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Research Article

Forecasting Algerian Gross Domestic Product -GDP- Using The Box-Jenkins Methodology (1962-2023)

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ABSTRACT
This study aims to predict the values of GDP in Algeria, through a time series extending from 1962 to 2023, using the "Box-Jenkins" methodology as one of the most famous methods used in forecasting, the results showed that the appropriate model to represent the data of this series is the "ARIMA (1,1,1)" model, and after this model proved its effectiveness in forecasting, and finally we predicted the values of GDP for the next six years (until the end of 2030).

Keywords: Time Series; Box-Jenkins; Gross Domestic Product; Forecasting.

Jel Classification Codes : B22, C53.

1. Introduction

The Gross Domestic Product (GDP) is an important economic indicator that reflects the development of the economy because it represents the total value of goods and services produced in a country. In Algeria, this indicator has witnessed a significant development that reflects the economic efforts aimed at revitalizing the national economy.
The time series of gross domestic product (GDP) is the focus of this study. This is a statistical technique that pertains to time series data or trend analysis.
It is advantageous in determining how the set of values of goods and services produced fluctuates in response to the economic circumstances. In this study, we employ the Box-Jenkins methodology to calculate the moving average and regression analysis in order to identify the most suitable model for the time series.
Through the above, we have focused our main research question, namely, our main research question:
How does the BOX-JENKINS method predict Algerian GDP values over the next six years (to the end of 2030)?
In order to answer the main question, our research is based on the Box-Jenkins methodology of knowing the components of the time series and examining their stationarity, then extracting possible models, then estimating the parameters of the appropriate model and testing its quality through autocorrelation, independence of random errors, and following a normal distribution, and finally performing the forecasting process with the selected model.

2. Revue literature

2.1- Revue literature about: Box Jenkins

Time series forecasting has been widely used in time series forecasting using the Box-Jenkins methodology, developed by Box and Jenkins. The approach involves locating and applying autoregressive integrated moving average (ARIMA) models to time-series data. Box-Jenkins models can be a valuable tool in analyzing the effects of policy interventions, according to a study by (Hibbs, 1977)
Box-Jenkins models can preserve historical statistical properties, such as the rescaled adjusted range, which makes them advantageous for practical applications.
Research has shown that Box-Jenkins models outperform simpler forecasting approaches. Box-Jenkins time series models consistently produce better forecasts than martingale and submartingale earnings models, as shown so it is possible that more complex methods like the Box-Jenkins procedure are not always superior.

(Brown & Rozeff, 1978)
The Holt-Winters forecasting procedure, while simpler than Box-Jenkins, can be just as precise when subjective judgment is used to select the correct model for seasonality, according to (Chatfield C. , 1978.)
Neural networks have emerged as a competitor to traditional methods like Box-Jenkins in time series forecasting.
The Box-Jenkins model was superior for series with short memories, according to (Tang, Almeida, & Fishwick, 1991) In the same vein, (Hagan & Behr, 1987.) suggested that neural networks could be a superior long-term forecasting tool than Box-Jenkins for cumulative forecasting.
The optimal choice between neural networks and Box-Jenkins may depend on the complexity of the time series data being analyzed. Overall, the Box-Jenkins methodology remains a valuable tool in time series forecasting, especially for preserving historical statistical properties and analyzing the effects of policy interventions. It is a popular choice among researchers and practitioners in the field because of its versatility and effectiveness.

