European Journal of Business Startups and Open Society

Vol. 4 No. 11 (Nov - 2024): EJBSOS

http://innovatus.es/index.php/ejbsos

The Econometric Analysis of Electricity Consumption

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Abstract: This article presents an ARIMA (AutoRegressive Integrated Moving Average) model for forecasting electricity consumption in the residential sector of the Republic of Uzbekistan, with projections up to 2029. The model-building process is described in detail, with clear steps outlined. Correlations within the data were analyzed using a correlogram, and statistical methods were used to test the stationarity of the data. The accuracy and statistical significance of the model were verified through several tests, confirming the reliability of the forecast. This work proposes an effective approach for forecasting electricity supply in Uzbekistan's residential sector.

Key words: Residential electricity supply, household electricity consumption, electricity demand, ARIMA, model, regression, correlogram, model procedure, ACF, PACF.

Introduction: Forecasting household electricity consumption plays a significant role in the effective management of a country's energy system and meeting the population's needs. This process enables the planning of electricity generation capacity, efficient resource allocation, and the integration of renewable energy sources. Through forecasting, it is possible to ensure continuous energy supply, support economic development, protect the environment, and improve energy efficiency. Given the growth in population and urbanization processes, which lead to increased demand, having accurate and effective forecasting methods is crucial for ensuring the country's energy stability.

2010–2023 From 2010 to 2023, electricity consumption in Uzbekistan increased by 55.8%, rising from 11,449.3 million kWh to 17,839.5 million kWh (Figure 1). During this period, although there was an overall upward trend in consumption, some years experienced declines. Specifically, in 2016, electricity consumption decreased by 10.8% compared to the previous year, reaching 11,195.7 million kWh. Nevertheless, from 2017 onwards, stable growth resumed, and a sharp increase in electricity consumption was observed after 2020. In particular, in 2022, demand grew by 13% within a single year, reaching its highest level of 17,839.5 million kWh in 2023. The average annual growth rate during the observation period was 3.2%.

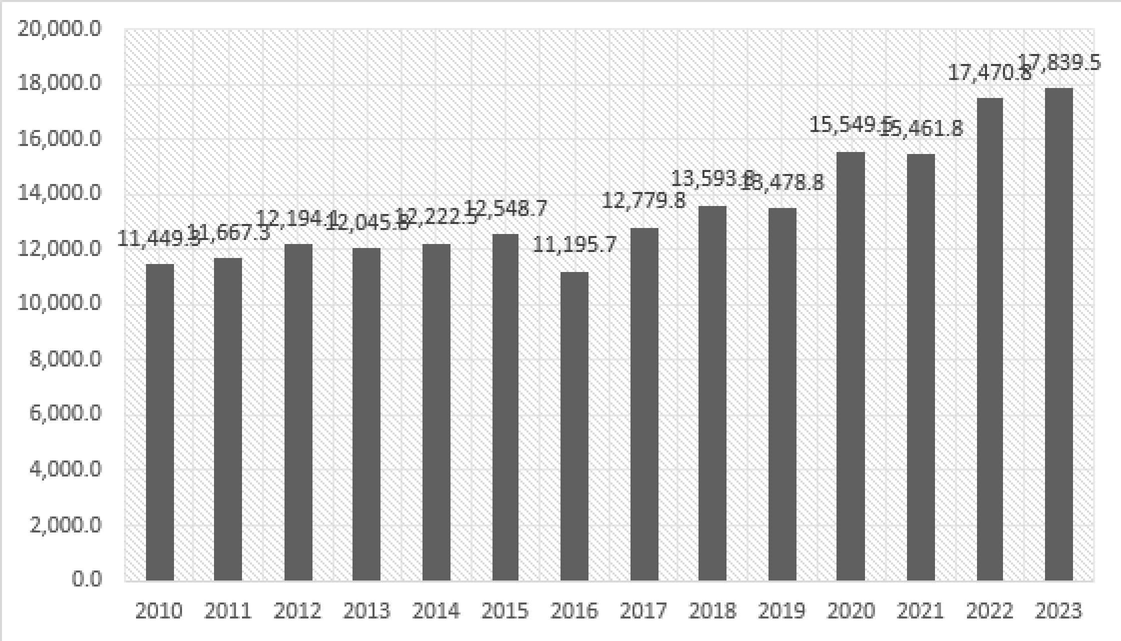

Figure 1. Residential electricity supply volume (million kWh)[1].

