

## Effectiveness of the Box–Jenkins Methodology in Determining the ARIMA Model for Forecasting Algeria’s Gross Domestic Product up to 2035

Salim Lagoune <sup>1</sup>, Mohamed Benzahia <sup>2</sup>

<sup>1</sup> Setif 1 University, (Algeria) LEMAC Research Laboratory, [salim.lagoune@univ-setif.dz](mailto:salim.lagoune@univ-setif.dz)

<sup>2</sup> Setif 1 University, (Algeria) LEMAC Research Laboratory, [mohamed.benzahia@univ-setif.dz](mailto:mohamed.benzahia@univ-setif.dz)

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### Abstract:

This study aims to examine the effectiveness of the Box–Jenkins methodology in identifying the optimal ARIMA model for forecasting Algeria’s Gross Domestic Product (GDP) through 2035, based on official annual data published by the Bank of Algeria. The results indicate that the ARIMA(0,1,1) model is the most appropriate according to statistical criteria. Forecasts suggest that Algeria’s GDP will follow an upward trend during the period 2025–2035, rising from about 42,072.6 billion dinars to 144,627.3 billion dinars. This trend reflects positive growth prospects for the Algerian economy, with the proposed model achieving acceptable long-term accuracy. The findings confirm the effectiveness of the Box–Jenkins methodology as a reliable tool for forecasting economic indicators, enabling policymakers to anticipate future economic directions and adapt policies in line with the projected growth trajectory.

**Keywords:** Gross Domestic Product, ARIMA Models, Box–Jenkins Methodology, Forecasting, Algerian Economy.

**JEL Classification Codes:** O47, C22, C53.

ملخص:

تهدف هذه الدراسة إلى اختبار فعالية منهجية (Box–Jenkins) في تحديد النموذج الأمثل من بين نماذج ARIMA للتنبؤ بالناتج المحلي الإجمالي في الجزائر حتى أفق 2035، بالاعتماد على البيانات السنوية الرسمية الصادرة عن بنك الجزائر. أظهرت النتائج أنّ النموذج ARIMA(0,1,1) هو الأنسب وفقاً للمعايير الإحصائية، وتُشير التنبؤات إلى أنّ الناتج المحلي الإجمالي في الجزائر سيتبع منحنى تصاعدياً خلال الفترة (2025–2035)، إذ يُتوقع أن يرتفع بين 42072.6 و144627.3 مليار دينار، ويعكس هذا الاتجاه آفاق نمو إيجابية للاقتصاد الجزائري، مع تحقيق النموذج المقترح دقة مقبولة على المدى الطويل، وتؤكد النتائج فعالية منهجية بوكس–جينكز كأداة موثوقة للتنبؤ بالمؤشرات الاقتصادية، كما تتيح صانعي القرار من استشراف الاتجاهات المستقبلية للاقتصاد وتكييف السياسات بما يتماشى مع المسار المتوقع للنمو.

كلمات مفتاحية: الناتج المحلي الإجمالي، نماذج ARIMA، منهجية بوكس-جينكز، التنبؤ، الاقتصاد الجزائري.

تصنيفات JEL: O47، C22، C53.

Corresponding author: Full name, e-mail: [salimaggoune@yahoo.fr](mailto:salimaggoune@yahoo.fr)

## **1. Introduction**

Forecasting is one of the essential tools that countries rely on to plan their future economic policies, and Gross Domestic Product (GDP) holds a central position among economic indicators of interest and relevance in this context, due to its direct impact on the overall economic level of the country and its role in evaluating economic performance and determining growth trends to achieve sustainable development (Ismail & Fabrice , 2023). Moreover, the accuracy of its forecasting contributes to guiding strategic economic decisions, especially given the rapid economic and structural fluctuations experienced worldwide. Therefore, achieving accurate GDP forecasts requires the use of strong and effective statistical models capable of representing the dynamics of economic time series.

In Algeria, forecasting GDP presents a genuine challenge due to the economy's high dependence on natural resources and its vulnerability to global market fluctuations, particularly in oil and gas prices, alongside political changes and volatile global conditions. These factors make it essential to minimize the gap between actual and predicted GDP values, necessitating the adoption of strong and appropriate statistical models to achieve accurate forecasts. Although numerous models are available, selecting the most suitable model is crucial for reducing this discrepancy and providing a more accurate interpretation of results (Ismail & Fabrice , 2023) .

Within this context, the importance of using modern quantitative methods for time series analysis and building precise predictive models has emerged. Among these methods, the Box–Jenkins methodology, based on ARIMA models, stands out for its flexibility and effectiveness in capturing the dynamics of economic variables and forecasting them over the medium and long term.

### **Research Problem:**

Given the vital role of GDP as a key indicator for measuring economic strength, the economic structure, and the overall development rate of a country, improving the accuracy of its forecasting is an urgent necessity to enable policymakers to adapt economic policies to future trends and anticipate potential shifts in the trajectory of the Algerian economy during the upcoming period (2025–2035).

Accordingly, the research problem is formulated in the following main question:

**How effective is the Box–Jenkins methodology in determining the appropriate ARIMA model to forecast GDP in Algeria up to 2035?**

This main question is further divided into the following sub-questions:

✓ What are the statistical characteristics of the GDP time series in Algeria during the period 1980–2024?

✓ What is the most appropriate ARIMA model identified by the Box–Jenkins methodology to represent the GDP time series in Algeria?

- ✓ How accurate are the forecasts generated by the ARIMA model when comparing actual GDP values with predicted future values?
- ✓ Do the residuals of the selected model satisfy the assumptions of independence and random distribution?
- ✓ To what extent does forecasting using ARIMA contribute to supporting economic decision-makers in Algeria, and what are the potential economic implications of these forecasts on Algerian economic policies?

**Research Hypotheses:**

Based on the research problem, the following hypotheses were formulated to test the effectiveness of the Box–Jenkins methodology in forecasting GDP in Algeria:

**Main Hypothesis 1:**

The ARIMA model is an effective tool for forecasting Algeria’s Gross Domestic Product (GDP) up to the year 2035.

**Sub-hypothesis 1:**

The time series of the logarithm of GDP in Algeria during the study period is unstable at its original level but becomes stable at the first difference, allowing it to be modeled using the ARIMA approach.

**Sub-hypothesis 2:**

After transforming the logarithmic GDP series in Algeria into a stationary series, the steps of the Box–Jenkins methodology contribute to identifying the most appropriate ARIMA model, based on information criteria (AIC, BIC, HQ), achieving the best representation of the time series dynamics.

**Sub-hypothesis 3:**

According to Theil’s U statistical accuracy measure, the selected model provides a reliable long-term forecasting ability (up to 2035), such that the predicted values are close to the actual values or reflect the general trend of the series.

**Sub-hypothesis 4:**

Analysis of the residuals of the final model shows that they are independent, random, and normally distributed, validating the model’s suitability for forecasting purposes up to 2035.

**Main Hypothesis 2:**

Forecasting GDP using the ARIMA model contributes to providing accurate quantitative indicators that help economic decision-makers in Algeria formulate more effective policies to address future economic fluctuations.

**Research Objectives:**

This study aims to test the effectiveness of the Box–Jenkins methodology in identifying the most suitable ARIMA model to forecast GDP in Algeria up to 2035, by analyzing historical GDP time series data and applying all stages of the ARIMA model—from testing for stationarity, determining the optimal model, to generating

future forecasts and comparing them with actual data to measure the model's reliability in the Algerian economic context.

