363/2313-2329-2025-33-3-495-504

Introduction

In recent years, Russia's energy sector has faced a number of different challenges caused by the unprecedented pressure of foreign sanctions. These have necessitated changes in logistics routes, the development of a new customer base and changes in the sales system. The relevance of the article is due to both the importance of the energy sector and energy efficiency for the economic development of Russia and the need to apply econometric models in the current conditions of development of the energy sector (Stankevich, 2024; Chernyaev, Gavryusev, 2019a). To date, various approaches are used to model the energy industry: software and hardware complexes (perform calculations considering every microsecond of time), integrated (analyses and considers the operation of several systems at once). Along with rather popular simulation and agent-based models, such purely econometric models as autoregressive analysis are actively used for the purposes of applied analysis; this article is devoted to its application by means of creating an appropriate model (Barbashin, 2017; Perifanis, Dagoumas, 2017; Paleev, Chernyaev, Nezhnikova, 2018). Previously, in practice, when analysing the energy sector, such classical econometric models were applied, which allowed only to simulate the relationship between different indicators. It did not include regression analysis, which allows assessing how a change in one variable affects another.

The aim of the study is to develop and propose an econometric model of the fuel energy system of Russia as an integral part of the energy complex. In accordance with the set goal, the article details the main methodological and methodological aspects of developing an econometric model in the form of autoregressive analysis for the purposes of analysing the energy sphere of Russia, and shows the key stages of such development. This is the scientific and methodological significance of the presented publication.

Materials and methods

To achieve this goal, the statistical materials of Rosstat 'Consumption of fuel and energy resources per person employed in the economy' from 2012[1] and the data presented on the website of the State Information System of Fuel and Energy Complex

[1] Rosstat. Retrieved 7 February 2025 from https://rosstat.gov.ru/folder/11189

(GIS FEC)[2] are used. Data omissions (e.g. for the period 2020–2022 due to crisis events) were handled using simple algorithms based on simple arithmetic operations as well as regression modelling (Table 1). A decrease in this absolute indicator of energy resources consumption means a reduction in the consumption of these resources, as well as in employment in the real sector of the economy.

Table 1

Consumption of fuel and energy resources in the national economy per 1 employed person (t.o.t.), 2000–2023

Years	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Consumption	6	6	6.1	6.1	6.2	6.2	6.4	6.6	6.8	6.9	7.3
Years	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Consumption	8.2	9.9	9.8	9.9	9.3	9.5	9.8	10.1	10	9.6	9.8
Years	2022	2023									
Consumption	9.6	9									

Source: compiled by A.E. Borodin, M.V. Chernyev.

Econometric analysis and statistics are used as a methodology, in particular, the autoregressive analysis model is applied. The methodological advantage of the autoregressive model (compared, for example, with structural models, Gaussian multimodal models and MIDAS models with Markov switching) is its high flexibility in dealing with a wide range of different time series patterns (Hansen, 2005; Kosova, Potanin, 2022; Svetunkov, 2011).

Data Science and Machine Learning methods (In particular, cMLE) are used to develop the model (Heckman, 2008). The autoregressive model is written in the high-level language Python with the help of libraries and modules Pandas, Numpy, Statsmodels, Sklearn.metrics, Matplotlib. Another main difference with other models, such as SARIMA and LSTM, is that it uses a huge number of different methods and approach for analysis. Despite the popularity of LSTM in forecasting, it requires more data and deeper analysis of indicators. It can also be noted about the SARIMA model, which is suitable for analysing seasonal indicators and requires deep analysis of indicators in contrast to the AR system used in the study.

The Breusch-Godfrey test was applied to evaluate the sensitivity and estimate the residuals. This test allows us to assess the adequacy of the autoregressive analysis.

Results

The first stage of construction for any model is data selection (Mitsek, Mitsek, 2021). The following data were selected for the development of the econometric model: 'Consumption of fuel and energy resources per person employed in the country's economy' from 2012 to 2022. At the time of the econometric model development. The indicator 'Consumption of fuel and energy resources per person

[2] State Information System of the Fuel and Energy Sector. Retrieved 1 February 2025 from https://gis-tek.ru/documents

employed in the country's economy' is calculated by Rosstat on 31 December based on the analysis of available fuel and energy balance (FEB) data and labour balance data on an annual basis. It represents the ratio of final consumption of fuel and energy resources to the output expressed in tonnes of fuel equivalent.

Figure 1. shows that there is no obvious trend, cyclicality or clear directionality. The absence of seasonality is indicated by irregular patterns of peaks and dips in the data, which is understandable since the time periods are taken over several years and such data are not seasonal. The analysed data are stationary, i.e., their statistical characteristics are preserved regardless of the selected time period. Thus, the use of autoregressive model is methodologically justified.