The growth in demand for electricity is attributed to factors such as population growth, economic development, and the expansion of industrial capacity. The sharp increase in demand after 2020 is linked to the modernization of energy supply systems and the development of renewable energy sources. However, considering the stable increase in demand, it is important to focus on increasing energy generation capacity, diversifying resources, and strengthening energy-saving measures in the future. These actions will ensure the stable supply of electricity and the continuous operation of the country's energy system.

Literature Review. Research on the economic analysis of household electricity consumption primarily focuses on the economic aspects of the energy market, consumer demand for electricity, energy efficiency, and socio-economic factors. Several scholars have contributed to this field. For example, S.V. Guzhov[2] discussed the requirements for data and their accuracy in forecasting electricity demand for a city with an isolated electricity supply, as well as the methods for monitoring this demand. Modern approaches to forecasting energy resource demand do not provide a systematic methodology. The author proposed both deterministic and stochastic methods for this purpose. Additionally, T.T. Shayuxov[3] studied the impact of external factors on energy consumption parameters through mathematical modeling, while D.E. Korbyleva[4] explored the planning of heat energy consumption using SARIMA models.

Among researchers in Uzbekistan, M.B. Khudayev, M.M. Fayziev, B.S. Bobonazarov, and A.N. Kamilov[5] have worked on evaluating electricity losses in distribution networks using artificial neural networks.

Research Methods. One of the effective tools for forecasting electricity consumption is the ARIMA (AutoRegressive Integrated Moving Average) model. This model takes into account trends, seasonality, and random variations in time series data, allowing for high-accuracy

[1] www.stat.uz Information from the Statistical Agency under the President of the Republic of Uzbekistan
[2] Гужов С.В. (2020). Forecasting the demand for electrical energy by an isolated city energy system. Energy policy, (6 (148)), 50-57.
[3] Shayukhov T. T. (2017). Mathematical modeling of the influence of external factors on power consumption parameters. Bulletin of Eurasian Science, 9 (5 (42)), 86.
[4] Korbyleva D. E. (2018). Using the ARIMA model for planning thermal energy consumption. Academy (10 (37)), 3-8.
[5] Khudayarov M.B., Fayziev M.M., Bobonazarov B.S., Kamilov A.N. (2021). Estimation of power losses in distribution networks using artificial neural networks. Innovative technologies, (3 (43)), 47-52.

forecasts. The ARIMA model enables the prediction of future demand based on the historical dynamics of electricity consumption.

The ARIMA model consists of three main parameters (p, d, q), which govern the autoregressive, differencing, and moving average components of the time series. The general form of the model is as follows:[6 7]:

$$\Delta^d x_t = a + \sum_{i=1}^{p} \varphi_i \Delta^d x_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \qquad (1)$$

In this context, a, φ_i, θ_j – are the model parameters, Δ^d – epresents the differencing operator, and, ε_t – is the error term.

In the modeling process, the data is first tested for stationarity, and if necessary, trends or seasonality are removed through differencing. Then, optimal parameters are determined using ACF and PACF plots, and the model is trained. The accuracy of the forecasts is evaluated through residual analysis and statistical measures. After that, forecast values are generated[8 9].

The results of electricity consumption forecasting are crucial for planning generation capacity, optimal resource allocation, and organizing infrastructure projects effectively. Using ARIMA models in this context allows for obtaining short- and medium-term forecasts of electricity demand.

Results. In Figure 1, the average values of the time series of electricity supply in Uzbekistan's residential sector show a clear variation over time, with an observable trend. This indicates that the time series is not stationary. Therefore, it is appropriate to apply the first difference (Figure 2) for analysis.

