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

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Dedication:

To the light that illuminated my path, and to the heart that surrounded me with love and prayers,

I dedicate to you the fruit of my effort and the labor of my days, asking Allah to prolong your life, bless your health, and grant you ever-increasing light.

And to my dear father,

To my first role model and source of inspiration,

To you, whose footsteps I proudly followed, and whose wisdom guided my journey,

I offer this work with immense pride and gratitude, praying that Allah preserves you for me and keeps you a crown upon my head for all my life.

And to my dear siblings,

Chayma, Oumelkhire and Fatima

The companions of success and pillars of support,

I extend to you my sincerest expressions of love and appreciation, for with your encouragement and support my steps were steadier and my dreams closer.

BEKHTI Sara

Dedication:

To the angel who watches over me, the embodiment of love and compassion, the

Radiant smile that lights up my life, and the heart behind my every success

My beloved mother.

To my father, whose memory I cherish, I offer my heartfelt prayers for his eternal peace

To my siblings, my constant companions on this journey, my deepest gratitude.

To my esteemed teachers, who have ignited the

Flame of knowledge within me. To all those who have believed in

Me and supported my endeavors

To my friends, old and new, who have enriched my life.

I dedicate this humble work, a testament to your unwavering support.

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We pray to Allah that this work is sincerely dedicated to His sake and that it may serve the advancement of knowledge and benefit its seekers.

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Abstract:

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 (GDP), Economic growth, Box-Jenkins Methodology, Forecasting, Artificial Neural Networks.

الملخص:

تهدف هذه الدراسة إلى تحليل التطورات الاقتصادية في الناتج المحلي الإجمالي للجزائر خلال الفترة الممتدة من 1960 إلى 2023، والتنبؤ بمساره لغاية سنة 2028؛ ولتحقيق هذا الهدف، تم تطبيق منهجين مختلفين: منهجية بوكس-جينكنز التقليدية لتحليل السلاسل الزمنية، ومنهجية الشبكات العصبية الاصطناعية (ANNs) المعتمدة على تقنيات الذكاء الاصطناعي، وذلك بهدف مقارنة أدائهما في توقع الناتج المحلي الإجمالي.

وقد أظهرت نتائج الدراسة تفوق نموذج بوكس-جينكنز في تقديم توقعات أكثر دقة وجودة مقارنةً بالشبكات العصبية، كما بيّنت ذلك مؤشرات تقييم دقة التنبؤ والمتوسط المرجح المعتمد في المقارنة بين النموذجين.

الكلمات المفتاحية: ناتج محلي اجمالي، نمو اقتصادي، منهجية بوكس-جينكنز، تنبؤ، شبكات عصبية اصطناعية.

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List of Abbreviations:

Abbreviation	Full Term
GDP	Gross Domestic Product
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
PACF	Partial Autocorrelation Function
ACF	Autocorrelation Function
AR	Auto regressive
MA	Moving Average
ARMA	Autoregressive Moving Average
ME	Mean Error
MSE	Mean Squared Error
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ADF	Augmented Dickey-Fuller
WA	Weighted Average
AIC	Akaike Information Criterion
HQIC	Hannan–Quinn Information Criterion
BIC	Bayesian Information Criterion
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
NLP	Natural Language Processing
MLP	Multi-layer Perceptron
RBF	Radial Basis Function

INTRODUCTION

Preface:

In light of growing economic challenges and the accelerating pace of global changes—and in the era of big data and artificial intelligence—forecasting Gross Domestic Product (GDP) has become a complex task that requires the use of advanced techniques. Accurate forecasting of GDP trends is of critical importance to policymakers and investors, as this indicator represents a fundamental pillar reflecting the health and growth of the national economy.

Accurate GDP forecasting enables governments to make sound fiscal and monetary decisions, allows businesses to direct their investments strategically, and helps citizens understand future economic trends. In this context, two key methodologies have emerged in the field of time series forecasting: the Box-Jenkins methodology, which represents a traditional tool that relies on historical data patterns, and Artificial Neural Networks (ANNs), which reflect a modern trend based on machine learning techniques.

The Box-Jenkins methodology is known for its systematic ability to analyze economic time series and produce accurate forecasts. On the other hand, Artificial Neural Networks are characterized by their flexibility and capacity to uncover complex relationships among variables, making them a powerful tool for forecasting in dynamic and changing economic environments.

Accordingly, based on the above, the research problematic can be formulated in the following question:

To what extent are Box-Jenkins models effective in comparison to Artificial Neural Networks (ANNs) in forecasting the Gross Domestic Product (GDP) in Algeria?

Based on the previously stated research problematic and in order to gain a deeper understanding of the various aspects of the topic, we have chosen to break down

The main problem into a number of sub-questions that this study seeks to answer, as follows:

- How has Algeria's Gross Domestic Product (GDP) evolved during the period 1960–2023?
- To what extent is the Box-Jenkins methodology capable of formulating an appropriate and efficient forecasting model?
- Is there an advantage to applying the Box-Jenkins model over the Artificial Neural Networks (ANNs) model in forecasting Gross Domestic Product (GDP)?

Research Hypotheses:

- 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 achieving high forecasting accuracy.
- The Box-Jenkins model outperforms the Artificial Neural Networks (ANN) model in forecasting Gross Domestic Product (GDP).

Reasons for Choosing the Topic:

Personal Justifications:

- A strong enthusiasm for statistical analysis and forecasting.
- A deep interest in exploring the potential of artificial intelligence.

Objective Justifications:

- The need to provide solutions to evolving economic challenges through advanced forecasting techniques.
- Highlighting the importance of Gross Domestic Product (GDP) as a key economic indicator.

Study Objectives:

- To highlight both the Box-Jenkins methodology and Artificial Neural Networks (ANNs) as effective approaches in the field of forecasting.
- To compare the results of applying the Box-Jenkins methodology and Artificial Neural Networks to the time series of Algeria’s Gross Domestic Product (GDP).
- To contribute to expanding the understanding of Algeria’s Gross Domestic Product.

Significance of the Study:

- Gross Domestic Product (GDP) is considered one of the most important macroeconomic indicators that reflect a country’s level of economic performance. Therefore, forecasting its future trajectory serves as a strategic tool for making effective decisions in the field of economic policy. The importance of such forecasts increases amid the rapidly changing global economic environment, highlighting the need for accurate quantitative tools that support economic agents in better planning for the future.

- The significance of this study lies in its comparison between two different approaches to economic forecasting: the traditional Box-Jenkins methodology and Artificial Neural Networks (ANNs), which are based on artificial intelligence. The added value of this comparison is to identify the most accurate and effective method for handling economic time series in the Algerian context, thereby providing a more efficient quantitative tool for sound economic decision-making.

- Moreover, the study derives additional significance from its reliance on real data for Algeria's Gross Domestic Product during the period 1960–2023, which lends it scientific credibility and enhances the applicability of its results for policymakers in Algeria.

Scope of the Study:

- Geographical Scope: The study will be conducted in Algeria, using data related to the Gross Domestic Product (GDP).
- Temporal Scope: The period covered by the study is limited to the years from 1960 to 2023. And forecasting for the period 2024–2028

Research Methodology:

To address the stated research problem and achieve the objectives of the study, we adopted both the descriptive-analytical approach to examine the aspect related to Gross Domestic Product (GDP) in Algeria, and the statistical approach. This was carried out using a set of statistical and econometric software programs, including Excel, EViews 12, Gretl 2024d, and MATLAB R2015a.

Research Difficulties:

- **Complexity of Mathematical and Statistical Models:** Handling the Box-Jenkins methodology and neural network modeling required a deep understanding of statistical theories and programming techniques, which compelled us to intensify our research efforts and engage in extensive self-learning.
- **Programming Challenges:** Developing the models using software such as MATLAB demanded significant time to master the tools and fine-tune the parameters to achieve accurate predictions.
- **Time Constraints and Academic Workload:** Balancing the demands of other academic requirements with the work on this extensive dissertation was one of the major organizational challenges we faced.

Structure of the Study:

We divided the study into two chapters. **The first chapter**, titled "A Conceptual and Econometric Analysis of Gross Domestic Product (GDP)," presents a comprehensive theoretical framework for understanding the concept of GDP. It addresses definitions, calculation methods, types of prices used, its importance, influencing factors, and its relationship with economic growth. In addition, it includes a brief review of previous studies. **The second chapter** is titled "Forecasting Algeria's Gross Domestic Product: A Comparative Applied Study Using the Box-Jenkins Methodology and Artificial Neural Networks." It covers both the theoretical and practical aspects of the two methodologies, applying them to Algeria's GDP data over the study period. This chapter also includes an analysis and comparison of the results to assess performance and forecasting accuracy.

CHAPTER ONE:

A CONCEPTUAL AND QUANTITATIVE ANALYSIS OF GROSS DOMESTIC PRODUCT

Preface:

Gross Domestic Product (GDP) is considered one of the most prominent economic indicators for measuring economic activity, as it reflects the total value of the final output of goods and services produced by a country's economy over a specific period.

Accordingly, through this chapter, we will address the following topics:

1. **The Conceptual and Methodological Framework of Gross Domestic Product (GDP)**
2. **The Theoretical Analysis of GDP and Its Relationship with Economic Growth**
3. **Review of Previous Studies**

1. The Conceptual and Methodological Framework of Gross Domestic Product:

Given the significant importance of Gross Domestic Product (GDP) in economic life, there has been a need to establish a conceptual and methodological framework for understanding this indicator. Accordingly, this section aims to provide a comprehensive overview of the definition of GDP, its calculation methods, its importance, the factors determining it, and its relationship with economic growth.

1.1 Definition of Gross Domestic Product:

Gross Domestic Product (GDP) has many diverse and multiple definitions, as these vary in their formulation but ultimately convey the same meaning. These definitions are used to highlight the importance and role of GDP in economic performance and in assessing the economic growth of different countries. Among these definitions are the following:

- Gross domestic product includes the monetary value of all goods and services produced within the geographical boundaries of a given country in a given time frame. [1]
- GDP 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.[2]
- Gross domestic product (GDP) is the most common measure for the size of an economy, and it measures the value of total final output of goods and services produced by that economy in a certain period. The aim is to quantify[3]

[1] - Prabhu, T. L. (2021). Gross domestic product: Vital concepts about GDP unveiling economic power: Understanding gross domestic product (GDP). Nestfame Creations Pvt. Ltd. p 6

[2]- Leamer, E. E. (2009). Macroeconomic patterns and stories: A guide for MBAs. Springer-Verlag. p19

[3] - Eurostat. (n.d.). Beginners: GDP – What is gross domestic product (GDP)? Statistics Explained. Retrieved July 15, 2024

- The additional value coming from goods and services newly produced, the so-called value added, not taking into consideration the value of goods and services used to produce them (intermediate consumption). This indicator can be compiled for a country, a region, or for groups of countries.[3]
- Gross domestic product (GDP) is the value of the goods and services produced by the nation's economy less the value of the goods and services used up in production. GDP is also equal to the sum of personal consumption expenditures, gross private domestic investment, net exports of goods and services, and government consumption expenditures and gross investment.[4]

❖ Based on the previous definitions, we can derive a comprehensive definition of Gross Domestic Product (GDP) as the monetary value of all goods and services produced within the geographical boundaries of a country over a specified time frame. This definition highlights its role and importance in economic performance, as well as in evaluating economic growth and measuring the value added from goods and services.

1.2 Understanding the Key Terms in Gross Domestic Product:

To understand the meaning of GDP, we need to highlight its essential components, which are "Gross," "Domestic," and "Product." Each of these terms carries a specific significance within the concept of GDP.

What does the term "GROSS" mean?

The term "gross" (as in "Gross Domestic Product") denotes that goods are counted regardless of how they are used. A product can be consumed, invested in, or used to replace an asset. In every case, the final "Sales receipt" for the product will be added to the total GDP figure. [5]

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[4]- Dynan, K., & Sheiner, L. (2018). GDP as a measure of economic well-being (Hutchins Center Working Paper No. 43). The Brookings Institution. p 4

[5] - Prabhu, T. L. Previous reference. p 1

"Net" on the other hand does not take into account products used to replace an asset (in order to offset depreciation). The term"net" only refers to products that are intended for consumption or investment.

What does "Domestic" stand for?

The term "domestic" (as in "Gross Domestic Product") denotes a geographical inclusion criterion: goods and services counted are those product within the country's borders, regardless of the producer's nationality. the output of a German-owned factory in the united states, or example will be counted as part of the country's GDP.[5]

What does the term "Product" mean?

The term "product" (as in "Gross Domestic Product") refers to the final goods and services that are sold on the market. [5]

1.3 Approaches to Viewing Gross Domestic Product:

GDP may be seen from three roughly equivalent points of view:[6]

- **Expenditure-based:** the value of domestic final expenditure on goods and services. This includes purchases of consumer goods and services by households, gross private investment in structures, equipment and software, residential investment and change in inventories, and government consumption and investment, plus the value of exports, less the value of imports during a certain period of time (usually a year).
- **Income-based:** all payments made in production, such as wages and other labor costs, interest, rental costs, depreciation, profit, and taxes paid by companies, less subsidies during a certain period of time, usually a year.

Output-based: Gross Domestic Product (GDP) can be defined as the sum of the value added by all production units within a specific geographic boundary

[6] - Argandoña, A. (2016). Gross domestic product (GDP) and gross national product (GNP) (Working Paper No. WP-1153-E). IESE Business School. p 2. (With modifications)

- Over a certain period, which includes the monetary value of final goods and services produced, as well as net taxes on products.

1.4 Methods of Calculating Gross Domestic Product:

Gross Domestic Product is calculated in various ways, each method providing a different perspective on GDP, but ultimately yielding the same result. Among these methods, we have the production method, the income method, and the expenditure method, which we will explain each of these methods in detail below:

1. Output Approach: [7]

- **Value Added Approach :**

In this approach, GDP is calculated by the General Authority for Statistics through calculating increases added by each sector during the production process. Then, such additions in all economy sectors are summed to come up with the GDP. The added value is the difference between total production and cost of intermediate products during each stage of production.

Added value = gross production values - intermediate consumption + net taxes (taxes - subsidies)

- **Finished Goods Value Approach :**

In this approach, the GDP is calculated by multiplying the quantity produced of each finished goods or services during a year by its price, and then summing the processes to come up with the GDP.

[7] - Al-Bakr, A. B., & Al-Salman, M. A. (2016). The concept of gross domestic product: A descriptive study (Working Paper No. WP/16/3). Saudi Arabian Monetary Authority, Economic Research Department. Pp 10–13. (With modifications).

2. **Income Approach:**

In this approach, GDP is calculated through the income received by the factor of production. Then, using this approach, we get the income earned by the factors of production.[8]

GDP according to Income Approach = Employees Compensations (wages and salaries of the labor factor) + Total operating surplus (operating surplus + depreciation of fixed capital + net taxes (indirect taxes production subsidies))

3. **Expenditure Approach:** [8]

In this approach, GDP is calculated by calculating the total final expenditure at buyers' prices earned by the production factor in exchange of its contribution to the GDP. The number of factors of production that has contributed to the production process is almost hundreds of thousands in a single economy. In simple words, we determine expenditure parts in accordance with the spending of each productive sector, where each certain type of these sectors makes certain spending, the total of which constitutes the GDP.

GDP Using Expenditure Approach = Private final consumption expenditure + investment expenditure (gross fixed capital formation + changes in inventory) + Government final consumption expenditure + net external expenditure (exports-imports)

Note:

The Output Method, Income Method, and Expenditure Method ultimately provide the same result despite the differences in their variables and components. This is because each of these methods relies on the same underlying economic values and activities, which leads to consistency in the results when calculating GDP.

[8] - Al-Bakr, A. B., & Al-Salman, M. A. Previous reference. p14

1.5 Prices Used in Calculating Gross Domestic Product:

Gross Domestic Product (GDP) can be calculated based on prices using two methods: the current prices method and the constant prices method, as follows:[9]

- **Nominal GDP (GDP at Current Prices):**

The nominal or monetary value of goods and services (GDP) is calculated at current market prices during a specific period. This is the result of multiplying the total quantity of goods and services produced within the domestic economy by their respective prices, or what is known as current prices. Nominal GDP, therefore, takes into account the continuous price changes that occur due to market fluctuations. As a result, nominal GDP does not reflect the real change in output because, simply put, when prices rise (inflation occurs), GDP increases due to higher prices, not because of an increase in the actual quantity of goods and services produced domestically.

- **Real GDP (GDP at Constant Prices):**

Real GDP refers to the total amount of goods and services purchased by society that are produced domestically during a specific period based on a reference price calculated according to a benchmark year, which is used as a basis for other years. Prices are fixed based on an agreed-upon base year to calculate the real GDP of a country, known as the "base year." Therefore, real GDP is considered a good indicator for measuring the economic growth rate because it reflects the actual quantity produced in a country without the influence of price fluctuations, thus eliminating any distortion caused by price changes.

[9] - Mejdi, N. (2021). Basic economic concepts: Gross domestic product (GDP). Arab Monetary Fund, Series of Educational Booklets, (19). Pp 13–15

2. The Theoretical Analysis of GDP and Its Relationship with Economic Growth:

Gross Domestic Product (GDP) plays a fundamental role in economic life. Through this study, we aim to examine the significance of GDP, the key determinants influencing its size, its relationship with economic growth, and the inherent limitations of GDP as an economic indicator

2. 1 The importance of Gross Domestic Product:

The Gross Domestic Product (GDP) is considered a miniature representation of the entire economy, as it reflects the level of economic growth and a country's ability to provide goods and services. From this perspective, we can see the importance of this indicator in understanding economic performance as follows: [10]

- GDP summarizes economic activities carried out by a community during a certain period (often a year.)
- GDP summarizes returns earned by production factors as a result of their contribution to domestic production.
- GDP is considered an important economic indicator that can be used for economic analyses, making development plans and policies and identifying economy's current trends.

- The expenditure approach for calculating GDP helps in identifying consumption trends for key and targeted sectors.
- GDP time series are used to prepare important economic forecasts for decision makers.
- GDP per capita indicator can be used as an approximate measure of the living standard.
- GDP is used as an indicator to compare countries to measure the economic performance of a country.

[10] - Al-Bakr, A. B., & Al-Salman, M. A. Previous reference. P7

❖ From the above, we conclude that: The Gross Domestic Product (GDP) is a key measure of economic health and citizen welfare, as it reflects the overall economic activity of a country and helps in evaluating its economic performance.

2. 1 .1 The importance of Gross Domestic Product in macroeconomics:

The primary importance of Gross Domestic Product (GDP) in macroeconomics lies in its role as a key indicator for determining various economic realities, including:[11]

- Monitoring economic fluctuations (cyclical and non-cyclical) over the short, medium, and long term.
- Assessing the state of the studied economy and comparing it with other economies in terms of progress or backwardness in growth efficiency.

❖ Based on this, the following can be concluded that :
GDP is a key element in macroeconomics, playing a significant role in evaluating economic performance and determining whether the economy is in a state of recession or growth. It also helps in studying production patterns and income efficiency, which in turn influences financial and monetary decisions. Moreover, GDP aids in developing economic policies and identifying whether a specific sector needs support or funding. Ultimately, GDP plays an important role in achieving economic sustainability and comprehensive growth.

[11] - Mohammed, M. A. A. (2023). Using Box–Jenkins methodology to forecasting GDP in Sudan 2010–2030. Journal of Economic Studies, University of Khartoum, 13(1). p126

2. 2 Factors Determining the Size of Gross Domestic Product:

The Gross Domestic Product (GDP) is influenced by a variety of economic, social, and political factors that interact with each other in a complex way, impacting the level of production and economic growth in any country As outlined below:[12]

- **Natural conditions:** that are beyond human control or prediction, such as natural disasters and climate change, can have a significant impact on the quantity and quality of goods and services produced.
- **Political stability:** is crucial for a country's economic growth. Political instability can lead to a decrease in production and investment, as well as damage to infrastructure.
- **The quantity and quality of economic resources:** available to a country play a significant role in determining the level of output. A shortage of resources can limit production and economic growth.
- **Technological advancement:** and government policies that promote innovation and investment can increase productivity and economic growth.

❖ Therefore, we conclude, the Gross Domestic Product (GDP) is the result of a complex interaction between a variety of economic, social, and political factors, with each factor directly or indirectly affecting the level of production and economic growth.

2. 3 Gross Domestic Product and economic growth:

Economic growth, usually measured by the change in Gross Domestic Product (GDP), is a vital indicator of the economy's health and the population's well-being. It reflects the economy's ability to generate wealth and provide job opportunities

[12]- Al-Bakr, A. B., & Al-Salman, M. A. Previous reference. p 29

2.3.1 Definition of economic growth:

The concept of economic growth is a quantitative one, representing an increase in production over the long term. Economic growth is defined as "the long-term increase in a country's output." We can also refer to the concept of economic expansion, which is a situational increase in output. Thus, we can say that economic growth is a result of an increase in domestic production, while expansion refers to the immediate increase in output. Economic growth takes into account the share of output per individual, that is, the per capita income growth rate. Accordingly, economic growth is manifested in:[13]

- An increase in real national output between two periods.
- An increase in per capita income.

