

Forecasting Indonesia's Final Energy Consumption Using ARIMA Models: Evidence from 2001–2024 and Projections to 2030

Mukhlis^{1*}, Helmi Noviar², Mardaleta²

¹Student in the Master's Program in Development Economics, Faculty of Economics and Business,
Universitas Teuku Umar / Economic Department Staff of the Nagan Raya Regency Government

²Master's Program in Development Economics, Faculty of Economics and Business, Universitas Teuku Umar

***Corresponding Author:** mukhlis628@gmail.com

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Abstract

Reliable projections of energy consumption are essential for designing effective and sustainable energy policies in emerging economies such as Indonesia, where demand continues to rise alongside economic growth and population expansion. This study forecasts Indonesia's final energy consumption using the Autoregressive Integrated Moving Average (ARIMA) approach, with historical annual data covering 2001–2024 and projections extending to 2030. Accurate forecasting is essential for Indonesia because rising economic activity, urbanization, industrial expansion, population growth, and increasing household energy demand continue to place pressure on national energy security and sustainability. The study applies the Box–Jenkins procedure through stationarity testing, model identification, parameter estimation, diagnostic checking, and out-of-sample forecasting using EViews. The Augmented Dickey–Fuller test indicates that the original series is non-stationary at level, but becomes stationary after first differencing. Model comparison based on the Akaike Information Criterion, Schwarz Criterion, R-squared value, residual correlogram, and diagnostic probability values identifies ARIMA (1,1,1) as the most appropriate specification for forecasting Indonesia's final energy consumption. The empirical results show a persistent upward trend, with final energy consumption increasing from 3,807,815 TJ in 2001 to 7,930,428 TJ in 2024. Forecasts suggest that consumption will continue to rise from 7,948,819 TJ in 2025 to 8,926,521 TJ in 2030. These findings indicate that Indonesia will face growing pressure to secure reliable, affordable, and sustainable energy supplies. The study contributes to energy policy planning by providing quantitative evidence for strengthening energy infrastructure, improving energy efficiency, accelerating renewable energy adoption, and reducing dependence on fossil fuels. The results also highlight the importance of integrating demand forecasting into long-term national energy strategies to support sustainable development and energy resilience.

Keywords: Energy Consumption Forecasting, ARIMA, Final Energy Consumption, Renewable Energy Transition, Sustainable Energy Policy.

Introduction

Energy consumption forecasting is a crucial aspect in designing efficient and sustainable energy policies, particularly in Indonesia, which faces significant challenges due to the continuous increase in energy demand. Energy consumption is an essential component of a country's economic development process. Several factors, including population growth, rising living standards, improvements in the production sector, and increasing economic competitiveness, have become major drivers of the growing demand for energy. Based on data from 2001 to 2024, Indonesia's energy consumption has continued to increase, particularly in the industrial and household sectors. In addition, fluctuations in global oil prices, which substantially affect energy costs, also play an important role in shaping Indonesia's energy consumption patterns, especially in the transportation and industrial sectors. As explained by [13], urbanization and industrialization have contributed to the increasing demand for modern energy sources. Projections further indicate that energy consumption will continue to rise, particularly in urban centers [13]. Therefore, forecasting remains an essential tool in decision-making processes and long-term energy planning.

Energy plays a crucial role and is a fundamental requirement in supporting economic activities and development. However, the majority of countries still rely heavily on fossil fuels such as oil, coal, and natural gas. This dependency raises concerns as fossil resources are finite and have significant negative impacts on environmental degradation and climate change. From the perspective of economic growth theory, an increase in economic output is generally accompanied by a rise in the demand for production factors, including energy. Consequently, economic expansion tends to drive higher energy demand, particularly in the industrial, manufacturing, and transportation sectors. Therefore, a high economic growth rate is often structurally linked to increased consumption of fossil energy sources [16].