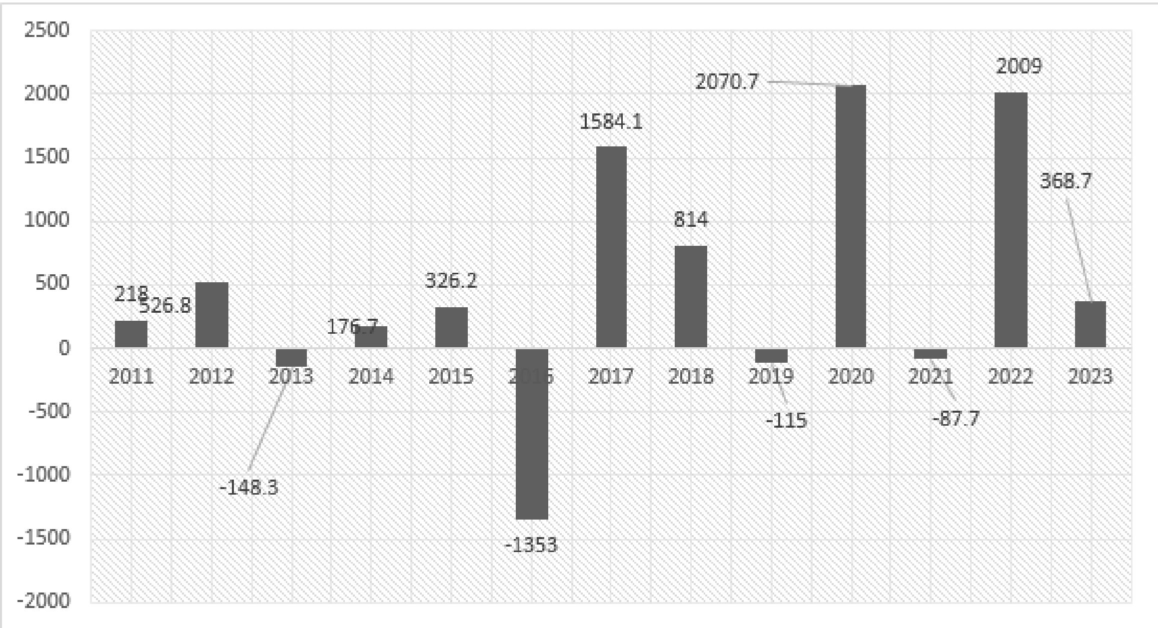

Figure 2. Graph of the first difference of the time series.[10].

[6] https://ru.wikipedia.org/wiki/ARIMA
[7] Artamonov N. V., Ivin E. A., Kurbatsky A. N., Fantazzini D. (2021) Introduction to time series analysis: a textbook for universities. Lomonosov Moscow State University, Moscow School of Economics, Department of Econometrics and Mathematical Methods of Economics. – Vologda: VolSC RAS – 134 p.
[8] Turaev B. E. (2021). Forecasting the volume of construction work using the arima model (on the example of surkhandarya region). Scientific progress, 2(2), 1287-1290.
[9] Turaev B. E., Khatamov O. Q. (2021) Forecasting the volume of construction works using the Arima model (in Surkhandarya region as an example). "UzBridge" electronic magazine,74-84.
[10] Author development

The results of the Augmented Dickey-Fuller test (ADF test) are presented in

Table 1. Results of the Augmented Dickey-Fuller test on the first difference of the time series. [11]

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Augmented Dickey-Fuller test for d_Uyjoysektoridaelektrenergiy
testing down from 4 lags, criterion AIC
sample size 10
unit-root null hypothesis: a = 1

  test without constant
  including 2 lags of (1-L)d_Uyjoysektoridaelektrenergiy
  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): 0.0373986
  test statistic: tau_nc(1) = 0.0699101
  asymptotic p-value 0.7051
  1st-order autocorrelation coeff. for e: 0.026
  lagged differences: F(2, 7) = 3.289 [0.0984]

  test with constant
  including 0 lags of (1-L)d_Uyjoysektoridaelektrenergiy
  model: (1-L)y = b0 + (a-1)*y(-1) + e
  estimated value of (a - 1): -1.39526
  test statistic: tau_c(1) = -4.82049
  asymptotic p-value 4.687e-005
  1st-order autocorrelation coeff. for e: 0.049
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The test results with a constant from Table 1 indicate that the first difference of the time series is stationary ($p = 4{,}687 \cdot 10^{-005} < 0{,}05$). However, the test results without a constant suggest the opposite. Therefore, models of order $d = 1$ va $d = 2$ can be tested.