Growth can also be considered a simultaneous condition for economic progress if the growth rate of national output is higher than the population growth rate. On the other hand, it may not be associated with economic progress if the growth rate of national output is equal to the population growth rate. If the population growth rate is higher than the national output growth rate, then growth would be accompanied by economic decline.

Economic growth is considered a necessary condition, but it is not sufficient to raise the material standard of living of individuals. Another factor is the method of distributing the achieved increase among individuals, which is an intertwined subject linked to the nature of the economic and political structures in each country.

In this regard, Simon Kuznets, a Nobel laureate in economics in 1971 and a pioneer in this field pointed out the possibility of presenting various economic industries in a balanced manner to accommodate population growth. These balanced capabilities rely on advanced technology and the required institutional and ideological adaptation.

[13] - Khachib Jalal, (n.d.), Economic Growth, Al-Waka'a Publishing Company, p 4

2.3.2 The relationship between Gross Domestic Product and economic growth:

Gross Domestic Product (GDP) is considered the primary indicator for measuring the size and growth of economic activity. An increase in GDP leads to higher levels of production, investment, and consumption, thereby contributing to effective economic growth. This, in turn, results in improved living standards and the creation of new job opportunities. Conversely, a decline in GDP often indicates economic slowdown or recession, which negatively affects the overall economic performance. Accordingly, there exists a strong, positive, and interconnected relationship between GDP and economic growth.

2. 4 Limitations of Gross Domestic Product:

GDP is a useful economic concept but it is important to be aware of its meaning and its limitations in economic, social and ethical terms.[14]

1. GDP includes the goods and services that are the object of exchange in the market, for which there are set market prices, plus certain other goods, such as the services of owner-occupied housing or the consumption of farm produce by farmers, for which prices are imputed. However, it excludes many goods and services that are not the object of exchange in the market, such as housework, childcare and elder care (when not carried out as paid work) and voluntary work. In other words, its scope is limited.
2. Some countries, such as the United States, do not include illegal activities (drug trafficking, smuggling, prostitution) or undeclared activities (the underground economy). However, in 2008, the United Nations recommended as a “best practice” the inclusion of the value of these illegal activities, and the European Union introduced them in the ESA 2010 standard. This implies an extension of GDP’s content but at the cost of less precision because the figures for illegal activities are based on gross estimates. On the other hand, once it

[14] - Argandoña, A. Previous reference.p3

has been admitted that these activities contribute positively to GDP, there is likely to be increased pressure to consider them as legal or ethically correct.

3. It does not include activities entailing mere transfers of assets between people, such as the sale of a house, the sale of a company's shares, the increase in value of works of art, donations, or thefts, because they do not represent new production of goods and services.
4. GDP does not measure a country's accumulated wealth, but only the value of the goods and services produced in one period.
5. It does not include the value of leisure – though it is assumed that the market wage should reflect this, at least ideally. Nor does it include spiritual, moral or cultural values, unless they are reflected in the production of goods and services.
6. Market prices do not reflect all the opportunity costs of production, nor the harm (or the benefits) caused by economic activity outside the market, such as environmental damage or traffic congestion. Paradoxically, GDP may not reflect the environmental damage caused by production or the insecurity resulting from crime and yet it will reflect the value of the goods and services produced in order to combat those ills. In particular, the productive use of nonrenewable resources increases GDP but their depletion does not lead to its reduction.

❖ GDP is a powerful statistical measure if its limitations are recognized. Failure to take them into account can lead to erroneous recommendations.[15]

[15] - Argandoña, A. Previous reference. p4

3. Review of Previous Studies:

Previous studies hold great importance in scientific research, as they serve as a reference upon which the current study is based. Through previous studies, it is possible to add to, modify, confirm, or refute existing scientific knowledge. In our dissertation, we will focus on previous research related to Gross Domestic Product (GDP), as well as studies that have addressed both the Box-Jenkins methodology and Artificial Neural Networks (ANNs). Accordingly, we will review previous studies written in both English and Arabic, and then conduct a comparison between the current study and the existing literature.

3.1 National Studies :

- Study: **Mesloub, M (2024)**. which was titled: **Forecasting Algerian Gross Domestic Product -GDP-Using The Box-Jenkins Methodology (1962-2023)** This study aimed to forecast the Gross Domestic Product (GDP) in Algeria by relying on annual data covering the period from 1962 to 2023, using the Box-Jenkins methodology. The study ultimately concluded that the ARIMA (1, 1, 1) model is the most appropriate for forecasting Algeria's GDP for the period from 2024 to 2030.
- Study: **Sellami, A (2022)**.entitled: Estimation **and Projection of the Cereal Food Gap and Its Implications for Food Security in Algeria**. This study aimed to assess and analyze the magnitude and impact of the cereal food gap in Algeria during the period from 1970 to 2019, in addition to forecasting the cereal gap for the period from 2020 to 2025. The researcher employed both the Box-Jenkins methodology and Artificial Neural Networks (ANNs) for the forecasting process. The study relied on a combination of descriptive analytical and econometric approaches. The results revealed that an increase in per capita GDP and population size tends to deepen the food gap, whereas an improvement in agricultural yield contributes to its reduction. Moreover, 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.
- Study: **Mouniri, I (2020)**. Entitled: **Forecasting Exchange Rate Fluctuations: An Econometric Study of the Algerian Case Using**

ARIMA and ANN Models during the Period 1960–2018. This study aimed to measure the fluctuations of the Algerian Dinar exchange rate against the US Dollar during the period from 1960 to 2018, by applying both the Box-Jenkins (ARIMA) methodology and the Artificial Neural Networks (ANNs). The research was based on the descriptive-analytical approach in addition to the case study method. The study concluded that Artificial Neural Networks outperformed the Box-Jenkins methodology in modeling the exchange rate of the US Dollar against the Algerian Dinar.

- Study: **Atrous, S (2018)**. entitled :**The Use of Box-Jenkins Methodology and Artificial Neural Networks for Forecasting Electricity Consumption in the SONELGAZ Company – A Case Study of Biskra Province**. This study aimed to forecast electricity consumption by applying both the Box-Jenkins methodology and Artificial Neural Networks (ANNs). The researcher relied on monthly data of low and medium voltage electricity consumption in the province of Biskra during the period from January 2014 to December 2017. Quantitative methods were adopted for the analysis and processing of the data. 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. Accordingly, the Box-Jenkins methodology was deemed the most suitable tool for future forecasting of electricity consumption at SONELGAZ.

3.1.1 Comparison between National Studies and the Current Study:

Our current study stands out from previous National studies in its direct focus on comparing the performance of ARIMA and ANN models in forecasting Algeria's Gross Domestic Product (GDP). In contrast, studies such as **Sellami (2022)** focused on food security, **Mouniri (2020)** on exchange rate fluctuations, and **Atrous (2018)** on electricity consumption, while **Mesloub (2024)** relied solely on the ARIMA model without conducting any comparative analysis with alternative models. Furthermore, our study differs in its findings, as it challenges the prevailing trend in previous research which favored intelligent models; both **Sellami** and **Mouniri** concluded that artificial neural networks outperformed ARIMA, whereas our study demonstrated the superiority of the ARIMA model in the context of GDP forecasting.

3.2 <u>international Studies:</u>

- Study: **Chaudhary, S., & Uprety, D (2023).** which was titled: **Hybrids ARIMA-ANN Models for Accurate GDP Forecasting in Nepal** This study aimed to enhance the accuracy of Gross Domestic Product (GDP) forecasting by combining the strengths of linear models (ARIMA) and non-linear models (Artificial Neural Networks – ANN). The study relied on Nepal's GDP data covering the period from 1960 to 2021. The findings revealed that hybrid models, particularly the multiplicative ARIMA-ANN model, outperformed standalone models—whether ARIMA or ANN—in both in sample and out-of-sample forecasting.
- Study: **Ngige, I. W (2020).** which was titled: **Forecasting Kenya's GDP using a hybrid neural network and ARIMA model** This study aims to evaluate the forecasting performance of both the ARIMA model and the Artificial Neural Network (ANN) model in predicting the Gross Domestic Product (GDP) in Kenya. The study relied on data covering the period from 1960 to 2017. It was concluded that the hybrid model possesses significant potential, making it a strong competitor to the ARIMA model in short-term GDP forecasting.
- Study: **Sunitha, S., Sampath Kumar, P., Jyothi Rani, K., & Haragopal, G (2018)**. Which was titled: **Forecasting GDP using ARIMA and Artificial Neural Networks Models under Indian Environment**. This study aimed to use the Artificial Neural Networks (ANN) methodology and ARIMA models to forecast the Gross Domestic Product (GDP) within the Indian economic environment, and to compare the performance of both models. The study relied on annual GDP data covering the period from 1951 to 2016, and employed the analytical approach. The findings revealed that the Artificial Neural Network model outperforms traditional statistical models in forecasting accuracy. This study aimed to use the neural networks approach and ARIMA models for forecasting the GDP in Indian Environment In this study.

- Study: **Hamid, I. Y (2011)**. Entitled: **The Use of Box-Jenkins Models and Artificial Neural Networks for Time Series Forecasting in the Sudanese Agricultural Sector**. This study aimed to forecast the productivity of the following agricultural crops in Sudan: wheat, maize, and sesame, during the period from 1954 to 2005, by applying both the Box-Jenkins methodology and the Artificial Neural Networks (ANNs), followed by a comparison of the performance of the two approaches. The researcher employed both the descriptive approach and the statistical-analytical method. The findings of the study indicated that Artificial Neural Network models outperformed the Box-Jenkins model in terms of forecasting accuracy. Moreover, the ANN approach was considered a more suitable option, especially for long-term forecasting, compared to traditional statistical models.

3.2.1 Comparison between international Studies and the Current Study:

Our current study distinguishes itself from previous international studies through its direct focus on comparing the performance of ARIMA and ANN models in forecasting Algeria's Gross Domestic Product (GDP). In contrast, international studies such as **Chaudhary & Uprety (2023)** in Nepal, **Ngige (2020)** in Kenya, **Sunitha et al. (2018)** in India, and **Hamid (2011)** in Sudan have primarily emphasized the superiority of intelligent or hybrid models in enhancing forecasting accuracy. These studies concluded that neural networks or hybrid models (such as ARIMA-ANN) outperform traditional models in both short-term and long-term forecasting. However, our study challenges this prevailing trend by demonstrating, through a rigorous quantitative analysis and direct comparison, the superiority of the ARIMA model in the specific context of forecasting Algeria's GDP.

Summary of the Chapter one:

Based on the discussion presented in this chapter, we conclude that Gross Domestic Product (GDP) stands as one of the most prominent indicators for measuring economic activity. It serves as a crucial tool for formulating economic policies and achieving sustainability and inclusive growth, as it measures the final value of goods and services produced over a specific period. The prices used in GDP calculation vary between current prices, which take into account prevailing market prices, and constant prices, which are based on a fixed base year to measure real changes, isolated from the effects of inflation. Moreover, the methods of calculating GDP include the production approach, the income approach, and the expenditure approach, each providing a comprehensive understanding of the sources of value creation. The importance of GDP lies in its role as a key tool for forecasting future economic trends, comparing economic performance across countries, and assessing living standards.

The size of GDP is influenced by several factors, most notably political stability and natural conditions ,which impact the pace of production and economic growth. Finally, the relationship between GDP and economic growth is closely intertwined, as GDP is regarded as the fundamental variable through which the expansion of economic activity and the achievement of sustainable development are measured.

CHAPTER TWO:

Forecasting Gross Domestic Product in Algeria: A Comparative Applied Study Using the Box-Jenkins Methodology and Artificial Neural Networks

Preface:

Forecasting phenomena is considered a necessary process due to its importance in making future decisions. Numerous forecasting methods exist, including classical approaches such as the Box-Jenkins methodology, and modern approaches such as artificial neural networks.

Accordingly, through this chapter, we will address the following topics:

1. **Box-Jenkins Methodology**
2. **Artificial Neural Networks**
3. **Forecast accuracy evaluation and comparison of modeling Methodologies**
4. **Application of the Box-Jenkins Methodology to the Time Series under Study**
5. **Application of Artificial Neural Networks to the Time Series under Study**
6. **Comparison between the Results of the Box-Jenkins Methodology and Artificial Neural Networks**

1. Box-Jenkins Methodology:

The Box-Jenkins methodology is one of the most important statistical approaches used for time series analysis and forecasting future values. This methodology follows several stages, which will be discussed below.

1.1 Definition of Box-Jenkins Methodology:

The Box-Jenkins methodology is one of the most famous techniques for analyzing time series, as it reflects the behavior of these series, whether seasonal or non-seasonal. In 1970, the scientists George Box and Gwilym Jenkins in the United States of America published their work on the processing of time series and how to use them in forecasting. This methodology relies on four stages in order to build an accurate model for analyzing and forecasting time series

1.2 Stages of the Box-Jenkins Methodology:

The Box–Jenkins methodology goes through several essential stages, including:

a) The identification stage

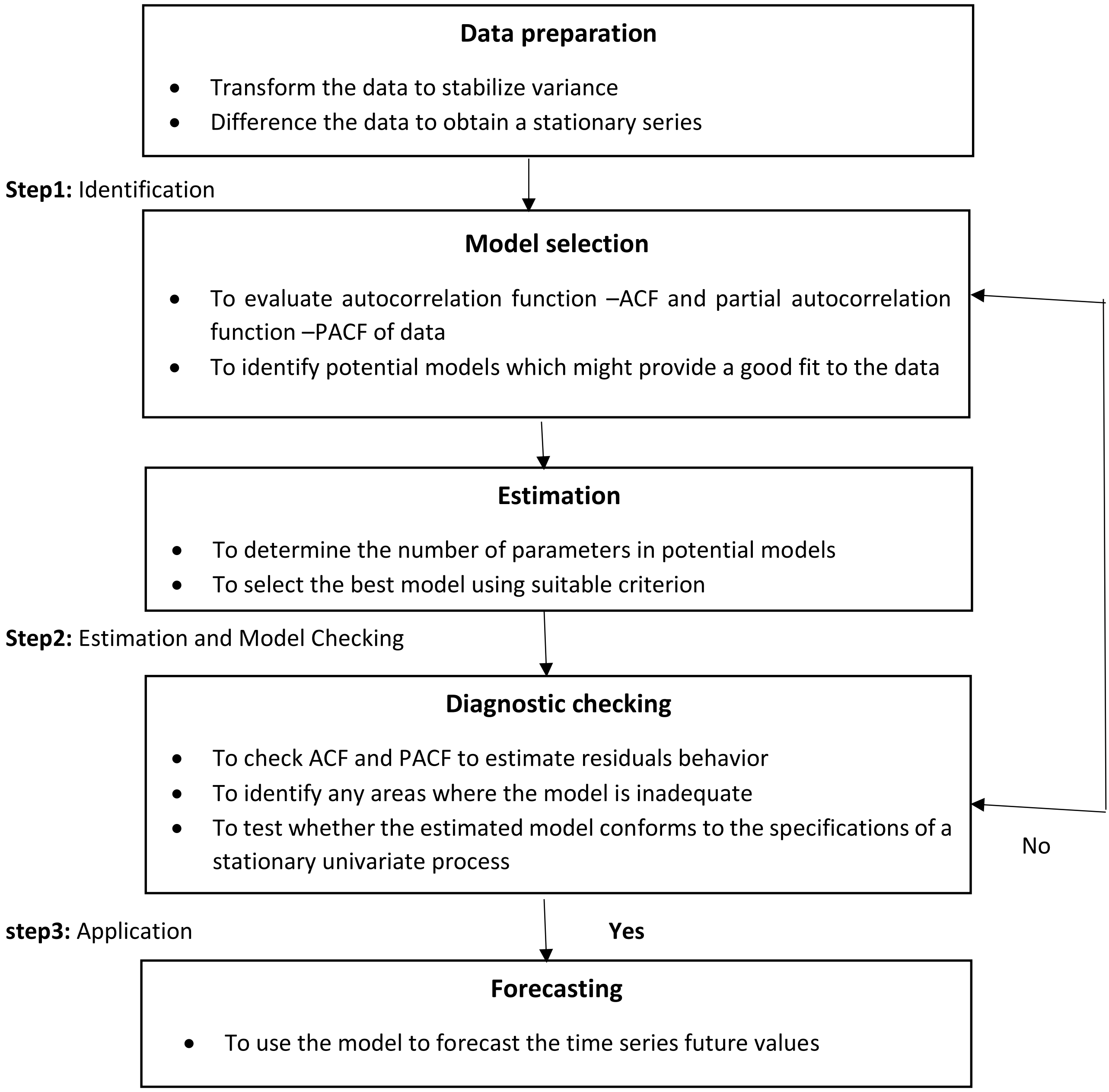
b) The estimation stage

c) Testing and Validation Stage

d) The forecasting stage

These stages are illustrated in Figure (1-1), and each stage will be discussed in detail below:

Figure (1-1): Schematic representation of the Box-Jenkins methodology for time series modeling



Source: Dritsakis, N., & Klazoglou, P. (2018). Forecasting unemployment rates in USA using Box-Jenkins methodology. International Journal of Economics and Financial Issues, 8(1) p 11

a. Identification Stage :

In this stage, the appropriate model for the time series is identified using the autocorrelation function (ACF) and the partial autocorrelation function (PACF). This phase involves examining the stationarity of the series, ensuring its transformation into a stationary series if necessary, and subsequently determining the most suitable model.

❖ **Examining the Stationarity of the Time Series:**

In this stage, the stationarity of the original time series is assessed. If the series exhibits an increasing or decreasing trend, first-order differences are calculated, followed by second-order differences, and so on until the series becomes stationary. The stationarity of the time series can be evaluated by analyzing the autocorrelation function (ACF) and the partial autocorrelation function (PACF), relying on the following:[16]

- **Analysis of the Autocorrelation and Partial Autocorrelation Functions:**

The autocorrelation function (ACF) measures the simple correlation between a variable at a given time and the same variable in previous periods.

The partial autocorrelation function (PACF) represents the relationship between sequential values of a variable over two different time periods, assuming the other periods remain constant.

To determine the stationarity of the time series, we analyze the correlation coefficients. If the correlation coefficient falls within the confidence interval, it is considered statistically insignificant (i.e., equal to zero), indicating that the series is stationary at a significance level of

[16] - Atrus, S., & Atrus, S. (2018). Using Box-Jenkins methodology to forecast some indicators of the Saudi stock market during the period from January 2010 to December 2017. Economic and Administrative Research Journal, (23). p 75

$\alpha = 0.05$. Conversely, if the coefficient is statistically significant, the series is non-stationary.

- **Unit Root Test:**

To determine whether the time series contains a unit root, several tests can be employed, including the Augmented Dickey-Fuller (ADF) test. The following hypotheses will be tested :

$$\begin{cases} \boldsymbol{H_0}: \emptyset = \mathbf{1} \\ \boldsymbol{H_1}: |\emptyset| < \mathbf{1} \end{cases}$$

$\emptyset$: The unit root represents non-stationarity and is calculated using the following equation:

$$\hat{\emptyset}: \frac{\sum_{t=1}^{n} y_{t-1} y_t}{\sum_{t=1}^{n} y_{t-1}^2}$$

Where:

$\mathrm{H_0}$: It corresponds to the null hypothesis of non $-$ stationarity.

$\mathrm{H_1}$: It corresponds to the null hypothesis of stationarity.

- **Determining the Model Order :**

This step involves identifying the values of p and q, which define the autoregressive (AR) and moving average (MA) components of the model. This is achieved by analyzing the autocorrelation function (ACF) and the partial autocorrelation function (PACF):[17]

- The value of q is determined by identifying the last lag where the ACF coefficients approach zero.
- The value of p corresponds to the last lag where all PACF coefficients are equal to zero.

[17] - Atrus, S., & Atrus, S. Previous reference. p76

b. Estimation Stage :

In this stage, the identified linear models from the previous step are estimated and compared to determine the most appropriate model.

- **Estimation Auto Regressive Model (AR):**

The autoregressive (AR) model represents the relationship between the dependent variable and the independent variables, which consist of past values of the same dependent variable over a specified number of lag periods. The notation AR (p) denotes an autoregressive model of order P and is expressed by the following equation:[18]

$$\boldsymbol{y_t = \emptyset_1 * y_{t-1} + \emptyset_2 * y_{t-2} + \cdots + \emptyset_p * y_{t-p} + \mu_t}$$

Where:

p: Represents the order of the autoregressive model.

$\boldsymbol{y_t}$: Represents the observations of the time series.

$\boldsymbol{\emptyset_1, \emptyset_p}$: Represent the autoregressive parameters.

- **Estimation Moving Average Model (MA):**

The moving average (MA) model represents the dependent variable as a function of the weighted average of past values of the random error term, up to lag q. It is expressed by the following equation:[19]

$$\boldsymbol{y_t = \mu_t + \theta_1 * \mu_{t-1} + \theta_2 * \mu_{t-2} + \cdots + \theta_q * \mu_{t-q}}$$

Where:

$\boldsymbol{q}$: Represents the order of the moving average.

$\boldsymbol{y_t}$: Represents the observations of the time series.

$\boldsymbol{\theta_1, \theta_q}$: Represent the model parameters.