The challenge faced by the government is energy security, which involves ensuring a continuous, reliable, and stable energy supply over the long term at affordable prices for

the public. This aligns with the research conducted by [13], which states that energy security has become an increasingly important policy issue due to the volatile global energy market. The role of energy policies in shaping consumer behavior is crucial to ensure long-term energy sustainability [13]. Therefore, the government needs to take concrete steps through policy measures to maintain the balance between supply and demand, ensuring that energy prices remain stable and do not cause market shocks. One of the steps the government can take is through energy demand forecasting

The Autoregressive Integrated Moving Average (ARIMA) model has proven effective in forecasting Indonesia's energy consumption, particularly in handling time series data that exhibits high fluctuations, such as those caused by economic factors and energy prices. A study by [5], which examines electricity production cost forecasting, also highlights the importance of the ARIMA model in projecting energy-related variables that are interconnected with economic variables.

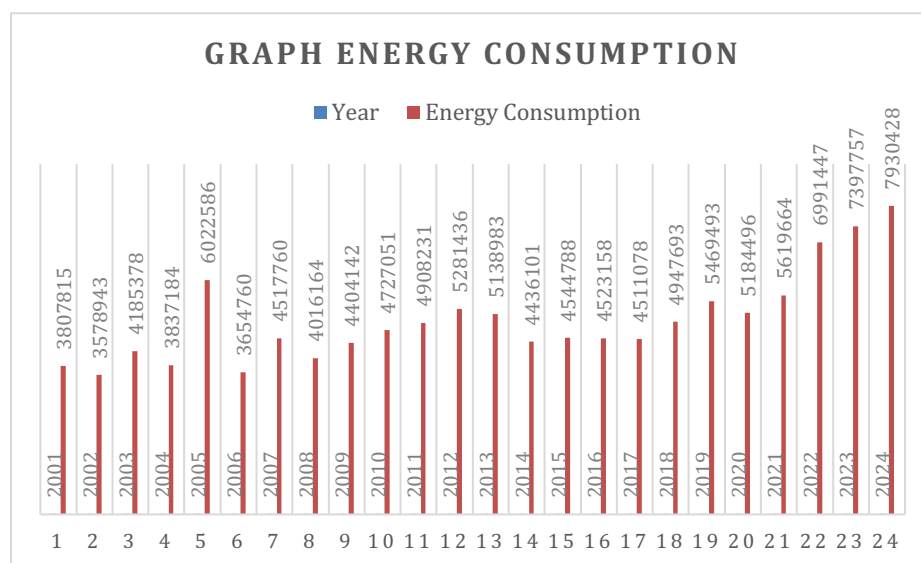


Figure 1. Indonesia's Energy Consumption Graph 2001-2024

Energy consumption forecasting is an important topic in energy economics studies, as it can assist in planning more efficient and sustainable energy policies. In Indonesia, energy consumption continues to rise along with rapid economic growth, the development of the industrial sector, and an increasing population. Therefore, several studies have been conducted to predict energy consumption trends using various methods, including the

ARIMA (Autoregressive Integrated Moving Average) model, which is known to be effective in handling time series data with high fluctuations [5].

A study by [18] also highlights the importance of long-term energy consumption forecasting. Their research indicates that factors such as GDP per capita, oil prices, and population size influence energy consumption in Indonesia. However, most previous studies have focused more on the short term and have not adequately integrated macroeconomic variables for long-term projections. This highlights a gap in the literature regarding energy consumption forecasting models that consider the long-term economic and social impacts.

Additionally, another study by [14] emphasizes that energy consumption in Indonesia is influenced by the ongoing energy transition, as well as technological advancements that impact energy consumption patterns. The shift to renewable energy and the electrification of transportation are two key factors expected to increase energy consumption, although with differing impacts on energy resources and infrastructure. This study aims to fill the research gap by focusing on forecasting final energy consumption in Indonesia up to 2030 using the ARIMA model. Additionally, the study seeks to identify the most suitable model for forecasting final energy consumption in Indonesia.

