

Application of Box-Jenkins models and artificial neural networks for predicting Gross Domestic Product (GDP) in Algeria

Sara BEKHTI^{1,*}, Silia BENAMOR², Asma SELLAMI³

¹ Faculty of Economic, Commercial and Management Sciences, Kasdi Merbah University - Ouargla (Algeria)

² Faculty of Economic, Commercial and Management Sciences, Kasdi Merbah University - Ouargla (Algeria)

³ Laboratory of Quantitative Applications in Economic and Financial Sciences, Faculty of Economic, Commercial and Management Sciences, Kasdi Merbah University - Ouargla (Algeria)

Received: 26/05/2025; **Revised:** 25/09/2025; **Accepted:** 06/12/2025

Summary: This study aims to analyze the economic developments in Algeria's Gross Domestic Product (GDP) over the period from 1960 to 2023 and to forecast its trajectory through to 2028. To achieve this objective, two different methodologies were employed: the traditional Box-Jenkins approach for time series analysis, and Artificial Neural Networks (ANNs), which are based on artificial intelligence techniques. The aim was to compare their performance in forecasting GDP.

The findings of the study revealed that the Box-Jenkins model outperformed the neural networks in terms of forecasting accuracy and quality, as demonstrated by the forecast evaluation metrics and the weighted average used for comparing the two models.

Keywords: Gross Domestic Product, Box-Jenkins Methodology, Forecasting, Artificial Neural Networks.

JEL Classification Codes : C22 ; C45 ; E37 ; O55

I- Introduction:

Amid growing economic challenges and sharp fluctuations in global energy markets—upon which the Algerian economy heavily relies—forecasting the trajectory of Gross Domestic Product (GDP) has become critically important for policymakers and investors alike. As a key indicator, GDP reflects the health and growth of the national economy. It informs governments in making fiscal and monetary decisions, enables institutions to strategically direct their investments, and helps citizens better understand future economic trends.

Algeria witnessed a significant increase in its GDP, rising from 2.72×10^9 DZD in 1962 to approximately 2.32×10^{11} DZD in 2023¹. The GDP peaked in 2014 at 2.39×10^{11} DZD due to the oil boom, but it declined sharply to 1.65×10^{11} DZD in 2020 as a result of the COVID-19 crisis. These fluctuations highlight the vulnerability of economic growth to external shocks, underscoring the urgent need for accurate forecasting tools that enable governments to anticipate crises and mitigate their effects.

In response, this study compares two distinct forecasting methodologies: the Box-Jenkins methodology, a traditional tool based on historical data patterns, and Artificial Neural Networks (ANNs), a modern approach rooted in machine learning techniques.

* Corresponding author, e-mail: bekhtisar@gmail.com

I.1- Research Problem, Hypotheses, and Objectives of the Study:

a) Research Problem:

Given the importance of forecasting macroeconomic indicators, including Gross Domestic Product (GDP), especially in light of the challenges facing the Algerian economy, the main research problem addressed in this study can be formulated as follows:

To what extent are Box-Jenkins models effective compared to Artificial Neural Networks in forecasting Algeria's Gross Domestic Product (GDP)?

b) Hypotheses of the Study:

Based on the above, the following hypotheses have been adopted:

- Algeria's Gross Domestic Product (GDP) has experienced increasing growth during the period 1960–2023, with variations in the dynamics of this growth across different time intervals.
- The Box-Jenkins methodology enables the achievement of high forecasting accuracy.
- The Box-Jenkins model outperforms the Artificial Neural Network model in forecasting Gross Domestic Product (GDP).

c) Objectives of the Study:

This study aims to address the research problem and test the validity of the proposed hypotheses, namely to determine whether the Box-Jenkins methodology is more accurate in forecasting Algeria's Gross Domestic Product (GDP) compared to Artificial Neural Networks.

I.2- Previous Studies:

- Study: Sunitha, G., Sampath Kumar, K., Jyothi Rani, S. A., & Haragopal, V. V. (2018). Which was titled: Forecasting GDP using ARIMA and Artificial Neural Networks Models under Indian Environment. The results indicated that the ANN model outperformed the traditional ARIMA model in terms of forecasting accuracy, demonstrating the superiority of intelligent models in handling complex economic data.²
- Study: Al-Doub, T., Al-Talbani, S., & Abu Dahrouj, S (2020). Entitled: A Comparative Statistical Study between ARIMA and ANN Models for Forecasting Global Copper Prices during the Period (1990–2018). The study ultimately concluded that the Artificial Neural Network model was the most appropriate and effective for forecasting global copper prices, as it provided more accurate and reliable predictions compared to the ARIMA model.³
- Study: Sellami, A (2022).entitled “Estimation and Projection of the Cereal Food Gap and Its Implications for Food Security in Algeria.”, the study concluded that the Artificial Neural Network model outperformed the Box-Jenkins methodology in short-term forecasting, due to its superior ability to capture nonlinear patterns in the data.⁴
- Study: Kahforoushan, E., Zarif, M., & Mashahir, E. B (2020). Entitled “Prediction of Added Value of Agricultural Subsectors Using Artificial Neural Networks: Box-Jenkins and Holt-Winters Methods.” the study concluded that both the ANN and Box-Jenkins methodologies were suitable for this type of forecasting, demonstrating satisfactory performance across the evaluated models.⁵
- Study: Atrous, S (2018). Entitled “The Use of Box-Jenkins Methodology and Artificial Neural Networks for Forecasting Electricity Consumption in the SONEGAS Company A Case Study of Biskra Province.” The study ultimately concluded that the Box-Jenkins methodology proved to be more efficient and accurate in forecasting, as it produced results that were very close to the actual values when compared to the ANN approach.⁶

