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Forecasting Government Final Consumption Expenditure in Algeria: Comparative Performance of the ARIMA (Box-Jenkins) Model and Artificial Neural Networks (MLP & LSTM) up to 2034

Salim LAGOUNE [1,*]

[1]Setif 1 University Ferhat Abbas, Laboratory of the Evaluation of Algerian Capital Markets in Light of Globalization, Setif, (Algeria) (Salim.lagoune@univ-setif.dz)

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Summary: This study aims to compare the performance of forecasting models for final government consumption expenditure in Algeria up to 2034, using the ARIMA model based on the Box-Jenkins methodology as a traditional approach and artificial neural network models (MLP and LSTM) as modern forecasting methods.

The study results showed that although the ARIMA(0,2,1) model was the most appropriate according to statistical criteria within the Box-Jenkins methodology, the artificial neural network models significantly outperformed it in forecasting accuracy, as reflected by lower error metrics (RMSE, MSE, MAE), making them effective tools for supporting strategic planning and financial policymaking. Furthermore, when comparing the two neural network models, the MLP model clearly outperformed the LSTM model, recording the lowest error metrics and the highest coefficient of determination (R^2), establishing it as the optimal and most efficient model for accurate forecasting of this series up to 2034.

Keywords: Final Government Consumption Expenditure; Forecasting Models; Box-Jenkins Methodology; Artificial Neural Networks; MLP and LSTM Models.

Jel Classification Codes: H50; H68; C53; C22; C45.

* Corresponding author.

I-Introduction:

Government expenditure is one of the most prominent fiscal policy tools used by the state to influence aggregate demand and achieve overall equilibrium in income and gross domestic product. By controlling the size of this expenditure, the government can regulate its contribution to aggregate demand in a way that ensures a level of income that achieves optimal use of available economic resources.(Ali & Imad , 2014, p. 17)

Final government consumption expenditure (GFCE) constitutes one of the main components of government expenditure. It serves as an effective tool for influencing the economic and social structure, in addition to its central role in achieving macroeconomic balances for the national economy. This expenditure also contributes, directly or indirectly, to enhancing the performance of the state's overall economic activity.

With the increasing importance of government consumption expenditures in national economies, forecasting them, like other macroeconomic variables, has become vital, particularly for rentier economies, including the Algerian economy, given its heavy reliance on oil revenues and its strong connection to and particular vulnerability to fluctuations in global oil prices.

With these rapid economic changes, reliance on multiple forecasting models has become a necessity for analyzing the development of government consumption expenditures in Algeria, whether traditional, advanced, or hybrid, as these models help policymakers set economic plans and guide fiscal and monetary policies, and they also enable the tracking of macroeconomic variable trends in general.

In this context, the field of time series forecasting has witnessed significant development in recent years, particularly with advancements in big data processing techniques and the increasing use of artificial intelligence (AI) applications. These technologies have proven their effectiveness, achieving high forecasting accuracy in various economic and social domains. Applications of forecasting models have also extended to energy, healthcare, and computer science. Artificial neural networks (ANNs) are considered one of the most widely used methods for processing complex time series characterized by non-linearity and noise in the data (Musleh, 2023, p. 134).

The Autoregressive Integrated Moving Average (ARIMA) model, based on the Box-Jenkins methodology, is one of the most widely used traditional forecasting approaches for studying the evolution of economic phenomena and is extensively applied in time series data analysis. These methods typically rely on fitting data to a predefined relationship (Araujoa & Gaglianone, 2023, p. 2)While ARIMA can capture linear trends, it lacks the ability to detect the complex and nonlinear patterns in the data that characterize many economic variables.

In contrast, Artificial Neural Network (ANN) models, particularly Multi-Layer Perceptron (MLPs) and Long Short-Term Memory (LSTMs) networks, offer a modern approach to statistical analysis and forecasting. They are considered a powerful alternative to traditional standard models, including ARIMA, due to their ability to explore nonlinear patterns inherent in data, which are often hidden from standard linear models (Tchoketch-Kebir & Madouri, 2024, p. 220). Additionally, ANNs are well-suited for representing relationships between variables and are capable of handling linear and nonlinear data, as well as incomplete or noisy datasets (Musleh, 2023, p. 134).

Given the vital role played by forecasting models, whether traditional or advanced, in predicting economic and social indicators and variables, selecting the most appropriate model to improve forecast accuracy is a pressing and essential necessity to enable decision-makers to adapt economic policies to future trends and anticipate potential shifts in the trajectory of the Algerian economy during the upcoming period 2025–2034.

Based on the above, this study seeks to conduct a comparative analysis of the performance of ARIMA models, following the Box-Jenkins methodology, and Artificial Neural Network models (MLP and LSTM) in forecasting final government consumption expenditure in Algeria during the period (2025–2034), with the aim of identifying the most efficient and accurate model, relying on a set of standard evaluation criteria recognized in the scientific literature.

I.1.Research Problem

From this standpoint, the research problem is formulated in the following main question:

Which model is more efficient in forecasting final government consumption expenditures (GFCE) in Algeria up to 2034: the ARIMA model based on the Box–Jenkins methodology, or the Artificial Neural Network models (MLP and LSTM) ?

The following sub-questions branch from this main question:

- How effective is the ARIMA model, developed using the Box–Jenkins methodology, in forecasting final government consumption expenditures in Algeria up to 2034 ?
- How effective is the Multi-Layer Perceptron (MLP) model in forecasting final government consumption expenditures up to 2034?
- To what extent is the Long Short-Term Memory (LSTM) neural network model effective in forecasting final government consumption expenditures up to 2034?
- Which of the three models (ARIMA, MLP, LSTM) is the most suitable and efficient for forecasting final government consumption expenditures in Algeria up to 2034?