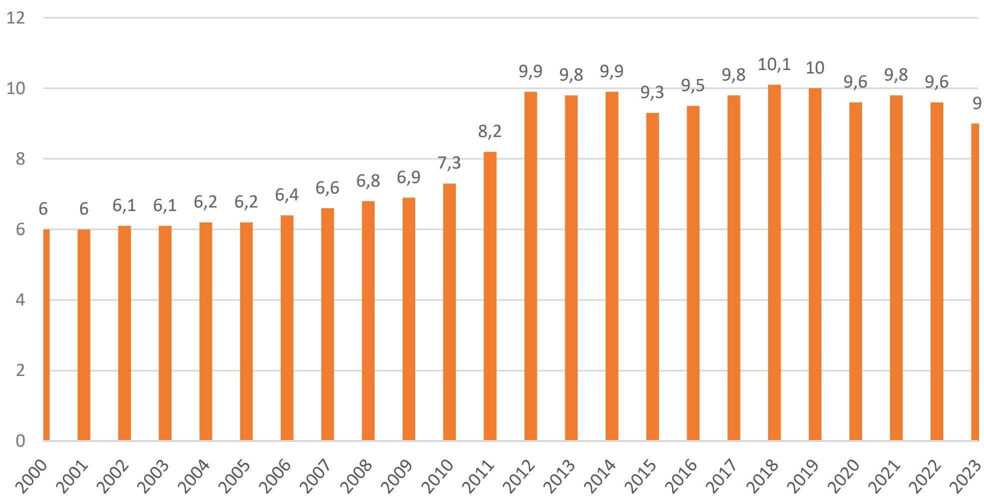

Figure 1. Dynamics of energy intensity change by years, 2000–2023

Source: compiled A.E. Borodin, M.V. Chernyev.

After visualisation and checking for stationarity, it is necessary to formulate the formula of the time series forecasting model (Low, Meghir, 2017). The AR-model of order p is written as follows:

$$Yt = \mathrm{c} + \Theta t Yt_{-1} + \Theta_2 Yt_{-2} + \ldots. + \Theta p Yt_{-2} + \varepsilon t, \tag{1}$$

where c = constant; $\Theta_{1\,\ldots}$ Θp — parameters (autoregressive coefficients) of the model. Their change leads to changes in time series patterns; εt = normally distributed white noise with mean 0 and variance 1.

The next step in model development is to divide the temporal data into test and training samples.

To train the Autoreg model, the required number of lags is set on the training sample. The lag variables create a sliding window, which is updated as a new forecast is obtained. At the next iteration, the forecast becomes the last observation of the window, and the model is shifted one step forward. For example, the first forecast is obtained by adding the product of the observation values and coefficients to a constant. The second prediction is obtained when the first prediction takes the place of the last observation, and the observation that was second in the last iteration is used as the first. As new data become available, the model is updated by re-training.

Then we set parameters for the beginning and end of forecasting and make forecasts for the next several time periods. Application of this model in practice shows the efficiency of its calculations for the indicator of fuel and energy resources consumption in the national economy per 1 employed person (Table 2).

Table 2

Forecasts of the autoregressive model according to the indicator "Consumption of fuel and energy resources in the national economy per 1 employed person" for 2018–2023

Years	Prognosis	Actual
2018	9.682331	10.1
2019	9.601342	10
2020	9.638107	9.6
2021	9.659775	9.8
2022	9.648431	9.6
2023	9.111111	9.1

Source: compiled by A.E. Borodin, M.V. Chernyev.

These models capture the relationship between observations and several lagged observations (previous time steps). The basic idea is that the value of a time series can be expressed as lines calculating its previous results with some random 'noise'. The last important step in developing an autoregressive model is to determine the root mean square error (RMSE), which characterises the average distance between the model predicted values and the actual data that were provided for the model. The p-value of Breusch-Godfrey test showed a level of 0.05, which means rejecting the independence of the residuals, which in turn indicates the presence of autocorrelation.

Discussions

Econometric studies have been experiencing an obvious upsurge in recent years (Ayvazyan, Bereznyatsky, Brodsky, 2018; Mullainathan, Spiess, 2017; Phillips, 2009). They are used to analyse both general socio-economic phenomena and economic issues (In particular, general equilibrium) and to analyse the main trends in the development of the Russian economy, individual sectors (industry, innovative developments and goods, oil sector, etc.) (Polbin, Sinelnikov-Murylev, 2024; Benedictow, Fjaertoft, Lofsnaes, 2013; Chernyaev, Gavryusev, 2019b; Dmitriev, Dubanevich, 2021; Kulebyakina, 2019; Jorgenson, Bernt, 2003).