The current study differs from most previous research in that it reached an opposite conclusion, demonstrating the superiority of the ARIMA model over artificial neural networks in forecasting

Algeria's Gross Domestic Product (GDP), in contrast the majority of earlier studies concluded that neural networks were more effective.

II– Methods and Materials:

II.1-Data and Methodology of the Study:

This study relied on annual data related to Algeria's Gross Domestic Product (GDP) covering the period from 1960 to 2023. The data were obtained from the World Bank database, updated on (15/004/2025). In order to address the stated research problem and achieve the objectives of the study, both the descriptive-analytical and statistical methodologies were employed. This was done using a set of statistical tools and software programs, including EViews 12, Gretl 2024d, and MATLAB R2015a.

The study adopted the Box-Jenkins methodology, which is a traditional tool based on historical data patterns and is recognized as one of the most prominent methods for time series analysis. It effectively captures the behavior of time series whether seasonal or non-seasonal⁷. This methodology involves four essential stages:⁸ model identification, parameter estimation, diagnostic checking, and forecasting. Additionally, the study made use of the Artificial Neural Networks (ANNs) model, which represents a modern approach based on machine learning techniques. The name and structure of neural networks are inspired by the human brain, simulating how real neurons communicate with one another⁹.

The forecasting process using ANNs can be summarized as follows:¹⁰ selecting appropriate variables, followed by data preprocessing to ensure its quality and suitability for modeling, splitting the data into training and testing sets, designing the neural network model based on a well-structured architecture, determining a suitable performance evaluation criterion, training the model using the back propagation algorithm to optimize prediction accuracy, and finally executing the model to assess its effectiveness in forecasting and achieving the study's objectives.

III- Results and discussion :

III.1-Economic and Statistical Analysis of the Evolution of the Log of Algeria's Gross Domestic Product:

Gross Domestic Product is the market value of goods and services produced within a selected geographic area (usually a country) in a selected interval in time (often a year). Rightly or wrongly, this has become the standard by which we measure the size and health of a country.¹¹ Gross domestic product (GDP) can be valued on a price basis by two methods. The current-price method produces nominal GDP by measuring goods and services at prevailing market prices during a specified period; it multiplies the aggregate quantities of domestically produced goods and services by their corresponding current prices. The constant-price method yields real GDP, which reflects the total quantity of goods and services purchased by society and produced locally within a given period, but values them at reference prices set in a designated base year that serves as the benchmark for all subsequent years.¹²

The logarithmic transformation of the GDP series (LogGDP) was employed in place of the original GDP series because the log-transformed series exhibited greater stationarity and overall stability.

Based on the data in Figure (1), the curve traces the evolution of the logarithm of gross domestic product over the 1960–2023 period, revealing an overall upward trend in LogGDP. This trajectory produced marked accelerations in economic growth at certain times, whereas other periods experienced slowdowns or declines in performance. The curve also displays cyclical fluctuations that may stem from various crises, such as the downturn recorded in 2020 owing to the Covid-19 pandemic. These cyclical movements indicate that Algeria's GDP is highly sensitive to external shocks, especially those related to international oil price fluctuations. Despite these short-term variations, the overall long-term trajectory of GDP remains predominantly linear, reflecting the

structural dependence of the Algerian economy on hydrocarbon revenues. This dependence generates noticeable growth during boom periods and significant contraction phases during downturns. Such behaviour suggests that linear models like ARIMA are well-suited to capturing the dominant components of Algeria's GDP evolution.

The LogGDP series exhibits a distribution characterized by moderate fluctuations around the mean, as illustrated in Figure (2).

The highest recorded value is (11.38003), whereas the lowest is (9.301344). The series mean stands at (10.59248) dinars, with a standard deviation of (0.63173), indicating a moderate dispersion of values around the mean. The skewness coefficient is (-0.664272), signaling a negatively skewed distribution that is, a non-symmetric distribution whose curve is tilted to the left. The kurtosis coefficient equals (2.273910), which is below three, indicating that the distribution is flatter than the normal distribution, its peak is less pronounced than that of the normal curve. Moreover, the Jarque–Bera statistic ($JB = 6.112627$) exceeds the critical chi-square value at the 5 % significance level ($\chi^2_{0.005}(2) = 5.991$). As ($JB \geq \chi^2_{0.005}(2)$), the null hypothesis is rejected, implying that the time series does not follow a normal distribution.