Literature Review

Final energy consumption refers to the energy used directly by end users, such as households and the industrial sector, after undergoing conversion from primary energy. The main difference between primary energy and final energy lies in their function: primary energy includes raw sources such as oil, gas, coal, and renewable energy, while final energy refers to energy that is ready for use by society and the industrial world [7,8].

Income refers to the earnings individuals or society receive from their economic activities. In the context of macroeconomics, this income is used for consumption, with the remainder being saved (invested) [12]. Economic growth is a primary factor driving fossil energy consumption, especially in developing countries. According to classical and endogenous growth theories, an increase in economic production requires more energy to

support production activities, transportation, and industry, with fossil fuels such as oil, coal, and natural gas remaining the primary energy sources. On the other hand, the Environmental Kuznets Curve (EKC) hypothesis proposed by [11] provides a theoretical framework suggesting that environmental damage, including reliance on fossil fuels, tends to rise during the early stages of development but may decline as income increases and more environmentally friendly technologies are adopted.

The Box-Jenkins model, or ARIMA model, has become the most popular method for predicting and forecasting time series data. This model has been applied in various fields. The Box-Jenkins approach combines time series analysis with statistical methods to predict future values based on previously available data [3]. There are three main components in the ARIMA model: autoregressive (AR), integration (I), and moving average (MA), which allow for the analysis of non-stationary data [3].

Various literatures have employed ARIMA or ARIMA-based hybrid models for energy forecasting. Other studies compare different forecasting models, highlighting the superiority of ARIMA or ARIMA-based hybrid models, particularly for medium/long-term predictions (5-20 years). [1] conducted energy demand forecasting for Jordan using the ARIMA model up to 2030, focusing on energy consumption in key sectors. Scientifically, ARIMA is superior because it combines three key components: autoregressive, differencing, and moving average. The autoregressive component captures the dependency of current energy consumption on past consumption; the differencing process transforms non-stationary data into stationary data; while the moving average accounts for historical error patterns. This combination makes ARIMA not just a tool for extrapolating trends but a time series econometrics framework that can interpret the historical memory in energy consumption. This is important because energy demand is strongly influenced by long-term behaviors, sectoral structures, changes in economic activities, as well as dynamics in household, industrial, transportation, service, and other sectors [1]. Another advantage highlighted in the article is the parsimonious nature of ARIMA, which is capable of producing relatively simple yet informative models.

Research Methods

This study aims to forecast energy consumption in Indonesia from 2025 to 2030 using the ARIMA (Autoregressive Integrated Moving Average) model. To achieve this objective, the study utilizes Eviews software as an analytical tool to model and forecast Indonesia's energy consumption. The data used in this research is annual time series data, covering Indonesia's energy consumption in terajoules from 2001 to 2024, obtained from various official sources, including the Ministry of Energy and Mineral Resources (ESDM), the Central Statistics Agency (BPS), and the National Energy Council of Indonesia.

When studying a phenomenon, researchers do not always apply a cause-and-effect approach, as is commonly found in correlation regression analysis. In regression analysis, research typically involves two or more variables to determine the extent to which one or more variables influence others. In the field of economics, there is also time series data, which is data that is expected to exhibit specific patterns or characteristics, causing its values to change over time. The analysis of time series data is referred to as time series analysis.

According to Gujarati [6], one approach in economics based on time series data is the Autoregressive Integrated Moving Average (ARIMA), which is derived from a combination of Autoregressive (AR) and Moving Average (MA) components that have been differenced. This concept is based on the assumption that "data speak for themselves," as the current value of the data is influenced by the values of the data from previous periods.

The empirical model used in this study is the ARIMA (p,d,q) model. This model is formulated as follows:

$$Y_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (1)$$

Where:

- Y_t = variables at time t.
- μ = constant.
- $\phi_1, \phi_2, \dots, \phi_p$ = coefficient autoregressive (AR).
- $\theta_1, \theta_2, \dots, \theta_q$ = coefficient moving average (MA).
- ϵ_t = residual at time t.