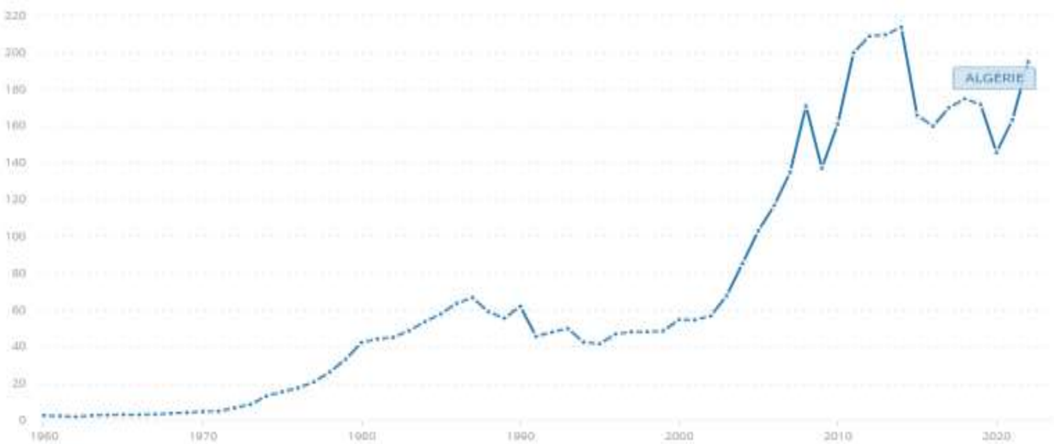
2.2- Revue literature about :Forcastinf GDP by Box-Jenkins

Neural networks have been studied as models for time series forecasting in comparison to the Box-Jenkins method for both long- and short-term memory series (Tang & Fishwick, 1993). The ability of neural networks to easily build multiple-step-ahead forecasting models may make them a better long term forecast model.
Post-sample forecasting accuracy of ARIMA models using the Box-Jenkins methodology is generally worse than simpler time series methods, with the main issue being the method of differencing to make the series stationary in its mean. In the context of GDP prediction, studies have applied both neural networks and the Box-Jenkins method to forecast GDP in various countries, such as the Czech Republic. The significance of the Box-Jenkins methodology in economic forecasting has been demonstrated by these studies. (Abonazel & Abd-Elftah, 2019)
Other economic indicators such as tourism demand in Croatia and Aman Rice production in Bangladesh have been forecast using the Box-Jenkins methodology. (Hossen, Hossain, Chakraborty, & Ismail, 2020)
These studies have shown the utility of the Box-Jenkins approach in modeling and forecasting various economic variables (Reshid, 2020). In the context of economic indicators such as GDP, tourism demand, and agricultural production, the Box-Jenkins methodology continues to be a valuable tool. Economic research and policy-making is influenced by this approach, which has been shown to be effective in comparison to other forecasting methods. (Nwokike & Okereke, 2021)

3. RESULTS AND DISCUSSION

The GDP index in Algeria has changed a lot from the beginning of independence to 2023, and we show the changes in the following curve.

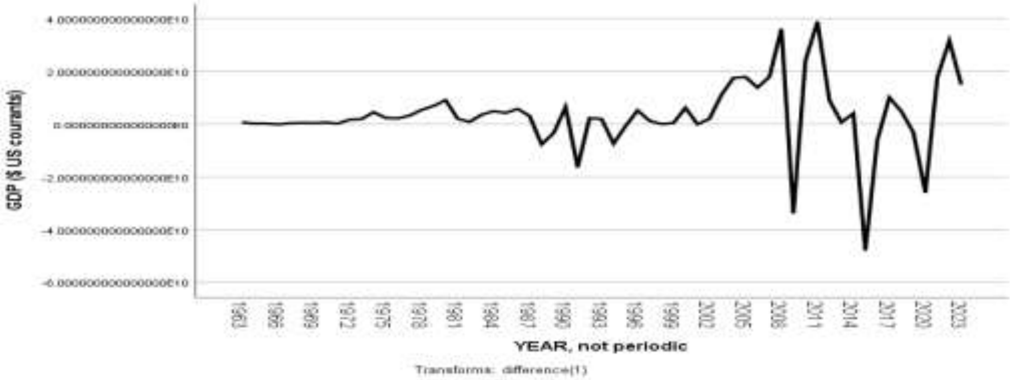
Fig 1: Algerian GDP



Source: (W.Bank, 2024)

From the figure above, we can see that the time series of GDP values contains the general trend component, as its general shape suggests that it is in an increasing development, but it stabilized somewhat between 2010 until the end of 2014, then the GDP values decreased to reach the lowest level since 2008, and finally the curve witnessed a continuous upward trend from 2020 until 2023
We can also see from the shape of the curve that there is no seasonal component, so there is no need to demonstrate this, as it is evident from the graph
In order to obtain time series stationarity, we set the difference value to 1, "d=1", so the shape of the curve is as follows:

Fig 2: Time Serie with differentiation



Source: Based on SPSS 25 output.