III.2-Econometric Results of the Study:

III.2.1-Stationarity Analysis of the Time Series:

Prior to applying the Box–Jenkins methodology, it is necessary to verify the stationarity of the time series under investigation. Accordingly, we examined the autocorrelation function (ACF) and the partial autocorrelation function (PACF) for this series (Table 1) and found that most ACF and PACF coefficients fall outside the confidence bounds; therefore, the series is non-stationary. To confirm this conclusion, we conducted the augmented Dickey–Fuller (ADF) test (Table2) relying on the ADF results, we note that the null hypothesis of a unit root cannot be rejected because the probability values (Prob) are greater than 0.05 across all specifications. This confirms that the LogGDP series is non-stationary and contains a unit root, reflecting an overall trend in the time series. To achieve stationarity, first-order differencing was applied, and the ADF test was re-estimated for the differenced LogGDP series (Table 3). The results for all tested models show that the probability values (Prob) are below the 0.05 significance level, indicating that the series became stationary after first-order differencing (Figure 3).

III.2.2-Results of the Box–Jenkins Methodology:

After confirming the stationarity of the logarithmically transformed GDP time series (DLogGDP) using the augmented Dickey–Fuller (ADF) test, we move to the first phase of the Box–Jenkins methodology—the model-identification stage (Table4). Because the graphical display of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) does not allow a clear determination of the model order, the order is selected automatically with EViews 12 (Table5). The automatic selection procedure identifies ARIMA (3, 1, 4) as the most suitable model according to the Akaike information criterion (AIC). Next, the chosen specification is estimated (Table6). All estimated coefficients are statistically significant ($\text{Prob} < 0.05$), so the model is provisionally acceptable.

Final acceptance requires diagnostic testing of the residual independence (Table7) this table shows that all residual autocorrelations lie within the confidence bounds and that the Ljung–Box statistic is below $\chi^2_{0.05}(20)$, leading us to accept the null hypothesis and conclude that the residuals are independent. A residual-stability test (Table8) further confirms that all coefficients fall within the confidence limits, validating the stationarity of the residual squares. Regarding normality (Figure4), the p-value = 0.000495 is below 0.05, and the Jarque–Bera statistic (15.22054) exceeds the critical value of 5.99, indicating that the residual series is not normally distributed. Although the model does not pass the normality test, it can still be considered reliable for forecasting purposes because it satisfies the essential conditions of residual independence and stability required for the final acceptance of the selected ARIMA model. After the final acceptance of the estimated model, we proceed to the last stage forecasting.

To obtain the predicted values for the period 2024–2028, the statistical package Gretl 2024d was employed, yielding five-year forecasts (Table9). When the predicted and actual values were plotted on the same graph (Figure5), the two curves were found to be nearly identical. To verify the quality of the forecasts, we relied on the recognized forecast-accuracy criteria, which constitute the fundamental gauge for assessing the performance of any forecasting method that is, the extent to which the chosen technique reproduces the available data.¹³ The forecast accuracy indicators (Table10) show that the mean absolute error (MAE) equals 0.0313, a small value indicating that the average deviation between actual and predicted values was minimal. The root mean square error (RMSE) of 0.0453 confirms that large Forecast errors were rare. The mean absolute percentage error (MAPE) equals 0.2984 %, an exceedingly low figure (below 1 %) that reflects an excellent level of predictive accuracy, as the forecasts were very close to the actual observations. The mean squared error (MSE) equals 0.0021, further supporting the model's precision and confirming that the magnitude of the error was limited. Finally, the mean error (ME) equals only 0.0028, a value very close to zero, indicating that the model is unbiased and does not systematically over- or under-estimate. Accordingly, these results demonstrate that the model possesses high accuracy and can be relied upon with confidence for forecasting purposes.

III.2.3- Results of the Artificial Neural Network Methodology:

In order to reach the GDP forecasting stage using artificial neural networks, several sequential steps are undertaken. First, the network inputs are specified: the logarithmic GDP series extending from 1960 to 2023. The data are then pre-processed with the Nonlinear Autoregressive (NAR) model and partitioned into three subsets: a training set comprising 70% of the observations (44 data points), a validation set containing 15% (10 data points), and a test set also containing 15% (10 data points). The next step is to define the neural-network architecture. The network has three layers: an input layer with one neuron representing LogGDP, a hidden layer, automatically set to a single layer, with the number of hidden neurons automatically determined as ten, and an output layer with a single neuron, with two default time delays specified.

After defining the model, the training phase begins, during which training options are established, including the choice of learning algorithm and the momentum parameter. The final execution phase tests the reliability and accuracy of the network. In this context, the Levenberg–Marquardt back-propagation algorithm was adopted (Figure6) this figure shows that the correlation coefficient measuring the strength of the relationship between outputs and targets is high, equaling $R = 0.997330$ for the training set $R = 0.994354$ for the validation set, and $R = 0.997031$ for the test set. To verify the network's validity, a regression plot illustrating the relationship between network outputs and targets was generated (Figure7) the plot indicates that the correlation between outputs and targets across the three data subsets and for the trained network as a whole is close to unity, demonstrating efficient training and high-quality learning.

