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Assessing the Stability of Regional Energy Supply Systems: Econometric Models and Forecasts

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Abstract: This study investigates the econometric modeling and forecasting of energy consumption dynamics within the energy supply system. Per capita primary energy consumption was selected as the indicator of energy consumption in the energy supply system, and the analysis was conducted using annual data covering the period from 1990 to 2025. First, the descriptive statistical characteristics of the indicator were assessed, revealing an overall declining trend in energy consumption over the study period. The dynamics of energy consumption were modeled using the ARIMA(1,1,3) model, and the forecasting accuracy of the model was evaluated using the MAPE, MAE, and RMSE metrics. The estimated ARIMA(1,1,3) specification yields $R^2 = 0.93$, while the forecast evaluation reports MAPE = 3.14%, MAE = 597.96 kWh/person, and RMSE = 749.64 kWh/person. The baseline forecast indicates a decline in per capita primary energy consumption from 15,355.95 kWh/person in 2026 to 13,760.47 kWh/person in 2030, equivalent to approximately 86.3% of the 2025 level. The results demonstrate the usefulness of a transparent time-series benchmark for short- and medium-term energy planning while also highlighting the need to interpret forecasts conditionally on historical dynamics.

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1. Introduction

Today, the stability of energy supply is one of the key factors ensuring the continuous development of the global economy. As a result of the expansion of industrial production, urbanization, digitalization, and the electrification of transport and other sectors of the economy, the volume and structure of demand for energy resources are undergoing continuous changes. According to data from the International Energy Agency (IEA), global energy demand increased by 1.3% in 2025, while electricity demand rose by nearly 3%. Thus, the growth rate of electricity demand was approximately 2.3 times higher than that of overall energy demand.

Energy-supply stability is not determined by demand volume alone; it also depends on resource availability, infrastructure adequacy, diversification, efficiency, and the ability of the system to respond to shocks. In the present study, per capita primary energy consumption is used as a demand-side indicator that captures the long-run intensity of energy use. It should therefore be interpreted as one quantitative component of supply-system stability rather than as a complete measure of reliability or security.

Alongside the growth in energy consumption, significant changes are also being observed in its regional and structural composition within the global energy system. In 2024, global energy demand increased by 2.2%, reaching approximately 650 EJ, with more than 80% of this growth attributable to developing and emerging economies. During the same period, electricity demand increased by 4.3%. This growth was driven by such factors as the electrification of the economy, the expansion of industrial production, increased use of air conditioning, the electrification of transport, and the rapid development of data centers and artificial intelligence technologies [1, 2].

These trends are increasing the need for an accurate assessment of energy consumption within the energy supply system and for anticipating its future changes. Energy consumption is shaped by factors such as economic activity, production volume, living standards, and technological development. Therefore, assessing the current state of energy consumption, identifying patterns in its changes over time, and forecasting its future values are of considerable importance for the efficient allocation of energy resources, enhancing supply stability, and developing appropriate strategic decisions.

The research objective is to model the long-term annual dynamics of per capita primary energy consumption and to generate a reproducible short- and medium-term baseline forecast. The study asks whether the historical series can be rendered stationary with an appropriate degree of differencing, whether a parsimonious ARIMA specification can capture the remaining temporal dependence, and whether the resulting forecast errors are sufficiently low for planning-oriented use. By focusing on annual observations, the analysis emphasizes structural movement rather than short-term seasonal fluctuations.

Changes in energy consumption indicators over time are not necessarily constant and may exhibit trends, periodic fluctuations, and random variations. Therefore, assessing such processes solely through conventional statistical methods may not be sufficient. Econometric models that account for the dynamic characteristics of time series represent an effective tool for analyzing and forecasting energy consumption. In particular, the ARIMA (Autoregressive Integrated Moving Average) model makes it possible to account for the stationarity of a time series, the relationships between values in previous periods, and the influence of random errors from earlier periods [3][4][5].

Literature Review

Time-series models such as ARIMA and SARIMA have been widely used in studies on energy consumption forecasting. A.K. Dubey et al. applied SARIMA and LSTM models to forecast energy consumption and comparatively evaluated their performance [6]. P. Cihan used the ARIMA model to forecast electricity and natural gas consumption and compared its results with those obtained using the Holt-Winters model [7]. A.M. Khan and M. Osińska evaluated the forecasting accuracy of ARIMA and other time-series models using energy consumption data from Brazil and India based on the MAPE, MSE, and RMSE criteria [8]. S. Chaturvedi et al. conducted a comparative analysis of SARIMA, LSTM, and Prophet models for energy demand forecasting [9]. Research on forecasting energy consumption and electricity demand widely employs econometric, time-series, machine learning, and deep learning models [10][11][12][13][14]. These studies evaluate forecasting methods, forecasting horizons, and model performance using various criteria. ARIMA models make it possible to account for the dynamic characteristics of time series, differencing, as well as autoregressive and moving average components [15]. In addition, the potential of big data and deep learning methods for energy forecasting has been extensively investigated [16]. Furthermore, research has also addressed the use of artificial intelligence in energy systems, risk assessment, and energy demand forecasting [17][18][19].