After confirming the stationarity of the time series, we extract p and q in order to identify the appropriate forecasting model, and this process is done by analyzing the Autocorrelation and Partial Autocorrelation values:

Tab 1: AC Values

Series: GDP($ US courants)

Lag	AC	Std. Error[a]	Box-Ljung Statistic Value	df	Sig.[b]
1	.101	.125	.654	1	.419
2	-.121	.124	1.607	2	.448
3	.099	.123	2.262	3	.520
4	-.002	.122	2.262	4	.688
5	.053	.121	2.457	5	.783
6	.158	.120	4.193	6	.651
7	-.175	.119	6.385	7	.496
8	-.180	.117	8.742	8	.365
9	-.210	.116	12.013	9	.213
10	-.060	.115	12.285	10	.266
11	.116	.114	13.324	11	.273
12	-.136	.113	14.772	12	.254
13	-.147	.112	16.493	13	.224
14	-.011	.111	16.503	14	.284
15	.019	.109	16.532	15	.348
16	-.050	.108	16.748	16	.402

Source: Based on SPSS 25 output.

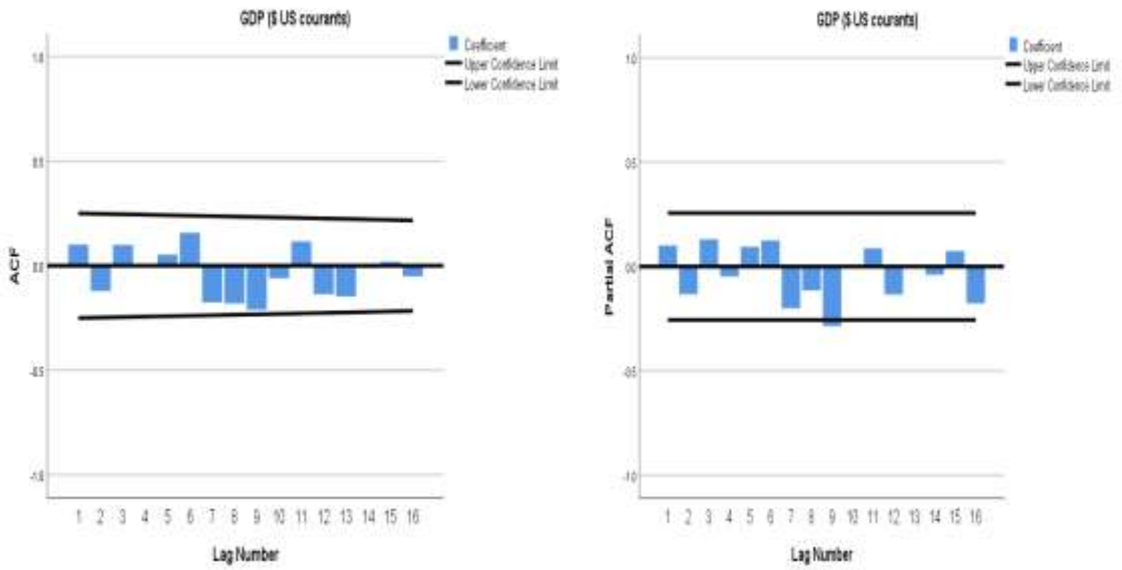
Tab 2: PACF values

Series: GDP ($ US courants)

Lag	PACF	Std. Error
1	.101	.128
2	-.133	.128
3	.130	.128
4	-.048	.128
5	.095	.128
6	.124	.128
7	-.200	.128
8	-.115	.128
9	-.286	.128
10	-.004	.128
11	.087	.128
12	-.134	.128
13	-.002	.128
14	-.039	.128
15	.074	.128
16	-.177	.128

Source: Based on SPSS 25 output.