Neural networks generally exhibit superior performance when the underlying time series contains strong nonlinear dynamics, irregular fluctuations, or complex structural patterns. The training and validation results obtained in this study indicate that the ANN model learned the data structure efficiently and achieved high forecasting accuracy. This is confirmed by the overall correlation coefficient $R = 0.99605$, which reflects the network's strong capability to forecast the logarithm of GDP (LogGDP). Furthermore, the histogram (Figure8) it is evident that the network errors decrease as training progresses and remain symmetrically distributed about the zero axis, which indicates no structural problem in the phenomenon to be forecast. From the residual autocorrelation function (Figure9), we observe that all autocorrelation coefficients lie within the confidence bounds, implying that the forecast errors are not serially correlated; accordingly, the trained network is ready for prediction. After confirming the Network's readiness, the best artificial neural network obtained is ANN (1, 10, 1) (Figure 10) the figure shows that the ANN consists of one input layer, a single hidden layer with ten neurons, and one output layer.

To generate the predicted values for 2024–2028, the statistical software MATLAB R2015a was employed, producing five-year forecasts (Table11) when the predicted and actual values were plotted on the same graph (Figure10), the curve of the network outputs almost coincided with the original time-series values, confirming the network's capacity to compute accurate outputs. To assess

model quality, standard forecast-accuracy measures were applied (Table 12) the results show that the mean squared error (MSE) equals 0.0029, confirming that the magnitude of error was limited. The root mean squared error (RMSE) is approximately 0.0543, indicating that large forecast errors were rare. The mean absolute percentage error (MAPE) equals 0.3613 %, an extremely low value (below 1 %) that reflects an excellent level of predictive accuracy. The mean absolute error (MAE) is about 0.0379, a small figure showing that the average difference between actual and predicted values was slight. Finally, the mean error (ME) equals -0.0008842 , a value very close to zero, indicating that the model is unbiased and does not systematically over- or under-estimate. Consequently, these results demonstrate that the model exhibits a high degree of accuracy and can be relied upon with confidence for forecasting purposes.

III.2.4- Comparison between the Results of the Box–Jenkins Methodology and the Artificial Neural Networks:

After applying both the Box–Jenkins methodology and artificial neural networks to Algeria's LogGDP time series for the period 1960–2023, it was found that both techniques are applicable to the series under study, as each produced forecasts close to reality and demonstrated a high level of accuracy. To measure forecast accuracy for both methods, the indicators MAE, RMSE, MAPE, MSE, and ME were calculated. On the basis of Muttar's¹⁴ study, however, it is not advisable to rely on these individual indicators alone; that study proposes using the weighted average of the three criteria MAE, RMSE, and MAPE. According to Table (13) the values of the following indicators mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), mean squared error (MSE), and the weighted averages (WA1, WA2, WA3) were all lower for the Box–Jenkins methodology than for the artificial neural network. The sole exception was the mean error (ME), which was lower for the ANN than for Box–Jenkins. Overall, the ARIMA (3,1,4) model outperformed the ANN (1,10,1) in forecasting.

This superiority can be attributed to the structural characteristics of Algeria's GDP time series, where the relatively weak nonlinear dynamics limited the ability of the ANN to outperform the ARIMA model. The GDP data display stable and repetitive cycles influenced primarily by exogenous macroeconomic shocks rather than intrinsic nonlinear interactions. Consequently, the neural network model was unable to achieve higher predictive accuracy than the ARIMA model. Figures ((5) and (11)) further shows that the graph of the original series and the series forecast with the Box–Jenkins ARIMA (3, 1, 4) model displays superior predictive accuracy compared with the ANN (1, 10, 1) model.

Therefore, we conclude that the more appropriate methodology for forecasting the time series under study is the Box–Jenkins approach, specifically the ARIMA (3, 1, 4) model.

IV- Conclusion:

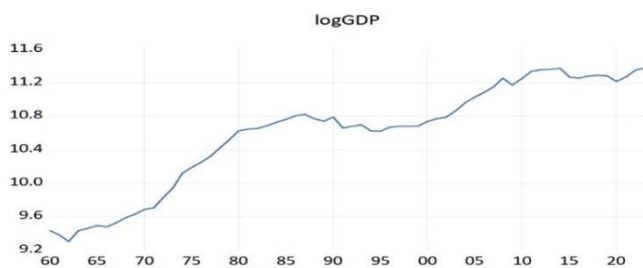
The econometric estimation, employing both the Box–Jenkins methodology and Artificial Neural Networks (ANNs), confirms that Algeria's GDP follows a long-term upward trajectory, albeit with marked variation in its growth rates across successive periods. Forecast-accuracy metrics highlight the superiority of the ARIMA model, which recorded lower error levels than the ANN specification, thereby reinforcing this study's hypothesis regarding ARIMA's higher predictive precision and its outperformance of neural networks in GDP forecasting. However, the superiority of the ARIMA model should not be regarded as a general rule; rather, it is closely linked to the structural characteristics of the LogGDP time series under investigation. The relatively weak nonlinear dynamics observed in this dataset limited the ability of the ANN model to extract additional predictive information beyond that captured by the linear structure of ARIMA. Consequently, the comparative performance of these models may vary in other economic contexts or when applied to variables exhibiting stronger nonlinear behavior. Based on these findings, the following recommendations are offered:

- Support the systematic use of modern quantitative models for analysing and tracking Algeria's GDP path, as they enhance the accuracy of economic decision-making.