These studies demonstrate the effectiveness of time-series models in forecasting energy consumption dynamics. However, the long-term annual dynamics of per capita primary energy consumption have not been sufficiently investigated using the ARIMA

model. Therefore, this study aims to address this research gap by modeling and forecasting the long-term dynamics of per capita primary energy consumption using the ARIMA approach.

The reviewed literature also shows that energy forecasting is methodologically plural. Classical ARIMA and SARIMA models provide interpretable benchmarks for autocorrelation and differencing, while LSTM, Prophet, hybrid, optimization-based, and other machine-learning approaches offer alternative ways to capture nonlinear or high-dimensional patterns [6]–[16]. The appropriate model therefore depends on data frequency, sample length, forecasting horizon, interpretability requirements, and the purpose of the forecast. For a relatively short annual series, the ARIMA framework remains useful because it can be estimated transparently and evaluated with established residual and forecast-error diagnostics.

Research on artificial intelligence, energy-system risk, and energy-demand models further indicates that forecasting should be viewed as part of a broader decision-support process rather than as an isolated statistical exercise [17]–[19]. The practical value of a forecast depends on how it is incorporated into planning, efficiency measures, resource allocation, and risk management. The present study contributes to this process by providing a clearly specified univariate benchmark that can later be compared with multivariate or machine-learning extensions.

2. Materials and Methods

Research Methodology

The study employed dynamic, correlation, and descriptive statistical analysis methods. The ARIMA econometric model was applied to model the energy consumption time series, while stationarity tests and information criteria such as AIC and BIC were used as the basis for determining and selecting the model parameters. Model adequacy was assessed using the Ljung–Box test, while forecasting accuracy was evaluated using the MAPE, MAE, and RMSE metrics. All calculations and econometric analyses were performed using the Gretl software.

The dataset contains 36 annual observations covering 1990–2025. The modeling workflow follows the standard Box–Jenkins logic: descriptive examination of the level series, assessment of stationarity, differencing where required, identification of candidate autoregressive and moving-average orders, parameter estimation, model comparison using information criteria, residual adequacy checking, and out-of-sample-oriented forecast evaluation. The selected specification, ARIMA(1,1,3), uses first differencing ($d = 1$), one autoregressive term, and three moving-average terms.

AIC and BIC are used to balance goodness of fit against model complexity, thereby discouraging unnecessary parameters. The Ljung–Box test is used to assess whether residual autocorrelation remains after estimation. Forecast accuracy is summarized by Mean Error (ME), which indicates systematic bias; Mean Absolute Error (MAE), which measures the average magnitude of absolute forecast deviations; Root Mean Squared Error (RMSE), which gives greater weight to relatively large errors; and Mean Absolute Percentage Error (MAPE), which expresses average absolute error in percentage terms. Together these diagnostics provide complementary evidence on model adequacy and practical forecast precision.

All reported estimates are interpreted as time-series relationships conditional on the historical information contained in the series. Because the model is univariate, it does not directly identify the causal effects of prices, income, industrial structure, weather, policy, renewable-energy deployment, or other external drivers. Those factors may influence future energy consumption but are not separately estimated in the current specification.

3. Results

Descriptive Dynamics

Assessing the dynamics of primary energy consumption and forecasting its future changes are of significant importance for ensuring the sustainable development of the energy supply system. From this perspective, a time-series model was developed in the study based on the indicator of per capita primary energy consumption (kWh/person). Using data for the period 1990–2025 [20], the dynamic characteristics of the indicator were analyzed, its stationarity was tested, and future values were forecast using the ARIMA model (Table 1).

Table 1. Main statistical characteristics of the per capita primary energy consumption indicator

Mean	Median	Minimum	Maximum
19365.	18743.	15075.	24758.
Std. Dev.	C.V.	Skewness	Ex. kurtosis
2966.9	0.15321	0.16457	-1.4147

According to the results of the descriptive statistical analysis, the mean value of per capita primary energy consumption during the study period was 19,365 kWh/person, while the median value was 18,743 kWh/person. The minimum value of the indicator was 15,075 kWh/person, whereas the maximum value was 24,758 kWh/person. The difference between these values amounted to 9,683 kWh/person, indicating that significant changes in the level of primary energy consumption were observed during the study period. A comparative analysis of the values at the beginning and end of the period indicates the formation of a long-term downward trend in primary energy consumption. In particular, per capita primary energy consumption amounted to 24,757.94 kWh/person in 1990, while in 2025 this indicator decreased to 15,948.53 kWh/person. As a result, during the study period, the indicator decreased by 8,809.41 kWh/person, or by 1.55 times. This reflects a significant long-term reduction in primary energy consumption per capita.