[18]- Darwish, M. (2018). Using Box–Jenkins methodology to forecast cash flows in Palestinian banks: A case study of Bank of Palestine. Journal Title, (9). p 156

[19] - Darwish, M. Previous reference. p157

- **Estimation ARMA Model:**

Also known as autoregressive moving average models, they are a type of time series analysis models that combine the characteristics of autoregressive (AR) models and moving average (MA) models. This model depends on the previous values of the time series in addition to the previous random errors. It is denoted by the symbol ARMA (p,q) and is written as follows:

$$y_t = \emptyset_1 * y_{t-1} + \emptyset_2 * y_{t-2} + \cdots + \emptyset_p * y_{t-p} + \mu_t + \theta_1 * \mu_{t-1} + \theta_2 * \mu_{t-2} + \cdots + \theta_q * \mu_{t-q}$$

<u>Comparison of Estimated Models:</u>

After estimating the models, it is essential to compare them using selection criteria. This is done by relying on the Akaike Information Criterion (AIC), Schwarz Criterion (BIC), and Hannan-Quinn Criterion (HQIC). The optimal model is chosen based on the one that yields the lowest value for these criteria.

- **Akaike Information Criterion (AIC):**

The Akaike Information Criterion (AIC) is used to determine the order of time series models and is also applied in various other statistical fields. It is one of the key criteria for comparing models and selecting the most appropriate one for a given time series. This widely used criterion is calculated using the following equation:[20]

$$AIC = \hat{\sigma}^2 \exp\left(2\left(\frac{p+q}{t}\right)\right)$$

Where:

[20] - 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]. p132

$\hat{\sigma}^2 = \frac{\sum e_t^2}{t}$**:** The residual variance is estimated using the maximum likelihood method, which is calculated by dividing the sum of squared residuals by the number of observations.[21]

(p+q) It refers to the number of model parameters, not the sum of the model orders.

When the model is reformulated in logarithmic form, it takes the following equation:

$$\mathbf{AIC} = \mathbf{Ln}(\hat{\sigma}^2) + \left(2\left(\frac{\mathbf{p}+\mathbf{q}}{\mathbf{t}}\right)\right)$$

- **Schwarz Criterion:**

The Schwarz Information Criterion (SIC), also known as the Bayesian Information Criterion (BIC), is a modified version of the Akaike Information Criterion (AIC). Schwarz introduced this adjustment to improve model selection. The criterion is mathematically expressed as follows: [21]

$$\mathbf{BIC} = \mathbf{Ln}\hat{\sigma}^2 + \frac{(\mathbf{p}+\mathbf{q})}{\mathbf{t}}\mathbf{Ln}(\mathbf{t})$$

- **Hannan-Quinn Criterion:**

The Hannan-Quinn Criterion (HQC) is calculated using the following equation: [21]

$$\mathbf{HQ}(\mathbf{p},\mathbf{q}) = \mathbf{Ln}(\hat{\sigma}^2) + (\mathbf{p}+\mathbf{q})\mathbf{c}^{\frac{\mathbf{Ln\,LnT}}{\mathbf{T}}}$$

Where: C>2, and the best model according to this criterion is the one that yields the lowest value.

[21] - Atrus, S. Previous reference. p133

c. Testing and Validation Stage :

After identifying and estimating the model, this stage involves evaluating its statistical validity to determine whether it can be used for forecasting future values. The model is accepted based on several tests, including :[22]

- **Significance Test of Model Parameters:**

For a model to be statistically valid and suitable for forecasting, its parameters must be significantly different from zero. If a parameter in the proposed model is found to be statistically insignificant, the model should be reformulated by removing the AR or MA term that lacks statistical significance.

- **Residual Testing :**

To validate the model, the residuals must be examined for independence, stationarity, and normality. The key tests include :

1. **Stationarity Test :**

Residual stationarity is assessed by testing the statistical significance of the autocorrelation coefficients of the squared residuals. If these coefficients fall within the confidence interval, the squared residuals are considered stationary, indicating homogeneous conditional variance.

2. **Independence Test :**

Residual independence is tested using the autocorrelation function (ACF). This involves computing and plotting the ACF of the residuals and checking whether the autocorrelation coefficients lie within the confidence interval. If they do, the residuals are statistically insignificant, confirming their independence; otherwise, the residuals exhibit dependence.

[22] - Atrus, S., & Atrus, S. Previous reference. p76-77

3. Normality Test :

To determine whether the residuals follow a normal distribution, the Jarque-Bera test is used. This test relies on two key statistics:[23]

- Kurtosis (K), which measures the sharpness of the distribution peak.
- Skewness (S), which measures the symmetry of the distribution.

$$\mathbf{S} = \frac{\left[\frac{1}{t}\sum_{t=1}^{t}(y_t - m)^3\right]^2}{\left[\frac{1}{t}\sum_{t=1}^{t}(y_t - m)^2\right]^3} = \beta_1$$

$$\mathbf{K} = \frac{\frac{1}{t}\sum_{t=1}^{t}(y_t - m)^4}{\left[\frac{1}{t}\sum_{t=1}^{t}(y_t - m)^2\right]^2} = \beta_2$$

Where:

m represents the mean of the stationary time series The Jarque-Bera statistic is then computed using the following formula:

$$JB = \frac{T}{6}\beta_1 + \frac{T}{24}(\beta_2 - 3)^2$$

We reject the assumption of normality. The null hypothesis (H_0) for this test is formulated as follows:

$$H_0: \beta_1^{1/2} = \beta_2 = 0$$

[23] - Atrus, S., & Atrus, S. Previous reference. p77-78

d. Forecasting Stage :

The forecasting stage is the final and most crucial phase of the Box-Jenkins methodology. The primary objective of this stage is to utilize the final model developed after passing through the previous stages—to predict future values of the studied time series. [24]
There are two main types of forecasting:

- **One-step-ahead forecasting:** This involves generating a prediction for the next immediate value only.
- **Multi-step-ahead forecasting:** This method allows for forecasting future values up to k steps ahead, where k = 1, 2, 3 ...

1.3 Assumptions of the Box-Jenkins Methodology:

The Box-Jenkins methodology is a powerful tool for analyzing and forecasting time series. To ensure the accuracy and success of this methodology, there are a set of assumptions that must be apply, including the following:

- **Stationarity**: This means that the time series is stationary and fluctuates around a constant mean and variance.
- **Linearity:** The Box-Jenkins methodology assumes that the relationship between future and past values must be linear.
- **Independence of Residuals:** The Box-Jenkins methodology assumes that the residuals are independent, meaning there is no autocorrelation between the residuals.
- **Normality of Residuals:** The Box-Jenkins methodology assumes that the residuals are normally distributed.

[24] - Atrus, S. Previous reference. p136

1.4 Advantages and Disadvantages of the Box-Jenkins Methodology:

The Box-Jenkins methodology is considered one of the traditional approaches in time series analysis. It offers numerous advantages, but it is also not without certain drawbacks. Below, we present the most important advantages and disadvantages:

1. The Advantages:

We will now discuss the key advantages of the Box-Jenkins methodology, which are as follows:[25]

- This methodology provides a structured, comprehensive, and reliable framework for modeling and forecasting. It offers a holistic solution for all stages of time series analysis, beginning with the selection of an appropriate initial model, followed by parameter estimation and model diagnostics, and concluding with forecasting future observations.

- This approach does not assume independence between observations; rather, it intelligently exploits correlation patterns within the available data using ARMA models. This enhances its robustness and effectiveness in representing various types of time series, ultimately leading to statistically consistent and reliable forecasts.

- It yields more accurate forecasts than those obtained through alternative methods, particularly when sufficient data are available for its application.

- It provides appropriate confidence intervals for future observations in both seasonal and non-seasonal data, whereas many other methods fail to offer such intervals.

[25] - Shaarawi, S. M. (2005). Introduction to modern time series analysis. Scientific Publishing Center, King Abdulaziz University. p 356

2. The Disadvantages:

Although the Box-Jenkins methodology offers several advantages, it also presents certain drawbacks, which are:[26]

- Requires specialized skills and expertise: The Box-Jenkins methodology is criticized for requiring specialized skills and expertise that may not be available to many researchers, particularly in selecting the appropriate model for the data.

- Demands complex calculations and computational power: Implementing the Box-Jenkins methodology requires a large amount of complex calculations and can only be carried out using a computer.

- Difficulty updating results: When new data becomes available, the process of updating the forecast is cumbersome. With new observations, all stages of the analysis must be repeated to generate new predictions.

- Requires a substantial number of observations: The methodology requires at least 50 observations to build a good model, and this large number may not always be available, especially in the case of annual data.

[26] - Shaarawi, S. M. Previous reference. p 357

2. Artificial Neural Networks:

Artificial neural networks are considered among the most prominent tools of artificial intelligence today, as they have been developed to simulate the way the human brain processes information. In this section, we aim to address the key aspects related to these networks.

2. 1 Definition of Artificial Neural Network Methodology:

these networks are called neural because they are loosely inspired by neuroscience. Each hidden layer of the network is typically vector-valued. The dimensionality of these hidden layers determines the width of the model. Each element of the vector may be interpreted as playing a role analogous to a neuron. Rather than thinking of the layer as representing a single vector-to-
vector function, we can also think of the layer as consisting of many units that act in parallel, each representing a vector-to-scalar function. Each unit resembles a neuron in the sense that it receives input from many other units and computes its own activation value.[27]

- ❖ In summary, neural networks are powerful computational models that mimic the human brain to process complex data. Their ability to learn and adapt makes them essential in various applications, including image recognition, speech processing, and predictive analytics.

2. 2 Components of artificial neural networks:

Artificial Neural Networks are built from several key components that work together to process data these components include:

a. Layers:

A neural network consists three layers, which are the input layers, hidden layers, and output layers:

[27] - Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press. p 168

- **Input Layer:** The input layer is the first layer in an ANN and is responsible for receiving the raw input data. This layer's neurons correspond to the features in the input data. The input layer doesn't perform any computations but passes the data to the next layer.[28]
- **Hidden Layers:** are the intermediate layers between the input and output layers. They perform most of the computations required by the network. Hidden layers can vary in number and size, depending on the complexity of the task. A network with one hidden layer is called a Single-layer network, while a network with more than one hidden layer is called a Multi-layer network.[29]
- **Output Layer:** The Output Layer is the final layer in an ANN. It produces the output predictions. The number of neurons in this layer corresponds to the number of classes in a classification problem or the number of outputs in a regression problem.[29]

b. <u>Interconnections (Weights):</u>

Interconnections refer to the connections between different layers, linking them together or connecting units within each layer through associated weights. These weights accompany each interconnection and play a crucial role in transmitting weighted signals between processing units or layers.[30]

c. <u>Processing Units (Neurons):</u>

Processing units, or neurons, are the fundamental components responsible for processing information within the neural network. These units are interconnected in various ways through interconnections (weights).

[28] - GeeksforGeeks. (n.d.). Layers in artificial neural networks (ANN). Retrieved July22, 2024, from

[29]- Atrus, S. Previous reference .p156

[30] - Derbal, A. (2014). An attempt to distinguish Arab financial market indicators using econometric models: Case study – Dubai Financial Market Index [Unpublished doctoral dissertation, University of Abou Bekr Belkaid – Tlemcen]. p 91

A processing unit or neuron consists of the following key components:[31]

- **Weight Parameters:**

The weight is a fundamental element in artificial neural networks, representing the various connections through which data is transmitted from one layer to another. It signifies the relative strength or importance of each input to a processing unit. Weights serve as the primary mechanism for storing knowledge within the neural network by adjusting their values. The weight between processing units i and j is denoted by w_{ij}

- **Summation Function:**

The first processing step performed by a processing unit is calculating the weighted sum of the inputs using the summation function. This function computes the weighted average for all inputs to the processing unit by multiplying each input value by its corresponding weight and then summing the resulting products.

Mathematically, this is expressed as follows:

$$\mathbf{S_j = \sum_{i=1}^{n} X_i \, w_{ij}}$$

$\boldsymbol{S_j}$: The summation result for each processing unit j

$\boldsymbol{X_i}$: The input value coming from unit i and entering unit j.

$\boldsymbol{w_{ij}}$**:** The weight that connects processing unit j to unit i in the previous layer.

d. **<u>Transfer Function:</u>**

After the summation function, the second process in the processing unit is transforming the summation output into one of the values expected

[31] - Derbal, A. Previous reference. p92

to be within the desired network outputs. This step is performed using the transfer function, which converts the weighted summation result from the first step into a value constrained within a specific range.[32]

This is achieved by comparing the summation result with a threshold value, denoted by θ, which determines the output. The result is usually subjected to a specific activation function before comparison, and the network outputs primarily depend on this distribution. Based on these functions, the network produces outputs constrained within the range $(0,1)$ or $(-1,1)$.

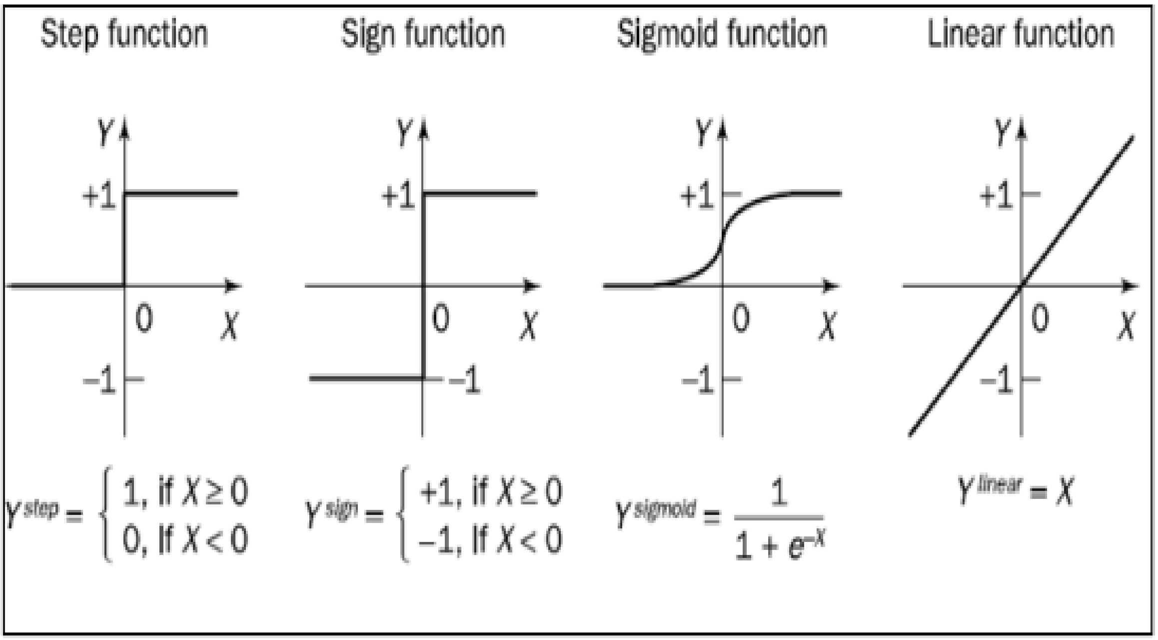
Among the most important transfer functions or activation functions are:[32]

- **Step Function:** This function produces an output value from the processing unit within a specific range.
- **Sign Function:** This function produces an output value from the processing unit within a specific range.
- **Linear Function:** This function generates outputs that are equal to the inputs and provides multiple and unrestricted classifications.
- **Sigmoid Function:** This function transforms or limits the outputs to a value within a specific range. In this case, it is referred to as the binary sigmoid activation function or the transformation of outputs to values within a given range. It is also known as the bipolar sigmoid activation function when transforming outputs to values within a different range.

[32] - Derbal, A. Previous reference. Pp 92-93

The following figure illustrates the most common activation functions:

Figure (1-2): Most Common Activation Functions



Source: Derrbal, A. (2014). An Attempt to Distinguish Arab Financial Market Indicators Using Econometric Models: Case Study - Dubai Financial Market Index (Doctoral dissertation, University of Abou Bekr Belkaid, Tlemcen, Algeria). Faculty of Economic Sciences, Management Sciences, and Commercial Sciences, University of Abou Bekr Belkaid, Algeria, p. 93.

e. <u>Output Function:</u>

In most cases, the outputs are equal to the results of the transfer function. However, in some networks, the processing unit modifies the outcome of the transfer function. This modification occurs through competition among neighboring processing units. The competition typically takes place in processing units with higher activation levels, where this competition determines the processing unit that will be active or responsible for generating the output.[33]

[33] - Derbal, A. Previous reference. p 93

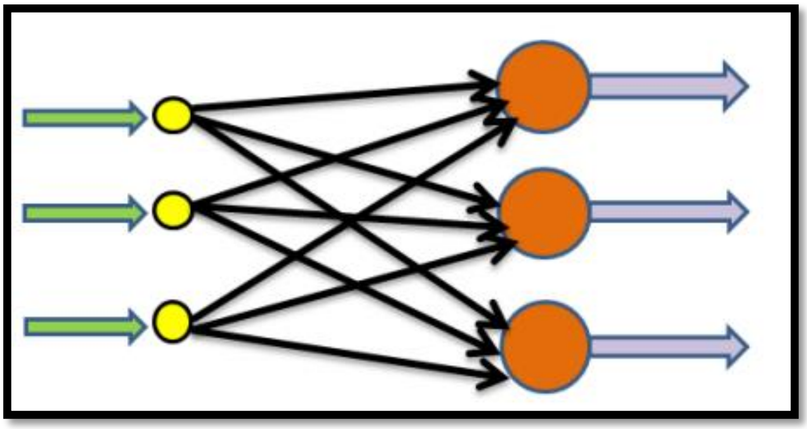
2. 3 TYPES OF NEURAL NETWORK:

There are different types of neural networks, each used depending on the nature of the task or the type of data. Among these types are the following:

a) Feed -Forward Neural Networks (FNNs):

Also known as feed- forward networks, they are a type of shallow neural network where connections between the nodes do not form a cycle. They form a multi-layered network where information moves in only one direction—from input to output, through one or more layers of nodes, without any cycles or loops.[34]

Figure (1-3): Feed-Forward Neural Network



Source : Qamar, R., & Zardari, B. A. (2023). Artificial neural networks: An overview. Mesopotamian Journal of Computer Science, 2023(1). p133

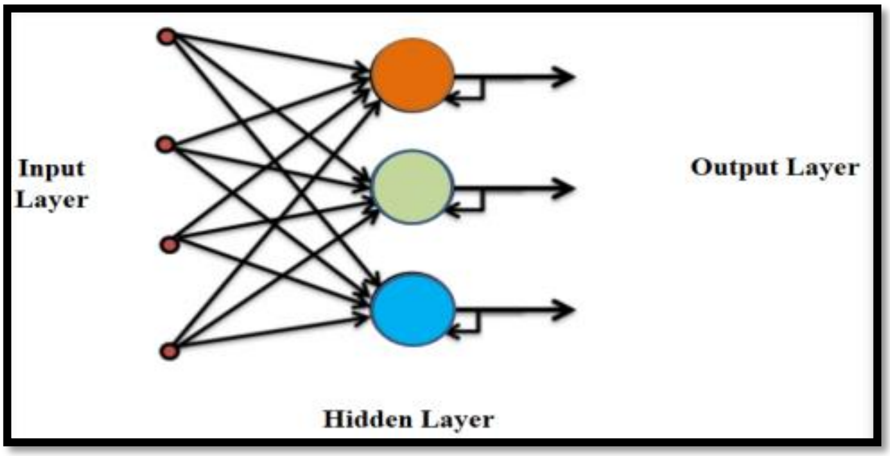
b) Recurrent Neural Network(RNN):

A recurrent neural network is a network that has backward linkages from the output to the input and a hidden layer. Recurrent neural networks are frequently used in deep learning, model construction, and simulation of human brain neural activity. A recurrent neural network (RNN) is an advanced artificial neural network (ANN) with a direct memory cycle. The ability to construct new network types using fixed-

[34] - Data Science Dojo. (n.d.). Feed Forward Neural Networks (FNNs). DataScienceDojo. Retrieved July 2, 2025

size input vectors. The recurrent neural networks use these input vectors. [35]

Figure (1-4): Recurrent Neural Network

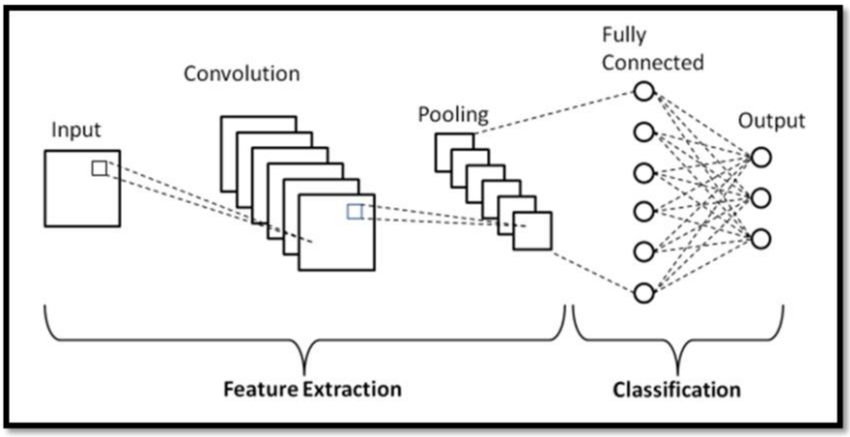


Source : Qamar Roheen & Zardari Baqar Ali, Previous reference

c) <u>Convolutional neural networks(CNN):</u>

Being a highly popular neural networking model, convolutional neural networks leverage a type of multilayer perceptron and include one or more convolutional layers. These layers can be either pooled or entirely connected.[36]

Figure (1-5): Convolutional neural networks



Source : Mahmood, H. (2024, June 11). 5 main types of neural networks and their applications. Data Science Dojo.