- Give greater attention to both the Box–Jenkins framework and ANNs when forecasting key economic indicators—especially GDP—while placing stronger emphasis on Box–Jenkins owing to its superior predictive performance in this study.
- Adopt hybrid approaches such as ARIMA–ANN to capture both linear and nonlinear patterns inherent in time-series data.
- Broaden the scope of analysis to include additional macroeconomic variables related to GDP, such as investment and government expenditure.
- Employ multiple, diverse evaluation criteria when comparing alternative methodologies to ensure the most accurate model selection.

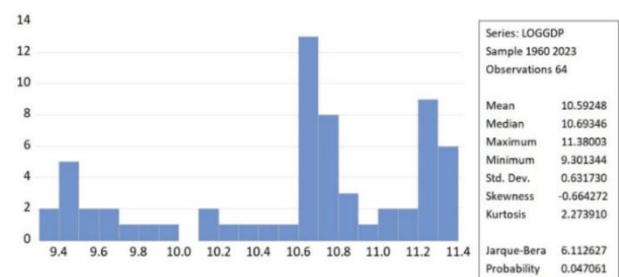
- Appendices :

Figure (1):Graphical Representation of the Log-Transformed Time Series of Algeria's GDP



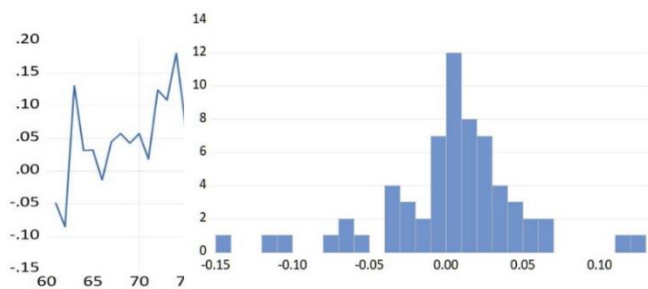
Source: Prepared based on the output of EViews 12

Figure (2): Statistical data of the Log GDP series



Source: Prepared based on the output of EViews 12

Figure (3): DLogGDP series after applying first-order differencing



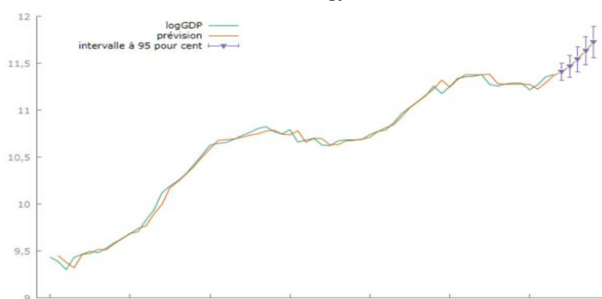
Source: Prepared based on the output of EViews 12

Figure (4):Results of the Normality Test for the Residual Series

Series: Residuals	
Sample	1961 2023
Observations	63
Mean	0.002784
Median	0.005014
Maximum	0.122354
Minimum	-0.142369
Std. Dev.	0.045627
Skewness	-0.642034
Kurtosis	5.037025
Jarque-Bera	15.22054
Probability	0.000495

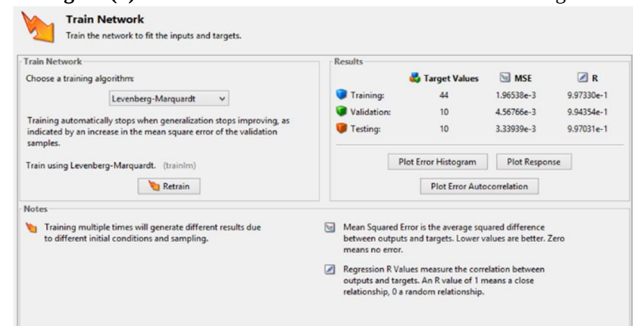
Source: Prepared based on the output of EViews 12

Figure (5):Forecasted Values of Algeria's LogGDP Using the Box-Jenkins Methodology Until 2028



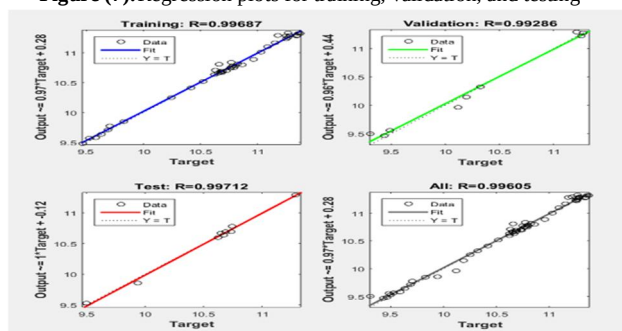
Source: Prepared based on the output of Gretl 2024d