The decline from 24,757.94 kWh/person in 1990 to 15,948.53 kWh/person in 2025 corresponds to an absolute reduction of 8,809.41 kWh/person. The moderate coefficient of variation indicates that the long-run trend is substantial but is not accompanied by extreme dispersion around the sample mean. The near-zero skewness and negative excess kurtosis further suggest that the level distribution is relatively symmetric and flatter than a normal distribution, although these distributional properties alone do not establish time-series stationarity.

At the same time, the year-by-year dynamics of the indicator were not uniform. During certain stages of the study period, the declining process was interrupted by temporary increases. This indicates the presence of time-dependent changes in the formation of primary energy consumption and demonstrates that the dynamics of this indicator cannot be adequately explained solely by a simple trend.

The standard deviation of the indicator was 2,966.9 kWh/person, while the coefficient of variation was 15.32%. This result indicates that primary energy consumption fluctuated to a certain extent around its mean value during the observation period, although its variation was not excessively high. The skewness coefficient was 0.16457, and its proximity to zero indicates that the distribution did not exhibit strong asymmetry. The excess kurtosis was -1.4147, indicating that the distribution was relatively flatter compared with a normal distribution. Although these results show that there were no pronounced deviations in the distributional characteristics of the per capita primary energy consumption indicator, its stationarity level was additionally examined to determine the dynamic properties of the time series.

ARIMA Model Estimation

In modeling the primary energy consumption time series, the ARIMA model makes it possible to account for the variability, temporal dependence, and random fluctuations of the series. The ARIMA model is represented by three main parameters.

In the ARIMA(p,d,q) model, the parameter p represents the order of dependence of the time series on its previous values, the parameter d represents the degree of differencing performed to make the series stationary, and the parameter q represents the order of the influence of random errors from previous periods on the current value. In this model, a first-order autoregressive component AR(1) and a third-order moving average component MA(3) were applied, with d=1 (Table 2).

Table 2. Results of parameter estimation for the ARIMA(1,1,3) model of per capita primary energy consumption

ARIMA(1,1,3)	Coefficient	Std. Error	z	p-value	R2	ARIMA(1,1,3)
$(1-L)PPEC_t = -261.76 + 0.59(1-L)PPEC_{t-1} - 0.94\varepsilon_{t-1} + 0.49\varepsilon_{t-2} - 0.54\varepsilon_{t-3} + \varepsilon_t$						
const	-261.764	39.8697	-6.565	<0.0001	const	0.93
phi_1	0.593463	0.203479	2.917	0.0035	phi_1	
theta_1	-0.947906	0.184863	-5.128	<0.0001	theta_1	
theta_2	0.490123	0.224185	2.186	0.0288	theta_2	

The results presented in the table show that the constant term of the model is -261.764, with a p-value of less than 0.0001. This indicates that the parameter is statistically highly significant. The AR(1) coefficient is 0.593463, with a p-value of 0.0035, indicating a statistically significant dependence of the first-differenced per capita primary energy consumption (PPEC) series on its value in the previous period.

The MA components are also statistically significant. Specifically, $\theta_1 = -0.947906$, $\theta_2 = 0.490123$, and $\theta_3 = -0.542217$, with corresponding p-values of $p < 0.001$, $p = 0.0288$, and $p = 0.0194$, respectively. These results indicate that all MA components are statistically significant at the 5% significance level. Thus, the model adequately captures the dynamics of PPEC not only through its previous values but also through random innovations from previous periods.

The reported $R^2 = 0.93$ indicates that the model explains approximately 93% of the variation in the PPEC indicator. This result demonstrates a high degree of correspondence between the observed values and those estimated by the model. Overall, the statistical significance of all major parameters in the ARIMA(1,1,3) model supports the adequacy of the model specification to the empirical data (Table 3).

The signs and magnitudes of the estimated coefficients indicate that changes in PPEC contain both persistence and correction from past innovations. The positive AR(1) coefficient captures dependence on the immediately preceding differenced value, whereas the statistically significant MA terms show that shocks from several previous periods contribute to current adjustments. The model therefore represents the series through a combination of inertia and short-memory error dynamics rather than through a deterministic trend alone.