There are various methods for determining the p and q order of the model. One such method is to review the ACF and PACF correlograms (Table 2).

Table 2. Autocorrelation and Partial Autocorrelation Functions[12].

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Autocorrelation function for Uyjoysektoridaelektrenergiy
***, **, * indicate significance at the 1%, 5%, 10% levels
using standard error 1/T^0.5

  LAG      ACF          PACF         Q-stat. [p-value]

    1   0.7047  ***   0.7047 ***      8.5573  [0.003]
    2   0.4610  *    -0.0708         12.5245  [0.002]
    3   0.2961       -0.0038         14.3099  [0.003]
    4   0.0424       -0.2935         14.3501  [0.006]
    5  -0.0286        0.1572         14.3705  [0.013]
    6  -0.1716       -0.2979         15.1950  [0.019]
    7  -0.2875       -0.0041         17.8409  [0.013]
    8  -0.2404        0.0250         19.9993  [0.010]
    9  -0.2844       -0.1203         23.6222  [0.005]
   10  -0.3124       -0.1494         29.0879  [0.001]
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In Table 2, the ACF and PACF levels are presented. Although not shown graphically, it can be observed that the ACF decreases steadily starting from the first lag, while the PACF shows insignificant lag levels after the first lag. Consequently, the optimal model order would be.$p = 1$ and $q = 0$. However, experiments revealed that neither ARIMA(1, 1, 0) nor ARIMA(1, 2, 0) provided a suitable model for the economic process.

As a solution, Akaike and Schwarz information criteria were utilized (Table 3).

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Table 3. Information criteria for various model orders.[13]

Estimated using AS 197 (exact ML)
Dependent variable Uyjoysektoridaelektrenergiy, T = 12
Criteria for ARIMA(p, 2, q) specifications

p, q	AIC	BIC	HQC	loglik
0, 0	212.8777	213.3626	212.6982	-105.4389
0, 1	205.1371	206.1069	204.7780	-100.5685
0, 2	203.7158	205.1705	203.1772	-98.8579
0, 3	204.2347	206.1744	203.5166	-98.1174
1, 0	205.3774	206.3473	205.0184	-100.6887
1, 1	203.6995	205.1542	203.1609	-98.8497
1, 2	204.6994	206.6390	203.9812	-98.3497
1, 3	207.5440	209.9685	206.6463	-98.7720
2, 0	201.5095*	202.9643*	200.9709*	-97.7548
2, 1	203.4477	205.3873	202.7296	-97.7238
2, 2	204.6344	207.0590	203.7368	-97.3172
2, 3	206.6284	209.5378	205.5512	-97.3142
3, 0	203.4752	205.4149	202.7571	-97.7376
3, 1	204.7542	207.1787	203.8565	-97.3771
3, 2	206.6303	209.5397	205.5531	-97.3151
3, 3	208.6277	212.0221	207.3710	-97.3139

'*' indicates best, per criterion
Log-likelihood ('loglik') is provided for reference

In Table 3, when $p = 2$ and $q = 0$, the Akaike, Schwarz, and Hannan-Quinn information criteria have the smallest values. Thus, the ARIMA (2, 2, 0) model can be tested (Table 4).

$$\Delta^2 y_t = -1{,}18997\Delta^2 y_{t-1} - 0{,}620598\Delta^2 y_{t-2} + \varepsilon_t \qquad (2)$$

Analysis: All parameters of the model (2) are statistically significant ($p_{z_{\varphi_1}} = 0{,}0001 < 0{,}05$ and $p_{z_{\varphi_2}} = 0{,}0024 < 0{,}05$). Furthermore, it was determined that the approximation error of the model in the experiments is $MAPE = 4{,}3581\% < 10\%$.