The initial step in ARIMA modeling is conducting a stationarity test on the data. This stationarity test is essential to prevent misleading regression models, which could result in meaningless and biased regression outcomes. The test involves a thorough examination to detect trends, seasonality, cycles, or random elements, as well as an Autocorrelation Function (ACF) analysis. In addition to the ACF, the Partial Autocorrelation Function (PACF) pattern is observed to measure the additional correlation between the time series Y and its lag values, without considering the lower-order lags. The stationarity of the data is assessed using the Augmented Dickey-Fuller (ADF) test, with a significance level set at 0.05.

Data with a p-value less than the significance level of 0.05 is considered to be free of unit roots. Hypothesis testing is performed by comparing the ADF statistic with the critical value. If the ADF statistic exceeds the critical value, it can be concluded that the data is stationary and does not require differencing. Conversely, if the data is found to be non-stationary, differencing is required until the data becomes stationary.

Subsequently, estimation and calibration of the model are performed to build a preliminary ARIMA model by determining the orders of p , q , and d . The determination of the maximum AR order (p) requires observation of the PACF, while the maximum MA order (q) must be examined through the ACF. The maximum differencing order (d) is determined based on the stationarity of the data. According to Firdaus [4], the optimal ARIMA model is selected by considering the smallest values of the Akaike Information Criterion (AIC) and the Schwartz Criterion (SC), the highest R-squared value in the model, and the p-value in the model. After identifying the optimal model, diagnostic checks must be performed using residual tests. These residual tests include histogram analysis and correlogram analysis.

Results and Discussion

Figure 1 shows a significant increase in energy consumption year after year, with minor fluctuations during certain periods. Starting with an energy consumption of 3,807,815 Terajoules in 2001, energy consumption continued to rise, reaching the highest level in 2024

at 7,930,428 Terajoules. This trend reflects the growing demand for energy in line with economic development, urbanization, and technological advancements. In general, the graph demonstrates how energy consumption is directly proportional to economic growth, creating challenges in terms of ensuring a sustainable and environmentally friendly energy supply. The significant surge in 2024 also indicates the potential for an energy crisis or a significant change in consumption patterns, which must be addressed in the formulation of future energy policies. This aligns with the findings of [13], which state that the last decade has seen a shift towards more efficient energy consumption sources, with an increased use of modern energy sources such as LPG and electricity.

Stationarity Test

The first step in identifying the ARIMA model is to ensure the stationarity of the data. As shown in Figure 1, the Augmented Dickey-Fuller (ADF) test at the level indicates that the data is non-stationary, as evidenced by a p-value of 0.7362, which is greater than 0.05, suggesting the presence of a unit root. However, after performing first differencing, the results of the Augmented Dickey-Fuller (ADF) test show that the p-value for the variable is significant at the 5% level, or less than 0.05. The ADF test result for energy consumption (p-value = 0.000), which is below the 0.05 significance level, is shown in Figure 2. This result indicates that the original time series data for energy consumption is stationary, as evidenced by the absence of a unit root. The stationarity of the data is crucial because it facilitates the estimation of future values within the context of time series analysis [17]. Stationarity is defined as a condition where the mean and variance remain constant over the entire observation period [4].

Null Hypothesis: KONSUMSI has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-0.998191	0.7362
Test critical values: 1% level	-3.752946	
5% level	-2.998064	
10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KONSUMSI)
Method: Least Squares
Date: 04/25/26 Time: 00:03
Sample (adjusted): 2002 2024
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
KONSUMSI(-1)	-0.181391	0.181720	-0.998191	0.3296
C	1060221.	899432.5	1.178766	0.2517

R-squared	0.045298	Mean dependent var	179244.0
Adjusted R-squared	-0.000164	S.D. dependent var	831186.6
S.E. of regression	831254.9	Akaike info criterion	30.18220
Sum squared resid	1.45E+13	Schwarz criterion	30.28094
Log likelihood	-345.0953	Hannan-Quinn criter.	30.20703
F-statistic	0.996385	Durbin-Watson stat	2.654438
Prob(F-statistic)	0.329551		