[35] - Qamar Roheen & Zardari Baqar Ali, Previous reference, P 134

[36] - Spiceworks. (2022). *what is a neural network? Definition, working, types, and applications in 2022*. Retrieved July5, 2025

2. 3. 1 Types of Neural Networks Used for Time Series Prediction:

There are many neural network architectures used for time series prediction, and the most commonly used architectures include:[37]

- Multi-Layer Perceptron (MLP)
- Radial Basis Function (RBF) Networks
- Recurrent Networks
- Sigma-pi & pi-Sigma Networks
- Ridge Polynomial Networks

The following section will discuss Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) networks:

❖ Multi-Layer Perceptron (MLP) Networks:

The Multi-Layer Perceptron (MLP) is one of the most widely used neural network architectures for time series prediction. The fundamental principle of this network is based on utilizing past values of the time series as inputs. The weights are aggregated in the hidden layer concerning the inputs, and a nonlinear activation function (sigmoid) is applied. The output layer of the network receives the outputs of the hidden layer and applies a linear transformation to generate the predicted values of the time series.

The standard architecture of the MLP network, which is frequently employed in predictive modeling, is characterized by the following:

- A fully connected network architecture.
- Direct shortcut connections from the inputs to the output units.
- A single hidden layer with a logistic activation function to enhance nonlinearity in the hidden units.
- An output layer that employs a linear activation function to scale the output range, which is typically between (0,1).

[37]- Hamid, I. Y. (2011). Use of Box–Jenkins and artificial neural networks models in time series prediction for Sudanese agricultural sector [Published research, Nyala University, Sudan, Issue 501]. p 13

The general model of the MLP network used for time series prediction is expressed as follows:[38]

$$\hat{x}(t) = w_0 + \sum_{j=1}^{h} w_j \, f_j \left[\sum_{i=1}^{n} w_{ij} \, x(k-i) \right]_j + w_{j0}$$

Where:

h: Number of hidden layer units

n: Number of input units

w_{ij}: Weights between the input layer and the hidden layer

w_j: Weights between the hidden layer and the output layer

f_j: Sigmoid activation function in the hidden units(j_{it})

❖ **Radial Basis Function (RBF) Networks:**

This type of network consists of two layers: a single hidden layer with radial basis activation functions and an output layer with linear activation functions. RBF networks are characterized by several advantages, the most notable being their architectural simplicity compared to Multi-Layer Perceptron (MLP) networks.[39]

2. 4 Prediction Steps Using Neural Networks:

Prediction using artificial neural networks is a modern approach that has proven effective in analyzing nonlinear data and extracting complex patterns without requiring strict conditions. These networks excel in learning and adapting to new data, making them more accurate and flexible compared to traditional models. Additionally, algorithms such as back propagation enhance performance over time, reinforcing their applicability across various predictive tasks.

[38] - Hamid, I. Y. Previous reference. p14

[39]- Atrus, S. Previous reference. p171

Accordingly, the forecasting methodology using the artificial neural network can be summarized through the following stages:

Step 1: Variable Selection

The observations for the variables should be carefully chosen to ensure an accurate representation of the problem.[40]

Step 2: Data Processing

Various operations are performed on the data, such as identifying the overall trend, focusing on relationships between observations, and determining the data distribution.[41]

Step3: Dividing Data into Sets (Divide Data into Sets)

The available data is divided into the following sets:[42]

- **Training Set:** A set used for learning and defining the data model.
- **Testing Set:** A set used to assess the skill of the virtual network and its general usability.
- **Validation Set:** A set used for conducting a final performance evaluation of the network.

Step 4: Neural Network Model Specification:

When defining the neural network model, the following aspects should be considered: [43]

- The number of input neurons, which corresponds to the number of independent variables.

40- 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

41 - Atrus, S. Previous reference. p172

42- Kadri, R., & Mekideche, M. (2017). A comparative study between the artificial neural networks method and the Box-Jenkins methodology for forecasting electricity sales: An applied study in the Sonelgaz Company. Journal of Economics and Management, 16(1). p97

43 - Sahad, A., & Mekideche, M. Previous reference. p112

- The number of hidden layers, determined based on the error function used in the network.
- The number of hidden neurons, which is typically determined through experimentation.
- The output layer, which usually consists of a single neuron.

Step 5: Evaluation Criterion

the criterion used in the backpropagation network for error evaluation is the Mean Squared Error (MSE).

Step 6: Network Training

this step includes: [46]

- **Model Learning:** Determining the set of weights between neural nodes that minimize the mean squared error.
- **Backpropagation Algorithm:** Utilizing the training algorithm to reduce the gradient.

Step 7: Implementation

It is one of the most critical steps, as the network is tested in terms of its adaptability, the mechanism of retraining, and its ability to achieve the lowest mean squared error when data changes.[44]

[44] - Kadri, R., & Mekideche, M. Previous reference. p98

2. 5 Advantages and Disadvantages of Artificial Neural Networks:

Artificial neural networks are among the techniques of artificial intelligence. These networks possess many advantages, but they are also not without their drawbacks. Below, we will explore the most important advantages and disadvantages:

➢ **the Advantages of Artificial neural networks:**

The use of Artificial Neural Networks (ANNs) provides numerous benefits, such as:

- **Storing information on the entire network:** information such as in traditional programming is stored on the entire network not on a database. The disappearance of a few pieces of information in one place does not prevent the network from functioning [45]
- **Ability to work with incomplete knowledge:** After ANN training the data may produce output even with incomplete information the loss of performance here depends on the importance of the missing information
- **Parallel processing capability:** Artificial neural networks have numerical strength that can perform more than one job at the same time.
- **Adaptive learning:** A capacity to figure out how to do undertakings in view of the information given for preparing or starting knowledge.[46]
- **Fault Tolerance via Redundant Information Coding:** Fractional decimation of a system prompts to the relating corruption of execution. Be that as it may, some system abilities might be held even with real system harm.

[45] - Mijwel, M. M. (2018). Artificial neural networks: Advantages and disadvantages. University of Baghdad, College of Science, Department of Computer Science. p1

[46] - Sarker, T., Noor, S., & Acharjee, U. K. (2017). Basic application and study of artificial neural networks. SK International Journal of Multidisciplinary Research Hub, 4(4) p2

- **the Disadvantages of Artificial neural networks:**

Despite the numerous advantages offered by Artificial Neural Networks (ANNs), their use is not without a set of challenges and limitations, most notably:

- **Hardware dependence:** Artificial neural networks require processors with parallel processing power, in accordance with their structure. For this reason, the realization of the equipment is dependent[47]
- **Unexplained behavior of the network:** This is the most important problem of ANN. When ANN produces a probing solution, it does not give a clue as to why and how. This reduces trust in the network.[49]
- **ANN is not a daily life general purpose problem solver.[48]**
- **The black box problem:** the network autonomously identifies the relationships among variables and demonstrates how these relationships are extracted or which elements have been used to interpret them. However, it remains difficult for the user to discern these relationships, as they are internally embedded within the system.[49]

[47] - Mijwel, M. M. Previous reference. P 1

[48] - Sarker, T., Noor, S., & Acharjee, U. K. Previous reference. p10

[49] - Derbal, A. Previous reference. P 105

3. Forecast accuracy evaluation and comparison of modeling methodologies:

Evaluating forecast accuracy is fundamental in assessing the efficiency of time series models. This section aims to present the key metrics used for evaluating forecast accuracy, followed by a comparison of the performance of the Box-Jenkins methodology and Artificial Neural Networks in economic forecasting.

3.1 Forecast Accuracy Evaluation Metrics:

Forecast accuracy metrics aim to assess how well the applied models perform in producing results that are close to actual values. These metrics are used in both traditional models (such as ARIMA) and intelligent models (such as neural networks). Common indicators include ME ,MAE, RMSE, MSE and MAPE

- ✓ **Mean Error Indicator (ME - Bias):**

It expresses a measure of bias and is used to evaluate the accuracy of forecasts by calculating the average of the total errors resulting from applying a specific forecasting method:[50]

$$ME = {\sum_{i=1}^{N} e_i}/{N}$$

Where :

N: represents the number of errors

The closer this average is to zero, the more accurate the forecasting method is. Any forecasting method should not produce large errors, whether positive or negative. It is also noted that using the mean absolute error allows the identification of the direction of the errors, where two directions emerge:

[50] - Atrus, S. Previous reference. p103

- Positive error direction: This occurs when the mean error is positive, indicating that the adopted forecasting method gives pessimistic results (as most errors are positive).
- Negative error direction: This occurs when the mean error is negative, indicating that the adopted forecasting method gives optimistic results (i.e., most of the resulting errors are negative).

The mean error indicator faces the problem of hiding the forecasting error, and thus the problem of not distinguishing between a forecasting method that produces small errors and one that produces large errors, since the negative error values cancel out the positive ones.

✓ **<u>Mean Squared Error (MSE):</u>**

The Mean Squared Error is widely used, as it goes beyond the effect of elimination in the previous indicator — that is, it does not remove negative values by converting them to positive. This indicator is calculated using the following formula:[51]

$$\mathbf{MSE} = \sum_{i=1}^{N} e_i^2 / N$$

This metric takes into account both negative and positive prediction errors by relying on the squared values of the errors. However, a notable drawback is that it amplifies large error values and gives them greater importance

✓ **<u>Root Mean Squared Error (RMSE):</u>**

This metric is also referred to as the standard error of estimation. RMSE is considered one of the most important criteria used to compare a set of models, with preference given to the model that yields the smallest RMSE value. It is expressed by the following formula:[52]

[51] - Salami, A. (2022). Estimation and projection of the grain food gap and its implications on food security in Algeria [Undergraduate thesis, Kasdi Merbah University – Ouargla, Faculty of Economics, Commercial and Management Sciences, Department of Economics]. p149

[52] -Atrus, S. Previous reference.P105

$$\mathbf{RMSE} = \sqrt{\mathbf{MSE}} = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}}$$

This metric helps eliminate the effect of large error values and the amplification caused by the mean squared error. To evaluate the accuracy of a forecasting method, the approach with the lowest RMSE value is preferred.

- ✓ **Mean Absolute Error (MAE):**

The Mean Absolute Error (MAE) represents the sum of the absolute error values divided by the number of observations in the time series. It is one of the widely used and simple metrics. Instead of squaring the prediction error to address the issue of canceling out positive and negative error values—as is the case with other indicators—this metric uses the absolute value of the error. It is also referred to as the Mean Absolute Deviation (MAD). The formula for calculating this metric is as follows:[54]

$$\mathbf{MAE} = \sum_{i=1}^{N} |e_i| / N$$

This metric provides insight into the average magnitude of the total prediction error when using a specific forecasting method. However, despite its widespread use, it does not clearly distinguish between forecasting methods that produce small or near-zero errors and those that result in larger errors.

- ✓ **Mean Absolute Percentage Error (MAPE):**

This indicator measures the mean absolute error as a percentage of the actual values of the studied phenomenon, rather than over a time period. The Mean Absolute Percentage Error can be calculated using the following formula: [53]

[53] - Salami, A. Previous reference. p 150

$$\mathbf{MAPE} = \frac{\sum_{i=1}^{N}\left|\frac{e_i}{y_i}\right|}{N}$$

MAPE is one of the metrics that relies on percentage calculations. It is considered less sensitive to the data scale, as it is not significantly affected by extreme values. Additionally, it uses absolute values to eliminate negative values in order to express the error as a proportion of the actual value.

3.2 The problem of Comparison between the Box-Jenkins Methodology and Artificial Neural Networks:

In the following points, we will highlight the key aspects that form the basis of the trade-off problem between artificial neural networks and the Box-Jenkins methodology, which we outline as follows:[54]

a) Linearity of Time Series :

Artificial neural networks demonstrate a significant capability in handling the nonlinearity of time series data, which provides them with an additional advantage compared to the Box-Jenkins methodology, which is primarily designed to handle linear data. That is:

- The Box-Jenkins methodology is more efficient and effective than artificial neural networks in cases of ideal autoregressive models, where the error follows a normal distribution with a mean of zero and a variance of one. It is also more efficient in moving average models, mixed models (ARIMA), and seasonal models, making it more suitable for linear models. However, it becomes less efficient in dealing with quasi-linear models.
- Artificial neural networks, on the other hand, exhibit high efficiency in processing quasi-linear models, whereas the Box-Jenkins methodology fails to effectively handle this type of time series. This highlights the superior capability of artificial neural networks in managing quasi-linear and nonlinear time series.

[54] - Atrus, S. Previous reference. Pp 179-180

b) Forecasting:

Forecasting future values of the studied phenomenon is a fundamental objective pursued by both artificial neural networks and the Box-Jenkins methodology. However, it is important to note that artificial neural networks were developed to address many of the forecasting challenges in time series that second-generation models failed to resolve. One of the key reasons why neural networks outperform other forecasting methods, particularly the Box-Jenkins methodology, is their unique ability to handle nonlinear time series. Additionally, they demonstrate high effectiveness in forecasting nonlinear time series, regardless of the presence or absence of white noise.

c) Usage Conditions :

Artificial neural network models are characterized by the absence of any assumptions or predefined conditions when applied in the field of forecasting, unlike the Box-Jenkins methodology, which requires the fulfillment of specific conditions, such as ensuring stationarity before constructing the model.[55]

d) Data Type :

Neural networks perform optimally when all their inputs and outputs vary within a range between (0, 1). Consequently, all data must be transformed before being used in a neural network model, unlike the Box-Jenkins methodology, which processes data as it is without any modifications.

e) Time Series Stationarity :

Artificial neural networks are preferred over the Box-Jenkins methodology in cases where there is a problem of variance instability in time series, and vice versa.

[55] - Atrus, S. Previous reference. p181

f) Data Size :

Artificial neural network models are directly influenced by the amount of available data, i.e., the length of the time series. The larger the dataset, the more variations in the series become apparent, enhancing the network's learning capacity and subsequently improving the predictive performance of neural network models. However, if the time series length is insufficient, the Box-Jenkins methodology is preferred.

g) Data Complexity :

The Box-Jenkins methodology is more suitable for less complex time series. As the complexity of the series increases, neural network models become the preferred choice.[56]

[56] - Atrus, S. Previous reference. p182

4. Application of the Box-Jenkins Methodology to the Time Series under Study:

In order to build an accurate forecasting model for the time series under study, the Box-Jenkins methodology will be applied as detailed below.

4.1 Descriptive analysis of the Time Series under Study:

This section aims to define the characteristics of the time series under study and conduct a descriptive analysis of it. This will be achieved through a set of key points that will be elaborated in the following subsections.

4.1.1 Defining the Time Series Data Under Study:

In this study, we focus on examining the general and fundamental characteristics of the time series of Algeria's Gross Domestic Product (GDP), given its significance as an economic indicator that reflects the performance of the national economy over the years. Analyzing this time series allows us to understand the economic developments that Algeria has experienced over the past decades, enabling us to identify general trends in economic growth, cyclical fluctuations, and any economic shocks that may have affected GDP.

It is important to note that certain economic variables, such as sectoral components of GDP, are excluded from our analysis, as this study focuses on the overall GDP of the country. The data used in this study has been obtained from the World Bank.

The time series of Algeria's GDP represents annual GDP data in Algerian Dinar, covering the period from 1960 to 2023. These data reflect the economic changes experienced by the country, including periods of economic growth, slowdowns, and fluctuations resulting from both internal and external factors.

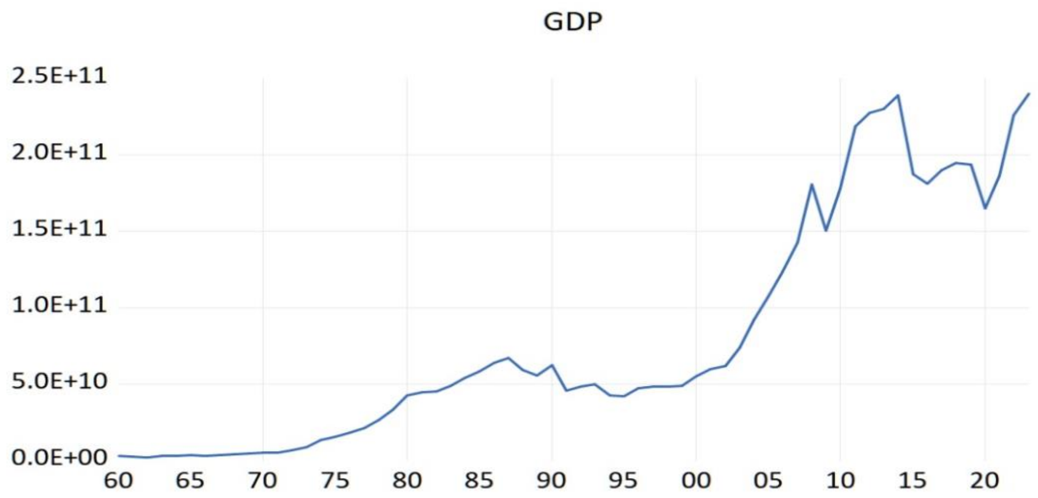
4.1.2 Graphical Representation of the Time Series of Algeria's Gross Domestic Product (GDP)

We represent the dataset provided in the appendices section (**Appendix N[1], pages 99 to 101**) in a consistent and standardized format based on the following equation:

$$F(t) = \text{GDP}$$

where GDP represents the annual Gross Domestic Product of Algeria. By plotting the GDP time series (measured in Algerian Dinar) for the period 1960 to 2023, we obtain the following graph:

Figure (1-6):Graphical Representation of the GDP Time Series



Source: Prepared based on the output of EViews 12

The curve (1-6) reflects the evolution of GDP over time during the period 1960-2023, showing a general upward trend in GDP. This has led to a significant acceleration in economic growth, especially after the year 2000, while other periods experienced slowdowns or declines. The curve also exhibits cyclical fluctuations that may be caused by various crises, such as the one observed in 2020 due to the COVID-19 pandemic.

Overall, the curve reflects a fluctuating economic trajectory but tends to rise in the long run.

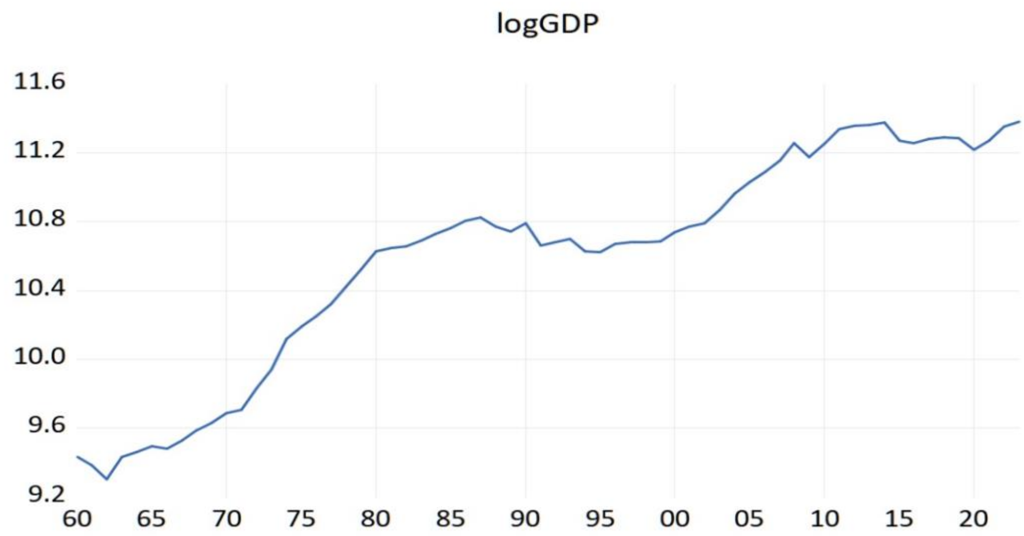
4.1.3 Graphical Representation of the Log-Transformed Time Series of Algeria's GDP (log(GDP))

We also consider the logarithmic transformation of the GDP time series to stabilize variance and improve model performance. This transformation is defined as follows:

$$F(t) = \log(GDP)$$

The following figure illustrates the log-transformed GDP series for the period 1960 to 2023:

Figure (1-7):Graphical Representation of the Log-Transformed Time Series of Algeria's GDP



Source: Prepared based on the output of EViews 12

We observe from the figure (1-7): that the logarithm of the Gross Domestic Product appears as a smoother and more stable curve compared to the original series. The overall trend remains upward.