Table 4. Results of the Regression Analysis[14]

Model 1: ARIMA, using observations 2012-2023 (T = 12)
Dependent variable: (1-L)^2 Uyjoysektoridaelektrenergiy
Standard errors based on Hessian

	Coefficient	Std. Error	z	p-value	
phi_1	-1.18997	0.201570	-5.904	<0.0001	***
phi_2	-0.620598	0.204194	-3.039	0.0024	***

Mean dependent var	12.55833	S.D. dependent var	1654.258
Mean of innovations	158.6554	S.D. of innovations	776.2555
R-squared	0.871787	Adjusted R-squared	0.858965
Log-likelihood	-97.75477	Akaike criterion	201.5095
Schwarz criterion	202.9643	Hannan-Quinn	200.9709

AR	Real	Imaginary	Modulus	Frequency
Root 1	-0.9587	-0.8320	1.2694	-0.3862
Root 2	-0.9587	0.8320	1.2694	0.3862

[13] Author development
[14] Author development

From Table 4, the general form of the model is as follows:

It is known that if the residuals of the model are normally distributed, this indicates that the model parameters and forecasts are statistically reliable. This can be verified using the Jarque-Bera test (Figure 3).

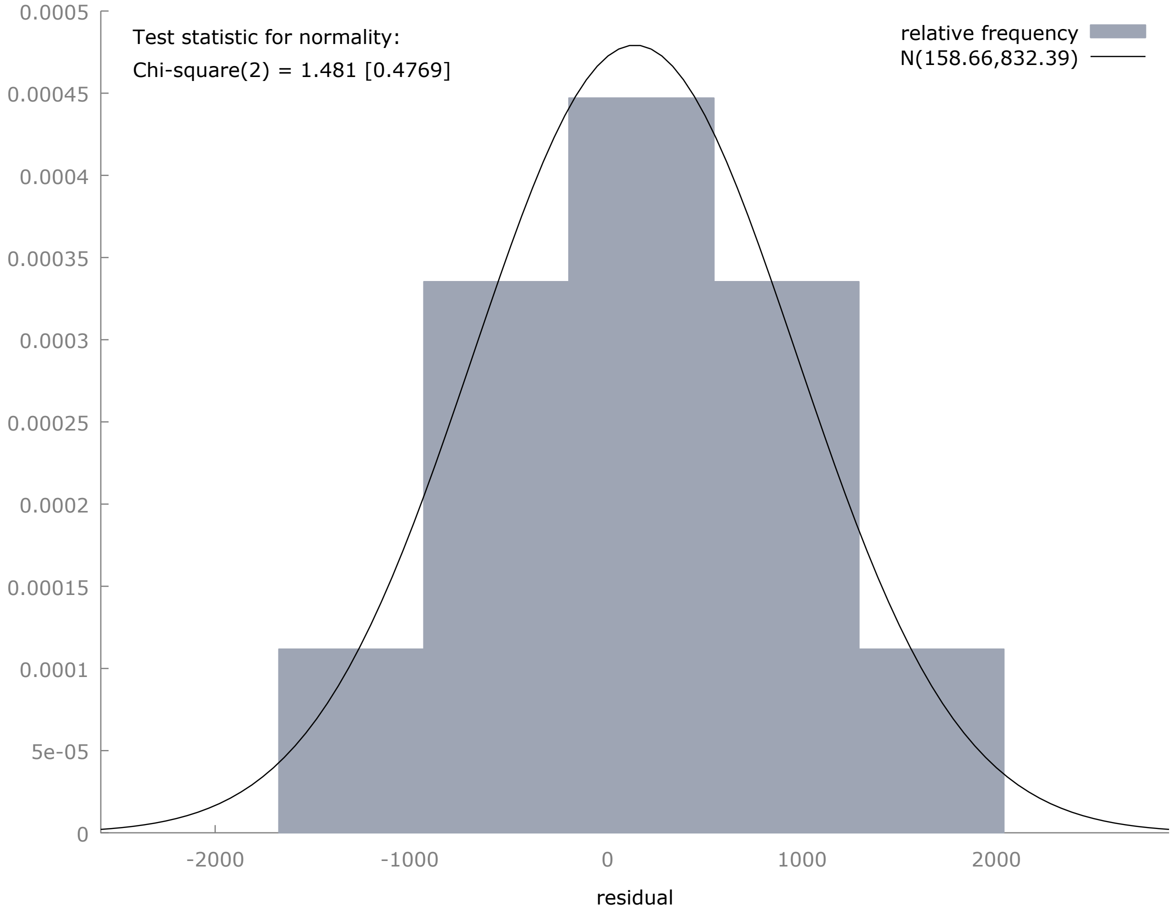

Figure 3. Results of the Jarque-Bera test for the normality of the residuals.[15].