Figure 2. Augmented Dickey-Fuller (ADF) Test at Level

Null Hypothesis: D(KONSUMSI) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-8.191017	0.0000
Test critical values: 1% level	-3.769597	
5% level	-3.004861	
10% level	-2.642242	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(KONSUMSI,2)
Method: Least Squares
Date: 04/25/26 Time: 00:08
Sample (adjusted): 2003 2024
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(KONSUMSI(-1))	-1.539273	0.187922	-8.191017	0.0000
C	285793.0	158520.2	1.802881	0.0865

R-squared	0.770360	Mean dependent var	34615.59
Adjusted R-squared	0.758878	S.D. dependent var	1485578.
S.E. of regression	729481.2	Akaike info criterion	29.92456
Sum squared resid	1.06E+13	Schwarz criterion	30.02375
Log likelihood	-327.1702	Hannan-Quinn criter.	29.94793
F-statistic	67.09276	Durbin-Watson stat	1.860117
Prob(F-statistic)	0.000000		

Figure 3. Augmented Dickey-Fuller (ADF) Test at First Differencing

Determination of Potential Model Based on ACF and PACF

The graphical representation of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) in Figure 3 indicates the stationarity of the data. Both functions show significance beyond the threshold level. Autocorrelation is important to consider when using the ARIMA model because it helps identify the appropriate AR and MA parameters for the accuracy and effectiveness of the ARIMA model. The tentative order (p, d, q) is determined by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), as shown in Figure 4 below.

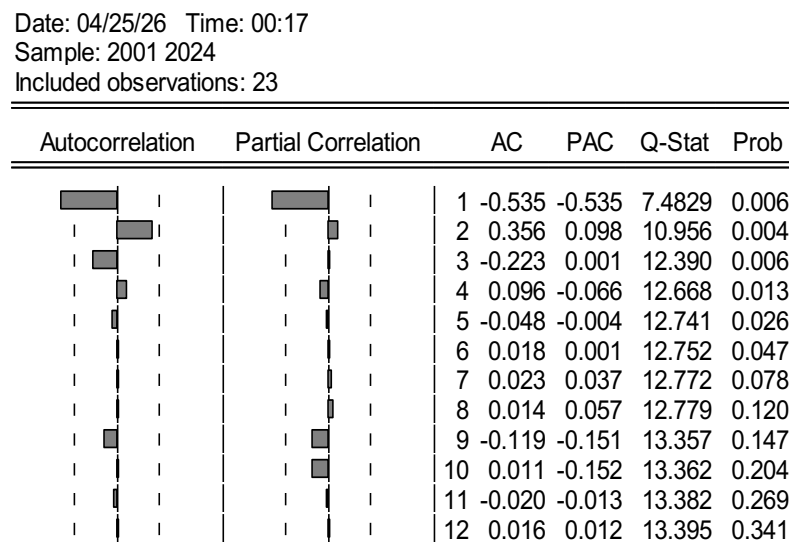


Figure 4. Augmented Dickey-Fuller (ADF) Test at First Differencing

The determination of the order in the AR model is based on substantial spikes in the PACF graph. The number of significant lag values will influence the order of the AR model, while the lag for the AR model is obtained from the number of significant lags in the PACF graph. In contrast, the MA model is determined by the number of significant lags in the ACF graph. The PACF is examined at the upper and lower bounds of the 95% confidence interval, which serves as an indicator of significance. In this graph, spikes exceeding the threshold are considered statistically significant. These spikes indicate the correlation between the observed data and the corresponding lag [20]. From the correlogram above, the Partial Correlation (AR values) that exceeds the dashed line occurs at lag 1, and the Autocorrelation (MA values) that exceeds the dashed line occurs at lag 1, with data being stationary at the

first level, resulting in an ADF value of 1. Therefore, the best potential model is $(p,d,q) = (1,1,1)$.