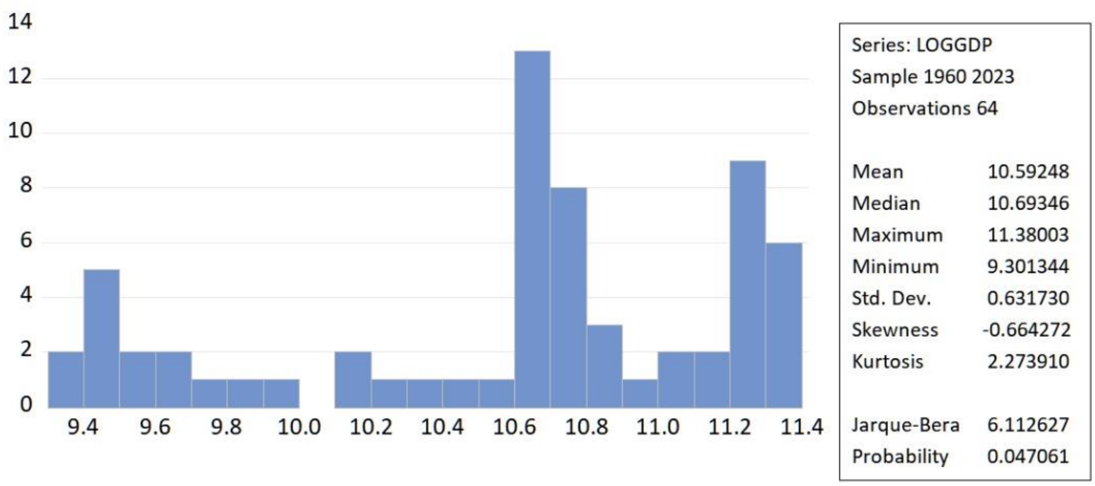
Note:

Since the logarithmic transformation of the GDP series resulted in greater stability and clarity compared to the original series, we decided to rely on it for the analysis and modeling.

4.1.4 Analysis of the Statistical Data of the LogGDP Series:

The following figure presents the statistical data of the Log-Transformed Time Series of Algeria's GDP (LogGDP):

Figure (1-8): Statistical data of the Log GDP series



Source: Prepared based on the output of EViews 12

Based on the statistical data presented in Figure (1-8), the logarithmically transformed GDP series of Algeria for the period (1960 – 2023) exhibits a distribution with moderate variation around the mean. The highest recorded value was (11.38003), while the lowest was (9.301344). The mean of the log(GDP) series was (10.59248) dinars, with a standard deviation of (0.63173), indicating a moderate dispersion of values around the mean.

The skewness coefficient was(-0.664272), indicating a negatively skewed distribution, meaning the probability distribution is asymmetrical and the curve is tilted to the left. The kurtosis value was (2.273910), which is less than 3, suggesting that the distribution is flatter than a normal distribution, with its peak lying below that of a normal curve.

Furthermore, the computed value of the Jarque-Bera test (JB = 6.112627) exceeded the critical chi-square value at the 5% significance level ($\chi^2_{0.05}(2) = 5.991$).

Since ($JB \geq \chi^2_{0.05}(2)$), we reject the null hypothesis, indicating that the time series does not follow a normal distribution.

4.2 Study of Series Stability of the Time Series under Study:

In this section, we will study the stability of the time series of the Log-Transformed Gross Domestic Product (LogGDP) through a series of stages, which we summarize in the subsections of this section.

4.2.1 Analysis of the Autocorrelation and Partial Autocorrelation Function of the LogGDP Time Series :

To assess the instability of the studied phenomenon, namely the LogGDP time series, we represent the autocorrelation and partial autocorrelation function with 20 lagged variables, as shown in the following table:

Table (1-1): Graphical Representation of the Autocorrelation and Partial Autocorrelation Function for the LogGDP Series

Date: 04/09/25 Time: 21:26
Sample: 1960 2023
Included observations: 64

	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

We observe from the Table (1-1) that most of the autocorrelation function (ACF) and partial autocorrelation function (PACF) coefficients fall outside the confidence interval $[\frac{-1{,}96}{\sqrt{T}}, \frac{+1{,}96}{\sqrt{T}}]$. This indicates that they are significantly different from zero, leading us to reject the stationarity hypothesis (as the p-values are significantly less than 0.05).

This suggests that the series exhibits correlation between observations, indicating that it is non-stationary. The lack of stationarity may be attributed to the presence of a trend component

4.2.2 Identifying and Removing the Trend Component from the LogGDP Time Series:

To verify the presence of a unit root and determine whether the time series under study is stationary or exhibits a general trend, we conducted the Augmented Dickey-Fuller (ADF) test. This test is applied through three models: a model without a constant and without a trend, a model with a constant, and a model with both a constant and a trend.

The following table (1-2) presents the results of the Augmented Dickey-Fuller (ADF) test applied to the time series of the logarithm of Gross Domestic Product (LogGDP), the test results obtained using the EViews 12

Table (1-2): Results of the Augmented Dickey-Fuller (ADF) test on the LogGDP series

1. Without constant and without a general trend

Null Hypothesis: LOGGDP has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.824454	0.9986
Test critical values:	1% level	-2.602794	
	5% level	-1.946161	
	10% level	-1.613398	

2. With constant

Null Hypothesis: LOGGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.649374	0.4517
Test critical values:	1% level	-3.538362	
	5% level	-2.908420	
	10% level	-2.591799	

3. With constant and general trend

Null Hypothesis: LOGGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.912382	0.9478
Test critical values:	1% level	-4.110440	
	5% level	-3.482763	
	10% level	-3.169372	

Source: Prepared based on the output of EViews 12

Based on the results of the Augmented Dickey-Fuller (ADF) test, we observe that the Prob is greater than 0.05 in all tested models, indicating that the null hypothesis, which assumes the presence of a unit root, cannot be rejected. Confirming that the LogGDP series is non-stationary and contains a unit root, reflecting a general trend in the time series.

To achieve stationarity, we apply first-order differencing, followed by a reapplication of the ADF test on the first-differenced LogGDP series (DGDP), yielding the following results:

Table (1-3): Results of the Augmented Dickey-Fuller (ADF) Test on the LogGDP Series After First-Difference Transformation

1. Without constant and without a general trend

Null Hypothesis: D(LOGGDP) has a unit root
Exogenous: None
Lag Length: 2 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.996198	0.0448
Test critical values:	1% level	-2.604073	
	5% level	-1.946348	
	10% level	-1.613293	

2. With constant

Null Hypothesis: D(LOGGDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.027208	0.0000
Test critical values:	1% level	-3.540198	
	5% level	-2.909206	
	10% level	-2.592215	

3. With constant and general trend

Null Hypothesis: D(LOGGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

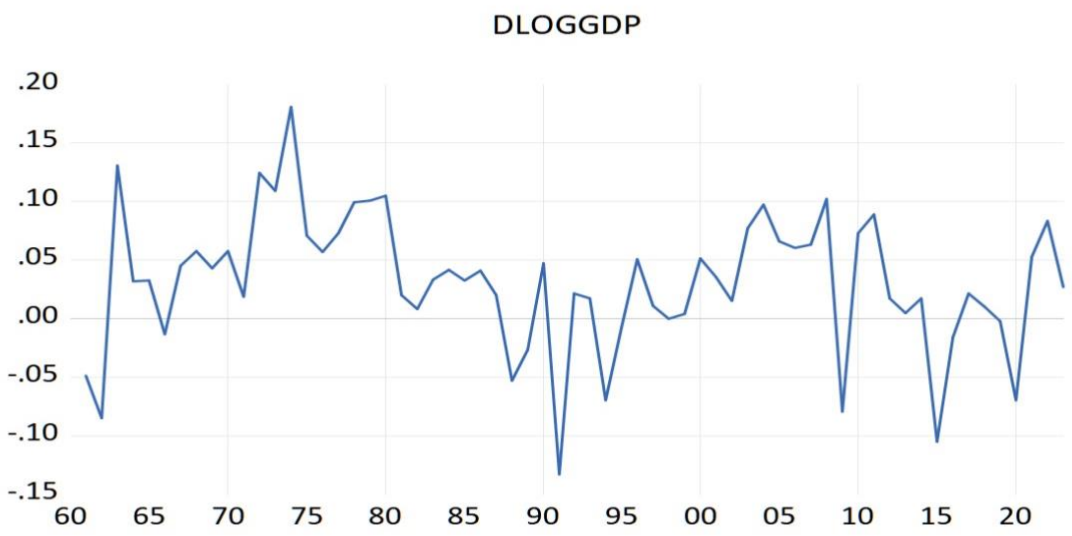
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.245362	0.0000
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

Source: Prepared based on the output of EViews 12

After applying first-order differencing to the LogGDP series, the stationarity of the adjusted series (DLogGDP) was re-examined using the Augmented Dickey-Fuller (ADF) test. The results across all tested models show that the probability value (Prob) is lower than the 0.05 significance level.

This indicates the rejection of the null hypothesis, which assumes the presence of a unit root, confirming that the series has become stationary after applying first-order differencing.

Figure (1-9): DLogGDP series after applying first-order differencing



Source: Prepared based on the output of EViews 12

We observe from the figure that the DLOGGDP series fluctuates around a constant mean, which suggests that it has become stationary after applying first-order differencing.

4.3 Forecasting the Time Series under Study using the Box-Jenkins methodology:

To apply the Box-Jenkins methodology, a series of steps must be followed. The following sections will outline these steps in detail :

4.3.1 Identification Phase:

After confirming the stationarity of the Log-Transformed Gross Domestic Product (DLogGDP) time series through the Augmented Dickey-Fuller (ADF) test, the first stage of the Box-Jenkins methodology, known as the identification phase, follows. In this stage, potential models that best fit the stationary time series are determined. To achieve this, the graphical representation of both the autocorrelation function (ACF) and the partial autocorrelation function (PACF) of the DLogGDP series will be utilized.

Table (1-4): Graphical Representation of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for the DLogGDP Series

Date: 04/09/25 Time: 22:14
Sample (adjusted): 1961 2023
Included observations: 63 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.261	0.261	4.5052	0.034
		2	0.150	0.088	6.0216	0.049
		3	0.288	0.248	11.691	0.009
		4	0.244	0.129	15.811	0.003
		5	0.179	0.071	18.078	0.003
		6	0.185	0.062	20.536	0.002
		7	0.059	-0.096	20.793	0.004
		8	-0.091	-0.213	21.410	0.006
		9	-0.133	-0.221	22.762	0.007
		10	-0.084	-0.099	23.312	0.010
		11	-0.073	0.005	23.730	0.014
		12	-0.306	-0.216	31.242	0.002
		13	-0.303	-0.129	38.747	0.000
		14	-0.217	-0.036	42.690	0.000
		15	-0.184	0.066	45.589	0.000
		16	-0.226	-0.001	50.033	0.000
		17	-0.270	-0.108	56.542	0.000
		18	-0.054	0.207	56.806	0.000
		19	-0.237	-0.134	62.053	0.000
		20	-0.100	0.051	63.008	0.000

Source: Prepared based on the output of EViews 12

The model order will be automatically determined using the EVIEWS 12 software, which allows for rank identification while simplifying many steps. Moreover, it provides a more accurate model order based on the AIC value.

Table (1-5): 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

Model Selection Criteria Table
Dependent Variable: D(LOGGDP)
Date: 04/30/25 Time: 23:09
Sample: 1960 2023
Included observations: 63

Model	LogL	AIC*	BIC	HQ
(3,4)(0,0)	101.507773	-2.936755	-2.630593	-2.816340
(2,4)(0,0)	100.482100	-2.935940	-2.663796	-2.828904
(2,3)(0,0)	98.861982	-2.916253	-2.678127	-2.822597
(3,2)(0,0)	98.834058	-2.915367	-2.677241	-2.821711
(2,2)(0,0)	97.351660	-2.900053	-2.695945	-2.819776
(3,3)(0,0)	99.178241	-2.894547	-2.622403	-2.787512
(1,3)(0,0)	96.371979	-2.868952	-2.664844	-2.788675
(1,4)(0,0)	96.944234	-2.855373	-2.617246	-2.761716
(1,1)(0,0)	93.760795	-2.849549	-2.713477	-2.796031
(3,0)(0,0)	94.532627	-2.842306	-2.672216	-2.775408
(1,0)(0,0)	92.168935	-2.830760	-2.728706	-2.790621
(3,1)(0,0)	95.049595	-2.826971	-2.622863	-2.746695
(0,1)(0,0)	91.867238	-2.821182	-2.719128	-2.781044
(1,2)(0,0)	93.808816	-2.819328	-2.649237	-2.752430
(2,1)(0,0)	93.784123	-2.818544	-2.648454	-2.751646
(0,4)(0,0)	94.548427	-2.811061	-2.606953	-2.730784
(2,0)(0,0)	92.495117	-2.809369	-2.673297	-2.755851
(0,3)(0,0)	93.100591	-2.796844	-2.626754	-2.729947
(0,2)(0,0)	91.956985	-2.792285	-2.656213	-2.738767
(0,0)(0,0)	89.908198	-2.790736	-2.722700	-2.763978

Source: Prepared based on the output of EViews 12

Based on the automatic ARIMA model selection process, the best-fitting model was identified as ARIMA (3,1,4). This model was selected among 25 estimated models using the AIC criterion as the selection tool, with an AIC value of (−2.936754)

4.3.2 Estimation Stage:

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

Method: ARMA Maximum Likelihood (BFGS)
Date: 04/10/25 Time: 10:45
Sample: 1961 2023
Included observations: 63
Convergence achieved after 240 iterations
Coefficient covariance computed using observed Hessian
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.032481	0.003419	9.500089	0.0000
AR(1)	2.428255	0.142916	16.99073	0.0000
AR(2)	-1.962060	0.275929	-7.110750	0.0000
AR(3)	0.513642	0.140121	3.665704	0.0006
MA(1)	-2.553354	0.048284	-52.88211	0.0000
MA(2)	2.090024	0.078353	26.67429	0.0000
MA(3)	-0.280612	0.042596	-6.587789	0.0000
MA(4)	-0.256056	0.018748	-13.65782	0.0000
SIGMASQ	0.002057	0.000492	4.177969	0.0001

R-squared	0.390192	Mean dependent var	0.030871
Adjusted R-squared	0.299850	S.D. dependent var	0.058540
S.E. of regression	0.048983	Akaike info criterion	-2.936755
Sum squared resid	0.129564	Schwarz criterion	-2.630593
Log likelihood	101.5078	Hannan-Quinn criter.	-2.816340
F-statistic	4.319050	Durbin-Watson stat	1.989359
Prob(F-statistic)	0.000454		

Inverted AR Roots	.93+.20i	.93-.20i	.56	
Inverted MA Roots	1.00	.90+.43i	.90-.43i	-.26

Source: Prepared based on the output of EViews 12

We observe from Table (1-6) that the Prob value is less than 0.05, which leads us to reject the null hypothesis that states the estimated model parameters are not significant. Therefore, the estimated model is statistically acceptable at a preliminary level.

Therefore, the optimal model that best captures the variations in the logarithm of Algeria's Gross Domestic Product (DLogGDP) is the ARIMA (3,1,4) model.

Accordingly, the selected model is formulated as follows:

$$\boldsymbol{\Delta LogGDP_t = 0,032481 + 2,428255\Delta \mathrm{LogGDP}_{t-1} - 1,962060\Delta \mathrm{LogGDP}_{t-2} + 0,513642\Delta \mathrm{LogGDP}_{t-3} - 2,553354\varepsilon_{t-1} + 2,090024\varepsilon_{t-2} - 0,280612\varepsilon_{t-3} - 0,256056\varepsilon_{t-4} + \varepsilon_t}$$

4.3.3 Testing and Diagnostic Stage:

After conducting the estimation process and obtaining the ARIMA model, we found that the model is initially acceptable. To ensure its final acceptance and reliability for forecasting, we will conduct the following diagnostic tests:

- ✓ **Individual Significance Test of the Estimated Parameters:**

From the estimated model, we observe that the estimated parameters are statistically significant, as the calculated Student t-statistics are greater than the tabulated values of the Student distribution at the 5% significance level. Additionally, the Prob values for the individual parameters are less than 0.05.

- ✓ **Overall Significance Test of the Model:**

We notice that the critical value of the Fisher test is given by Prob (F-statistic) = 0.000454 which is less than 0.05, indicating the statistical significance of the model as a whole.

- ✓ **Model's Explanatory Power Test:**

The R^2 value is 0.39, which means that the model has an acceptable explanatory power and can be used for forecasting purposes.

- ✓ **Autocorrelation Test of Residuals:**

The Durbin-Watson statistic is DW = 1.98, which provides evidence of no autocorrelation or serial correlation between the residuals.

- ✓ **Test for Residual Independence:**

In order to perform the residual independence test, we analyze the autocorrelation and partial autocorrelation functions of the residual series

Table (1-7): Autocorrelation and Partial Autocorrelation Function of the Residuals Series

Date: 04/10/25 Time: 11:38
Sample (adjusted): 1961 2023
Q-statistic probabilities adjusted for 7 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.016	-0.016	0.0169	
		2	-0.037	-0.037	0.1092	
		3	0.058	0.057	0.3423	
		4	0.015	0.015	0.3579	
		5	-0.019	-0.015	0.3843	
		6	0.059	0.057	0.6342	
		7	-0.011	-0.012	0.6432	
		8	-0.089	-0.084	1.2267	0.268
		9	-0.047	-0.057	1.3921	0.499
		10	0.054	0.047	1.6214	0.655
		11	0.151	0.164	3.4075	0.492
		12	-0.108	-0.098	4.3357	0.502
		13	-0.082	-0.088	4.8869	0.558
		14	0.001	-0.019	4.8870	0.674
		15	0.044	0.059	5.0515	0.752
		16	0.000	0.007	5.0515	0.830
		17	-0.127	-0.165	6.4784	0.774
		18	0.145	0.168	8.3861	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 EViews 12

It is clear from the results recorded in Table (1-7) that all autocorrelation coefficients of the residual series fall within the confidence interval, meaning they are not statistically different from zero. To confirm this, we rely on the Ljung-Box test. According to the results shown in the table above, the test statistic is: Q* =11,283

The critical value corresponding to this test (considering that the number of lags is K = 20) is: $x^2_{0,05}(20) = 31{,}41$

Therefore, since the calculated value is less than the critical value, we accept the null hypothesis of the test, which states that all autocorrelation coefficients are statistically equal to zero at the 0.05

significance level. This provides evidence of the independence of the estimation residuals.

- ✓ **<u>Test for Residual Stability:</u>**

In order to conduct the residual stability test, we examine the autocorrelation and partial autocorrelation functions of the squared residuals series

Table (1-8): 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

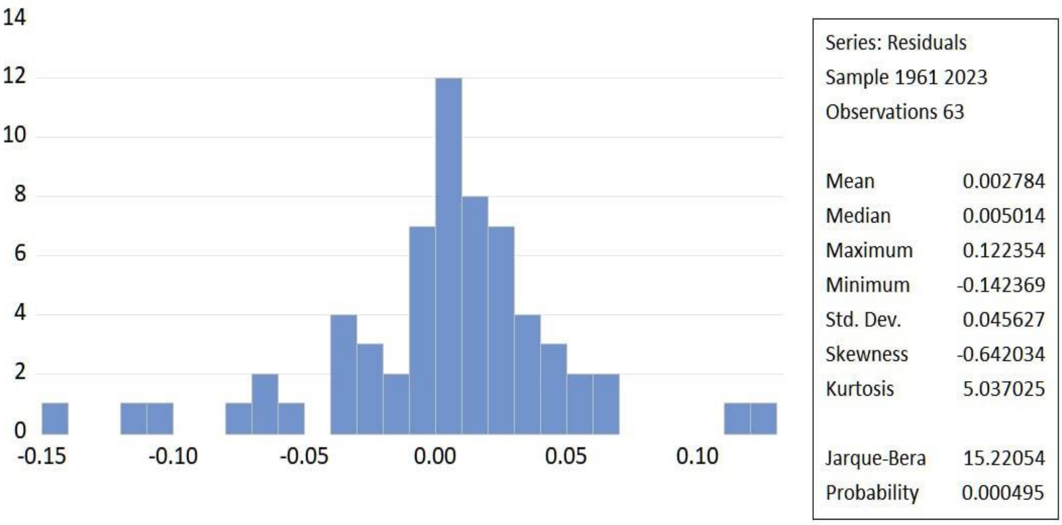
Source: Prepared based on the output of EViews 12

The results show that all the p-values of the test are greater than 0.05, indicating that the autocorrelation and partial autocorrelation coefficients of the squared residuals series are not statistically significant. As illustrated in the graphical representation, all coefficients fall within the confidence interval. This confirms the condition of the stability of the squared residuals.

✓ **Normality Test of the Residuals:**

We conduct the normality test to verify whether the residual series follows a normal distribution or not, as illustrated.

Figure (1-10): Results of the Normality Test for the Residual Series



Source: Prepared based on the output of EViews 12

The results of the normality test indicate that the p-value is 0.000495, which is less than 0.05, leading us to reject the null hypothesis. Additionally, the Jarque-Bera statistic, which equals 15.22054, is greater than the critical value of 5.99. This confirms that the residual series does not follow a normal distribution.