As seen in Figure 3, the histogram is symmetric with the highest value located at its center, forming a bell-shaped curve. The peak is neither excessively sharp nor very flat. The histogram indicates that most of the residuals are concentrated near the center, and extreme values are rare. Additionally, with $\chi^2 = 1{,}481$ and $p = 0{,}4769 > 0{,}05$ this suggests that the model residuals are normally distributed.

When verifying the model, it is important to check whether the residuals are uncorrelated. This is because the ARIMA model is built to explain autocorrelation in the time series. If autocorrelation remains in the residuals, it indicates that the model has not fully explained the data. This can be checked using the ACF and PACF functions for the residuals. The autocorrelation function correlogram shows the relationships (lags) between the residuals of the time series (Figure 4).

[15] Author development

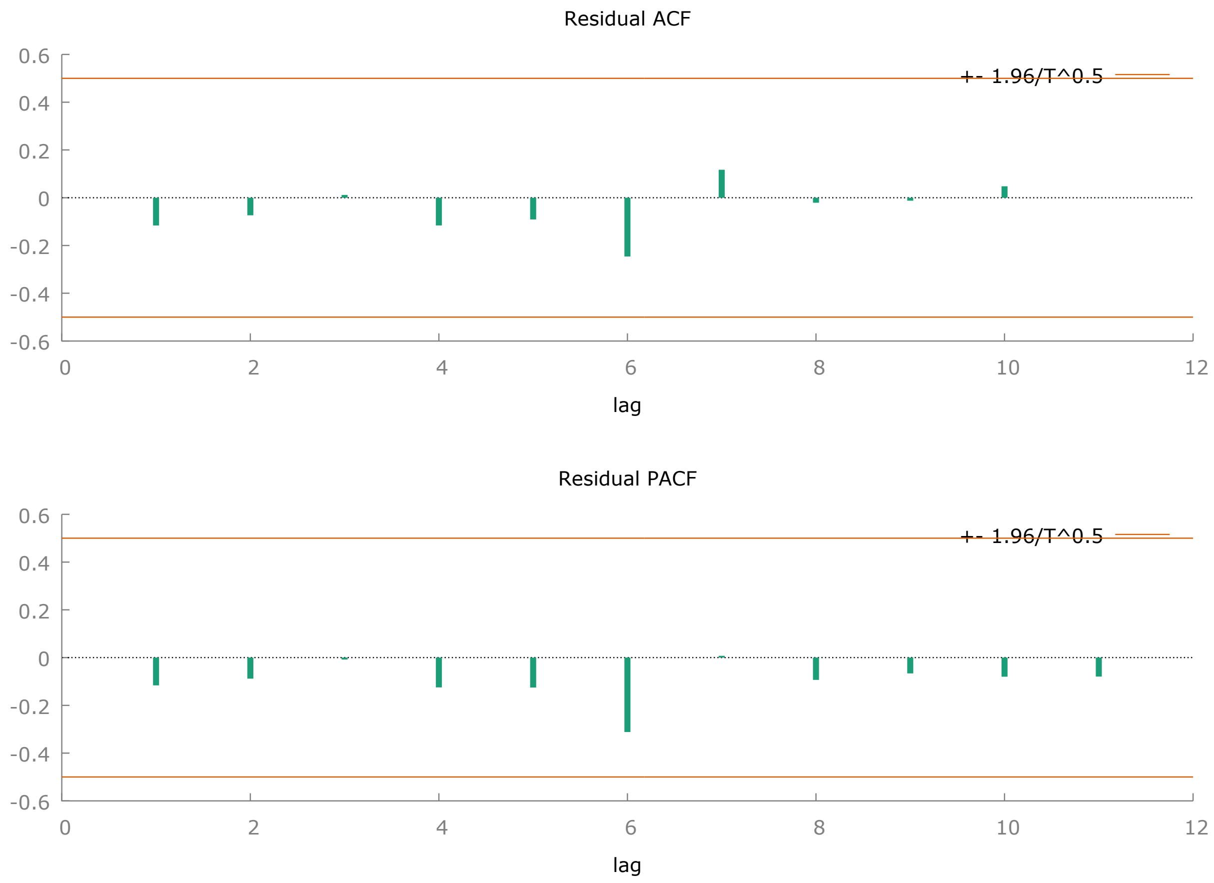

Figure 4. ACF and PACF functions for the residuals [16]

In Figure 4, the ACF and PACF correlograms show that for each lag, the autocorrelation values remain within the confidence intervals, and there is no pattern suggesting a consistent increase or decrease, or any seasonality. This indicates that the residuals are not correlated with each other and exhibit random behavior.

Thus, the (2) model is suitable for the economic process according to all statistical test conditions. It can be used for forecasting (Table 5).

Table 5. Forecast of electricity supply in the housing sector of the Republic of Uzbekistan.[17].

Years	y	Forecast	95% confidence interval lower bound	95% confidence interval upper bound	Standard error
2010	11 449,3				
2011	11 667,3				
2012	12 194,1	12 029,7			
2013	12 045,8	12 397,4			
2014	12 222,5	12 509,2			
2015	12 548,7	12 431,4			
2016	11 195,7	12 495,3			
2017	12 779,8	11 748,1			
2018	13 593,8	11 910,9			
2019	13 478,8	13 501,4			

[16] Author development
[17] Author development

2020	15 549,5	14 947,2			
2021	15 461,8	15 595,8			
2022	17 470,8	16 586,1			
2023	17 839,5	18 324,3			
2024		18 858,9	17337,5	20380,3	776,26
2025		20 122,0	18164	22079,9	998,97
2026		20 691,2	17780,7	23601,8	1485,02
2027		21 934,9	17925	25944,8	2045,9
2028		22 806,6	17805,6	27807,6	2551,58
2029		23 702,4	17384,6	30020,2	3223,44

The forecast levels are presented in graphical form in **Figure 5**.