Parameter Estimation and Residual Testing (Selecting the Best Model)

Choosing the most appropriate ARIMA model for forecasting is crucial. Several models are compared using the R-squared value, Akaike Information Criterion, Schwarz Criterion, p-value histogram, and p-value correlogram. Based on the analysis results, the ARIMA (1,1,1) model is identified as the most suitable, as shown in Figures 5 and 6.

Dependent Variable: D(KONSUMSI)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Date: 04/25/26 Time: 01:15				
Sample: 2002 2024				
Included observations: 23				
Convergence achieved after 26 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	181334.2	122632.3	1.478682	0.1556
AR(1)	-0.646913	0.549416	-1.177454	0.2536
MA(1)	0.175779	0.719360	0.244354	0.8096
SIGMASQ	4.64E+11	1.43E+11	3.237296	0.0043
R-squared	0.298245	Mean dependent var		179244.0
Adjusted R-squared	0.187442	S.D. dependent var		831186.6
S.E. of regression	749248.1	Akaike info criterion		30.06274
Sum squared resid	1.07E+13	Schwarz criterion		30.26022
Log likelihood	-341.7215	Hannan-Quinn criter.		30.11240
F-statistic	2.691665	Durbin-Watson stat		2.005565
Prob(F-statistic)	0.075242			
Inverted AR Roots	-.65			
Inverted MA Roots	-.18			

Figure 5. Results of the Best ARIMA Model Analysis

From the figure above, the Akaike Information Criterion value is 30.06274, the Schwarz Criterion value is 30.26022, with an R-squared value of 0.298245.

Date: 04/25/26 Time: 00:34

Sample: 2001 2024

Included observations: 23

Q-statistic probabilities adjusted for 2 ARMA terms

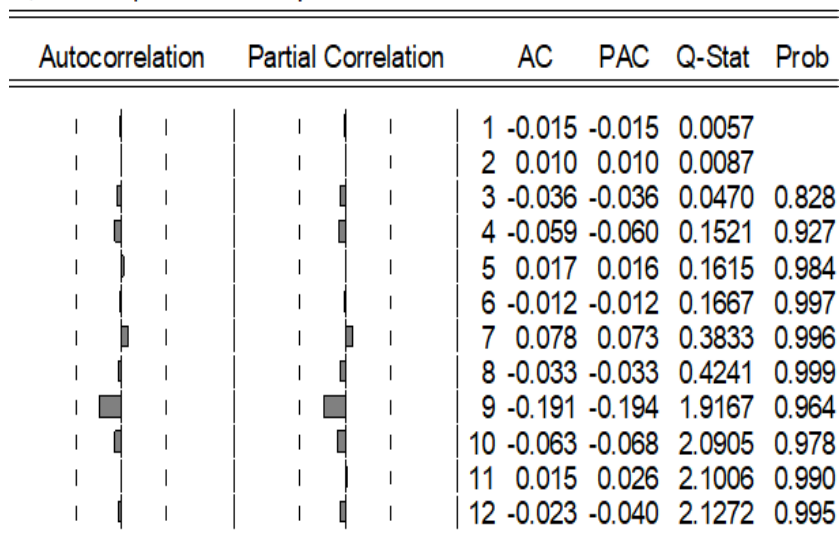


Figure 6. Residual Correlogram

Furthermore, the correlogram in the figure above shows that none of the values exceed the dashed line. This indicates that the ARIMA (1,1,1) model is the best model.