### **Research Significance:**

The significance of this study lies in contributing to improving the accuracy of economic forecasts in Algeria, as a developing country, using the ARIMA model, which supports policymakers in planning future economic policies based on reliable forecasts.

### **Methodology:**

The study employed a descriptive-analytical approach to examine the evolution of GDP in Algeria during the period 1980–2024, using the EViews-10 software for data processing. The statistical approach was applied through the collection of annual data and the implementation of the Box–Jenkins methodology steps to determine the most appropriate ARIMA model for forecasting.

### **Literature Review**

The economic literature highlights the importance of relying on statistical and econometric methods in analyzing macroeconomic variables, particularly in light of rapid economic developments. Many researchers have addressed GDP forecasting methodologies using time series models.

✓ In a study conducted by **Ismail Yenilmez and Fabrice Mugenzi (2023)**, entitled “**Estimation of conventional and innovative models for Rwanda’s GDP per capita**” (Ismail & Fabrice , 2023), the Box–Jenkins (BJ) methodology was employed alongside Artificial Neural Networks (ANNs) to model Rwanda’s GDP per capita data. The results showed that MLP and GRNN models outperformed the BJ model in terms of statistical accuracy, while the LSTM model was superior only in the Mean Absolute Percentage Error (MAPE) criterion. The study emphasized that relying solely on ANNs may be misleading, stressing the need to combine traditional and innovative methods to reach more accurate conclusions. It also highlighted the significant potential of ANNs in improving GDP per capita forecast accuracy, making them an important tool for policymakers and decision-makers.

✓ Another study by **Yanyi Peng (2023)**, entitled “**Forecasting USA GDP Based on ARIMA Model**” (Yanyi , 2023), applied the Box–Jenkins methodology to build an ARIMA model for forecasting U.S. GDP during the period 2000–2010. The study found that the most suitable model for representing U.S. GDP data was ARIMA(1,1,2). In the final stage, the model was used to forecast GDP after 2010, and the results indicated a slow upward trend in GDP.

✓ Similarly, a study by **Mutaz Adam Abdalraheem Mohammed (2023)**, entitled “**Using Box–Jenkins Methodology to Forecast GDP in Sudan 2010–2030**” (Mutaz, 2023), aimed to test the effectiveness of applying the Box–Jenkins methodology in analyzing time series to forecast Sudan’s GDP up to 2030. The study concluded that

the ARIMA model was the most suitable for GDP forecasting, as the estimated values were close to the actual ones, reinforcing the model’s reliability in forecasting future values.

✓ Another study was conducted by **Mesloub Mohammed** (2024), entitled "**Forecasting Algerian Gross Domestic Product (GDP) Using the Box–Jenkins Methodology (1962–2023)**" (Mesloub, 2024). The Box–Jenkins methodology was applied to data covering the period 1962–2023, and the results indicated that the most appropriate model to represent the data series was ARIMA(1,1,1). After confirming the effectiveness of this model in forecasting, it was used to estimate Algeria’s GDP values for the following six years, up to the end of 2030. These findings are consistent with another study conducted on the same time series extracted from World Bank data by **Nacer Hamidato** (2024), entitled "**Importance for Forecasting Algeria’s GDP Using ARIMA Models: An Applied Study on the Period 1960–2023**" (Nacer, 2024). In this study, the ARIMA(3,1,17) model was applied to data for the period 1960–2023, and the forecasting results indicated an upward trend in GDP during 2024–2030, with an estimated range between 253.15 and 427.35 billion USD.

Despite the abundance of literature, studies that have applied the Box–Jenkins methodology to Algeria remain relatively scarce and limited. The present study differs from previous Algerian research in terms of both the length of the time horizon and the number of observations, as it analyzes GDP data for the period 1980–2024, thereby providing a longer and more recent dataset compared to earlier works. Moreover, it relies on official annual data published by the Bank of Algeria, which enhances the reliability of the results. This approach made it possible to identify the most appropriate ARIMA model for forecasting Algeria’s GDP with greater precision and realism, while also offering long-term estimates up to 2035. The findings further confirm the effectiveness of the Box–Jenkins methodology in forecasting this key economic indicator, rendering the model and the predicted values more accurate than those of previous studies. Consequently, the study contributes fresh and reliable insights to support economic decision-making and national planning.

## **2. Theoretical Framework of the Study :**

The theoretical framework of this study is based on the concept of Gross Domestic Product (GDP) and its significance in the national economy. The study also relies on analyzing Algeria’s GDP data to assess the country’s economic strength and its rate of economic development. Furthermore, GDP can be used to analyze the structure of the Algerian economy, which constitutes a critical foundation for making macroeconomic policy decisions.

### **2.1 Definition of Gross Domestic Product (GDP)**

GDP is considered one of the most prominent economic indicators that reflect the level of economic activity in a given country, as it represents the total value of goods

and services produced within a specific period of time. This indicator is used to assess the health of the economy and to compare its performance with previous periods or with other countries.

GDP is defined as “an economic measure that expresses the monetary value of all final goods and services produced within the borders of a specific geographical area (such as a country) during a given period (such as a year or half a year)” (Hichem & belfodil, 2011).

It is also defined as “the market value of all final goods and services produced within a given country during a specific period of time.” (Yanyi , 2023).

From the aforementioned definitions, it can be observed that GDP represents the total market value of all final goods and services produced within an economy during a certain period of time.

GDP is one of the most comprehensive indicators of overall economic activity, as it covers all sectors of the economy and expresses the total value of a country’s production during a given period. This includes purchases by households, businesses, foreigners, and government institutions of domestically produced goods and services (Omer El-Amin & mohamed , 2010) . Beyond measuring the performance of the national economy, GDP is also used as an indicator of the average standard of living in a country. When positive growth in GDP is achieved, it indicates a significant economic improvement, which in turn reflects higher household income and increased consumption capacity. Consequently, the standard of living rises, and the national happiness index improves. Given its central role for both the state and individuals, GDP contributes to shaping government policies and determining economic directions (Yanyi , 2023).

## **2.2 Measuring Gross Domestic Product**

GDP can be measured using three different approaches: (James, Troy , & David, 2013)

✓ Under the expenditure approach, GDP is calculated as the sum of household, business, and government expenditures on final goods and services, plus net exports (exports minus imports) and changes in inventories.

✓ The income approach measures GDP based on the income generated by the use of production factors, such as wages, profits, and returns on capital.

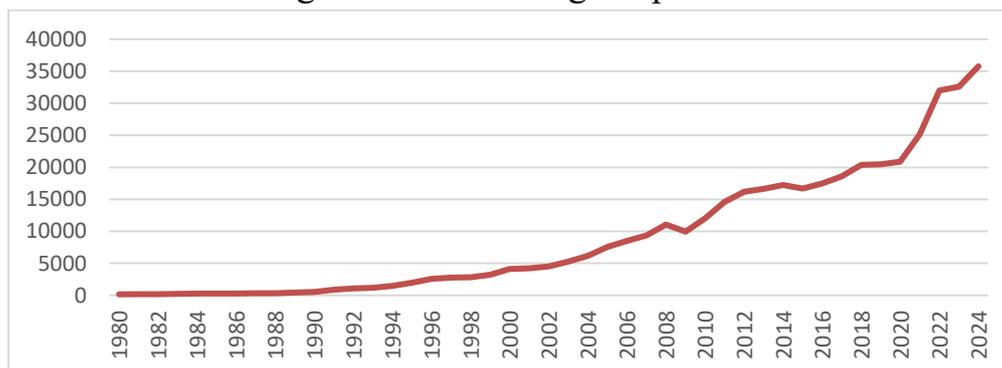
✓ The production approach (or value-added approach) calculates GDP as the difference between the total value of final outputs and the value of intermediate inputs consumed in the production process.