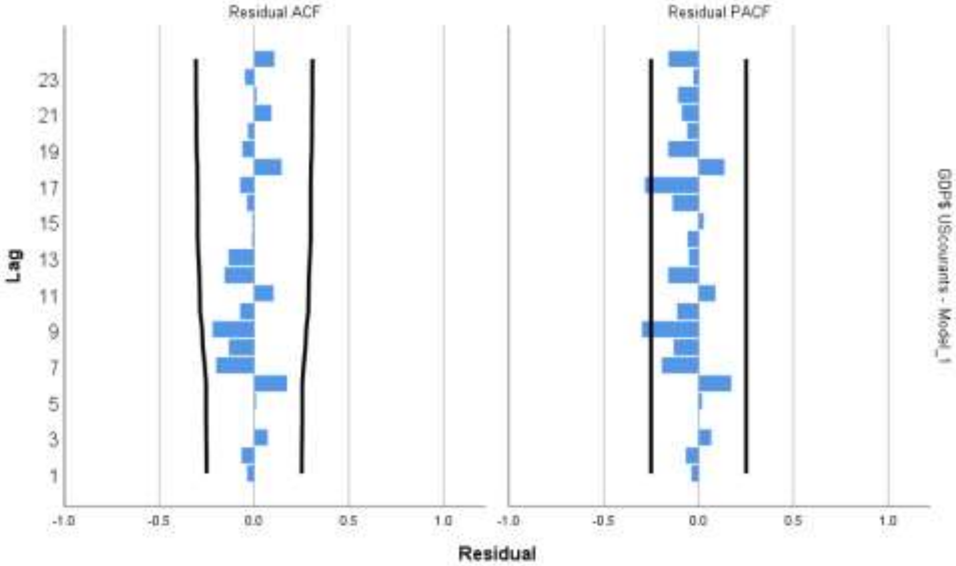
Fig 3:AC and PACF



Source: Based on SPSS 25 output.

Because the values of AC and PAC are zero after one value, we can say that p=1 and q=1, and by adding the previously applied d=1, we get the optimal prediction model ARIMA(p,d,q) is: ARIMA(1,1,1)

Fig 4: Residual AC and Residual PACF



Source: Based on SPSS 25 output.

From the above curves, we can see that both the Residual AC and Residual PAC values do not deviate from their respective confidence intervals, and from this point of view, the chosen model ARIMA (1,1,1) can be accepted
Finally, we predict the GDP values for the next six years up to 2030, through the following table:

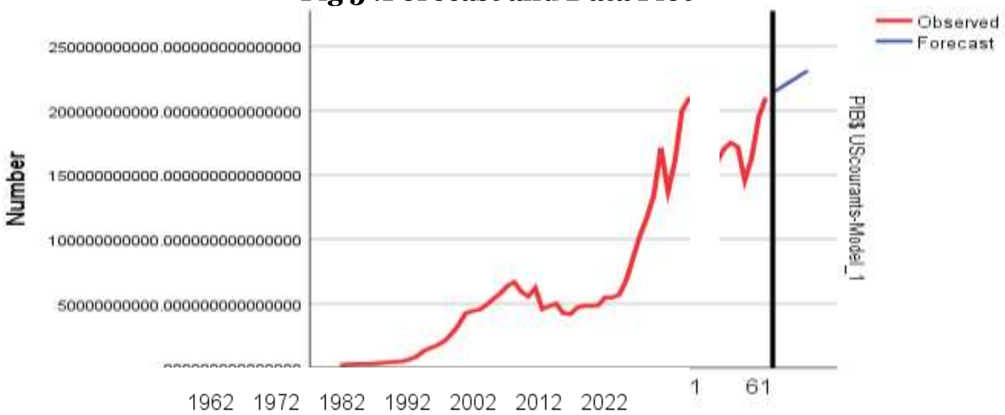
Tab 3: Forecasting GDP values

Year		2024	2025	2026	2027	2028	2029	2030
GDP ($ US courants)-Model_1	Forecast	2.14E+11	2.17E+11	2.21E+11	2.24E+11	2.28E+11	2.31E+11	2.34E+11
	UCL	2.41E+11	2.58E+11	2.71E+11	2.83E+11	2.93E+11	3.03E+11	3.12E+11
	LCL	1.88E+11	1.76E+11	1.71E+11	1.66E+11	1.62E+11	1.59E+11	1.56E+11
For each model, forecasts start after the last non-missing in the range of the requested estimation period, and end at the last period for which non-missing values of all the predictors are available or at the end date of the requested forecast period, whichever is earlier.								

Source: Based on SPSS 25 output.

This can be further illustrated by the following figure:

Fig 5 :Forecast and Data Plot



Source: Based on SPSS 25 output.

4. CONCLUSION

Our study is focused on forecasting GDP in Algeria using the Box-Jenkins methodology, as it is one of the most significant economic indicators that reflects the economic situation.
We processed the time series (1962-2023) to stabilize it by adopting the first level of differences, which became stationary. Subsequently, we estimated the parameters of the appropriate model and tested its

suitability and quality. Ultimately, we determined that the appropriate model is ARIMA (1,1,1), and based on this model, we executed the forecasting process for the next six years -until 2030-.

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6. Appendices

Tab 4 : Model Fit

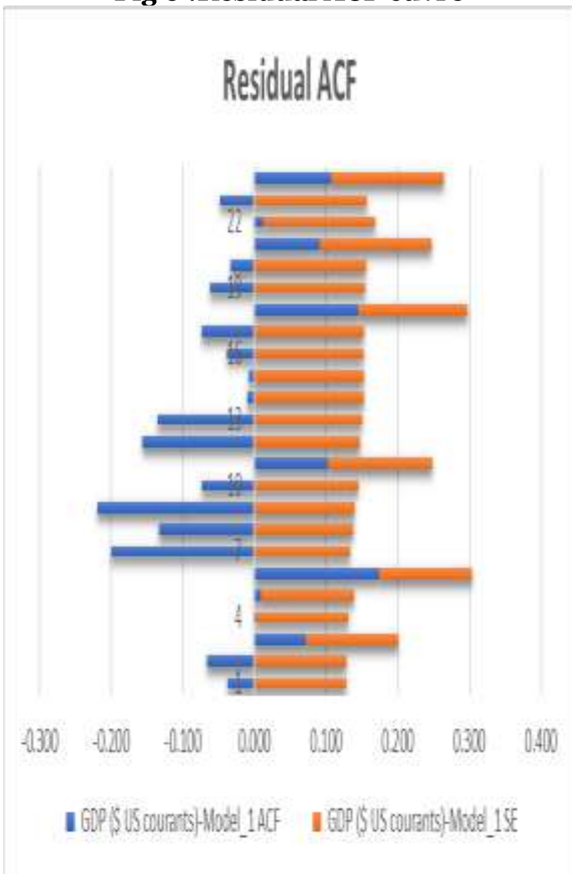
	Fit Statistic		MAPE	MaxAPE	Normalized BIC
Model Fit	Mean		10.012	44.023	46.899
	Minimum		10.012	44.023	46.899
	Maximum		10.012	44.023	46.899
	Percentile	5	10.012	44.023	46.899
		10	10.012	44.023	46.899
		25	10.012	44.023	46.899
		50	10.012	44.023	46.899
		75	10.012	44.023	46.899
		90	10.012	44.023	46.899
		95	10.012	44.023	46.899

Source: Based on SPSS 25 output.