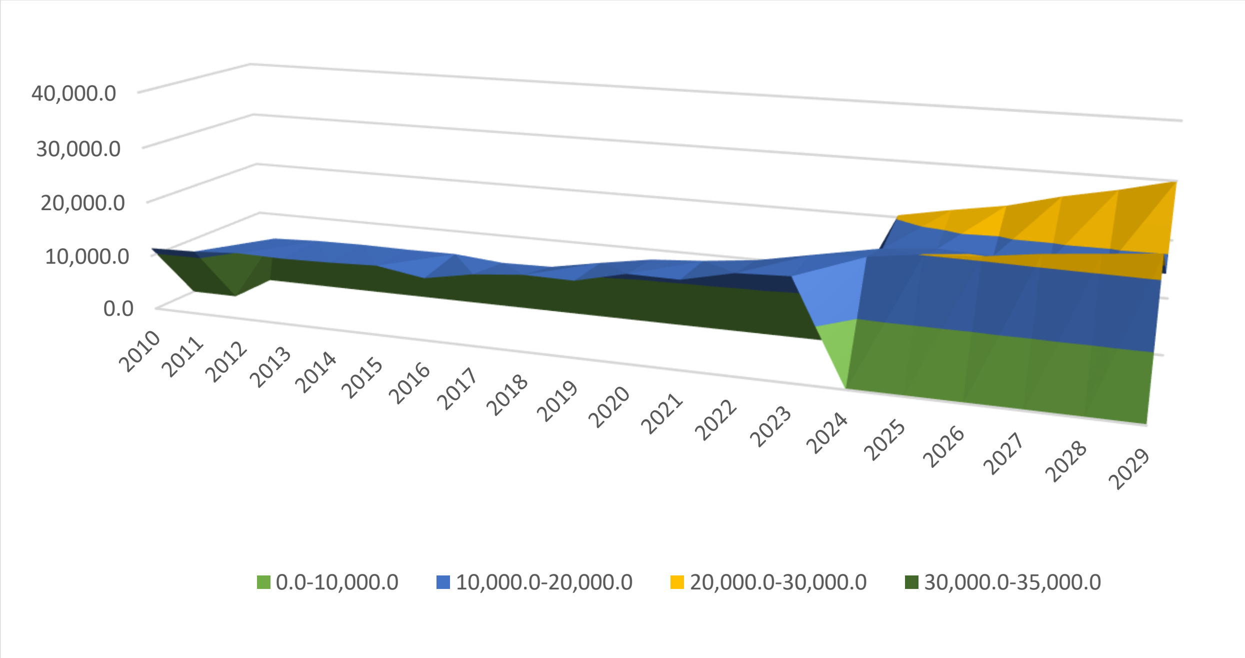

Figure 5. Actual values of the time series, forecasted values, and confidence intervals[18].

Conclusion. The forecasts show future changes in electricity supply in the housing sector of Uzbekistan. Between 2024 and 2025, a significant increase in electricity demand is expected (an average of 106.2%), with the highest value observed in 2025 (18,164 million kWh). This growth is likely associated with the acceleration of economic growth, an increase in the construction of new residential buildings, or the expansion of industrial enterprises. Additionally, the growing demand for energy resources could lead to a need for the expansion and modernization of the energy supply system. During this period, a steady development of energy supply is necessary, as infrastructure and production capacities will need to be expanded to meet the increased demand.

From 2026 onwards, the rate of growth is expected to slow down. By 2029, electricity supply in the housing sector will reach 23,702 million kWh, with growth dropping to 103.92%. This deceleration could be related to measures aimed at improving energy efficiency and the introduction of new types of energy sources. Specifically, the increased focus on energy efficiency will lead to the optimization of energy consumption in the housing sector. By 2029, the reduction in energy consumption may be explained by the widespread implementation of energy-saving technologies, the strengthening of energy efficiency standards in new buildings, and improvements in housing sector infrastructure. Meanwhile, the role of renewable energy sources will increase, which could lead to a decline in demand for traditional electricity supply systems.

[18] Author development

Thus, the forecasts obtained from the ARIMA model reflect future changes in electricity consumption in the housing sector of Uzbekistan. These changes are closely linked to economic, technological, and environmental factors, each of which influences electricity production and consumption. It is important to note that the energy supply forecasts indicate the need to develop effective strategies for managing energy resources in the future and ensuring sustainable development within this system.

References

1. Artamonov, N. V., Ivinn, E. A., Kurbatsky, A. N., & Fantazzini, D. (2021). *Introduction to Time Series Analysis: A Textbook for Universities.* Moscow State University named after M. V. Lomonosov, Moscow School of Economics, Department of Econometrics and Mathematical Methods of Economics. Vologda: VolNC RAS. – 134 p.
2. Guzhov, S. V. (2020). Forecasting electricity demand for an isolated power system of the city. *Energy Policy, 6(148),* 50-57.
3. Korbyleva, D. E. (2018). Using the ARIMA model for planning heat energy consumption. *Academy, 10(37),* 3-8.
4. Turaev, B. E. (2021). Forecasting the volume of construction work using the ARIMA model (on the example of Surkhandarya region). *Scientific Progress, 2(2),* 1287-1290.
5. Turaev, B. E., & Khatamov, O. Q. (2021). Forecasting the volume of construction work using the ARIMA model (on the example of Surkhandarya region). *"UzBridge" Electronic Journal,* 74-84.
6. Shayukhov, T. T. (2017). Mathematical modeling of the influence of external factors on electricity consumption parameters. *Bulletin of Eurasian Science, 9(5(42)),* 86.
7. Khudayarov, M. B., Faiziev, M. M., Bobonazarov, B. S., & Kamilov, A. N. (2021). Estimating electricity losses in distribution networks using artificial neural networks. *Innovative Technologies, 3(43),* 47-52.