In theory, all three methods should yield the same results, since they measure economic activity from different perspectives. However, in practice, discrepancies often arise due to differences in data sources used for each method and variations in measurement accuracy.

## 2.3 An Analytical Study of Algeria’s Gross Domestic Product (GDP) During the Period 1980–2023

Algeria’s GDP has witnessed remarkable development, reflecting the effectiveness of the Algerian government’s economic efforts to stimulate the national economy. Figure (1) below illustrates the evolution of Algeria’s GDP from 1980 to 2024, a sufficiently long period to extract significant economic trends. This period can be divided into several economic phases that Algeria went through, shaped by political and economic transformations as well as crises, as shown in the figure:

**Fig.01:** Evolution of Algeria’s GDP during the period 1980–2024



**Source:** Prepared by the researchers based on reports and publications of the Bank of Algeria (1980–2024) <https://www.bank-of-algeria.dz/ar/>

### Phase One (1980–1988):

This period coincided with Algeria’s implementation of economic development plans such as the first five-year plan and restructuring programs. As shown in the figure above, GDP was characterized by relative stability and fluctuating yet positive growth between 1980 and 1988. GDP reached its highest value in 1988 at 347.7169 billion dinars, representing a growth rate of 11.19% compared to 1987, largely due to the rise in oil prices and the resulting increase in government revenues (Farouk & salim, 2024).

### Phase Two (1989–1999)

This phase experienced weak and volatile growth in real GDP due to a severe economic, political, and security crisis (the “Black Decade”), coupled with declining oil prices following the 1986 oil crisis. These factors negatively impacted investment and production, leading to a sharp decline in most economic indicators and causing both economic and security instability. Algeria entered a debt and financial crisis in the mid-1980s, which forced the country to resort to external financing from international financial institutions and to implement economic reforms under the guidance of the International Monetary Fund. During this period, the government was compelled to reduce public spending, resulting in shortages of essential goods, high inflation, rising unemployment (Farouk & salim, 2024) , and overall economic and social instability.

### Phase Three (2000–2014)

During this period, Algeria experienced significant economic recovery driven by

rising oil prices in global markets. The average price per barrel increased from about USD 12.85 in 1998 to USD 98.6 in 2008 (Bank of Algeria, 2006) , then USD 111.3 in 2011 (Fouad , Abdul , & Jamal, 2022) , stabilizing at USD 96.29 in 2014 (OPEC, 2025). This rise in oil prices had a direct positive effect on Algeria's economy, with GDP showing notable improvement (an upward trend).

The government adopted economic policies aimed at enhancing and stimulating economic growth, with a focus on launching recovery programs that included large-scale projects under the Growth Support Plan 2001–2004 and the Supplementary Program for Economic Growth Support 2005–2009 (Bank of Algeria, 2011) . These programs contributed to increasing GDP and consequently raising the growth rate, particularly between 2000 and 2008. In 2008, GDP reached 11,043.7 billion dinars (Bank of Algeria, 2011) , with a growth rate of approximately 18.07% compared to the previous year. However, the global financial crisis of 2008 had a negative impact on the national economy, as oil prices during this period stood at USD 98.6 per barrel (OPEC, 2025) . Consequently, GDP fell in 2009 to 9,968 billion dinars, representing a decline of 9.74%. This drop was mainly due to fluctuations in real government spending during that period.

Starting from 2010, GDP increased to reach 17,228.6 billion dinars in 2014 (Bank of Algeria, 2017) , with a growth rate of 3.8% compared to the previous year. This growth was the result of the macroeconomic policies adopted by the Algerian government to stimulate economic growth and propel economic development.

#### **Phase four (2015–2024)**

In recent years, the Algerian economy has experienced significant fluctuations in GDP due to the decline in oil prices and the impact of global crises. This led to a noticeable decrease in GDP, beginning in 2015, when it dropped to 16,702.1 billion dinars (Bank of Algeria, 2017). However, it quickly rebounded until 2019, reaching 20,500.2 billion dinars (Bank of Algeria, 2023) , with a growth rate of 0.5% compared to 2018. In 2020, GDP declined again to 18,476.9 billion dinars (Bank of Algeria, 2023) , marking a decrease of 9.86% as a result of the COVID-19 crisis and its direct repercussions on both the national and global economy, which severely affected Algeria's exports and significantly reduced oil revenues.

Starting in 2021, GDP recorded a relative increase, attributable to the partial recovery of the national economy supported by rising oil prices and government efforts to implement partial reforms aimed at encouraging domestic investment, improving the business climate, and promoting economic diversification. As a result, GDP reached 35,787.76 billion dinars in 2024 (ONS, 2025), reflecting a growth rate of 42.25% compared to 2021. This performance is largely explained by the programs and policies adopted by the state to foster and stimulate economic growth during this period.

### **3. Empirical Study:**

In this section, the effectiveness of the Box–Jenkins methodology is tested in order to identify the optimal ARIMA model for forecasting Algeria’s Gross Domestic Product (GDP) up to the horizon of 2035, using the statistical software EViews-10.

#### **3.1 Data Source**

The data used in this study consist of the annual values of Algeria’s GDP for the period 1980–2024. These data were obtained from the official reports and publications issued by the Bank of Algeria, available on its website: <https://www.bank-of-algeria.dz/ar>

This specific time span was chosen due to the major structural transformations and recurrent crises that directly affected the pace of GDP growth in Algeria, notably the collapse in oil prices in 1986, the global financial crisis in 2008, and the sharp drop in oil prices again in 2018. This is primarily attributed to the rentier nature of the Algerian economy and its heavy dependence on oil revenues, which prevented the emergence of a clear and stable growth trend in GDP over the past decades.

#### **3.2 Presentation of the Box–Jenkins (ARIMA) Methodology**

The Box–Jenkins methodology is one of the most prominent statistical approaches used in time series analysis and forecasting. It was developed by George Box and Gwilym Jenkins in 1970 (Robert H & David S, 2011, p. 83) and is based on the use of Autoregressive Integrated Moving Average (ARIMA) models to identify the most suitable model for representing the phenomenon under study and forecasting its future values (Emaan & Mohammed, 2017) based on its past historical observations (Éric, 2009, p. 170).

These models are known for their accuracy and flexibility, as they do not rely on external explanatory variables but rather focus on the internal temporal behavior of the phenomenon. This has led to their widespread use in both academic research and practical applications, across economic, financial, technical, and administrative fields (Douglas C, Cheryl L, & Murat , 2015, p. 399).

The Box–Jenkins methodology is classified as a univariate forecasting approach, which means it is primarily designed as a tool for prediction rather than for explaining the causes of variation in the time series, since explanatory variables are absent from the model.

ARIMA models are defined by the parameters (p, d, q), which respectively denote the order of the autoregressive process, the degree of differencing, and the order of the moving average. The model is expressed mathematically by combining autoregressive (AR) and moving average (MA) components (Damodar N & Dawn C, 2009, p. 777) , with differencing applied to the series to achieve stationarity (Ismail & Fabrice , 2023) .

The mathematical solutions of these models involve complex calculations, which necessitate the use of specialized statistical software for their specification and

diagnosis (Abdelkader & Moatasem, 2021, p. 11).