I. 2. Research Hypotheses:

To address this research problem, the following basic hypotheses were formulated:

Hypothesis 1: The ARIMA model possesses an effective capability for forecasting final government consumption expenditures in Algeria up to 2034.

Hypothesis 2: The Multi-Layer Perceptron (MLP) model is an effective model for forecasting final government consumption expenditures in Algeria up to 2034.

Hypothesis 3: The Long Short-Term Memory (LSTM) neural network model is an effective model for forecasting final government consumption expenditures in Algeria up to 2034.

Hypothesis 4: Artificial Neural Network models (MLP and LSTM) are more efficient and accurate than the ARIMA model, developed using the Box–Jenkins methodology, in forecasting final government consumption expenditures in Algeria.

I. 3. Methodology

To achieve the study's objectives, the descriptive-analytical approach was adopted to examine the conceptual framework of government consumption expenditures and forecasting methodologies (Box-Jenkins and artificial neural networks). Additionally, a quantitative analytical approach was adopted, which included the use of traditional forecasting models (ARIMA) alongside modern models based on neural networks (MLP and LSTM) to forecast government consumption expenditures. The entire analysis was conducted using Python, benefiting from its advanced tools and libraries for time series processing, analysis, and the construction of accurate and highly efficient forecasting models.

I. 4. Literature Review:

Scientific literature points to the growing importance of using statistical models in forecasting economic phenomena, especially in light of the rapid changes and digital transformations that the world has witnessed in various fields, which have produced a vast amount of data that must be processed using advanced statistical methods, machine learning techniques, and artificial neural networks, in addition to traditional methods, to improve the accuracy of predictions. In this context, several previous international studies and applied studies in the Algerian context, are reviewed, as follows:

- **International Studies:**

In a study conducted by Ismail Yenilmez and Fabrice Mugenzi (2023), Rwanda's GDP per capita data were modeled using the Box-Jenkins methodology alongside artificial neural networks models (LSTM, GRNN, and MLP). The results showed that MLP and GRNN models outperformed the Box-Jenkins model in terms of statistical accuracy, while the LSTM model excelled specifically in the Mean Absolute Percentage Error (MAPE) metric.

Similarly, Chenyu Jiang (2024) conducted a comparative analysis of the performance of the Autoregressive Integrated Moving Average (ARIMA) model, the Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM) based architectures on various data types, including COVID-19 infection rates, stock prices, and cryptocurrencies prices. The results also demonstrated that neural network models (RNN and LSTM) outperformed the ARIMA model in capturing complex nonlinear patterns and temporal dependencies.

Also, Hakan Kaya and Batuhan Özkan (2025) conducted a comparison of GDP forecasting performance in Turkey between traditional models (ARIMA) and machine learning techniques (ANN, Elastic Net, SVM, and XGBoost). The results showed that the XGBoost model achieved the best forecasting accuracy, and it was also clear that the other machine learning models were better than the performance of the traditional ARIMA model.

- **Local Studies**

In a study by Ismail Hosni (2025), Fractionally Integrated Autoregressive Moving Average (ARFIMA) models were used alongside Multi-Layer Perceptron (MLP) artificial neural networks

to model fluctuations in monthly inflation rates and forecast their future trends in Algeria. The results showed that both methods were able to accurately track the studied time series. However, the criteria for measuring the accuracy of predictive performance showed that the MLP neural network model was the most accurate method because it achieved the lowest prediction error.

Also, a study by Kahoui Hacen et al. (2025) aimed to explore the role of machine learning techniques in improving the accuracy of forecasting domestic wheat consumption in Algeria, to support supply chain improvement and reduce the risks associated with stock imbalances. A comparative analysis was conducted using three models: the traditional ARIMA model, the Multi-Layer Perceptron Neural Network (MLPNN), and the Support Vector Machine (SVM) model. The results showed the superiority of machine learning models over traditional methods, especially when dealing with non-linear and unstable data.

From the above, we note that these international and local studies focused on comparing traditional statistical models, such as ARIMA, with its artificial neural network models and machine learning techniques, demonstrated that the latter outperformed traditional statistical models in most cases when forecasting complex and time- dependent economic data. Despite the availability of many studies of this type, the use of these models for forecasting government consumption expenditure in Algeria remains limited. In this context, the present study analyzed data for the period 1980 to 2024, providing a longer and more recent timeframe that allows for the more efficient use of neural network models. This approach enabled the identification of the most suitable model for forecasting government consumption expenditure more accurately and realistically, up to the year 2034, and it offers up-to-date and reliable insights to support decision-making and economic planning at the national level.

I. 5. Theoretical Framework:

The theoretical framework begins by defining final government consumption expenditures and their role in the economy, then reviews the most important time series forecasting models, from traditional models (ARIMA) based on the Box-Jenkins methodology, to modern neural network models such as Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) networks, which are currently being successfully applied to forecast complex time series.

I. 5. 1. Final Government Consumption Expenditure

I. 5. 1. 1. Definition of Government Final Consumption Expenditure:

In national accounts, the term Final Government Consumption Expenditure (GFCE) refers to the total final expenditure spent by the government on goods and services provided to society, excluding subsidies and cash transfers such as pension payments or public debt interest. This expenditure focuses on public services that benefit society as a whole, rather than specific individuals or groups(Ali & Imad , 2014, p. 119), and includes the government's purchase of consumer services such as education, health, defense, and security, as well as the acquisition of goods and supplies necessary for the performance of public functions, while excluding capital expenditure such as the purchase of land, buildings, or used equipment(Australian Bureau of Statistics, 2021).