Figure (6):Results of the Artificial Neural Network Training Process



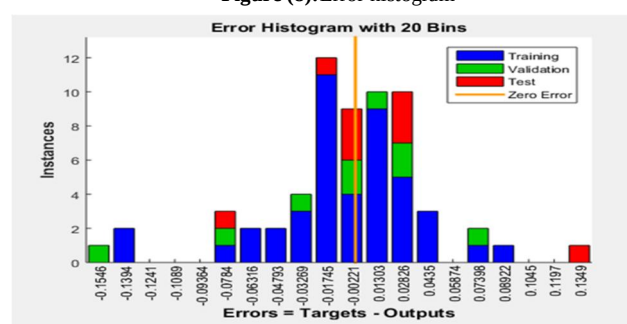
Source: MatlabR2015a

Figure (7):Regression plots for training, validation, and testing



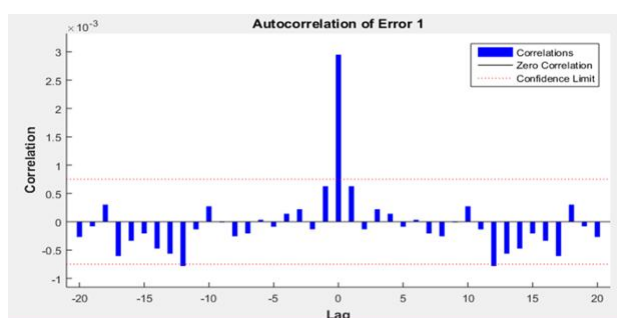
Source: Prepared based onMatlabR2015a

Figure (8):Error histogram



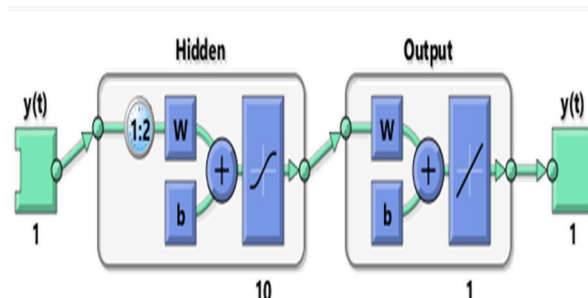
Source: Prepared based onMatlabR2015a

Figure (9):Error autocorrelation function



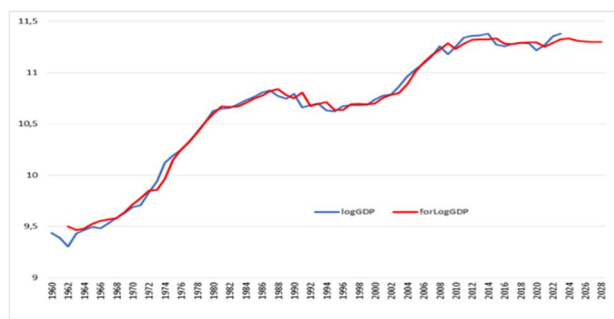
Source: Prepared based onMatlabR2015a

Figure (10):Readiness of the Ann for forecasting



Source: Prepared based onMatlabR2015a

Figure (11):Tracking the original log(GDP) series using the predicted series forLogGDP



Source: Prepared using MATLAB R2015a outputs and further processed in Excel

Table (1): ACF and PACF Plots for LogGDP Series

Date: 04/09/25 Time: 21:26 Sample: 1960 2023 Included observations: 64					
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	0.956	0.956	61.227	0.000	
2	0.905	-0.093	117.05	0.000	
3	0.850	-0.081	167.03	0.000	
4	0.797	0.011	211.75	0.000	
5	0.739	-0.091	250.88	0.000	
6	0.679	-0.059	284.46	0.000	
7	0.614	-0.076	312.44	0.000	
8	0.550	-0.039	335.24	0.000	
9	0.486	-0.030	353.36	0.000	
10	0.419	-0.077	367.09	0.000	
11	0.354	-0.022	377.05	0.000	
12	0.288	-0.055	383.77	0.000	
13	0.228	0.024	388.07	0.000	
14	0.177	0.048	390.71	0.000	
15	0.136	0.064	392.30	0.000	
16	0.096	-0.043	393.11	0.000	
17	0.062	0.023	393.45	0.000	
18	0.034	0.028	393.56	0.000	
19	0.011	-0.000	393.57	0.000	
20	-0.004	0.040	393.57	0.000	

Source: Prepared based on the output of EViews 12

Table (2): Results of the Augmented Dickey-Fuller (ADF) test on the LogGDP series