Forecasting Using the ARIMA Model

The selection of the appropriate ARIMA model allows for forecasting future prices over the next six years. The forecasting results indicate an increase in energy consumption in 2025 to 7,948,819 TJ, in 2026 to 8,235,422 TJ, in 2027 to 8,348,398 TJ, in 2028 to 8,573,954 TJ, followed by 8,726,680 TJ in 2029, and an estimated increase to 8,926,521 TJ in 2030. The Standard Error value is 144,493 TJ, with an upper confidence interval of 8,831,331 TJ and a lower confidence interval of 8,088,467 TJ. The forecasted energy consumption graph for the years 2025 – 2030 can be seen in Table 1 below:

Table 1. Forecasted Energy Consumption of Indonesia for 2025 - 2030

No	Year	Forecasted Energy Consumption (TJ)	Standard Error	Upper Confidence Interval	Lower Confidence Interval
1	2025	7.948.419			
2	2026	8.235.422			
3	2027	8.348.398			
4	2028	8.573.954	144.493	8.831.331	8.088.467
5	2029	8.726.680			
6	2030	8.926.521			

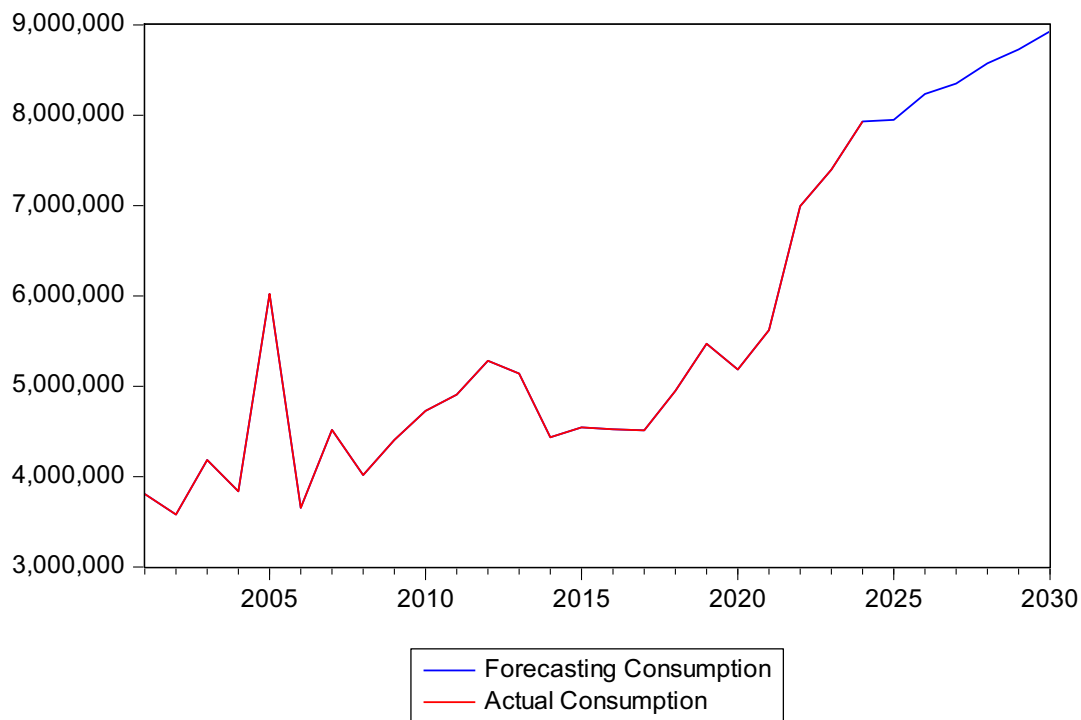


Figure 7. Forecasted Energy Consumption of Indonesia for 2025-2030

Energy consumption in Indonesia from 2001 to 2024 has experienced fluctuations, with both increases and decreases occurring each year. A significant increase in energy consumption was observed in 2005, followed by a decline in 2006. The rise in household income, alongside economic advancements, has also driven energy consumption, particularly for electricity and fuel needs. This aligns with the findings of [13], which noted that energy consumption in the transportation sector has surged due to increased mobility and urbanization.