I. 5. 1. 2. The Importance of Government Consumption Expenditure:

Consumption expenditures constitute one of the main components of public spending and economic activity, as they contribute to: (Ben Al-Ayeb, 2025, p. 404)

- Directing and utilizing available economic resources, which affects the size and composition of the national product, and in turn drives economic development and promotes stability;
- Meeting the basic needs of society, such as education, health, security, and administrative services, while improving quality of life and enhancing the level of social welfare without generating a direct financial return;
- Building human capital and increasing workforce productivity, which positively impacts the economic growth rate and strengthens the path towards sustainable economic development;
- Influencing the economic and social structure, in addition to its key role in achieving macroeconomic balance.

I. 5. 1. 3. Classifications of Government Consumption Expenditure:

Two main types of consumption expenditure can be distinguished: (Ben Al-Ayeb, 2025, p. 408)

- **Intermediate consumption expenditure:** This is the portion of expenditure allocated to acquiring goods and services used as inputs in the production process. It is a fundamental element

in Gross Domestic Product (GDP) calculations because it contributes to the production process without being considered final consumption for society;

- **Final consumption expenditure:** This includes the use of goods and services by individuals and society to satisfy their immediate needs and improve their standard of living, such as education, health, security, and administrative services. It is a fundamental component of aggregate demand, directly impacting economic growth and societal well-being.

In Algeria, this term is equivalent to current expenditure, which represents the largest part of these expenditures and includes employee salaries, public services, and operational expenses—in short, everything that constitutes the government's actual consumption for the benefit of society. This reflects the practical application of the concept of final government consumption expenditure in the local context.

I. 5. 2. Introducing the Box–Jenkins (ARIMA) Methodology

The Box-Jenkins methodology is one of the most widely used statistical methods in scientific research for analyzing and forecasting time series data, which fundamentally relies on past data of a time series (Éric, 2009, p. 170), and is named after George Box and William Jenkins (1970) (Robert H & David S, 2011, p. 83).

The Box-Jenkins methodology aims to identify the optimal model from the autoregressive integrated moving average models (ARIMA) by determining the model's coefficients (p, d, q). The model includes a combination of autoregressive (AR) and moving average (MA) components, in addition to applying differencing to the time series to make it stationary (Yenilmez & Mugenzi, 2023, p. 5). The mathematical formula for the ARIMA model is as follows (Aljandali & Tatahi, 2018, p. 112):

$$y_t = \mu_t + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots + e_t$$

Where $y_t$and y_{t-1}represent the stationary values at time t, while $e_t$and e_{t-1}represent the random error term. $\emptyset_i$ represents the autoregressive (AR) coefficients, θ_i represents the moving average (MA) coefficients, and μ_t is the model constant.

With the availability of specialized statistical software, these models can be easily and accurately characterized and diagnosed.

The Box-Jenkins methodology relies on a series of repetetive procedures to identify the optimal model. It starts with the diagnostic process by examining the stationarity of the data and selecting initial values for the model parameters. The model is then estimated, its suitability is tested, and it is used to forecast future values. If the model is found to be inadequate, the steps for identifying and estimating the model are revisited to ensure forecasting accuracy (Gujarati & Cheree Porter, 2009, p. 841).

I. 5. 3. Artificial Neural Networks (ANNs)

Artificial neural networks (ANNs) are machine learning techniques that mimic the way the human brain performs a specific task. They consist of interconnected nodes known as artificial neurons, which process and transmit data across a network and are organized into three main layers (Abdoon & Habib Al- Sharoot, 2017, p. 3): an input layer, a hidden layer, and an output layer. These networks are trained on a wide range of learning algorithms that rely on adjusting the weights of the connections between neurons. The major advantage of neural networks lies in their ability to model complex nonlinear relationships and produce reasonable outputs from data they have never handled before (Rodríguez, Genn, Font´an, & Galarza, 2021, p. 3), without assuming a prior nature of the relationship between variables (Buhamra, Smaoui, & Gabr, 2003, p. 808).

Artificial neural networks can be classified into two main types: Multilayer Perceptrons (MLPs) and recurrent neural networks (RNNs), which are more suitable for handling sequential and time-series data.

- **Multilayer Perceptron (MLP)**

The multilayer perceptron (MLP) is a type of feedforward neural network where the layers process information through neurons using nonlinear activation functions, while the output layer provides the network's predictions. During training, the MLP model uses supervised learning with a backpropagation algorithm to adjust the weights of connections between neurons and improve predictions. Unlike linear perceptrons, the MLP model has multiple layers and nonlinear activation functions, enabling it to detect complex patterns in data that cannot be linearly separated (Yenilmez & Mugenzi, 2023, p. 3).

- **Long Short-Term Memory (LSTM)**

Recurrent neural networks (RNNs) are a model that contains feedback connections between neurons. However, they sometimes suffer from instability problems during training, requiring complex learning algorithms and increasing training time (Muncharaz, 2020, p. 140). In this context Long Short-Term Memory (LSTM) networks were specifically designed to overcome these issues and to model and predict time series data and sequential patterns that include clear temporal relationships (Alharbi, 2025, p. 17)

LSTM networks are characterized by having memory cells that enable them to capture and retain long-term dependencies (Alharbi, 2025, p. 17). This allows the network to remember important information even if it is temporally distant within the time series (Mahin, Saman, Alireza, Gheisari, & kumar, 2024, p. 2). This is achieved through a gate mechanism that includes an input gate, a forget gate, and an output gate, which control the flow of information into and out of the memory cell, facilitating the retention and use of important information over time (Bousqaoui , Slimani, & Achchab, 2021, p. 3324)

These characteristics make LSTM networks particularly well-suited for tasks dealing with sequential data, such as time series prediction, natural language processing (NLP), and other applications where temporal relationships are central (Alharbi, 2025, p. 18). This architecture also allows LSTM models to learn long-range time dependencies effectively, overcoming the limitations of traditional networks, and can be used for regression problems and the forecasting of complex, multivariable time series (Mahin, Saman, Alireza, Gheisari, & kumar, 2024, p. 2).