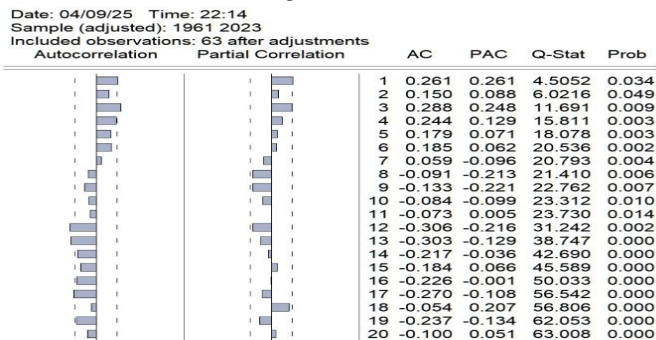
	t-statistic	Prob	Signif
With constant	-1.649374	0.4517	n0
With constant & trend	-0.912382	0.9478	n0
Without constant & trend	2.824454	0.9986	n0

Source: Prepared based on the output of EViews 12

Table (3): Results of the Augmented Dickey-Fuller (ADF) Test on the LogGDP Series After First-Difference Transformation

	t-statistic	Prob	Signif
With constant	-6.027208	0.0000	***
With constant & trend	-6.245362	0.0000	***
Without constant & trend	-1.996198	0.0448	**

Source: Prepared based on the output of EVIEWS 12

Table (4): Graphical Representation of (ACF) and (PACF) for the DLogGDP Series

Source: Prepared based on the output of EVIEWS 12

Table (5): Selected ARIMA Model for the D(LOGGDP) Series

Automatic ARIMA Forecasting
Selected dependent variable: D(LOGGDP)
Date: 04/09/25 Time: 22:21
Sample: 1960 2023
Included observations: 63
Forecast length: 0

Number of estimated ARMA models: 25
Number of non-converged estimations: 0
Selected ARMA model: (3,4)(0,0)
AIC value: -2.93675469345

Source: Prepared based on the output of EVIEWS 12

Table (6): Estimation Results of the ARIMA(3,1,4) Model Using EVIEWS 12

Method: ARMA Maxi
Date: 04/10/25 Time: 11:38
Sample (adjusted): 1961 2023
Included observation: 63
Convergence achieved
Coefficient covariance matrix
d.f. adjustment for str

Q-statistic probabilities adjusted for 7 ARMA terms

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
Variable						
C			1 -0.016	-0.016	0.0169	
AR(1)			2 -0.037	-0.037	0.1092	
AR(2)			3 0.058	0.057	0.3423	
AR(3)			4 0.015	0.015	0.3579	
MA(1)			5 -0.019	-0.015	0.3843	
MA(2)			6 0.059	0.057	0.6342	
MA(3)			7 -0.011	-0.012	0.6432	
MA(4)			8 -0.089	-0.084	1.2267	0.268
SIGMASQ			9 -0.047	-0.057	1.3921	0.499
R-squared			10 0.054	0.047	1.6214	0.655
Adjusted R-squared			11 0.151	0.164	3.4075	0.492
S.E. of regression			12 -0.108	-0.098	4.3357	0.502
Sum squared resid			13 -0.082	-0.088	4.8869	0.558
Log likelihood			14 0.001	-0.019	4.8870	0.674
F-statistic			15 0.044	0.059	5.0515	0.752
Prob(F-statistic)			16 0.000	0.007	5.0515	0.830
Inverted AR Roots			17 -0.127	-0.165	6.4784	0.774
Inverted MA Roots			18 0.145	0.168	8.3881	0.678
			19 -0.176	-0.151	11.256	0.507
			20 -0.017	0.001	11.283	0.587

Source: Prepared based on the output of EVIEWS12

Table (7): Autocorrelation and Partial Autocorrelation Function of the Residuals Series

Source: Prepared based on the output of EVIEWS 12

Table (8): Autocorrelation and Partial Autocorrelation Function of the Squared Residuals

Date: 04/10/25 Time: 11:39
Sample (adjusted): 1961 2023
Included observations: 63 after adjustments

	Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	-0.006	-0.006	0.0023	0.962		
2	-0.084	-0.084	0.4714	0.790		
3	-0.083	-0.085	0.9466	0.814		
4	-0.116	-0.126	1.8780	0.758		
5	-0.060	-0.081	2.1283	0.831		
6	0.126	0.097	3.2774	0.773		
7	-0.090	-0.123	3.8667	0.795		
8	-0.138	-0.157	5.2837	0.727		
9	-0.072	-0.105	5.6798	0.771		
10	-0.110	-0.155	6.6114	0.762		
11	0.125	0.063	7.8432	0.727		
12	0.027	-0.084	7.9009	0.793		
13	0.046	0.010	8.0759	0.839		
14	-0.125	-0.162	9.3746	0.806		
15	-0.012	-0.049	9.3876	0.856		
16	-0.065	-0.117	9.7519	0.879		
17	0.122	0.010	11.081	0.852		
18	0.216	0.171	15.313	0.640		
19	0.017	-0.008	15.341	0.701		
20	-0.042	0.017	15.508	0.747		

Source: Prepared based on the output of EVIEWS12

Table (9):Forecasted Values Using the Box-Jenkins Methodology for the Period (2024–2028)

Years	Forecasted Values LogGDP	Forecasted Values GDP	Confidence Interval 95%	
2024	11,4086	256215854411,29	11,3197	11,4975
2025	11,4658	292266473914,56	11,3477	11,5839
2026	11,5435	349548948468,88	11,4101	11,6770
2027	11,6322	428714329730,77	11,4830	11,7814
2028	11,7250	530851440278,53	11,5557	11,8943