### 3.3 Steps for Applying the Box–Jenkins Methodology

This methodology refers to a series of systematic procedures aimed at identifying, estimating, and validating ARIMA models using time series data, under the assumption that the studied series is stationary. The main steps for applying this methodology are as follows:

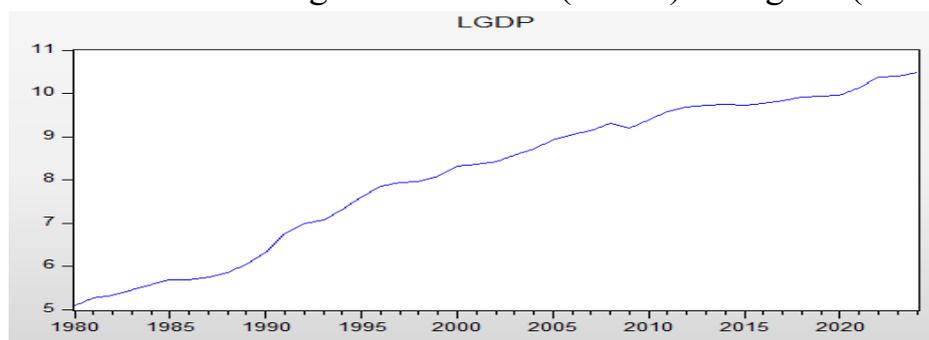
#### **First: Identification**

This is the first step in applying the Box–Jenkins methodology. Its goal is to determine the most appropriate model for the characteristics of the time series. This is done by analyzing the shape of the original data and plotting it graphically to detect patterns or trends, then applying differencing when necessary to remove trend or seasonality in order to achieve stationarity, thus preparing the ground for selecting the preliminary structure of the suitable model.

#### ✓ **Graph of the series under study:**

The following figure shows the evolution of the logarithm of GDP during the period (1980–2024), denoted by LGDP. This plot provides an initial impression of the characteristics of the time series and its description, and also offers a preliminary idea about the degree of stability of the series over time.

**Fig.02:** Evolution of the logarithm of GDP (LGDP) in Algeria (1980–2024)



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

From this figure, it is generally clear that the logarithm of GDP in Algeria recorded a noticeable upward trend throughout the study period. The data do not fluctuate around a constant level; instead, they show an increasing trend over time, indicating the presence of a trend component. Accordingly, it can be said that the logarithm of GDP series (LGDP) is non-stationary.

#### ✓ **Testing the Stationarity of the Time Series**

To verify the accuracy of the results regarding the stationarity of the studied time series, the Phillips–Perron (PP) unit root test was applied. The methodology of this test involves estimating three models : (Régis , 2015, p. 251)

- ❖ **Model 1:** includes both intercept and trend.
- ❖ **Model 2:** includes intercept only.
- ❖ **Model 3:** without intercept and without trend.

This test is effective in distinguishing between stationary and non-stationary series, even with small samples (Éric, 2009, p. 167) , and provides relatively accurate estimates. If the series is non-stationary, it can be corrected through differencing. The PP test is based on the following hypotheses (Régis , 2015, p. 256):

$H_0$  : The series contains a unit root (non-stationary)

$H_1$  :The series does not contain a unit root (stationary)

**Table 01:** Results of the Phillips–Perron unit root test for the **LGDP** series

	At Level		
	Model 1	Model 2	Model 3
<b>LGDP Series</b>	With Trend and intercept	With Intercept	Without Trend and Intercept
<b>Test Statistic</b>	-0.703973	-1.788064	4.608456
<b>P-Value</b>	0.9665	0.3814	1
	At 1st Difference		
	Model 1	Model 2	Model 3
<b>LGDP Series</b>	With Trend and Intercept	With Intercept	Without Trend and Intercept
<b>Test Statistic</b>	-4.504539	-4.324765	-2.354216
<b>P-Value</b>	0.0043	0.0013	0.0196

**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The results at the level show that the P-values in all three models are greater than 5%, which indicates the presence of a unit root, and thus the series is non-stationary. However, after taking the first difference, the P-values for all models decreased to less than 5%, which indicates that the series became stationary at the first difference. Accordingly, we can write:  $LGDP \sim I(1)$

✓ **Analysis of the Autocorrelation and Partial Autocorrelation Functions**

Verifying the stationarity of the time series is an essential step before using classical analysis tools such as the autocorrelation function (ACF) and the partial autocorrelation function (PACF), whose results are displayed in the correlogram. Analyzing this correlogram is a crucial part of the Box–Jenkins methodology, as it helps determine the initial values of the autoregressive order (p) and the moving average order (q) (Damodar N & Dawn C, 2009, p. 778).

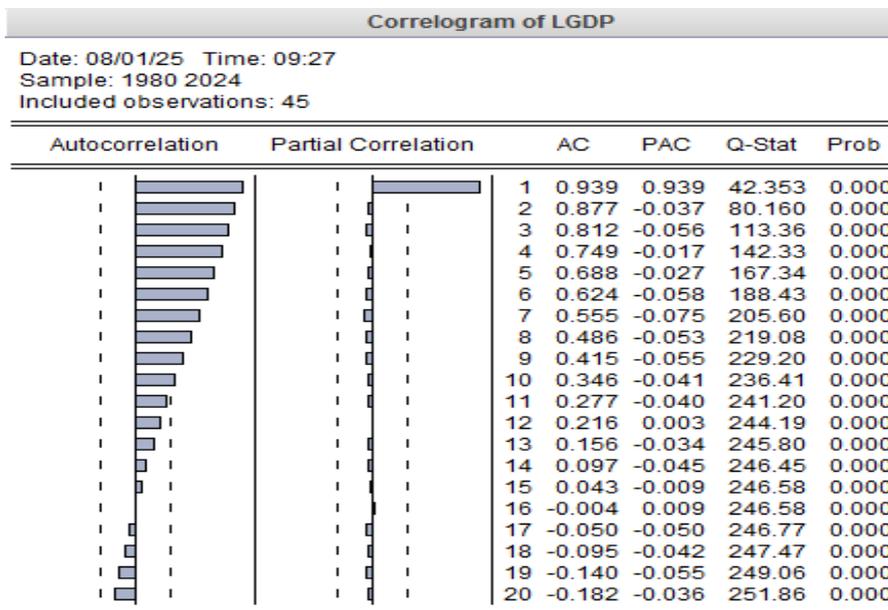
On the one hand, the autocorrelation function (ACF) highlights the nature of the relationship between the current and past values of the series, which helps in detecting the presence of moving average (MA) components. On the other hand, the partial autocorrelation function (PACF) shows the extent of the effect of each time lag after excluding the influence of previous lags, which assists in determining the order of the autoregressive (AR) component.

Based on the behavior of these two correlograms, a set of preliminary models can be proposed, and then compared according to statistical criteria to select the most

appropriate one for representing the time series data under study (Damodar N & Dawn C, 2009, p. 778).