In general, neural network models go through several fundamental stages, including data preparation, model design, training, and evaluation. These stages will be explained in detail in the applied part of the study.

II– Methods and Materials:

The research methodology aims to model the series of government consumption expenditures in Algeria for the period 1980–2024 and forecast it up to the year 2034 using the ARIMA model developed according to the Box–Jenkins methodology, in addition to two artificial neural network models (MLP and LSTM). The performance of these models in representing the data and forecasting future values will also be evaluated and compared, with a focus on predictive accuracy and model suitability.

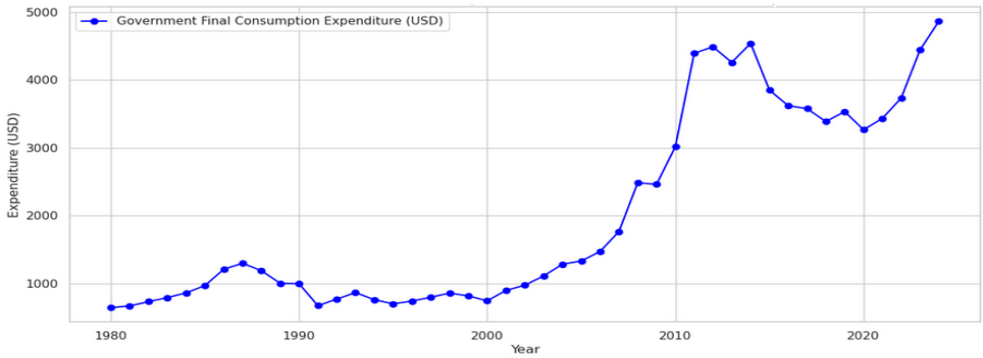
II.1.Data Source:

The data used consist of annual values of government consumption expenditures in Algeria for the period (1980-2024), sourced from the World Bank. Additionally, important official reports and publications issued by the Bank of Algeria were used to analyze the evolution of these expenditures over time.

II.2. Analysis of the Series Under Study

The following graph illustrates the evolution of government consumption expenditures in Algeria over the period 1980–2024. This period was chosen due to the profound economic transformations and recurring financial crises that impacted public spending.

Figure (1): Evolution of final government consumption expenditures in Algeria (1980–2024)



The source: Prepared by the researcher based on the outputs of the Python program.

During the period from 1980 to 1988, government consumption expenditures experienced a slight increase, reaching approximately $12.96 billion in 1987. This was due to Algeria's reliance at the time on development plans that affected several sectors, particularly health, education, and administrative services. However, this increase did not last long due to the financial crisis that followed the collapse of oil prices in 1986, which led to a decline in expenditures, reaching approximately $6.72 billion in 1991.

Throughout the period from 1992 to 1999, consumption expenditures exhibited fluctuations without an upward trend, as a result of the adoption of a contractionary fiscal policy aimed at rationalizing public spending and reducing the budget deficit. This occurred against a backdrop of declining oil revenues, on the one hand, and the financial deficits of public institutions, their inability to create new job opportunities, mass layoffs, and other economic factors, on the other (Lagoune, Bakouche, Sahnoune, & Mansour, 2025, p. 1374).

With the beginning of the new millennium, and the significant rise in oil prices, which reached approximately $111.3 per barrel in 2011 (Aldawood & Dandi, 2022), Algeria adopted an expansionary spending policy. This led to considerable increases in government consumption expenditures, which recorded their highest value during this period in 2014 at approximately $45.383 billion, reflecting significant increases in employee wages, along with the expansion of social, educational, and health services.

However, with the sharp decline in oil prices starting in mid-2014, and a further decrease in 2018, oil revenues decreased significantly. This negatively impacted consumption expenditures, which declined in 2020 to approximately $32.6501 billion, due to the government's adoption of a policy of rationalizing public spending, during which expenditures fluctuated considerably.

In the most recent period, government consumption expenditures experienced a slight increase compared to 2020, partly attributed to increased spending on health services to combat the COVID-19 pandemic. In 2021, the state allocated more than 12 billion Algerian dinars to provide vaccines, masks, sanitizers, gloves, medications, and other medical supplies ((Official Journal of the Algerian Republic, 2021), contributing to a rise in expenditure volume during this phase.

II.3. The Box-Jenkins methodology for determining the optimal ARIMA model

To identify the optimal model among ARIMA models for forecasting consumption expenditures, the Box–Jenkins methodology was followed, which is characterized by its ability to model and forecast linear trends, using the Python software.

- **Identification**

The model identification stage constitutes the first step, where the original time series of government consumption expenditures for the period (1980-2024) is analyzed to extract its characteristics, and descriptive analysis revealed that the economic events experienced by the Algerian economy, particularly fluctuations in oil prices, directly impacted the government consumption expenditures, which in turn affected the stability of the time series, as figure N°1 shows, a fluctuating upward trend throughout the study period, indicating the presence of a general trend component, which suggests that the time series is non-stationary.