Tab 5 :Residual ACF values

	Model	**GDP ($ US courants)-Model_1**	
		ACF	SE
Residual ACF	1	-0.037	0.128
	2	-0.066	0.128
	3	0.071	0.129
	4	0.002	0.129
	5	0.009	0.129
	6	0.174	0.129
	7	-0.200	0.133
	8	-0.133	0.138
	9	-0.219	0.140
	10	-0.074	0.146
	11	0.103	0.146
	12	-0.156	0.147
	13	-0.135	0.150
	14	-0.010	0.152
	15	-0.008	0.152
	16	-0.038	0.152
	17	-0.074	0.152
	18	0.145	0.153
	19	-0.062	0.155
	20	-0.033	0.156
	21	0.091	0.156
	22	0.012	0.157
	23	-0.048	0.157
	24	0.107	0.157

Fig 6 :Residual ACF cuvre



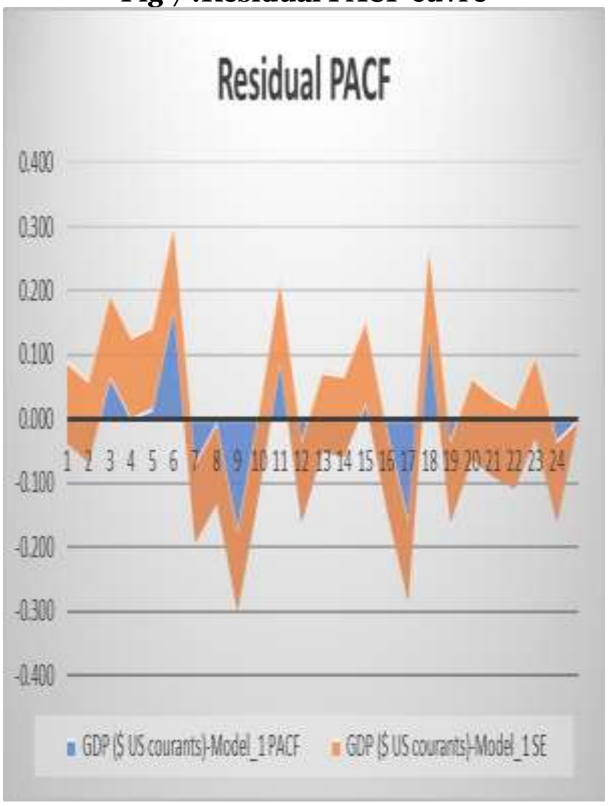
Source: Based on SPSS 25 output.

Tab 6 :Residual PACF

Residual PACF	Model	GDP ($ US courants)-Model_1	
		PACF	SE
	1	-0.037	0.128
	2	-0.067	0.128
	3	0.067	0.128
	4	0.003	0.128
	5	0.018	0.128
	6	0.172	0.128
	7	-0.194	0.128
	8	-0.131	0.128
	9	-0.299	0.128
	10	-0.113	0.128
	11	0.088	0.128
	12	-0.160	0.128
	13	-0.052	0.128
	14	-0.058	0.128
	15	0.026	0.128
	16	-0.138	0.128
	17	-0.283	0.128
	18	0.137	0.128
	19	-0.160	0.128
	20	-0.060	0.128
	21	-0.089	0.128
	22	-0.109	0.128
	23	-0.028	0.128
	24	-0.159	0.128

Source: Based on SPSS 25 output.

Fig 7 :Residual PACF cuvre



Source: Based on SPSS 25 output.

Tab 7 : ARIMA Model Parameters

					Estimate	SE	t	Sig.
GDP Model_1	GDP ($ US courants)	No Transformation	Constant		-1.9049E+11	1.3949E+11	-1.366	0.0177
			AR	Lag 1	-0.455	0.544	-0.836	0.0406
			Difference		1			
			MA	Lag 1	-0.613	0.485	-1.264	0.0211
	YEAR, not periodic	No Transformation	Numerator	Lag 0	97291325.5	64051663.7	1.519	0.134

Source: Based on SPSS 25 output.