The correlogram and its coefficients were generated using the EViews software, as illustrated in the following figures:

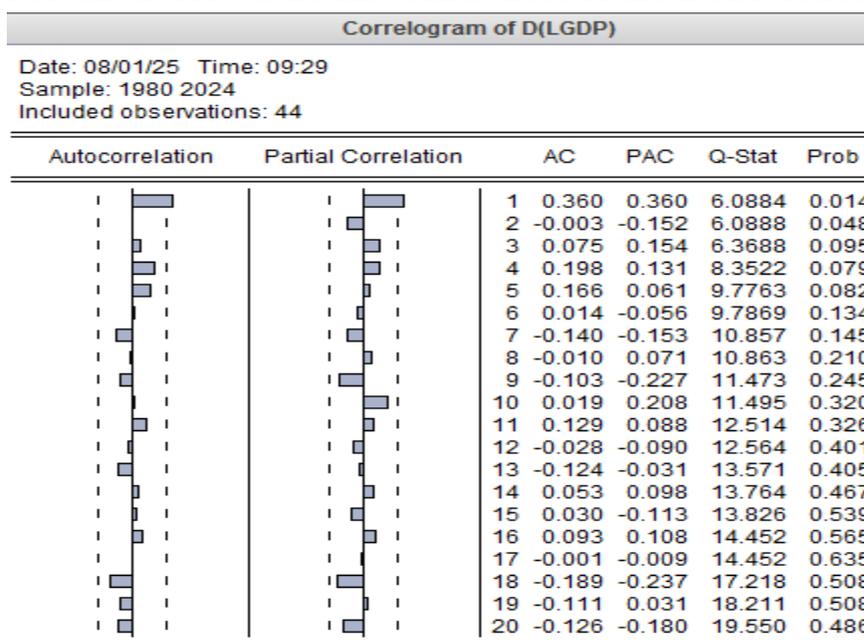
**Fig.03:** ACF and PACF of the LGDP series



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

From Figure (3), when examining the ACF of the logarithm of GDP (LGDP) in Algeria during 1980–2024, it is observed that the values gradually decline toward zero without cutting off after the first or second lag, indicating non-stationarity. However, the series becomes stationary at the first difference, as evident from the correlogram of the estimated ACF and PACF values for the first differences, shown in Figure (4).

**Fig.04:** ACF and PACF of the first differences of the LGDP series



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

Figure (4) shows that the PACF at lag 1 lies outside the confidence bounds with a positive value of 0.360, which is statistically significant. This suggests the possibility of adopting order ( $p=1$ ). Order ( $p=2$ ) could also be proposed, given another value close to the confidence bounds, indicating that either AR(1) or AR(2) may be suitable.

Similarly, the ACF at lag 1 also lies outside the confidence bounds, with the same positive value of 0.360, statistically significant, indicating that ( $q=1$ ) could be considered. Accordingly, the estimated ACF and PACF values point toward adopting low-order models such as ARIMA(1,1,1) or ARIMA(2,1,1)

It is worth noting that this selection remains exploratory at this stage, where all possible models are proposed, and subsequent tests and validations determine their statistical adequacy. Lower-order models such as ( $q=0$ ) or ( $p=0$ ) can also be considered to capture potential non-negative trends (Ma , Hu , Lin , & Han , 2018) .

Based on the analysis of the ACF and PACF of the first differences of the LGDP series, the following preliminary models can be proposed:

- ❖ **ARIMA(1,1,1)**: accounts for one autoregressive order (AR) and one moving average order (MA).
- ❖ **ARIMA(2,1,1)**: adds a second autoregressive order based on the significance of PACF at lag 2.
- ❖ **ARIMA(2,1,0)**: focuses on autoregression only with order 2.
- ❖ **ARIMA(1,1,0)**: an alternative model limited to the autoregressive component only.
- ❖ **ARIMA(0,1,1)**: an alternative model limited to the moving average component only.

### **Second: Estimation**

At this stage, the preliminary proposed models are estimated using the Ordinary Least Squares (OLS) method (Damodar N & Dawn C, 2009, p. 778) after transforming the logarithmic series of Algeria’s Gross Domestic Product (LGDP) into its first differences (DLGDP), considering it as integrated of order one. The detailed results are provided in Appendix (1).

Most ARIMA models are nonlinear and require the use of nonlinear estimation procedures. In this context, advanced statistical software such as Minitab, JMP, SAS, and EViews are typically employed, allowing the user to select the estimation method most suitable for the characteristics of the problem (Douglas C, Cheryl L, & Murat , 2015, p. 368).

To compare between the statistical models, several information criteria and accuracy measures are used, most notably: the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Hannan–Quinn Criterion (H-Q), in addition to forecast accuracy metrics such as: Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE), and Mean Absolute Percentage

Error (MAPE) (Emaan & Mohammed, 2017).

Table 02 presents the values of some comparison criteria for the proposed models:

**Table 02:** Comparison Criteria of the Proposed Models

<i>Proposed Models</i>	<i>Akaike Criterien</i>	<i>Schwarz Criterien</i>
<i>ARIMA(1,1,0)</i>	<b>-1.781492</b>	<b>-1.659843</b>
<i>ARIMA(2,1,0)</i>	<b>-1.645216</b>	<b>-1.523567</b>
<i>ARIMA(0,1,1)</i>	<b>-1.813827</b>	<b>-1.692178</b>
<i>ARIMA(1,1,1)</i>	<b>-1.768377</b>	<b>-1.606178</b>
<i>ARIMA(2,1,1)</i>	<b>-1.768777</b>	<b>-1.606578</b>

**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The comparison results indicate that the best model to represent the logarithmic GDP (LGDP) series of Algeria is the ARIMA(0,1,1) model, as it achieved the lowest values for both Akaike and Schwarz criteria, making it the most suitable for estimation and forecasting. The estimation results are shown as follows:

**Fig.05:** Estimation Results of the Model: D(LGDP) c MA(1)

Dependent Variable: D(LGDP)				
Method: ARMA Maximum Likelihood (OPG - BHHH)				
Date: 08/01/25 Time: 09:37				
Sample: 1981 2024				
Included observations: 44				
Convergence achieved after 10 iterations				
Coefficient covariance computed using outer product of gradients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.123476	0.020166	6.123029	0.0000
MA(1)	0.428963	0.147652	2.905238	0.0059
SIGMASQ	0.008290	0.001456	5.694419	0.0000
R-squared	0.159064	Mean dependent var	0.122605	
Adjusted R-squared	0.118043	S.D. dependent var	0.100436	
S.E. of regression	0.094322	Akaike info criterion	-1.813827	
Sum squared resid	0.364766	Schwarz criterion	-1.692178	
Log likelihood	42.90419	Hannan-Quinn criter.	-1.768714	
F-statistic	3.877595	Durbin-Watson stat	1.983041	
Prob(F-statistic)	0.028684			
Inverted MA Roots	-.43			

**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The estimation results show that the ARIMA(0,1,1) model is the most appropriate, as the MA(1) coefficient is statistically significant. In addition, the statistical goodness-of-fit indicators (AIC, BIC, DW) confirm the robustness of the model and the absence of serial correlation in the residuals. Therefore, this model can be reliably used for forecasting Algeria's future GDP values.