To examine stationarity more precisely, the Augmented Dickey–Fuller (ADF) Test, a well-known statistical unit root test , was applied. The results at a 5% significance level indicated that the series was non-stationary at its level, necessitating the application of the differencing process. After applying second-order differencing, the test statistic value reached -8.6366 with a p-value approaching zero, which is lower than the 5% significance level. This indicates that the series of government consumption expenditures does not contain a unit root and has become stationary at the second difference, meaning that consumption expenditures $\sim I(2)$. Accordingly, it became possible to apply the Box–Jenkins methodology and identify the optimal ARIMA model.

Table (1): Augmented Dickey–Fuller (ADF) test results for government consumption expenditures

Test Stage	ADF Statistic	p-value	Significance Level	Stationarity
At Level	-0.143	0.954	5%	Non-Stationary
Differenced (d=1)	-2.611	0.091	5%	Non-Stationary
Differenced (d=2)	-8.6367	5.57e-14	5%	Stationary

The source: Prepared by the researcher based on the outputs of the Python program.

After achieving stationarity, the initial values for the order of the autoregressive component (p) and the order of the moving average component (q) were determined by analyzing the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) and proposing a set of initial models. Using Python, a combination of parameters (p, 2, q) was determined, and candidate ARIMA models for estimating the optimal ARIMA model were identified.

- **Estimation**

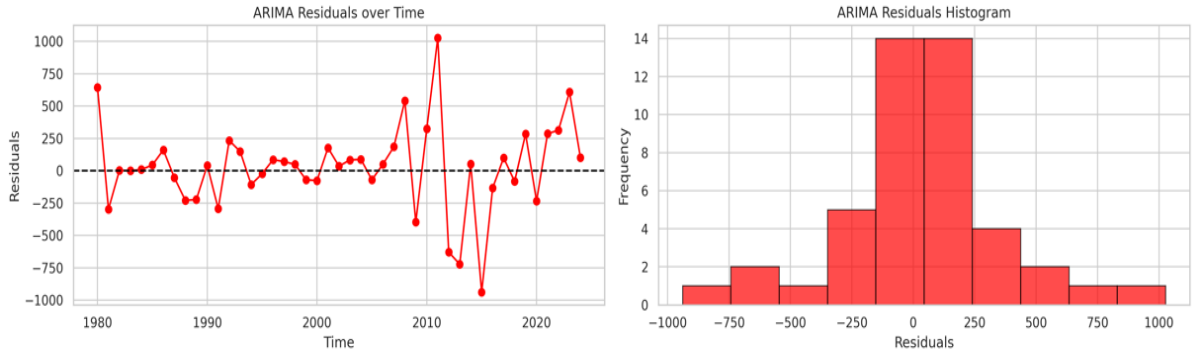
The proposed ARIMA(p,2,q) models were compared to select the most suitable model, based on statistical comparison criteria (AIC, BIC) and the significance of the estimated coefficients. The Python outputs indicated that the ARIMA(0,2,1) model is the most appropriate for representing the time series under study, as it recorded the lowest values for the comparison criteria compared to the other models. The optimal model is expressed as follows:

The dynamics of the time series for government consumption expenditures in Algeria, according to the obtained ARIMA(0,2,1) model, indicate that, due to the absence of an autoregressive component, it does not directly depend on its past values. Instead, it is primarily influenced by past random shocks represented by the first-order moving average component. This reflects the non-stationary nature of the series at its level and its stationarity only at the second difference. Consequently, the optimal model reflects the random nature of economic fluctuations in Algeria more than reliance on long-term autoregressive trends.

- **Diagnostic Checking**

To diagnose the estimated model and verify its efficiency and suitability for the data, a histogram of the residuals was plotted, as shown in figure N°2. The histogram approximately exhibits a bell-shaped form, but the Jarque–Bera test indicates a deviation from the normal distribution, with a p-value of 0.02794. Despite this, the residual behavior remains acceptable for forecasting purposes, and the model can still be considered valid.

Figure (2): Diagnostic Checking of ARIMA Model Residuals



The source: Prepared by the researcher based on the outputs of the Python program.

As for the Ljung–Box test for the ARIMA(0,2,1) model, its results showed that a p-value of 0.89, which indicates the absence of autocorrelation among the residuals, meaning they represent white noise. This confirms the ability of the ARIMA(0,2,1) model to represent the underlying temporal patterns in the data and accurately capture the relationship between past and present values in the time series.

- **Forecasting**

After adopting the ARIMA(0,2,1) model as the most suitable for representing the time series, it was used to forecast future values of government consumption expenditures for the next ten years, covering the period from 2025 to 2034, as shown in table N°2. It should be noted that the forecasted values reported in the table have been converted into billion US dollars for ease of interpretation.

Table (2): Forecasts of government consumption expenditures 2025–2034 (ARIMA Model)

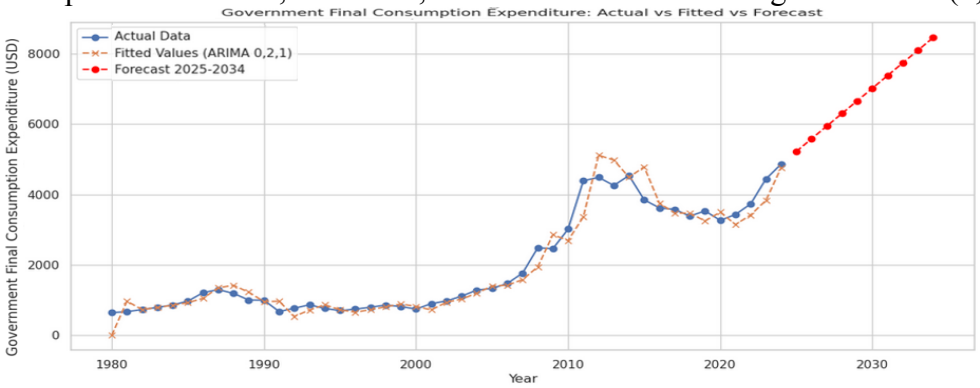
Year	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034
ARIMA	52.226	55.821	59.416	63.012	66.607	70.202	73.798	77.393	80.988	84.583

The source: Prepared by the researcher based on the outputs of the Python program.