Source: Prepared based on the output of Gretl 2024d

Table (10): Forecast accuracy evaluation metrics for the Box-Jenkins methodology

MAE	0,0313
RMSE	0,0453
MAPE	0,2984
MSE	0,0021
ME	0,00278351

Source: Prepared based on the output of Gretl 2024d

Table (11): Forecasted Values Using the ANN methodology for the Period (2024–2028)

Years	Forecasted LogGDP	Forecasted GDP
2024	11.3319	214732231116,72
2025	11.3096	203999212761,30
2026	11.3010	200001377936,15
2027	11.2980	198624793672,56
2028	11.2971	198180642460,73

Source: prepared based on MATLABR2015a

Table (12):Forecast accuracy evaluation metrics for the ANN methodology

MSE	0,002950042
RMSE	0,054314289
MAE	0,037911067
MAPE	0,361300214
ME	-0,00088424

Source: Prepared based on MatlabR2015a

Table (13):Comparison between the results of the Box-Jenkins methodology and ANN

Forecast Accuracy Indicators	Box-Jenkins Methodology	Artificial Neural Network Methodology
MAE	0,0313149	0,037911067
MSE	0,00205655	0,002950042
RMSE	0,0453492	0,054314289
MAPE	0,298399%	0,361300214%
ME	0,00278351	-0,00088424
WA1	0,014766677	0,256237702
WA2	0,035949282	0,10274474
WA3	0,028932132	0,094543129

Source: Prepared based on MatlabR2015a and Gretl 2024d

Referrals and references:

- [1] World Bank Data. Retrieved from: 25/03/2025; <https://donnees.banquemondiale.org/indicateur/NY.GDP.MKTP.KD.ZG?locations=DZ>
- [2] Sunitha, G., Sampath Kumar, K., Jyothi Rani, S. A., & Haragopal, V. V. (2018). Forecasting GDP using ARIMA and Artificial Neural Networks models under Indian environment. *International Journal of Mathematics Trends and Technology*, 56(1). pp60-70
- [3] Al-Doub, T., Al-Talbani, S., & Abu Dahrouj, S. (2020). A Comparative Statistical Study between ARIMA and ANN Models for Forecasting Global Copper Prices during the Period (1990–2018). *Algerian Journal of Economic Development*, 7(1). pp17-32
- [4] Sellami, A. (2022). Estimating and Forecasting the Cereal Food Gap and Its Implications for Food Security in Algeria [doctoral dissertation, Kasdi Merbah University – Ouargla, Faculty of Economics, Commercial and Management Sciences, Department of Economics].
- [5] Kahforoushan, E., Zarif, M., & Mashahir, E. B. (2020). Prediction of added value of agricultural subsections using artificial neural networks: Box-Jenkins and Holt-Winters methods. *African Journal of Agricultural Marketing*, 8(4). pp1-7
- [6] Atrus, S. (2018). The use of the Box–Jenkins methodology and artificial neural networks to forecast electricity consumption in Sonelgaz Company: A case study of Biskra Province [Master's thesis, Mohamed Khider University of Biskra Province [Master's thesis, Mohamed Khider University of Biskra].
- [7] Gorgess, H. M., & Ibrahim, R. (2013). Time series forecasting by using Box-Jenkins models. *Ibn Al-Haitham Journal for Pure and Applied Science*, 26(1), p340
- [8] Al-zahra, K. A., Moosa, K., & Jasim, B. H. (2015). A comparative study of forecasting the electrical demand in Basra city using Box-Jenkins and modern intelligent techniques. *Iraq Journal of Electrical and Electronic Engineering*, 11(1), p116
- [9] Qamar, R., & Zardari, B. A. (2023). Artificial neural networks: An overview. *Mesopotamian Journal of Computer Science*, 2023(1), p130
- [10] Sahad, A., & Mekideche, M. (2014). A comparative study of fuzzy regression using goal programming and artificial neural networks to forecast oil price. *Al-Bahith Journal*, University of Abu Bakr Belkaid – Tlemcen, (14), p112
- [11] Leamer, E. E. (2009). *Macroeconomic patterns and stories: A guide for MBAs*. Springer-Verlag, p19
- [12] Mejdi, N. (2021). Basic economic concepts: Gross domestic product (GDP). Arab Monetary Fund, Series of Educational Booklets, (19), pp13–15
- [13] Abdelrahman, A. (2004). *Principles of Managerial Forecasting*. Kingdom of Saudi Arabia: Scientific Publishing and Printing Press, p161
- [14] Mutar, T. (2008). A proposed technique for the problem of selecting the best forecasting model in time series: A case study. *Iraqi Journal of Statistical Science*, (14), 1–20. As cited in Sellami, A. (2022). Estimating and Forecasting the Cereal Food Gap and Its Implications for Food Security in Algeria [doctoral dissertation, Kasdi Merbah University – Ouargla, Faculty of Economics, Commercial and Management Sciences, Department of Economics], p150