### **Third: Diagnostic Checking**

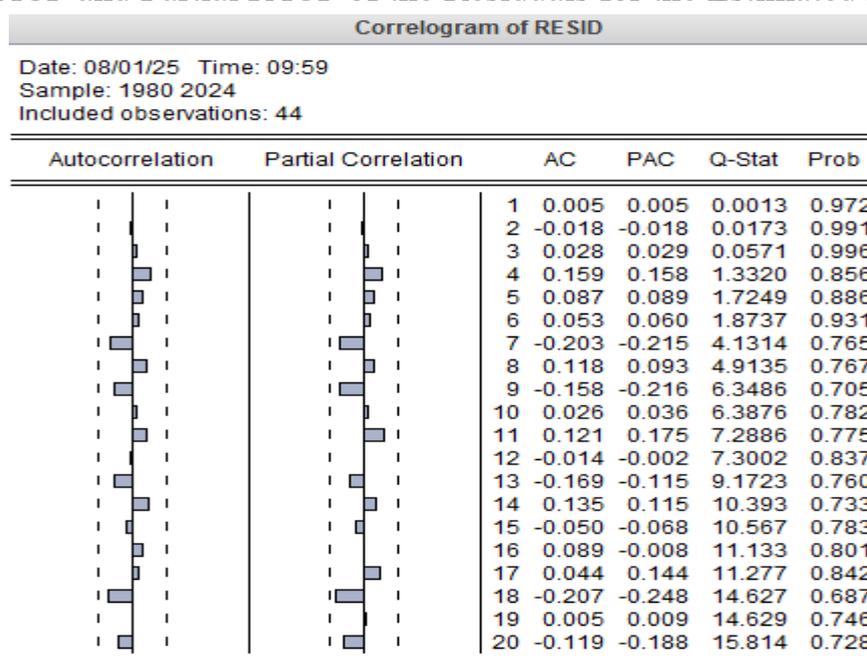
After selecting the appropriate model ARIMA(0,1,1) and estimating its parameters, the diagnostic stage follows to assess the efficiency and adequacy of the model for the data. This diagnostic process focuses on analyzing the residuals to ensure that they represent purely random behavior, or white noise (Damodar N & Dawn C, 2009, p. 778) —meaning they exhibit no statistically significant autocorrelation, have a mean close to zero, and display constant variance (Douglas C, Cheryl L, & Murat , 2015, p. 368) . This indicates the absence of any systematic or recurring pattern.

This is done by examining the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) of the residuals. If most of the correlation coefficients fall within the acceptable bounds, the model is considered adequate in explaining the underlying pattern of the original data. Conversely, if many coefficients lie outside these bounds, the model would be deemed insufficient and subject to reconsideration (Yanyi , 2023).

✓ **Residual Autocorrelation Analysis and the Ljung–Box Test**

In the present model, the ACF and PACF of the residuals were extracted and examined up to lag 20, as illustrated in Figure (6).

**Fig.06:** ACF and Partial PACF of the Residuals for the Estimated Model



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

By examining the correlogram of the residuals, it is observed that all correlation coefficients lie within the confidence bounds and are not significantly different from zero, suggesting the absence of autocorrelation in the residuals.

To further validate these results, the Ljung–Box test was applied to the residuals. The test yielded a p-value of 0.728, confirming the absence of autocorrelation, which demonstrates the ability of the ARIMA(0,1,1) model to capture the underlying time-series patterns in the data and explain the relationships between past and current values of the series.

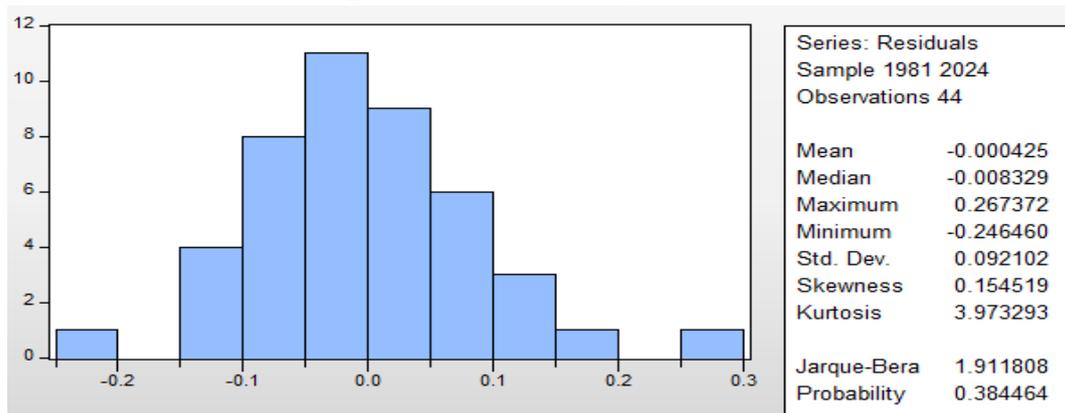
✓ **Jarque–Bera Test for Normality**

The Jarque–Bera (J-B) test was used to verify whether the residuals follow a normal distribution, based on the following hypotheses:

$H_0$  : The residuals follow a normal distribution.

$H_1$  :The residuals do not follow a normal distribution.

**Fig.07:** Result of the Jarque–Bera Normality Test for Residuals



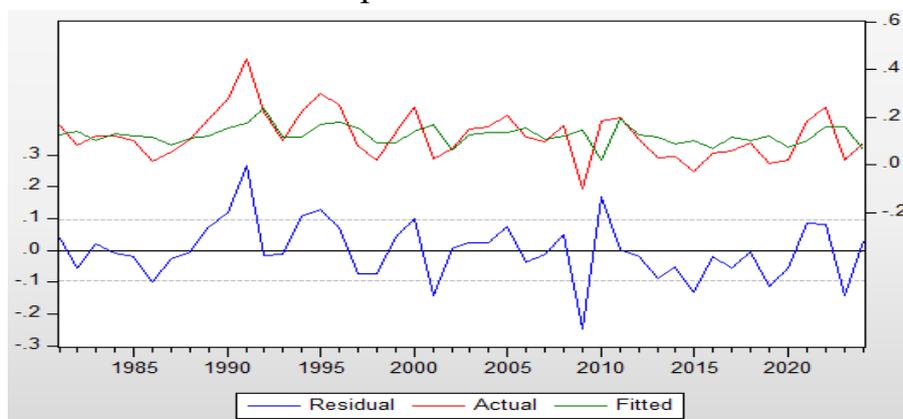
**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The results indicate that the Jarque–Bera statistic equals 1.911808 with a probability of 38.44%, which exceeds the 5% significance level. Thus, the null hypothesis is accepted, confirming that the residuals follow a normal distribution.

Accordingly, the residuals can be described as random white noise and normally distributed, which supports the efficiency of the chosen model and confirms that no alternative specification is needed. To reinforce this conclusion, a residual plot and a comparison between actual and fitted values were also used, as shown in Figure (8).

✓ **Residual Plot and Comparison with Actual Values**

**Fig.08:** Residual Plot and Comparison Between Actual and Fitted Values



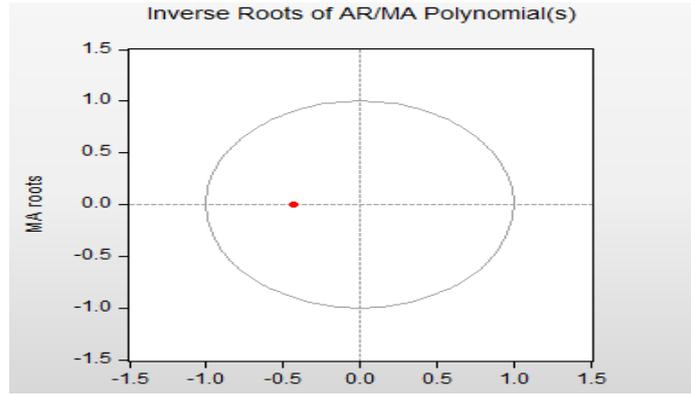
**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

It can be observed from the residual plot that the estimated values are very close to the actual values, almost coinciding with them. This reflects the ability of the selected model to represent the time series with high efficiency. Such closeness serves as an important indicator of the model’s reliability in explaining the historical behavior of the series, while also enhancing the accuracy of future GDP forecasts based on the ARIMA(0,1,1) model.

✓ **Roots of MA Parameters and Model Stability**

Figure (9) illustrates the analysis of the moving average (MA) roots.