The forecasted energy consumption graph from 2005 to 2030 shows a continuous increase. Dependence on fossil fuels exacerbates the challenge of balancing economic growth with environmental sustainability. The energy consumption graph indicates that as a country's development progresses, its energy demand also grows, necessitating a transition to more environmentally friendly and sustainable energy sources [15]. In this regard, reliance on fossil fuels becomes a major obstacle in achieving sustainable development goals, as emphasized by [16], who stresses the importance of reducing dependence on fossil-based energy.

Energy policies focused on improving energy efficiency and accelerating the transition to renewable energy play a crucial role in curbing energy consumption growth while reducing environmental impacts. This aligns with the findings of [7], which show that European countries with more advanced adoption of renewable energy tend to have more stable energy consumption growth compared to countries still reliant on fossil fuels. Therefore, reducing dependence on fossil fuels and increasing the utilization of renewable energy sources become key strategies in supporting energy sustainability and mitigating negative environmental impacts.

The energy consumption graph shows a trend of increasing energy demand, reflecting structural changes in consumption patterns, particularly with economic growth, industrialization, urbanization, and the expansion of the transportation sector. [15] emphasizes that understanding energy consumption patterns and their driving factors is essential for formulating more integrated and sustainability-oriented energy policies. In line with this, [13] explains that the shift in energy consumption from the household sector to the industrial and transportation sectors increases the challenges of ensuring energy security, necessitating policies that can balance economic growth with the sustainable management of energy resources.

The forecasting results up to 2030 indicate that energy consumption is expected to continue increasing year by year. A report by [7] suggests that economic growth, population growth, urbanization, and the expansion of the industrial and transportation sectors will drive the rising energy demand in Indonesia. [19] also notes that, as a developing country with the largest population in Southeast Asia, Indonesia will face a significant increase in energy consumption, particularly in sectors reliant on electrification and transportation. Therefore, strengthening energy infrastructure, improving energy efficiency, and accelerating the utilization of renewable energy are crucial foundations for national energy security and achieving sustainable development.

Renewable Energy Transition

The transition toward renewable energy in Indonesia has become increasingly important, given the country's high dependence on fossil fuels, which has negative impacts on carbon emissions and climate change. [14] emphasizes that Indonesia has substantial potential to develop renewable energy sources, such as solar, wind, and biomass energy, which can serve as alternatives to fossil fuels. This potential is crucial for meeting the continuously increasing energy demand driven by economic growth and population expansion.

With the right policies and strong support, the renewable energy transition in Indonesia has the potential not only to strengthen energy sustainability but also to create new job opportunities in the renewable energy sector. Furthermore, this transition can help achieve sustainable development goals, reduce the impacts of climate change, and enhance national energy security. Indonesia's energy transition efforts will be crucial in achieving sustainable development goals and fulfilling climate commitments [13].

Policies such as energy conversion programs, the use of renewable energy, and energy efficiency improvements play a crucial role in accelerating the energy transition. The role of energy policies in shaping consumer behavior is vital to ensuring long-term energy sustainability [13].

President Prabowo Subianto's vision in the energy sector focuses on achieving energy self-sufficiency and independence as a central pillar of national development. This strategy is realized through energy downstreaming, the optimization of natural gas, the development of biofuels (B50), and the acceleration of new renewable energy (NRE) ecosystems such as hydrogen to support national energy security.

Conclusion

Energy consumption in Indonesia continues to increase in line with rapid economic growth, urbanization, and industrialization. Based on available data, the industrial and household sectors are the main contributors to the surge in energy demand. The best model for forecasting energy consumption is ARIMA (1,1,1). Based on the forecasting results,

Indonesia's energy consumption in 2030 is projected to reach 8,926,521 TJ. The main policy implication is the need for a transition to renewable energy and energy efficiency, particularly in the industrial and transportation sectors, to reduce dependence on fossil fuels. Policies should also focus on strengthening energy infrastructure and diversifying energy sources to address global energy price fluctuations. Additionally, the development of energy efficiency technologies and public awareness will support the sustainability and security of national energy. This study is limited by the small amount of data available for forecasting. Future research could include more data and incorporate other external factors that influence energy consumption.

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