❖ Therefore, since the statistical significance of both the individual parameters and the overall model is confirmed, and the conditions of residual independence and stability — both of which are essential requirements — are satisfied, the model can be considered reliable for forecasting, despite its failure to pass the normality test.

4.3.4 Forecasting Stage:

After defining the model and selecting its validity, we move on to the final stage, which is the forecasting phase. To carry out this process, we used the statistical software Gretl 2024d, through which we obtained forecast values for a period of five years. The results are presented in the following table:

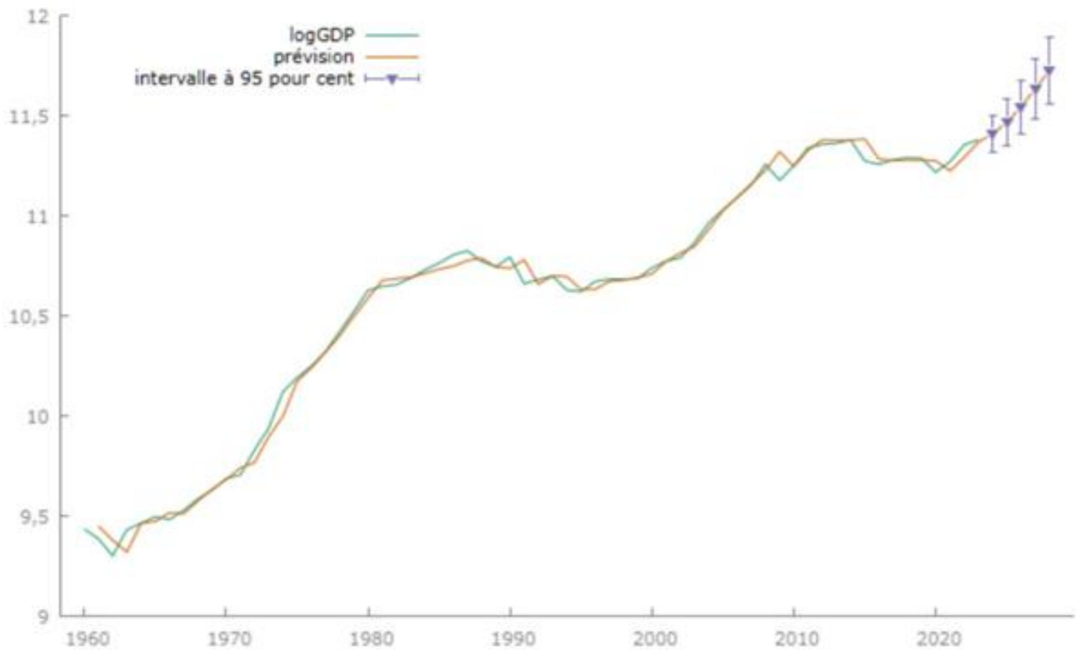
Table (1-9): Forecasted Values Using the Box-Jenkins Methodology for the Period (2024–2028)

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

Graphically, the forecast values can be represented in the following Figure:

Figure (1-11): Forecasted Values of Algeria's LogGDP Using the Box-Jenkins Methodology Until 2028



Source: Prepared based on the output of Gretl 2024d

The figure above shows a close correspondence between the two curves, namely between the predicted and actual values of log GDP in Algeria, which allows us to assess the suitability of the model used

4.4 Measuring the forecasting accuracy of the Box-Jenkins methodology:

To verify the accuracy of the forecasting model, the Gretl software was used to calculate forecast accuracy metrics, and the results are presented in the following figure:

Figure (1-12): Output of forecast accuracy metrics calculation using Gretl software

```
gretl version 2024d
Session courante: 2025-04-10 22:45

# Compute forecast errors
? series abs_error = abs(logGDP - forLogGDP)
Séries abs_error (ID 3) remplacées
? series sq_error = (logGDP - forLogGDP)^2
Séries sq_error (ID 4) remplacées
? series perc_error = abs((logGDP - forLogGDP)/logGDP)*100
Séries perc_error (ID 5) remplacées
? series error = logGDP - forLogGDP
Séries error (ID 6) remplacées
# Forecast accuracy indicators
? scalar MAE = mean(abs_error)          # Mean Absolute Error
Scalaire remplacé MAE = 0,0313149
? scalar RMSE = sqrt(mean(sq_error))    # Root Mean Squared Error
Scalaire remplacé RMSE = 0,0453492
? scalar MAPE = mean(perc_error)        # Mean Absolute Percentage Error
Scalaire remplacé MAPE = 0,298399
? scalar MSE = mean(sq_error)           # Mean Squared Error
Scalaire remplacé MSE = 0,00205655
? scalar ME = mean(error)               # Mean Error (Bias)
Scalaire remplacé ME = 0,00278351
# Display results

=== Forecast Accuracy Evaluation ===
MAE  = 0,0313
RMSE = 0,0453
MAPE = 0,2984 %
MSE  = 0,0021
```

Source: Prepared based on the output of Gretl 2024d

The results obtained from Gretl regarding forecast accuracy metrics are summarized in the following table:

Table (1-10): 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

The results of the forecast accuracy indicators showed that:

- The Mean Absolute Error (MAE) was 0.0313, which is a small value indicating that the difference between actual and predicted values was minimal on average.
- The Root Mean Squared Error (RMSE) was 0.0453, suggesting that large forecast errors were rare.
- The Mean Absolute Percentage Error (MAPE) was only 0.2984%, a very low percentage that reflects an excellent level of prediction accuracy, with forecasted values being very close to the actual ones.
- The Mean Squared Error (MSE) stood at 0.0021, which further supports the model's precision and confirms that the error magnitude was limited.
- Finally, the Mean Error (ME) was just 0.0028, a value very close to zero, indicating that the model is unbiased and does not tend to systematically overestimate or underestimate the values.

❖ Overall, these results indicate that the model is highly accurate and can be confidently relied upon for forecasting.

5. Application of Artificial Neural Networks to the Time Series under Study:

In order to build an accurate forecasting model, the artificial neural network model will be applied to the time series under study, as detailed below:

5. 1 Stages of applying artificial neural networks to forecast the Time Series under Study:

In order to forecast the logarithm of the Gross Domestic Product (LogGDP), it is essential to go through a series of stages, which are outlined as follows:

5.1.1 Variable Selection Stage:

In this stage, the variables — that is, the inputs of the neural network will be defined. These variables consist of the time series of the logarithm of Algeria's Gross Domestic Product (LogGDP) from the year 1960 to 2023. Accordingly, we have 64 observations

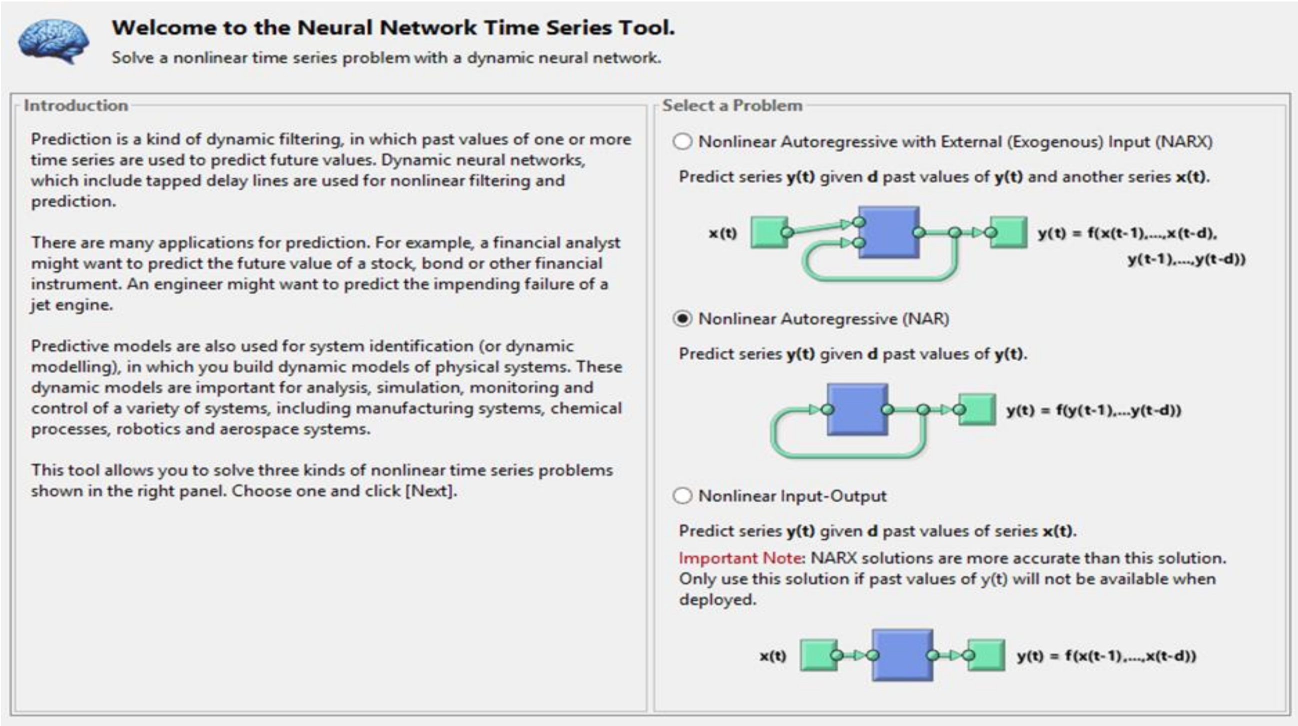
5.1.2 Data Processing Stage:

After identifying the inputs of the neural network, which are represented by the time series of the logarithm of Gross Domestic Product (LogGDP), we now proceed to data processing based on the Nonlinear Auto-Regressive model, commonly referred to as NAR. This model forecasts future values based on past observations. The time series under this model takes the following form:

$$\mathbf{y_t = f(y_{t-1}\, , \dots \dots \dots \dots \dots \dots , y_{t-d})}$$

The following figure illustrates this:

Figure (1-13): Data preprocessing using the Nonlinear Autoregressive (NAR) forecasting model



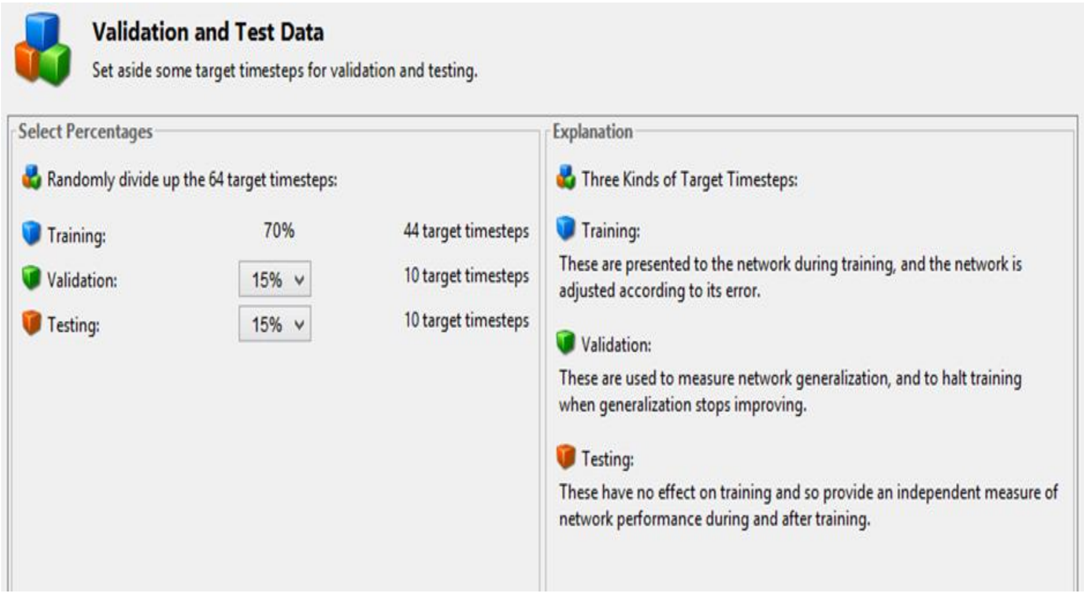
Source: MatlabR2015a

5.1.3 Dividing Data into Sets Stage:

At this stage, the data is divided into groups using MATLAB. The inputs are split into three sets, namely:

- **Training set:** 70% of the observations were allocated for training the network, which corresponds to 44 observations.
- **Validation set:** 15% of the observations, equivalent to 10 observations, were allocated to assess the network's performance and its forecasting capability
- **Testing set:** This set includes 10 observations, representing 15% of the total data, and is used to perform a final evaluation of the network's performance based on the knowledge it has acquired during training.

Figure (1-14): Validation and testing data



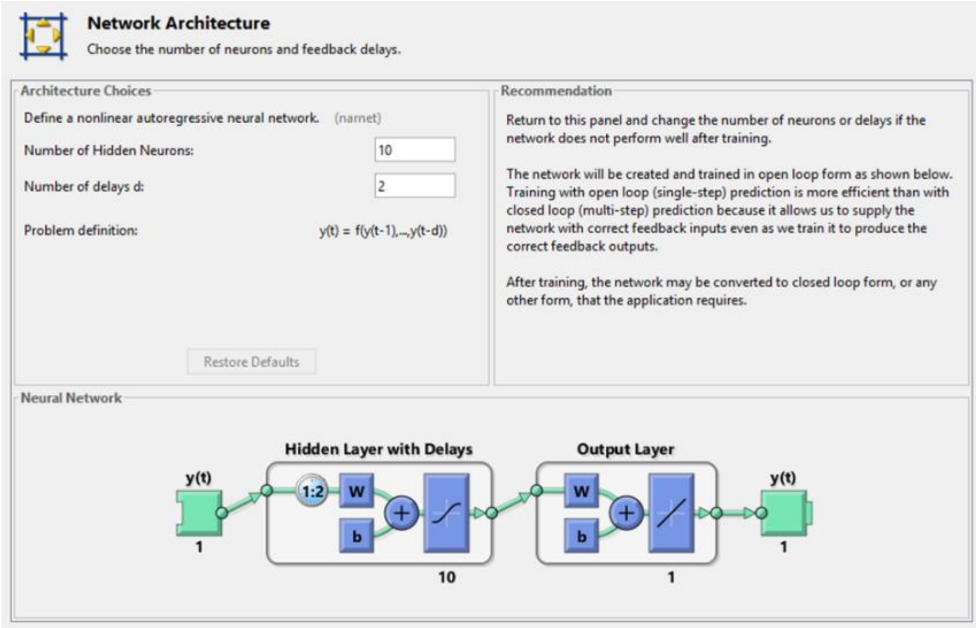
Source: MatlabR2015a

5.1.4 Neural Network Model Specification Stage:

The neural network used in this study consists of three layers, which are as follows:

- **Input layer:** This layer includes one input neuron, representing the time series of LogGDP.
- **Hidden layer:** This layer is based on the error value used in the network and was automatically configured with a single hidden layer containing 10 neurons.
- **Output layer:** This layer consists of a single output neuron.
- **The default number of delays:** was set to 2, with the possibility of adjustment during network training to enhance performance.

Figure (1-15): Artificial Neural Network Architecture



Source: MatlabR2015a

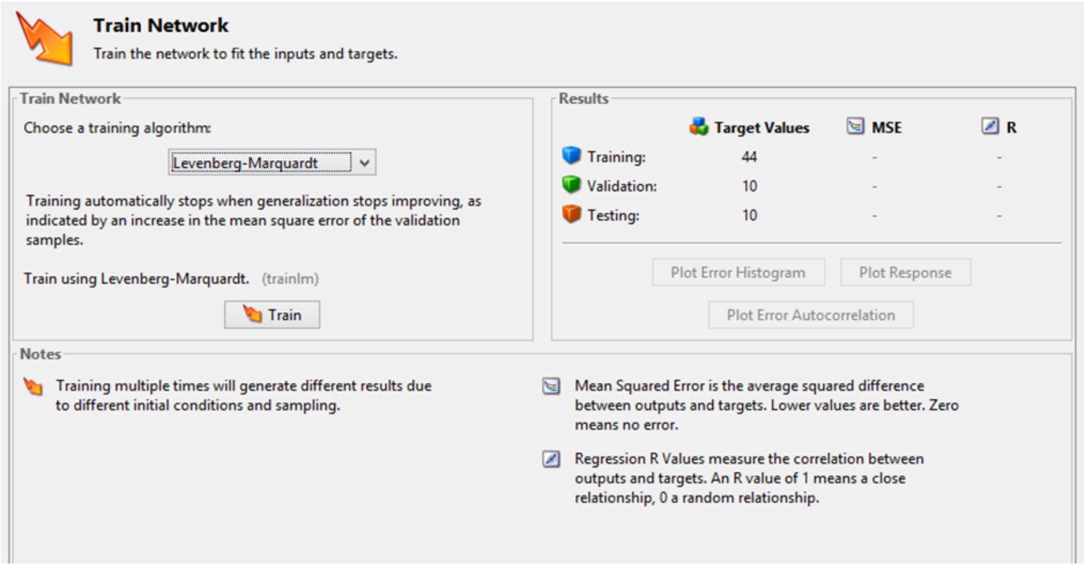
5.1.5 Network Training Stage:

In this stage, the training process options are defined, along with the selection of the learning algorithm and its rate, as well as the determination of the feeding parameter. This stage concludes with the extraction of the final results of the network and the evaluation of the prediction accuracy on both the training and validation datasets. As for the testing or implementation phase, it involves assessing the credibility and accuracy of the network, and this phase includes the following elements:

5.1.6 Training Algorithm Selection:

To train the neural network, the back propagation algorithm known as Levenberg-Marquardt was adopted. This algorithm aims to minimize the Mean Squared Error (MSE) in order to enhance the output efficiency. It is automatically selected within MATLAB R2015a, as illustrated in the following figure:

Figure (1-16): Training the neural network using the Levenberg-Marquardt algorithm



Source: MatlabR2015a

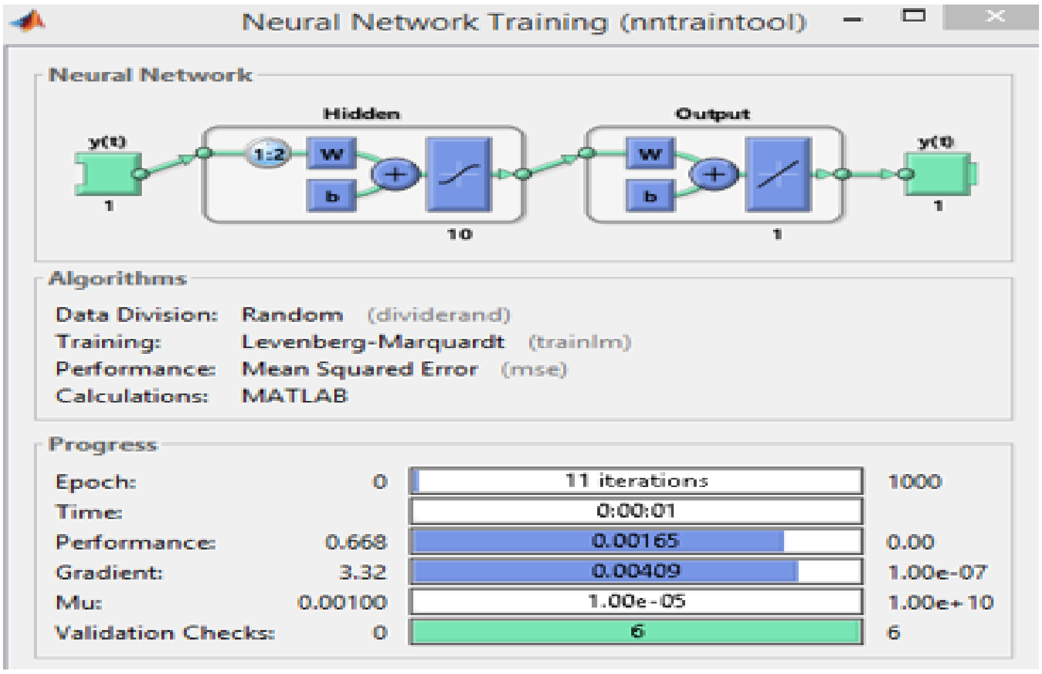
5.1.7 Model Training:

This refers to finding the set of weights between the neurons that yields the lowest value of the Mean Squared Error (MSE), which measures the random prediction error. The smaller the MSE value, the better the predictive capability of the network. To evaluate the training performance of the network, the correlation coefficient (R) was also used, as it reflects the measured relationship between the targets and the outputs. The closer this value is to one, the stronger the relationship.