The table indicates that the forecasted future values follow a continuous upward trend. It is expected that Algerian government consumption expenditures will range between $52.226 billion and $84.583 billion during the period 2025–2034. The results confirm the ability of the Box-Jenkins methodology to forecast future economic indicators with reasonable accuracy, based on the goodness of fit of the selected model. Furthermore, the diagnostic tests and the analysis of model residuals reveal the absence of autocorrelation, which reflects the adequacy of the model and its predictive capability.

The following figure shows the forecasted values along with a comparison between the actual values and the estimated values according to the ARIMA(0,2,1) model, it can be observed that the in-sample estimated values are relatively close to the actual values, which reflects the adequacy of the model and its ability to represent the behavior of the government expenditure time series.

Figure (3): Comparison of actual, estimated, and forecasted values using the ARIMA(0,2,1) Model



The source: Prepared by the researcher based on the outputs of the Python program.

II.4. Building and Applying Neural Network Models (MLP and LSTM)

Although the government consumption expenditure series is non-stationary and shows a general upward trend with limited short-term fluctuations, it is suitable for testing the ability of neural network models such as MLP and LSTM to capture non-linear relationships and complex temporal dependencies in time series data.

As a general rule, a common methodology is followed in building and training the models, whether the Multilayer Perceptron (MLP) neural network model or the Long Short-Term Memory (LSTM) network model. This methodology consists of the following steps:

- **Data Preparation and Processing**

The time series data representing final government consumption expenditures for the period (1980-2024) were confirmed to be free of missing values and outliers, and then the data were normalized using the Min-Max Scaling method to facilitate training, improve network performance, and prevent gradient-related issues that could affect the algorithm's efficiency.

- **Reformulating the time series data as a supervised learning problem**

The government consumption expenditure data was reframed as a supervised learning regression problem using lagged variables (Brownlee, 2020), which were automatically determined using the Python programming environment by adopting a sliding window approach with a window length of three years, where expenditure values from the previous three time periods are used as inputs to predict the next value in the time series.

- **Data Splitting**

To evaluate the models' ability to generalize, the input data was divided into two sets:

➢ **Training Set:** Comprising 31 consecutive observations of the available data from 1980 to 2010, representing 70% of the observations.

➢ **Test Set:** Consisting of 14 consecutive observations of the data from 2011 to 2024, representing 30% of the remaining observations that the model had not seen during training.

- **Building the Neural Network Models**

Both the MLP (Multi-Layer Perceptron) and LSTM (Long Short-Term Memory) artificial neural network models were built as follows:

➢ **Building the Multi-Layer Perceptron (MLP) Model**

The Multi-Layer Perceptron (MLP) model consists of a multi-layer neural network with two hidden layers. The number of neurons in each layer was determined experimentally to control the network's ability to capture complex, non-linear relationships within the time series and achieve optimal performance. Based on the characteristics of the final expenditure series data for the period 1980–2024, 64 neurons were used in the first hidden layer and 32 neurons in the second. This configuration ensures that the model can learn general non-linear relationships without overfitting.

Each neuron in the hidden layers is equipped with an activation function. The Rectified Linear Unit (ReLU), a non-linear function, was employed. It contributes to accelerating the learning process and improving training stability by mitigating gradient vanishing problems.

The model also includes an output layer consisting of a single neuron without an activation function, which predicts the continuous value for the next year in the consumption expenditure series each time. Subsequently, forecasts for the next ten years are generated.

The training settings were as follows: the number of epochs to 500, a batch size of 4, and the Mean Squared Error (MSE) as the loss function, and the Adam optimization algorithm was used to predict future values of the time series based on previous values.

➢ **Building the Long Short-Term Memory (LSTM) Model**

The Long Short-Term Memory (LSTM) model is based on a recurrent neural network, consisting of one hidden layer of type LSTM followed by a Dense layer meaning a sequential hidden layer rather than multiple LSTM layers. Based on the characteristics of the government expenditure series data, the number of neurons was determined to achieve the best performance, resulting in 64 neurons for the first layer and 32 neurons for the second layer.

Each node in these layers is supplied with an activation function, where ReLU was used. The model also includes an output layer consisting of a single neuron without an activation function, with forecasts generated for the next ten years.

Training settings for the LSTM model were the same as those used for the MLP model.

- **Future Forecasting**

A recursive forecasting mechanism was used to generate future values for the next ten years (2025–2034) for both models (MLP and LSTM), using the last three actual values as input to predict the next year, with each predicted value fed back as input for the subsequent step in a sequential manner.

The following table shows the predicted future values for Algerian final government consumption expenditures during the period 2025–2034 using the obtained MLP and LSTM model

Table (3): Forecasts of government consumption expenditures 2025–2034 (MLP and LSTM Models)

Year	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034
MLP	48.757	46.900	44.442	**43.100**	43.624	46.096	49.910	54.162	57.933	**60.686**
LSTM	46.819	43.887	41.157	**40.732**	42.294	45.268	48.415	50.944	52.456	**53.145**

The source: Prepared by the researcher based on the outputs of the Python program.

The table shows that, according to the MLP model, expenditures are expected to range between a minimum of $43.101 billion and a maximum of $60.686 billion, while for the LSTM model, they are expected to range between $40.732 billion and $53.145 billion. The results indicate a fluctuating upward trend in government consumption expenditures during the future period, which can be explained by the state's continued financing of public goods, services, and essential sectors.