**Fig.09:** Unit Root Analysis of MA Parameters



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The analysis of the moving average (MA) roots in Figure (9) shows that they all lie inside the unit circle, indicating the stability of the model and its suitability for forecasting purposes.

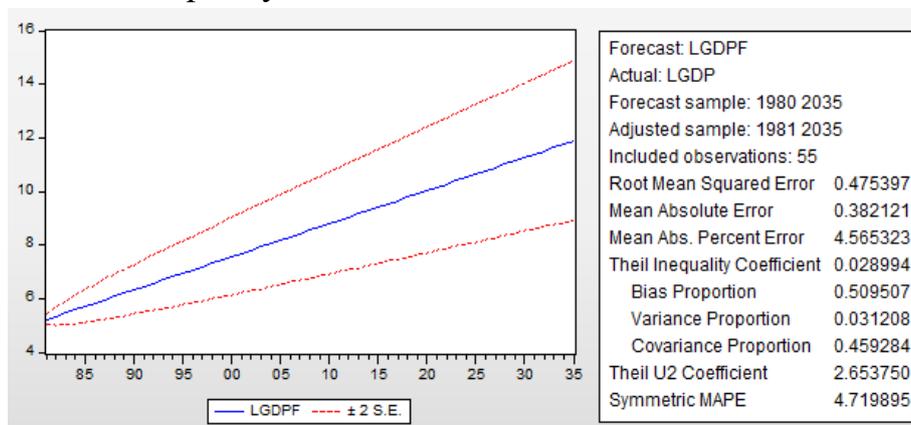
Based on these diagnostic tests, it can be concluded that the ARIMA(0,1,1) model provides a highly efficient representation of Algeria’s GDP time series and is reliable for forecasting future value.

**Fourth: Forecasting**

After identifying the most suitable ARIMA model for the time series and verifying its efficiency in the previous stages, the model can now be used to generate future values of the series. Forecasting represents one of the main advantages of this methodology and a key reason for its widespread application, as it allows the evaluation of model performance both within the sample (In-sample) and outside the sample (Out-of-sample).

In this context, the time series of Algeria’s real GDP logarithm (LGDP) was extended to forecast values for eleven future periods, based on the original series data. The forecasting procedure produced the results illustrated below:

**Fig.10:** Theil’s Inequality Coefficient Test Results



**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

The figure above shows several statistical indicators commonly used to assess forecasting accuracy, the most notable being Theil’s Inequality Coefficient. The

obtained value, 0.028994, is very close to zero, indicating the model's strong suitability for forecasting purposes.

Based on this model, predictive values were obtained for the logarithm of GDP (LGDPF) over eleven future periods. These logarithmic values were then converted into real GDP forecasts (GDPF) for the period 2025–2035, as presented in the following table:

**Table 03:** Forecasted LGDPF and GDPF Values for the Period 2025–2035

Years	2025	2026	2027	2028	2029	2030
<b>LGDPF</b>	10,64715	10,77063	10,89411	11,01758	11,14106	11,26453
<b>GDPF</b> (Billion DZD)	42072,6398	47601,9573	53857,9849	60936,1352	68944,552	78005,46
Years	2031	2032	2033	2034	2035	
<b>LGDPF</b>	11,38801	11,51149	11,63496	11,75844	11,88192	
<b>GDPF</b> (Billion DZD)	88257,1807	99856,2144	112979,629	127827,764	144627,288	

**Source:** Prepared by the researchers based on the outputs of Eviews-10 software.

Based on the table above, Algeria's gross domestic product (GDP) is expected to increase from about 42,072.6 billion dinars in 2025 to approximately 144,627.3 billion dinars in 2035.

#### 4. Results and Discussion

Based on the applied section presented regarding the effectiveness of the Box–Jenkins methodology in identifying the most appropriate ARIMA model, the obtained results are discussed:

✓ The results showed that the logarithmic GDP time series in Algeria was non-stationary at its original level during the study period (1980–2024). However, after applying the first difference, the series became stationary, which enabled the use of the Box–Jenkins methodology for modeling. Thus, **the first sub-hypothesis is confirmed.**

✓ After conducting the stationarity test (PP) and examining the autocorrelation (ACF) and partial autocorrelation (PACF) plots, it was found that the ARIMA(0,1,1) model is the most appropriate to represent the dynamics of Algeria's GDP. This conclusion was supported by statistical information criteria (AIC, BIC, HQ) and the significance of the estimated parameters. The model reflects the random nature of Algeria's economic fluctuations more than their reliance on long-term autoregressive trends. Hence, **the second sub-hypothesis is confirmed.**

✓ The forecasting results showed that, according to the accuracy measure (Theil's U), the selected model achieved an acceptable degree of predictive accuracy in the long run (2025–2035). The predicted GDP values generated by the model did not significantly deviate from the actual or observed values in the subsequent period, thereby **confirming the third sub-hypothesis.**

✓ Diagnostic tests demonstrated that the residuals of the selected model were independent, random, and normally distributed, with no signs of autocorrelation. This

confirmed the model’s validity for forecasting GDP up to 2035, thereby **validating the fourth sub-hypothesis**.

Accordingly, **the first hypothesis has been validated**: the study demonstrated the effectiveness of the Box–Jenkins methodology in identifying the optimal ARIMA(0,1,1) model to represent the dynamics of Algeria’s GDP. This conclusion is based on the results of statistical criteria (AIC, BIC), which confirmed the superiority of this model over alternatives, while achieving relatively accurate long-term forecasts (2024–2035). Thus, the Box–Jenkins methodology can be considered one of the reliable tools for forecasting economic indicators in Algeria.

✓ The forecasts obtained using the ARIMA(0,1,1) model indicated an upward trend in Algeria’s GDP up to 2035. According to the proposed model, GDP is expected to range between 42,072.6398 and 144,627.288 billion Algerian Dinars during the period 2025–2035. This provides the government with a quantitative indicator that allows policymakers greater opportunities for effective economic planning and the formulation of more efficient fiscal and development policies, particularly in the face of oil price fluctuations and structural challenges in the Algerian economy. Thus, **the second main hypothesis is confirmed**.

## **5. Conclusion**

This research paper aimed to examine the effectiveness of the Box–Jenkins methodology in identifying the optimal ARIMA model for forecasting one of the most important economic indicators, namely Algeria’s Gross Domestic Product (GDP), during the period (1980–2024) with projections up to 2035. To achieve this objective, annual data for the period (1980–2024) were collected and statistically processed using Eviews-10 software, following the time-series methodology. Based on both theoretical and applied analysis, the following results were obtained:

✓ The study revealed that Algeria’s GDP during the period (1980–2024) experienced significant fluctuations. This was mainly due to the strong dependence of the national economy on hydrocarbon revenues and its vulnerability to global oil crises, on the one hand, and domestic economic conditions and government policies, on the other.

✓ The findings indicated that Algeria has been striving to increase its GDP by implementing various strategies aimed at reducing oil dependency. This represents a major challenge by 2035, making it crucial for political and economic decision-makers to have a clear vision of the future economic outlook. In this regard, statistical and econometric tools play an essential role in analyzing and forecasting key macroeconomic variables.

✓ The Box–Jenkins methodology is designed to forecast and analyze the stochastic or probabilistic characteristics of economic time series. It allows the dependent variable  $Y_t$  to be explained through its past (lagged) values, as well as the current and lagged

values of residuals  $U_t$ . The methodology includes a set of techniques for time-series forecasting, based primarily on the assumption that the series under study is stationary.