5.1.8 Implementation:

The network is tested in terms of its ability to adapt to changes, and there is also the possibility of retraining in order to achieve the lowest possible mean squared error.
The following figure illustrates the network training process and its characteristics:

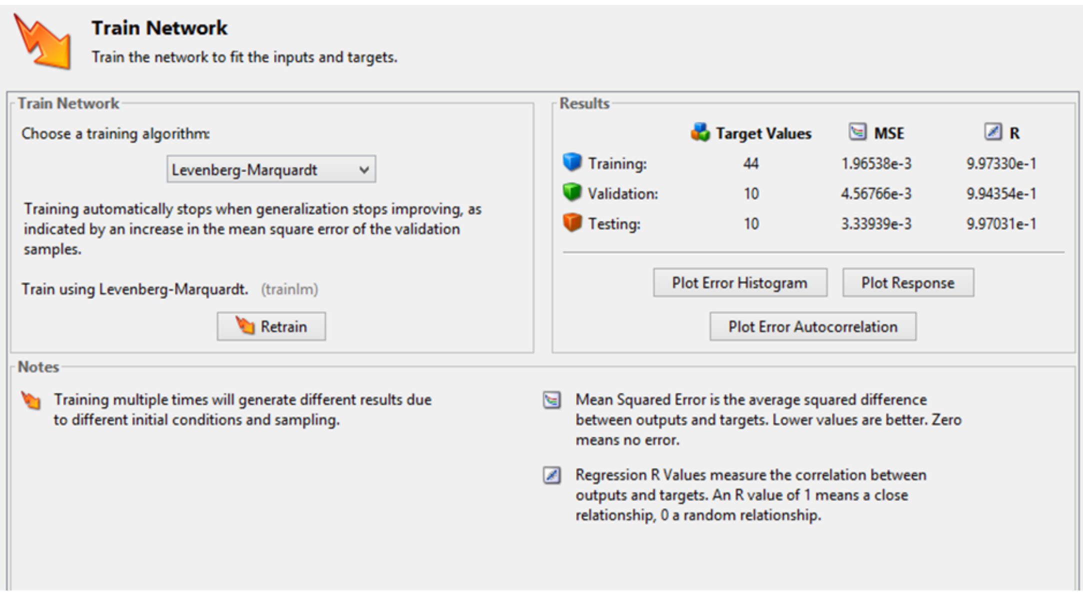
Figure (1-17): Characteristics of the Artificial Neural Network Training Process



Source: MatlabR2015a

The results of the training process are presented in the following figure:

Figure (1-18): Results of the Artificial Neural Network Training Process



Source: MatlabR2015a

The correlation coefficient measures the strength of the relationship between the targets and the outputs; the closer the value is to one, the stronger the relationship. The results presented in the figure above indicate a strong relationship between the outputs and the targets, as the values were as follows:

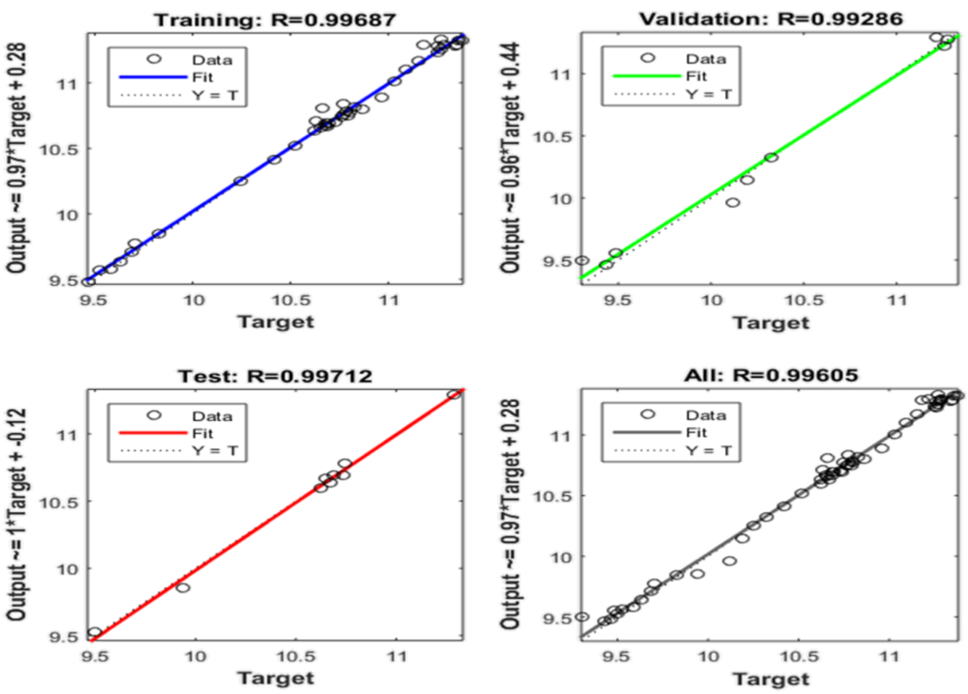
-Training criterion: R=0, 997330

-Validation criterion: R=0, 994354

-Testing criterion: R=0, 997031

The next step involves validating the network by generating a regression plot that illustrates the relationship between the network outputs and the target values.

Figure (1-19): Regression plots for training, validation, and testing

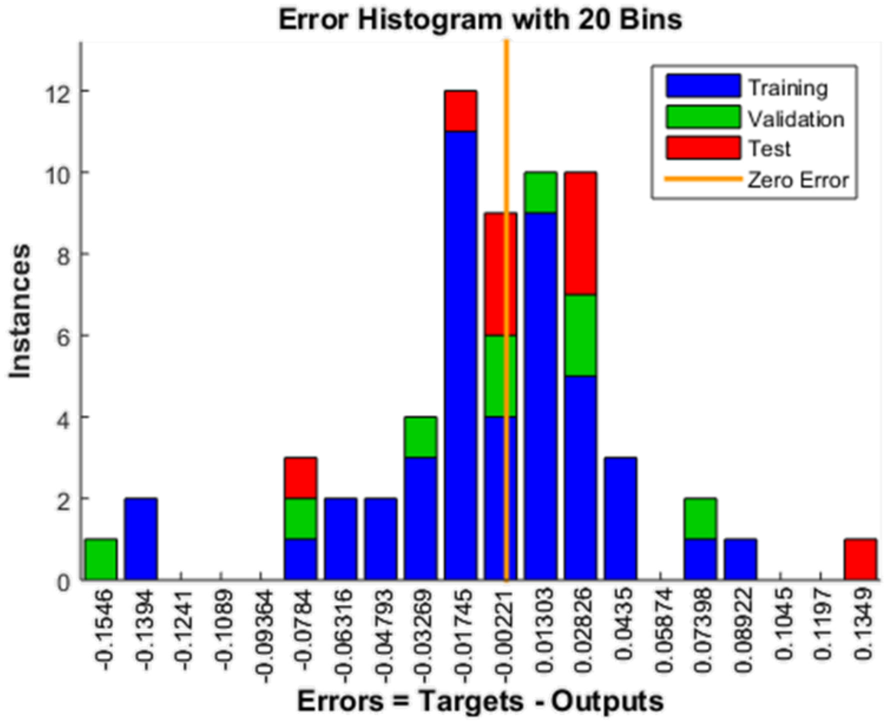


Source: Prepared based on MatlabR2015a

From Figure (1-19), it is observed that the strength of the relationship between the outputs and the targets in the three data subsets, as well as for the overall trained network, is close to one. This indicates the efficiency of the network training and the quality of its learning process. This is further confirmed by the overall correlation coefficient R=0.99605, which reflects the network's strong ability to predict the logarithm of the Gross Domestic Product (LogGDP).

Through the histogram in the figure (1-20), we observe that the network errors have decreased with increased training. They are symmetrical with respect to the zero axis, which means there is no problem with the structure we want to predict.

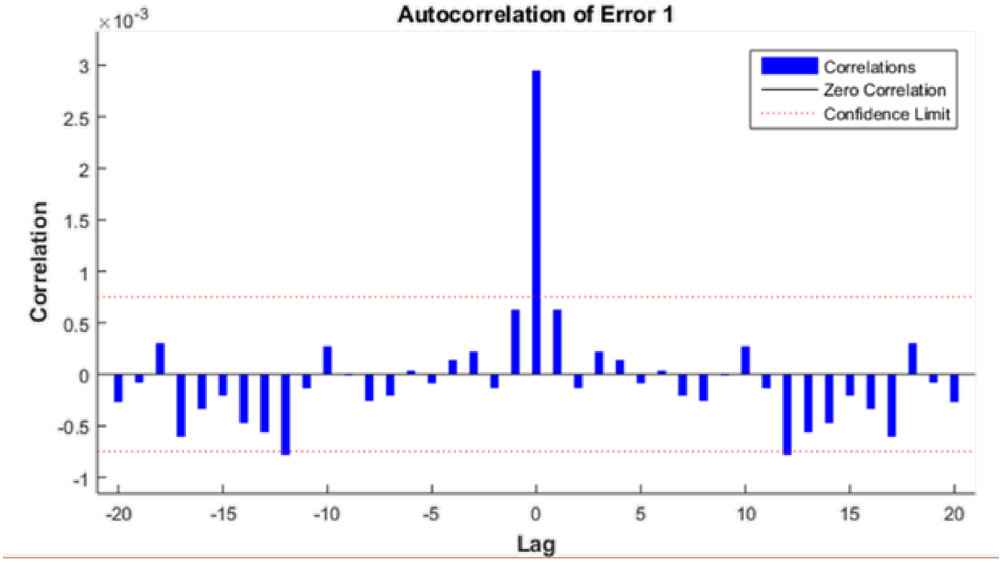
Figure (1-20): Error histogram



Source: Prepared based on MatlabR2015a

From Figure (1-21), we observe that all values of the autocorrelation function lie within the confidence bounds, indicating that the prediction errors are not autocorrelated.

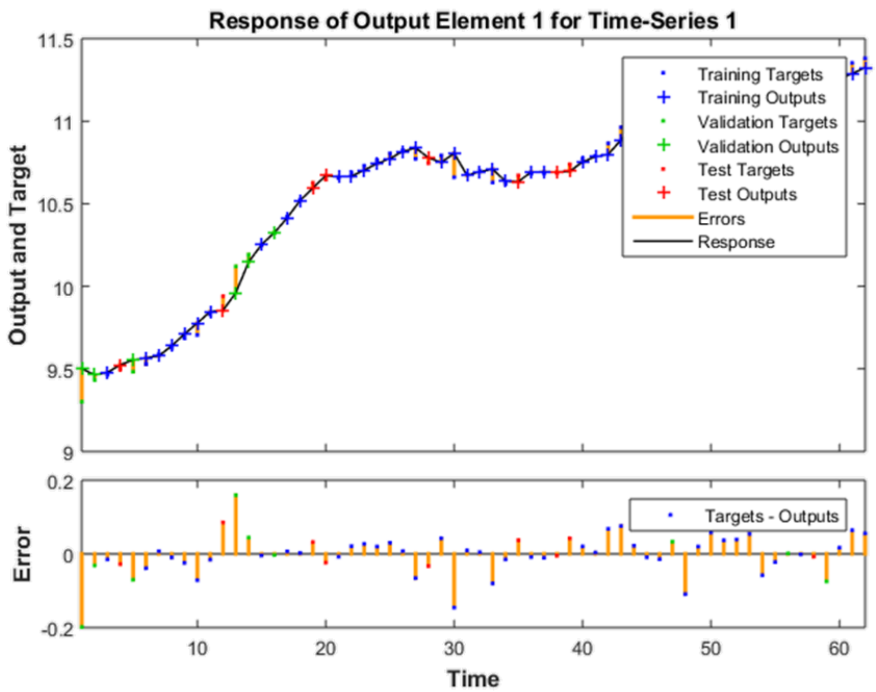
Figure (1-21): Error autocorrelation function



Source: Prepared based on MatlabR2015a

Based on the training process outputs, the following presents the time series responses of the inputs, targets, and errors over time. Figure (1-22) indicates the time points selected for training, validation, and testing

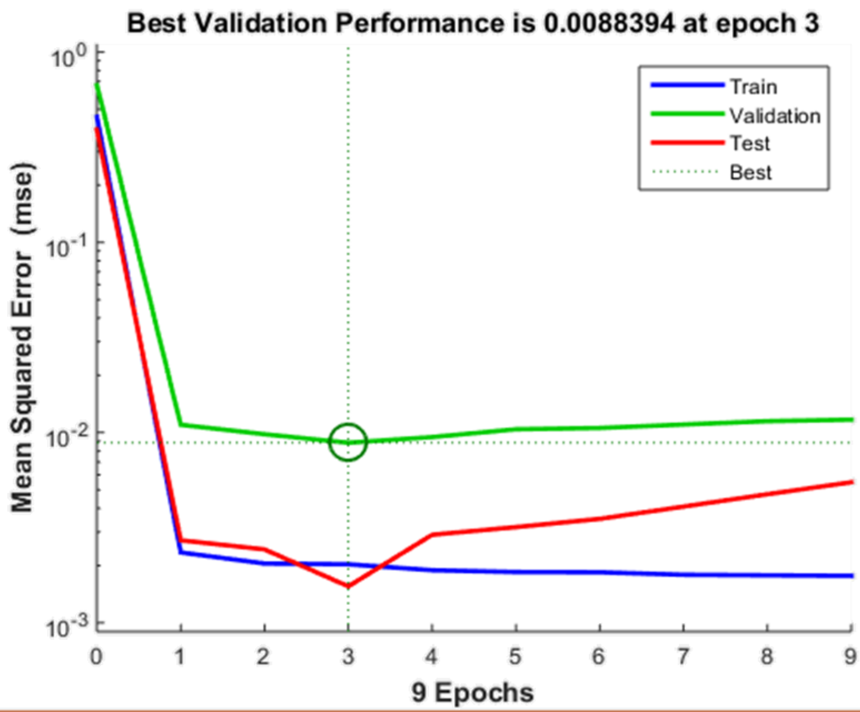
Figure (1-22): Time series response of inputs, targets, and errors over time



Source: Prepared based on MatlabR2015a

The following figure (1-23) shows that the training, validation, and testing errors (MSE) decrease until the specified point (point 3). It does not appear that any change occurred afterward, as the validation error did not increase before this point

Figure (1-23): Training performance record used to detect potential overfitting

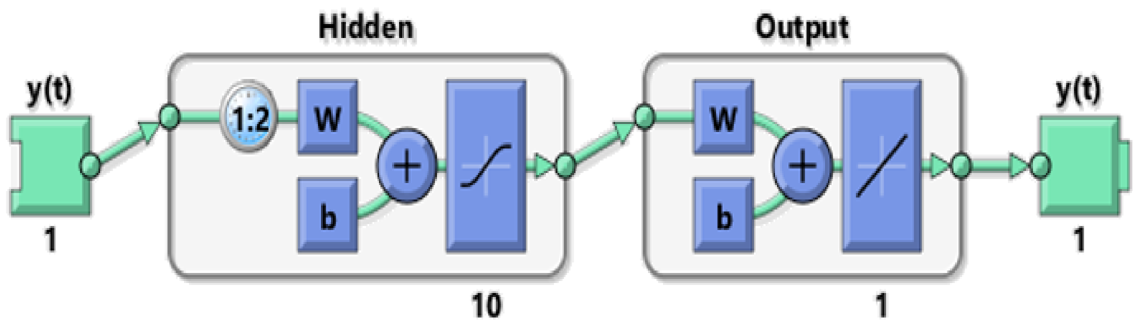


Source: Prepared based on MatlabR2015a

5. 2 forecasting the Time Series under Study using Artificial Neural Networks:

From the above, it is clear that the obtained network is acceptable and does not require retraining. Therefore, the network is ready for the prediction process, as shown in the following figure.

Figure (1-24): Readiness of the artificial neural network for forecasting



Source: Prepared based on MatlabR2015a

The previous figure shows that the optimal artificial neural network obtained is ANN (1.10.1), which consists of one input layer with a single processing unit, one hidden layer with 10 processing units, and one output layer with a single processing unit, with a delay order set to 2.

The following table (1-11) presents the predicted values of the logarithm of Gross Domestic Product (LogGDP) for the period 2024–2028, using artificial neural networks.

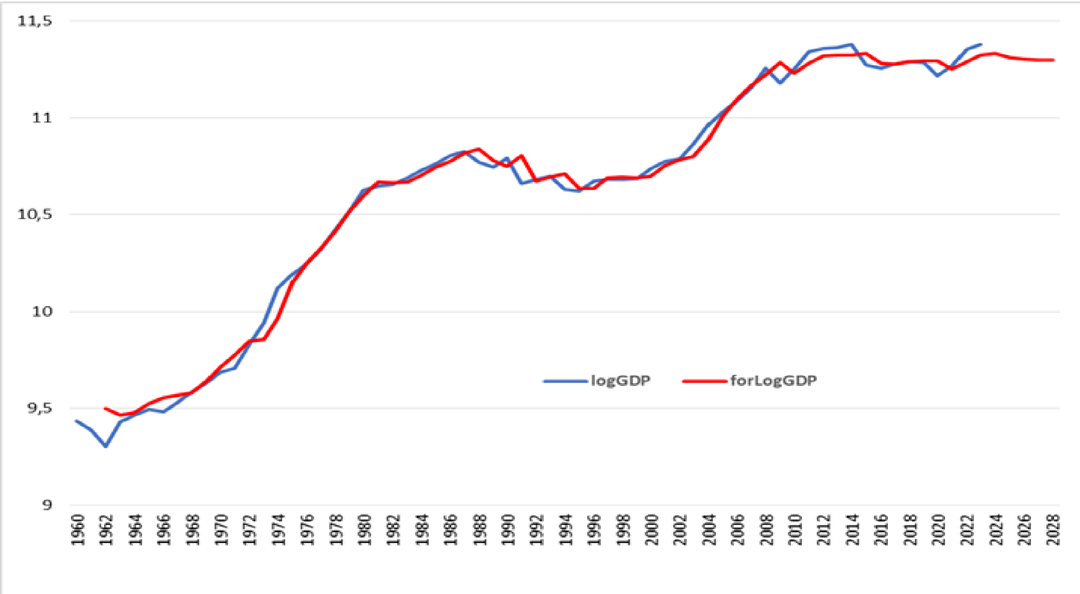
Table (1-11): Forecasted Values Using the ANN methodology for the Period (2024–2028)

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

Graphically, the forecast values can be represented in the following Figure:

Figure (1-25): Tracking the original log(GDP) series using the predicted series forLogGDP



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

From Figure (1-25), which illustrates the tracking of the original LogGDP series by the predicted series forLogGDP, it is evident that the predicted values closely resemble the actual values, as demonstrated by the near overlap between the curves of the original and predicted series. This reflects the network's ability to compute accurate outputs based on the weights obtained during the training phase. Therefore, the resulting network can be considered reliable for generating future forecasts of the logarithm of Gross Domestic Product in the upcoming period.

- The results previously discussed were obtained through the execution of a custom code developed in MATLAB R2015a, with the full script presented in (**Appendix N^2, Pages 102 to 105)**

5. 3 measuring the forecasting accuracy using artificial neural networks:

To verify the accuracy of the forecasting model, MATLAB R2015a was used to calculate forecast accuracy metrics, and the results are presented in the following figure.

Figure (1-26): Output of forecast accuracy metrics calculation using Matlab R2015a

```
>> errors = actual - predicted;
mseVal = mean(errors.^2);
rmseVal = sqrt(mseVal);
maeVal = mean(abs(errors));
mapeVal = mean(abs(errors ./ actual)) * 100;
meVal = mean(errors);
>> fprintf('MSE   = %.18f\n', mseVal);
fprintf('RMSE  = %.18f\n', rmseVal);
fprintf('MAE   = %.18f\n', maeVal);
fprintf('MAPE  = %.18f\n', mapeVal);
fprintf('ME    = %.18f\n', meVal);
MSE   = 0.002950042063241799
RMSE  = 0.054314289678148227
MAE   = 0.037911067580645247
MAPE  = 0.361300214850025281
ME    = -0.000884245709677543
```

Source: Prepared based on Matlab R2015a

The results obtained from MATLAB R2015a regarding forecast accuracy metrics are summarized in the following table:

Table (1-12): 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

The results of the forecast accuracy indicators showed that:

- The mean squared error (MSE) was 0.0029, which is a very low value, indicating that the difference between the predicted and actual values is small.
- The root mean square error (RMSE) was 0.0543, which is a small value and indicates that the deviation between the actual and predicted values is low.
- The mean absolute error (MAE) was 0.0379, which is a very low value, indicating that the difference between the actual and predicted values was minimal on average.
- The mean absolute percentage error (MAPE) was approximately 0.3613%, which is a low percentage (error rate less than 1%), reflecting an excellent level of prediction accuracy.
- The mean error (ME) is -0.00088, which is a negative and very small value. This indicates that the model slightly tends to underestimate the predicted values, although this effect is negligible.

❖ Overall, these results show that the model has a high level of accuracy and can be reliably trusted for the prediction process.

6. Comparison between the Results of the Box-Jenkins Methodology and Artificial Neural Networks:

After applying both the Box-Jenkins methodology and the Artificial Neural Network (ANN) approach to the time series of the logarithm of Algeria's Gross Domestic Product (LogGDP) over the period from 1960 to 2023, it was concluded that both methodologies are applicable to the series under study. Each of them provides forecasts that are close to reality and demonstrate a high level of accuracy. Therefore, a comparison will be conducted between the forecasting results of both methods based on forecasting accuracy indicators

In order to compare the Box-Jenkins methodology and Artificial Neural Networks (ANN), the following evaluation metrics were used: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean

Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Mean Error (ME).