The popularity of using econometric models for the purposes of applied economic analysis is due to both high mathematical technique and developed statistical apparatus of quality assessment underlying such models and good methodological elaboration of separate procedures (In particular, assessment of causality), which facilitates their application for applied economic purposes (Buraeva, Bobkova, 2016; Kotyrlo, 2024; Rosenzweig, 2018; Faritova, Fakhrutdinova, 2016; Basdevant, 2000).

From a large number of developed econometric models, the autoregressive model was chosen for the study, which allows taking into account the autocorrelation of errors. Autoregressive models are characterised by methodological flexibility in processing time data with different statistical characteristics (Athey, Imbens, 2017).

The Rosstat data were selected for the construction of the model, which are of high econometric quality, as they do not contain omissions and outliers, incorrect values and other noise. Rosstat statistics are collected according to a unified methodology and technique, which facilitates the construction of the econometric model, as it allows to skip such an important part of statistical work with data as cleaning.

However, most of the energy data are not characterised by the qualities required for regression analysis, as the time series is limited: for most statistical indicators Rosstat collects data from 2012, for some indicators — even from 2017. In addition, statistical data are given in an unnecessarily aggregated form: on an annualised basis, which does not allow for the creation of a data lake of sufficient volume. For the purposes of autoregressive analysis, it would be more useful if Rosstat provided data in monthly terms. Nevertheless, the model itself can be used even with existing data, although it is obvious that, as new statistics are accumulated, its autoregressive quality will improve.

The essence of the autoregressive model (AR-model) methodology is to use a linear combination of predictors (retrospective values) to predict the variable of interest to the researcher (Fig. 2).

The applicability of the developed model is evidenced by the high convergence between predicted and actual values. In addition, this is evidenced by the RMSE on the test sample, which is equal to 0.267. The low level of RMSE shows that the model methodologically fits the data set.

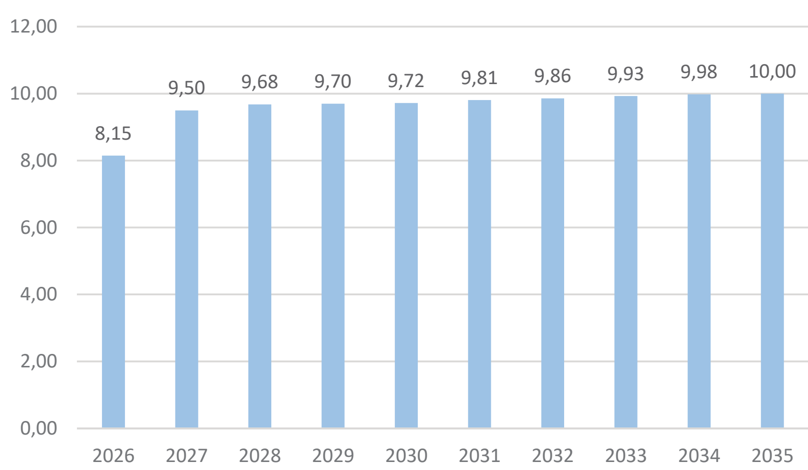

Figure 2. Graph of forecast values with confidence interval, 2026–2035
Source: compiled by A.E. Borodin, M.V. Chernyev.

Errors in long-term econometric forecasts in the energy sector are possible due to a number of factors. Such factors include: geopolitical factors (e.g., military conflicts and instability, trade restrictions and sanctions), economic factors (inflation growth, fluctuations in the global economy, technological shifts, etc.).

The data obtained are characterised by the absence of an obvious trend: since 2012, there have been both periods of decline in the consumption of fuel and energy resources per person employed in the country's economy and periods of growth in the corresponding consumption in tonnes of fuel equivalent. However, a significant decrease in the consumption of fuel and energy resources per person employed in the economy is observed in 2023.

The main objective of the model is to assess the natural trends of the Russian energy market, as well as to track changes and consequences for the industry. For this purpose, it is necessary to develop: 1) a baseline scenario — mainly using already available indicators; 2) forecasts of Russia's energy sector development, taking into account all trends affecting this market, as well as assessing the consequences of this impact.

Conclusion

Based on the analysed data, we can conclude that the autoregressive model is applicable to the analysis of the Russian energy sector. Although the time series of data is limited, the autoregressive model has high predictive characteristics. The developed model is 'conservative', as the convergence between predicted and actual data shows) works towards underestimation of forecast values. Further application of autoregressive models for the purposes of econometric analysis of the energy sphere is constrained by the lack of statistical valid data. As new energy statistics are accumulated, the autoregressive qualities of the models will improve. Improvement of the completeness of statistical data that contain information on fuel and energy production, consumption and prices is required. As new energy statistics are accumulated, the autoregressive qualities of the models will improve. It is necessary to include in the autoregressive model such additional functions as sensitivity to changes in various components and indicators, the possibility of developing various scenarios and forecasts of the energy sector development.

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