These results reflect the ability of the models to provide accurate quantitative indicators for the final government consumption expenditure (GFCE) time series, which helps decision-makers anticipate future trends in public spending and plan budget more effectively.

III- Results and discussion :

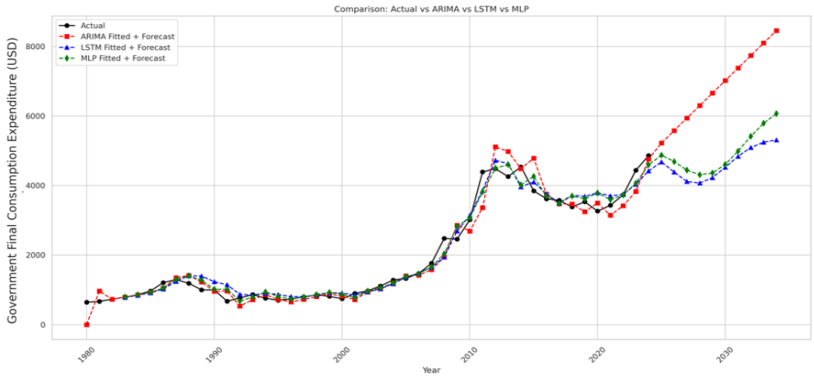
After applying the Box–Jenkins methodology to determine the most appropriate ARIMA model, and building and implementing the two neural network models (MLP and LSTM), the previously obtained results are discussed through evaluating the efficiency of these models in

representing the actual data of the government consumption expenditure series in Algeria, with the aim of identifying the model most capable of capturing the trends and fluctuations in the data.

III.1. Comparison of actual and forecasted values for ARIMA, MLP, and LSTM models

Figure N°4 presents a comparison between the actual, fitted, and forecasted values for the ARIMA(0,2,1) model and the neural network models MLP and LSTM, for government consumption expenditure data from 1980 to 2034. The results indicate that although all models are capable of tracking the actual data reasonably well, the forecasts of the MLP and LSTM neural network models are more in line with the actual data series, as they were able to capture the overall trend more effectively. This reflects a relative superiority in predictive performance compared to the ARIMA model, which will be confirmed later through prediction accuracy metrics.

Figure (4): Comparison of actual, fitted, and forecasted values for ARIMA, MLP, and LSTM models (1980–2034)



The source: Prepared by the researcher based on the outputs of the Python program.

III.2. Performance evaluation using error metrics

To evaluate the performance and forecasting accuracy of the models used (ARIMA, MLP, LSTM) for the study series, several error metrics, commonly referenced in the empirical literature for examining the accuracy of newly developed models , were employed. These included the Mean Absolute Percentage Error (MAPE), the Root Mean Squared Error (RMSE), and the Mean Absolute Error (MAE), in addition to the coefficient of determination (R^2) .These metrics allow for the evaluation of each model's forecasting ability and the accurate analysis of deviations, and they are also used to determine the best model among the proposed models for forecasting the final government consumption expenditure series in Algeria. The evaluation results are presented in the following table:

Table (4): Performance evaluation of ARIMA, MLP, and LSTM Models

Model	MAE	MSE	RMSE	R2
ARIMA	229,5380238	112672,5265	335,6672854	0,94415048
MLP	**162,5404283**	**53550,67728**	**231,4101927**	**0,973585777**
LSTM	192,1570156	65789,0858	256,4938319	0,967549102

The source: Prepared by the researcher based on the outputs of the Python program.

The comparison results shown in table N°4 indicate that the ARIMA model, developed following the Box-Jenkins methodology, achieved a relatively good performance, achieving a coefficient of determination (R^2) of 94.415%, indicating its acceptable ability to capture the general trend of the government consumption expenditure series. However, we find that the values for RMSE, MSE, and MAE are relatively high, indicating its difficulty and limitations in handling non-linear relationships and economic fluctuations, a common characteristic of economic data such as that under study.

In contrast, the MLP and LSTM neural network models achieved good performance, as evidenced by the lowest values for the aforementioned error metrics (RMSE, MSE, and MAE), alongside a strong explanatory power (R^2) of 97.35% for the MLP model and 96.75% for the LSTM model.This indicates their superior ability to capture the fluctuations of the time series under study compared to the ARIMA model.

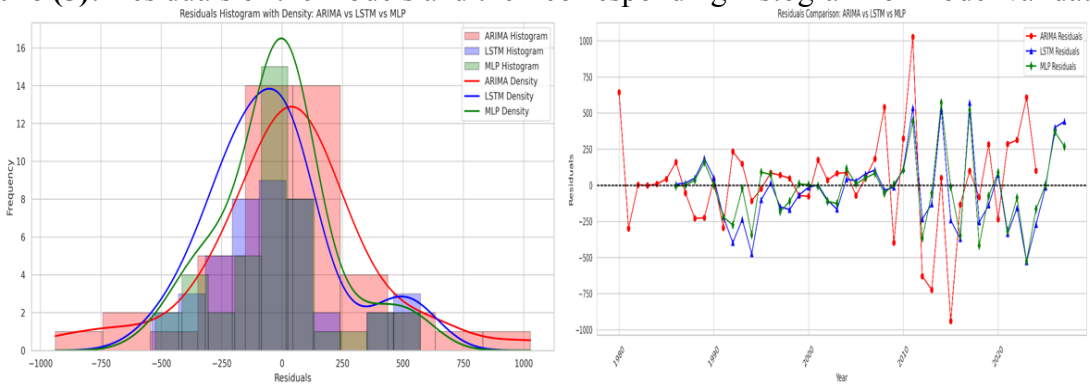
On the other hand, the analysis of forecasting accuracy metrics reveals that the MLP model outperformed the LSTM and ARIMA models in terms of prediction accuracy. It achieved the best performance with the lowest error metric values and a higher coefficient of determination, making the MLP model highly suitable for forecasting the government consumption expenditure series.