In addition, the weighted average of the three key indicators (MAE, RMSE, and MAPE) was also considered, which is calculated as follows:

WA1= (MAE+RMSE+4*MAPE)/6

WA2= (MAE+4*RMSE+MAPE)/6

WA3= (4*MAE+RMSE+MAPE)/6

The following table presents the forecast accuracy evaluation metrics along with the weighted average of the three key indicators.

Table (1-13): 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

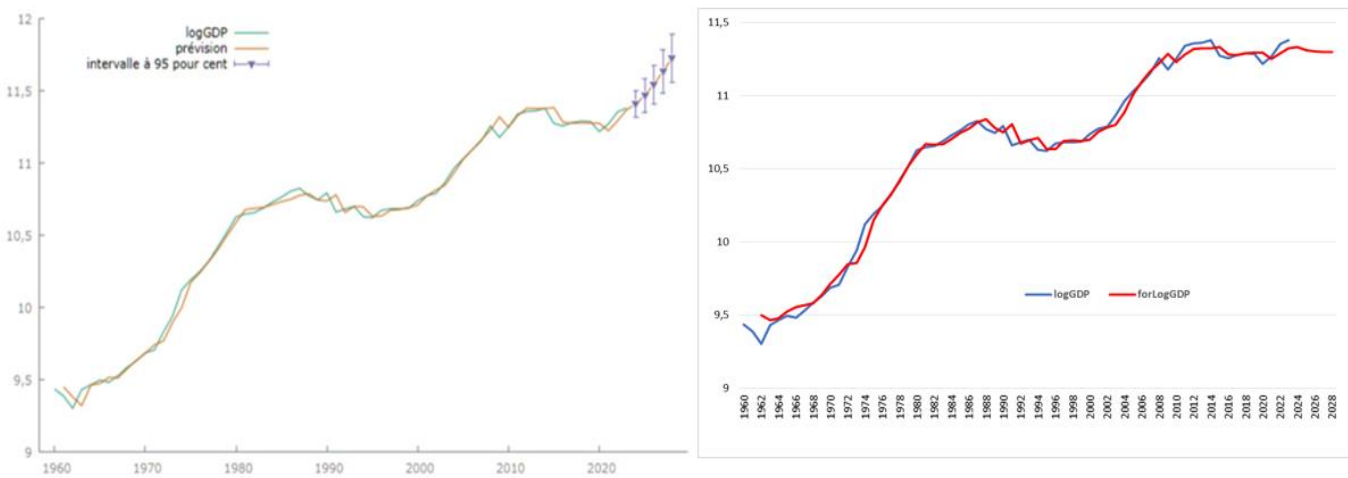
Source: Prepared by the two students

The results presented in Table (1-13) show that the values of the following indicators: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean

Squared Error (MSE), and the Weighted Average were all lower in the Box-Jenkins methodology compared to their values in the Artificial Neural Network (ANN) methodology. The only exception was the Mean Error (ME), which was lower in the ANN methodology than in the Box-Jenkins approach. This indicates the superiority of the Box-Jenkins methodology
(ARIMA (3.1.4)) in forecasting. This conclusion is further supported by tracking the behavior of the original LogGDP series against the predicted series using both ANN and ARIMA methodologies, as illustrated in the following figure.

Figure (1-27): Comparative Evaluation between the ANN and ARIMA Models

ARIMA (3.1.4) ANN(1.10.1)



Source: Prepared based on Gretl 2024d and MatlabR2015a

From Figure (1-27), it is clear that the graph of the original series and the forecasted series using the
Box-Jenkins model (ARIMA (3.1.4)) demonstrates better forecasting accuracy compared to the ANN (1.10.1) model. This is because the ARIMA model shows a stronger ability to follow the original LogGDP series, particularly by capturing its turning points.

- Therefore, based on both the forecast accuracy indicators and the graphical representation, it can be concluded that the most suitable forecasting methodology for our data represented by the time series of the logarithm of Gross Domestic Product is the Box-Jenkins methodology, specifically the ARIMA (3.1.4) model.

Summary of the Chapter two:

Based on what has been discussed in this chapter, it is evident that forecasting Gross Domestic Product (GDP) relies on classical statistical models, particularly the Box-Jenkins methodology, which is used to analyze and forecast time series through stages that include identifying the appropriate model, estimating it, testing its adequacy, and then carrying out the forecasting process. Artificial Neural Networks (ANNs) have also emerged as one of the applications of artificial intelligence, where forecasting using this approach involves selecting variables, processing data, dividing it into sets, identifying the model used for training the network, training the network, and finally, implementation. By applying both methodologies to Algeria's GDP time series for the period (1960–2023), it was found that both approaches yield good results and accurate forecasts. However, based on forecast accuracy indicators, the Box-Jenkins methodology (ARIMA (3,1,4)) provided more accurate results compared to the artificial neural network model (ANN (1,10,1)). Therefore, the Box-Jenkins methodology is considered more suitable for forecasting GDP in Algeria.

CONCLUSION

There are many variables whose future values can be predicted, among which is the Gross Domestic Product (GDP), one of the most important indicators reflecting the health of an economy. Given the significance of this indicator in supporting economic growth, the need has emerged to adopt precise and effective quantitative methods for analyzing its future trajectory.

In this context, the present study seeks to address a key research problem: assessing the effectiveness of Box-Jenkins models compared to Artificial Neural Networks (ANNs) in forecasting the Gross Domestic Product (GDP) in Algeria. This is achieved through a comparative approach between a traditional methodology (Box-Jenkins models) and a modern methodology based on artificial intelligence techniques (ANNs). Based on the hypotheses formulated at the beginning of this study, we proceed to evaluate their validity in the following sections.

The first hypothesis posited that Algeria's GDP has witnessed increasing growth during the period 1960–2023, with variation in the dynamics of this growth across time periods. This hypothesis was confirmed through statistical analysis of the GDP series. The GDP curve displayed a general upward trend, especially after 2000, despite cyclical fluctuations due to economic crises such as the 2020 COVID-19 pandemic.

The second hypothesis stated that the Box-Jenkins methodology is capable of achieving high forecasting accuracy. This was validated through the application of the Box-Jenkins methodology to the logarithmic GDP time series in Algeria during the period 1960–2023. Upon completing all stages of the methodology, the results showed high-quality and accurate forecasts, supported by forecasting accuracy metrics.

As for the third and final hypothesis, which asserted that the preference between Box-Jenkins and ANN methodologies should be based on forecasting accuracy, this was also confirmed. After applying both methodologies to the logarithmic GDP time series and conducting a comparative analysis using forecasting accuracy metrics and the weighted average, it was found that the Box-Jenkins methodology yielded more accurate future values with fewer errors and a lower weighted average. Therefore, the Box-Jenkins approach was found to be the most appropriate and suitable method for forecasting GDP in Algeria.

Following the confirmation of the study's hypotheses, the following key findings were obtained:

- Applying the Box-Jenkins methodology to the logarithmic GDP series demonstrated that it produces highly accurate and reliable forecasts, as reflected in the obtained forecasting accuracy indicators.
- The predicted values generated by the ANN model were close to the actual values, indicating the model's ability to produce precise forecasts.
- Based on forecasting accuracy indicators and the weighted average used to compare the ARIMA(3,1,4) and ANN(1,10,1) models in forecasting logarithmic GDP, the Box-Jenkins methodology was shown to provide more accurate and higher-quality results compared to Artificial Neural Networks. Thus, it is considered the most suitable and effective method for forecasting Algeria's GDP time series.

Based on these findings, the following recommendations are proposed:

- Governments should support the use of modern quantitative models in analyzing and tracking the trajectory of Algeria's GDP, given their importance in improving the accuracy of economic decision-making.
- Greater attention should be directed toward both the Box-Jenkins methodology and Artificial Neural Networks by applying them to forecasting key economic indicators, especially GDP, with a stronger emphasis on the Box-Jenkins method due to its superior forecasting performance in this study.

- Hybrid statistical approaches such as ARIMA-ANN should be used, as they are capable of addressing both linear and nonlinear patterns present in time series data.
- The scope of the study should be expanded to include additional economic variables related to GDP, such as investment and government expenditure.
- When applying two different methodologies in a comparative study, multiple and diverse evaluation criteria should be adopted to ensure more accurate model selection.

Based on the above recommendations, several research prospects emerge that could serve as scientific extensions of this work, including:

- Studying the impact of economic crises on GDP behavior using advanced forecasting methodologies.
- Expanding the scope of the analysis to include other economic variables related to economic growth, such as investment and unemployment.
- Forecasting GDP by applying hybrid models that combine the Box-Jenkins methodology with deep neural networks.

APPENDICES

Appendix N[1]: Gross Domestic Product in Algeria during the period 1960-2023

Year	➢ GDP	❖ LogGDP
1960	2723615451	9,4351458
1961	2434747056	9,3864538
1962	2001444544	9,3013436
1963	2702982018	9,4318432
1964	2909316435	9,463791
1965	3136284307	9,4964154
1966	3039859187	9,4828535
1967	3370870376	9,5277421
1968	3852147027	9,5857029
1969	4257253264	9,6291295
1970	4863526897	9,6869513
1971	5077183094	9,7056228
1972	6766743957	9,8303797
1973	8707858912	9,9399114
1974	1,321E+10	10,120899
1975	1,5558E+10	10,191951
1976	1,7728E+10	10,248666
1977	2,0972E+10	10,321642
1978	2,6364E+10	10,421019
1979	3,3244E+10	10,521709
1980	4,2346E+10	10,626811
1981	4,4349E+10	10,64688
1982	4,5207E+10	10,655207
1983	4,8801E+10	10,688432
1984	5,3699E+10	10,729963

1985	5,7938E+10	10,762963
1986	6,3692E+10	10,804085
1987	6,6746E+10	10,824424
1988	5,9089E+10	10,77151
1989	5,5635E+10	10,745346
1990	6,2049E+10	10,792731
1991	4,5716E+10	10,660065
1992	4,8003E+10	10,68127
1993	4,9946E+10	10,698497
1994	4,2543E+10	10,62883
1995	4,1764E+10	10,620805
1996	4,6942E+10	10,671557
1997	4,8178E+10	10,682845
1998	4,8188E+10	10,682937
1999	4,8641E+10	10,687
2000	5,479E+10	10,738704
2001	5,9413E+10	10,773884
2002	6,1516E+10	10,788989
2003	7,3482E+10	10,866183
2004	9,1914E+10	10,96338
2005	1,0705E+11	11,029573
2006	1,2308E+11	11,090203
2007	1,4248E+11	11,153762
2008	1,8038E+11	11,256198
2009	1,5032E+11	11,177009
2010	1,77785E+11	11,249895
2011	2,1833E+11	11,339117
2012	2,2714E+11	11,356301

2013	**2,297E+11**	**11,361164**
2014	**2,3894E+11**	**11,378294**
2015	**1,8749E+11**	**11,272987**
2016	**1,8076E+11**	**11,257112**
2017	**1,8988E+11**	**11,278481**
2018	**1,9455E+11**	**11,289041**
2019	**1,9346E+11**	**11,28659**
2020	**1,6487E+11**	**11,217151**
2021	**1,8627E+11**	**11,270132**
2022	**2,2556E+11**	**11,353263**
2023	**2,399E+11**	**11,380029**

Source:

- World Bank Data. Retrieved from: https://donnees.banquemondiale.org/indicateur/NY.GDP.MKTP.KD.ZG?locations=DZ
- Prepared based on Excel

Appendix N^2: Artificial Neural Network Programming Code in Matlab R2015a

```
% Solve an Autoregression Time-Series Problem with a NAR
Neural Network
% Script generated by Neural Time Series app
% Created 17-Apr-2025 15:50:32
%
% This script assumes this variable is defined:
%
%   logGDP - feedback time series.

T = tonndata(logGDP,false,false);

% Choose a Training Function
% For a list of all training functions type: help nntrain
% 'trainlm' is usually fastest.
% 'trainbr' takes longer but may be better for challenging
problems.
% 'trainscg' uses less memory. Suitable in low memory
situations.
trainFcn = 'trainlm';  % Levenberg-Marquardt backpropagation.

% Create a Nonlinear Autoregressive Network
feedbackDelays = 1:2;
hiddenLayerSize = 10;
net = narnet(feedbackDelays,hiddenLayerSize,'open',trainFcn);

% Choose Feedback Pre/Post-Processing Functions
% Settings for feedback input are automatically applied to
feedback output
% For a list of all processing functions type: help nnprocess
net.input.processFcns = {'removeconstantrows','mapminmax'};

% Prepare the Data for Training and Simulation
% The function PREPARETS prepares timeseries data for a
particular network,
% shifting time by the minimum amount to fill input states and
layer
% states. Using PREPARETS allows you to keep your original
time series data
% unchanged, while easily customizing it for networks with
differing
% numbers of delays, with open loop or closed loop feedback
modes.
[x,xi,ai,t] = preparets(net,{},{},T);

% Setup Division of Data for Training, Validation, Testing
% For a list of all data division functions type: help
nndivide
```

```
net.divideFcn = 'dividerand';  % Divide data randomly
net.divideMode = 'time';  % Divide up every sample
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;

% Choose a Performance Function
% For a list of all performance functions type: help
nnperformance
net.performFcn = 'mse';  % Mean Squared Error

% Choose Plot Functions
% For a list of all plot functions type: help nnplot
net.plotFcns = {'plotperform','plottrainstate', 'ploterrhist',
...
    'plotregression', 'plotresponse', 'ploterrcorr',
'plotinerrcorr'};

% Train the Network
[net,tr] = train(net,x,t,xi,ai);

% Test the Network
y = net(x,xi,ai);
e = gsubtract(t,y);
performance = perform(net,t,y)

% Recalculate Training, Validation and Test Performance
trainTargets = gmultiply(t,tr.trainMask);
valTargets = gmultiply(t,tr.valMask);
testTargets = gmultiply(t,tr.testMask);
trainPerformance = perform(net,trainTargets,y)
valPerformance = perform(net,valTargets,y)
testPerformance = perform(net,testTargets,y)

% View the Network
view(net)

% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, ploterrhist(e)
%figure, plotregression(t,y)
%figure, plotresponse(t,y)
%figure, ploterrcorr(e)
%figure, plotinerrcorr(x,e)

% Closed Loop Network
% Use this network to do multi-step prediction.
```

```
% The function CLOSELOOP replaces the feedback input with a
direct
% connection from the outout layer.
netc = closeloop(net);
netc.name = [net.name ' - Closed Loop'];
view(netc)
[xc,xic,aic,tc] = preparets(netc,{},{},T);
yc = netc(xc,xic,aic);
closedLoopPerformance = perform(net,tc,yc)

% Multi-step Prediction
% Sometimes it is useful to simulate a network in open-loop
form for as
% long as there is known data T, and then switch to closed-
loop to perform
% multistep prediction. Here The open-loop network is
simulated on the
% known output series, then the network and its final delay
states are
% converted to closed-loop form to produce predictions for 5
more
% timesteps.
[x1,xio,aio,t] = preparets(net,{},{},T);
[y1,xfo,afo] = net(x1,xio,aio);
[netc,xic,aic] = closeloop(net,xfo,afo);
[y2,xfc,afc] = netc(cell(0,5),xic,aic);
% Further predictions can be made by continuing simulation
starting with
% the final input and layer delay states, xfc and afc.

% Step-Ahead Prediction Network
% For some applications it helps to get the prediction a
timestep early.
% The original network returns predicted y(t+1) at the same
time it is
% given y(t+1). For some applications such as decision making,
it would
% help to have predicted y(t+1) once y(t) is available, but
before the
% actual y(t+1) occurs. The network can be made to return its
output a
% timestep early by removing one delay so that its minimal tap
delay is now
% 0 instead of 1. The new network returns the same outputs as
the original
% network, but outputs are shifted left one timestep.
nets = removedelay(net);
nets.name = [net.name ' - Predict One Step Ahead'];
view(nets)
[xs,xis,ais,ts] = preparets(nets,{},{},T);
```

```
ys = nets(xs,xis,ais);
stepAheadPerformance = perform(nets,ts,ys)

% Deployment
% Change the (false) values to (true) to enable the following
code blocks.
% See the help for each generation function for more
information.
if (false)
    % Generate MATLAB function for neural network for
application
    % deployment in MATLAB scripts or with MATLAB Compiler and
Builder
    % tools, or simply to examine the calculations your
trained neural
    % network performs.
    genFunction(net,'myNeuralNetworkFunction');
    y = myNeuralNetworkFunction(x,xi,ai);
end
if (false)
    % Generate a matrix-only MATLAB function for neural
network code
    % generation with MATLAB Coder tools.

genFunction(net,'myNeuralNetworkFunction','MatrixOnly','yes');
    x1 = cell2mat(x(1,:));
    xi1 = cell2mat(xi(1,:));
    y = myNeuralNetworkFunction(x1,xi1);
end
if (false)
    % Generate a Simulink diagram for simulation or deployment
with.
    % Simulink Coder tools.
    gensim(net);
end
```

Source: Prepared by the two students based on Matlab R2015a

Appendix N[3]: Actual and Forecasted Values of GDP Using ARIMA and ANN Models

Year	➢ GDP	❖ Forecasted GDP Using the ARIMA Model	❖ Forecasted GDP Using the ANN Model
1960	2723615451	-	-
1961	2434747056	2820031763,28	-
1962	2001444544	2395631417,48	3161541722,53
1963	2702982018	2093080829,41	2907402326,37
1964	2909316435	2902257886,46	3011281367,61
1965	3136284307	2976795496,61	3344650112,07
1966	3039859187	3280061600,78	3573022179,68
1967	3370870376	3253973411,82	3686287447,98
1968	3852147027	3761837227,91	3788617633,26
1969	4257253264	4303254187,13	4354021030,61
1970	4863526897	4806135380,91	5145294884,53
1971	5077183094	5503855205,10	5982642802,73
1972	6766743957	5858548100,97	7015527255,59
1973	8707858912	7891635176,79	7155186691,18
1974	1,321E+10	9966576394,39	9144288629,81
1975	1,5558E+10	14901157325,72	14045105300,15
1976	1,7728E+10	17384091532,09	17900079170,40
1977	2,0972E+10	20809373247,61	21124622056,73
1978	2,6364E+10	25165119671,25	25959396585,94
1979	3,3244E+10	31497566389,66	33092022705,71
1980	4,2346E+10	38800739244,95	39339911436,18
1981	4,4349E+10	47581266747,61	46819217236,97
1982	4,5207E+10	48452144080,69	45986106152,83
1983	4,8801E+10	49232965968,40	46530933928,08
1984	5,3699E+10	51533424124,52	50449597512,99
1985	5,7938E+10	54035602719,14	55372613497,17
1986	6,3692E+10	55976662379,44	59411349015,08

1987	6,6746E+10	59730616875,30	65587053432,82
1988	5,9089E+10	61326333440,21	68805277480,02
1989	5,5635E+10	55461294237,60	60042895202,61
1990	6,2049E+10	54579430527,16	56265339422,54
1991	4,5716E+10	60134125551,46	63941593940,49
1992	4,8003E+10	45459745493,81	46980697517,19
1993	4,9946E+10	50057020971,06	49420673821,81
1994	4,2543E+10	49621055728,00	51194347550,32
1995	4,1764E+10	42734635101,70	43239831130,11
1996	4,6942E+10	42909059937,11	43086522658,88
1997	4,8178E+10	46984217685,90	49146268057,81
1998	4,8188E+10	47647816112,50	49384000698,93
1999	4,8641E+10	48965478176,26	49191254952,68
2000	5,479E+10	51201301433,12	49692912526,31
2001	5,9413E+10	59070003963,74	56690052432,86
2002	6,1516E+10	65044113653,70	60964798598,72
2003	7,3482E+10	70023691159,25	62874521620,77
2004	9,1914E+10	85517303814,36	77165215840,78
2005	1,0705E+11	105817866247,03	101728039552,47
2006	1,2308E+11	123584498622,18	125660768743,66
2007	1,4248E+11	144370679319,04	147306847716,34
2008	1,8038E+11	168512452777,13	167143524445,64
2009	1,5032E+11	208630116226,03	193410180391,84
2010	1,77785E+11	176220731627,55	169907021723,51
2011	2,1833E+11	212286315806,10	191021179280,47
2012	2,2714E+11	238931824823,59	208708362139,10
2013	2,297E+11	238055927659,60	210102200626,96
2014	2,3894E+11	237889350182,12	210835760959,23
2015	1,8749E+11	241450995315,54	214296075755,94
2016	1,8076E+11	191478051761,07	190244207962,05
2017	1,8988E+11	188781311981,92	189344506532,21

2018	1,9455E+11	189897829126,99	195020561300,47
2019	1,9346E+11	189507324410,00	196788222040,26
2020	1,6487E+11	188157701861,05	195880070356,61
2021	1,8627E+11	167083667693,64	179124466519,55
2022	2,2556E+11	195531620691,61	194470561319,54
2023	2,399E+11	233011845722,02	211000895157,53
2024	-	256215854411,29	214732231116,72
2025	-	292266473914,56	203999212761,30
2026	-	349548948468,88	200001377936,15
2027	-	428714329730,77	198624793672,56
2028	-	530851440278,53	198180642460,73

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