✓ The results showed that the time series of the logarithm of Algeria's gross domestic product (GDP) is non-stationary in its original level during the study period (1980–2024). However, after applying the first difference, the series became stationary. Based on the stationarity test and the examination of the autocorrelation plots, it was found that the ARIMA (0,1,1) model is the most appropriate. This model indicates that the dynamics of the logarithm of GDP (LGDP) in Algeria do not directly depend on its past values (absence of an autoregressive AR component), but are mainly influenced by past random shocks represented in the first-order moving average component (MA(1)). This reflects the non-stationary nature of the series at the level, and its stationarity only after the first difference, which is consistent with the unit root tests and the autocorrelation analysis.

✓ It was found that Algeria's gross domestic product (GDP) is expected to follow an upward trend during the period 2025–2035, rising from approximately 42,072.6 billion DZD in 2025 to around 144,627.3 billion DZD in 2035.

This growth trajectory is primarily attributed to the country's reliance on the hydrocarbon sector, with the potential to benefit from improvements in global energy prices and the government's efforts to diversify the economy and enhance the performance of other sectors. Despite these positive prospects, economic growth remains vulnerable to fluctuations in oil prices and domestic factors related to economic policies, which underscores the importance of strengthening diversification to ensure more sustainable growth.

## **Recommendations**

Based on the findings obtained, the following recommendations can be proposed:

✓ Strengthen reliance on econometric and statistical studies to interpret and analyze macroeconomic time series in Algeria.

✓ Encourage researchers to adopt and further develop modern forecasting models in line with the specific characteristics of the national economy.

✓ Promote more applied studies on improving economic models in Algeria, in order to enhance predictive capacity and support the formulation of sustainable economic policies.

## **6. Bibliography List**

1. Abdelkader , E., & Moatasem, T. (2021). *Formulation of Financial and Economic Models with EViews* (éd. 1). Cairo, Egypt: Hamithra Publishing House.
2. Bank of Algeria. (2006). *Statistical Bulletin of the Bank of Algeria, Retrospective Series: Monetary Statistics (1964–2005), Balance of Payments Statistics (1992–2005)*. Algeria. doi:<https://www.bank-of-algeria.dz/stoodroa/2022/09/bulretro13-08-2006.p>

3. Bank of Algeria. (2011). Annual Report of the Bank of Algeria 2010: Economic and Monetary Developments in Algeria , Algeria. doi:<https://www.bank-of-algeria.dz/wp-content/uploads/2023/01/rapport-annuel-2010-fr.pdf>
4. Bank of Algeria. (2017). Annual Reports of the Bank of Algeria 2016: Economic and Monetary Developments in Algeria. , Ageria. doi:<https://www.bank-of-algeria.dz/wp-content/uploads/2022/05/Rapport-Annuel-BA-2016.pdf>
5. Bank of Algeria. (2023). Annual Report of the Bank of Algeria 2022: Economic and Monetary Developments in Algeria, Algeria. doi:<https://www.bank-of-algeria.dz/stoodroa/2023/11/Rapport-BA-2022-Fr.pdf>
6. Damodar N, G., & Dawn C, P. (2009). *Basic Econometrics* (éd. 5). USA, USA: McGraw-Hill Higher.
7. Douglas C, M., Cheryl L, J., & Murat , K. (2015). *Introduction to Time Series Analysis and Forecasting* (éd. 2). New Jersey, USA: John Wiley & Sons, Inc.
8. Emaan, Y., & Mohammed, H.-S. (2017). Prediction by using artificial neural networks and Box–Jenkins methodologies: comparison study. *Journal of AL-Qadisiyah for computer science and mathematics*, 9(2). doi:<https://doi.org/10.29304/jqcm.2017.9.2.325>
9. Éric, D. (2009). *Econometrics : Synthèse de cours & Exercices corrigés*. Paris, France: Pearson Education.
10. Farouk , S., & salim, L. (2024, May). The use of the joint simultaneous integration methodology to measure the impact of certain macroeconomic variables on the GDP: ARDL model. *Journal of Innovations and Sustainability*, 8(2). doi:<https://doi.org/10.51599/is.2024.08.02.04>.
11. Fouad , A., Abdul , F., & Jamal, E. (2022). *Annuaire Statistical Report*. Kuwait: OAPEC. doi:<https://oapceorg.org/Home/Publications/Reports/Annual-Statistical-report>
12. Hichem , s., & belfodil, k. (2011, june). Testing the impact of inflation shocks on Gdp growth in Algeria from 1970 to 2019. *Review POIDEX Journal*, 10(1), 72-89. doi:<https://asjp.cerist.dz/en/article/157093>
13. Ismail, Y., & Fabrice , M. (2023, November). Estimation of conventional and innovative models for Rwanda’s GDP per capita: A comparative analysis of artificial neural networks and Box–Jenkins methodologies. 22, 1-10. doi:<https://doi.org/10.1016/j.sciaf.2023.e01902>
14. James, B., Troy , G., & David, L. (2013, March). [www.rba.gov.au](http://www.rba.gov.au). doi:<https://www.rba.gov.au/publications/bulletin/2013/mar/pdf/bu-0313-2.pdf>
15. Ma , L., Hu , C., Lin , R., & Han , Y. (2018). ARIMA model forecast based on EViews software. *Earth and Environmental Science*, 208. doi:[doi:10.1088/1755-1315/208/1/012017](https://doi.org/10.1088/1755-1315/208/1/012017)
16. Mesloub, M. (2024, july). Forecasting Algerian Gross Domestic Product -GDP-Using The Box-Jenkins Methodology (1962-2023). *Educational Administration: Theory and Practice*, 30(7), 245-253. doi:<https://kuey.net/index.php/kuey/article/view/6611/4855>
17. Mutaz, A. (2023, june). Using Box- Jenkins methodology to forecasting GDP IN SUDAN 2010-2030. *Roa Iktissadia Review*, 13(1), 119-133. doi:<https://asjp.cerist.dz/en/article/226144>
18. Nacer, h. (2024, October). Importance for forecasting Algeria’s GDP using ARIMA models An applied study on the period 1960-2030. *Journal of business and finance economy*, 9(2), 389-404. doi:<https://asjp.cerist.dz/en/article/254851>
19. Omer El-Amin , m., & mohamed , k. (2010, December). The Impact Of Changes In The Amount Of Money On The Gross Domestic Product In Sudan, A Standard Study During The Period (1990-2019). *Algerian Journal of Economic and Financial Research*, 4(2), 124-146. doi:<https://asjp.cerist.dz/en/article/172798>
20. ONS. (2025). LES COMPTES NATIONAUX TRIMESTRIELS -1er trimestre 2025- : Situation économique nationale au premier trimestre 2025, Algéria. doi:<https://www.ons.dz/IMG/pdf/CNT1T2025.pdf>

21. OPEC. (2025). *OPEC Basket Price*. doi:[https://www.opec.org/opec\\_web/en/data\\_graphs/40.htm](https://www.opec.org/opec_web/en/data_graphs/40.htm).
22. Régis , B. (2015). *Économétrie :cours et exercices corrigés*. Paris, France: Dunod.
23. Robert H, S., & David S, S. (2011). *Time Series Analysis and Its Applications With R Examples* (éd. 3). New York, USA: Springer.
24. Yanyi , P. (2023). Forecasting USA GDP Base on ARIMA Model. 38, 1745-1752. doi:<https://doi.org/10.54691/bcpbm.v38i.3961>

## 7. Appendices

### Appendice(01)

Fig.01 : Model Estimation Results ARIMA(1,1,0)	Fig.02 : Model Estimation Results ARIMA(2,1,0)																																													
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