Therefore, these results highlight the importance of utilizing artificial neural network models, as they provide decision-makers with better opportunities for economic planning and the formulation of more effective fiscal and development policies, particularly in the face of oil price fluctuations and the structural challenges of the Algerian economy. This conclusion is consistent with findings reported in the literature, which regard artificial neural networks as a promising alternative to traditional time-series forecasting methods.

III.3. Residual Analysis and Model Forecasting Validity

The following figure N°5 shows the residuals of all models over time along with their corresponding histogram, for the purpose of analyzing the residuals and assessing their distribution to evaluate model validity.

Figure (5): Residuals of the models and their corresponding histogram for model validation



The source: Prepared by the researcher based on the outputs of the Python program.

The figures show that the residuals for all models are distributed approximately around zero and do not follow any specific or clear pattern, indicating that they almost follow a normal distribution, which is an indicator of models' validity for forecasting.

Table N°5 supports this conclusion with the results of statistical tests for the residuals for each model using the Jarque-Bera test and Skewness, and Kurtosis measurements.

Table (5): Statistical tests of residuals for all models

Model	JB_Stat	JB_p	Skew	Kurtosis	Interpretation
ARIMA	7,154953	0,027946	-0,070792	1,948314	**Non-normal**
MLP	1,579748	0,453901	0,375150	0,582891	**Normal**
LSTM	3,052978	0,217297	0,634729	0,364735	**Normal**

The source: Prepared by the researcher based on the outputs of the Python program.

The results indicate that the MLP model provides the best representation of the residuals distribution, with moderate JB values, skewness, and kurtosis coefficients, reflecting higher accuracy in representing the time series compared to other models. While the other models showed some minor deviations, their residual distributions are still acceptable for forecasting.

Based on this analysis, it can be concluded that all models are valid for forecasting government consumption expenditure, but the MLP model provides the best representation of residuals and demonstrates a strong ability to capture the temporal relationships in the series.

IV-Conclusion:

This research paper aimed to compare the performance of the ARIMA model, based on the Box–Jenkins methodology, and artificial neural network models in order to highlight the relative strengths and limitations of traditional and advanced models for forecasting final government consumption expenditures in Algeria up to the 2034 horizon, with the following results obtained:

- The data analysis revealed that government consumption expenditures during the study period (1980-2024) have followed an upward trend with noticeable fluctuations in recent years. This can be attributed to the link between consumption expenditures and the revenues of the hydrocarbon sector, and the impact of global oil crises on the national economy. In response, the government has recently sought to control and manage the overall scale of spending by adopting fiscal policies that are a mix of austerity and expansion, and by rationalizing expenditures. It is essential for decision-makers to have a clear vision of the future economic situation, as statistical models help in analyzing and forecasting key economic indicators;

- The results showed the suitability of the ARIMA(0,2,1) model prepared according to the Box-Jenkins methodology for simple time series, but through the analysis of the comparison results, it became clear that, unlike the proposed neural network models (MLP and LSTM), the highest error rates were recorded, and thus the ARIMA model showed its limitations in predicting public consumption expenditures in Algeria up to the horizons of 2034, due to the difficulty of adapting it to the complex dynamics of the data under study. Therefore, the first hypothesis is not realized;

- The results showed the effectiveness of both the Multi-Layer Perceptron (MLP) and the Long Short-Term Memory (LSTM) models, as it was observed that the predicted values take an upward, fluctuating trend that aligns with the actual values of Algeria's government consumption expenditure series through to 2034, in comparison with traditional models such as ARIMA, and therefore the second and third hypotheses are confirmed;

- The results of this study confirm the efficacy of artificial neural networks as an advanced method for forecasting economic indicators, given their ability to analyze complex time series data and anticipate future trends in government spending more accurately, and thus the possibility of adjusting policies in line with the expected path of government spending. Therefore, we conclude that deep learning, including artificial neural networks, is a promising alternative to traditional time series-based forecasting methods, and therefore the fourth hypothesis is confirmed;

- The study results indicate the superiority of the MLP model, which achieved better performance compared to the LSTM model in terms of performance metrics, as its predictions closely matched the actual data due to its ability to accurately capture complex historical trends and patterns. In contrast, the LSTM model showed limitations in capturing the full complexity of the time series making the MLP model the most suitable and best model for forecasting public consumption expenditures in Algeria, as the predicted future values follow a fluctuating upward trend. According to the MLP model, expenditures are expected to range between a minimum of $43.101 billion and a maximum of $60.686 billion. This positive forecast for government spending reflects the Algerian government's continued provision of public services and support for essential sectors such as education, health, and security.

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

- Enhance reliance on standard statistical studies to understand and analyze time series related to the Algerian macroeconomy, in order to clarify the dynamics of economic indicators;
- Encourage researchers to develop and use modern forecasting models based on machine learning techniques, designed with the specificities of the Algerian economy;
- Encourage researchers to use hybrid models, allowing them to get the best of both traditional statistical models and artificial neural network models, and apply them to improve time series forecasting in various cases;
- It is necessary to utilize the accurate quantitative indicators generated by forecasting models for economic planning and the development of effective fiscal and development policies, particularly in the face of oil price fluctuations and the structural challenges of the national economy;
- Open the field for further applied studies on improving forecasting models in Algeria, which will contribute to enhancing predictive capabilities and formulating appropriate economic policies.

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