Table 3. Forecast Parameters of Per Capita Primary Energy Consumption

Indicators	Forecast years					2030/2025
	2026	2027	2028	2029	2030	
PPEC	15355.95	15217.24	14610.36	14143.79	13760.47	

Forecast Accuracy and 2026–2030 Outlook

According to the results of the assessment of the forecasting accuracy of the ARIMA(1,1,3) model, the Mean Error (ME) was -37.536 , indicating a small negative bias in the model forecasts. The RMSE was 749.64 , while the MAE was 597.96 , indicating that the average absolute deviation of the model forecasts from the actual values was approximately 598 kWh/person. The MAPE was 3.14% , indicating a relatively low level of forecasting error and demonstrating the model's good forecasting performance.

The error metrics should be read jointly. The small negative ME indicates a modest tendency toward overprediction or underprediction depending on the sign convention used in the software, while MAE and RMSE quantify the forecast deviation in the original kWh/person units. The reported MAPE of 3.14% is comparatively low for the fitted forecasting exercise and supports the use of the model as a baseline planning tool, subject to the limitations of a univariate annual specification.

According to the forecast results, the declining trend in the PPEC indicator is expected to persist during 2026–2030. Specifically, the indicator is projected to decrease from $15,355.95$ kWh/person in 2026 to $13,760.47$ kWh/person in 2030. Consequently, in 2030, PPEC is forecast to reach 0.863 times its 2025 level, representing a decrease of approximately 13.7% .

4. Discussion

The estimated model and forecast extend the literature on statistical energy-demand modeling by showing that a conventional ARIMA structure can provide a compact representation of a long annual consumption series. The finding is consistent with the continued use of ARIMA-family models as interpretable benchmarks in energy forecasting studies [3]–[9], while the broader literature demonstrates that statistical models can also be compared with machine-learning and hybrid approaches when richer data are available [10]–[16]. The value of the present specification lies primarily in transparency, parsimony, and ease of diagnostic evaluation.

The projected decline to $13,760.47$ kWh/person by 2030 should be interpreted as a conditional baseline rather than as a deterministic policy target. ARIMA extrapolates the stochastic structure observed in historical data; it does not explicitly model future changes in economic growth, industrial composition, energy prices, climate conditions, efficiency standards, electrification, renewable deployment, or major supply disruptions. Consequently, the forecast is most useful as a reference trajectory against which alternative scenarios and policy assumptions can be compared.

From an energy-planning perspective, a sustained reduction in per capita primary energy consumption can have different meanings. It may reflect improvements in energy efficiency and structural transformation, but it can also coexist with constraints on energy access or production. For that reason, decision makers should interpret PPEC together with indicators of electricity consumption, industrial output, renewable-energy penetration, generation adequacy, network losses, import dependence, and reliability. The current model provides the demand-side time-series component of such a broader stability assessment.

Several limitations define the scope of the conclusions. The sample consists of annual observations and therefore cannot represent seasonal or intra-year demand patterns. The specification is univariate and does not include exogenous explanatory variables. Structural-break tests, alternative ARIMA specifications, forecast confidence intervals, and direct comparisons with machine-learning models are not reported in the source analysis. Future research should address these issues by applying ARIMAX or vector models, testing structural stability, producing interval forecasts, and benchmarking the results against SARIMA, Prophet, LSTM, and hybrid approaches using consistent training and evaluation windows.

5. Conclusion

The results of the study demonstrate that the time-series model (ARIMA(1,1,3)) can be effectively used for short- and medium-term forecasting of primary energy consumption dynamics. The model provides a reliable representation of the temporal patterns and changes in primary energy consumption and can therefore be applied to assess its future development trends. The obtained forecasting results can provide a practical basis for planning energy supply, assessing demand for energy resources, improving the efficiency of energy use, and developing strategic decisions aimed at ensuring the sustainable development of the energy supply system. Furthermore, the results can support decision-making related to the efficient allocation of energy resources and the development of measures to improve energy efficiency. In addition, the study shows that forecast quality should be evaluated through several complementary metrics rather than through a single goodness-of-fit statistic. The projected 2026–2030 decline provides a quantitative baseline for evaluating future deviations in demand and for designing alternative energy-efficiency and supply scenarios. The model should be updated as new observations become available so that parameter stability and forecast accuracy can be reassessed over time.

Recommendations

It is necessary to improve the system for regular monitoring and forecasting of energy consumption dynamics within the energy supply system based on econometric models.

Energy-efficient and innovative technologies aimed at reducing energy consumption should be widely implemented in energy and production processes.

In order to enhance the stability of energy supply, the use of renewable energy sources should be expanded.

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