

Modeling and forecasting of Afghanistan's GDP, Using ARIMA Model

Abdul Wahid Naderi

Research Scholar

Department of P.G Studies and Research in Economics

Mangalore University 574199

Dr. Jayavantha Nayak

Professor

Department of Economics University College-574001

ABSTRACT

This paper aims to provide a comprehensive analysis of Afghanistan's Gross Domestic Product (GDP) and to identify a suitable model for forecasting GDP using the Auto-Regressive Integrated Moving Average (ARIMA) methodology. The study utilizes 21 years of annual GDP data, spanning from 2002 to 2023, sourced from the World Bank. Based on the analysis, the researchers identify ARIMA (0, 1, 0) as the most suitable model for forecasting. The projected values indicate that Afghanistan's GDP growth is expected to continue rising in the coming years, as suggested by the statistical results.

Keywords: Stationary Time Series, GDP, Forecasting, ARIMA, Model.

1. Introduction:

Afghanistan's economy has faced significant volatility over the past decades, shaped by both internal and external factors that make accurate GDP forecasting particularly challenging. With its economy primarily dependent on agriculture, international aid, and remittances, forecasting tools are essential for planning and policy making in Afghanistan. Growth Domestic Product (GDP) is one of the most widely used indicators of a country's economic health and an essential measure of its overall economic performance. A sustained economic growth enables nations to reduce poverty, create employment opportunities, and invest in critical sectors such as education, healthcare, and infrastructure Nikzad and Thippeswamy (2004). However, achieving consistent growth requires the effective utilization of resources, sound policymaking, and the ability to adapt to global economic dynamics. For developing economies like Afghanistan, economic growth is not only a measure of progress but also a crucial element in fostering stability and resilience amid challenges such as dependency on foreign aid, political instability, and external shocks. Understanding and forecasting economic growth patterns is essential for designing strategies that promote sustainable development and long-term prosperity. Therefore, analyzing GDP through empirical modeling supports timely adjustments in government policies and plays a critical role in guiding the development of economic strategies.

The Autoregressive Integrated Moving Average (ARIMA) & Autoregressive Moving Average (AMA) models are recognized for its ability to forecast time series data, making it an ideal method for analyzing Afghanistan's GDP trends. ARIMA's flexibility allows it to adapt to the seasonal and non-seasonal variations often seen in Afghanistan's economy. Box and Jenkins (1970) model identification approach is also used for the initial determination of the appropriate model. The core concept of this method involves visually assessing the truncation and trailing patterns of the time series by analyzing the autocorrelation and partial correlation function graphs of the sample.

This study addresses the challenges of accurately forecasting Afghanistan's GDP growth, a critical component for informed economic planning and policymaking. Given the country's complex economic dynamics, this research explores the effectiveness of ARIMA models in predicting GDP trends to support evidence-based decision making.

This paper aims to provide a comprehensive review of the literature on the application of ARIMA models for GDP forecasting, with a specific focus on their effectiveness in the context of Afghanistan. Through this review, I seek to assess the model's utility, limitations, and any modifications that may enhance its applicability to Afghanistan's unique economic landscape.

The following sections will explore various studies that have applied ARIMA for GDP forecasting, identify common challenges, and analyze potential improvements relevant to Afghanistan's economic context.

2. Empirical Evidence Overview

In the analysis of univariate time series, ARIMA models are highly versatile and commonly applied. The ARIMA model integrates three key processes: (i) the Autoregressive (AR) process, (ii) the Differencing process, and (iii) the Moving Average (MA) process. These processes are regarded in statistical literature as fundamental models for univariate time series and are frequently utilized across various applications.

2.1. Auto-Regressive (AR) Model

An autoregressive model can be as below;

$$X_t = c + \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \dots + \alpha_p X_{t-p} + \varepsilon_t; \quad t=1,2,\dots,T, \quad (1)$$

In this equation, ε_t represents the error term, which follows a white noise process. This implies that ε_t is a series of independent and identically distributed random variables with an expected value of $E(\varepsilon_t)=0$, and $var(\varepsilon_t)=\sigma_2^2$; i.e. $\varepsilon_t \sim iid N(0, \sigma_2^2)$. In this model, all past values contribute additively to the current level X_t , resulting in a structure that exhibits long-term memory characteristics.

2.2. Moving Average (MA) Model

A moving average (MA) model expresses the current value of a time series as a linear combination of past error terms (random shocks) and a constant. It captures short-term dependencies in the data by smoothing out fluctuations using these error terms.

$$X_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (2)$$

This model is formulated using past errors as explanatory variables, meaning only the errors from the previous q periods influence X_t . Higher-order errors have no impact on X_t , indicating that it is a short-memory model.

2.3. Auto-Regressive Moving Average Model (ARMA)

The Auto Regressive Moving Average (ARMA) model combines two components: autoregressive (AR) and moving average (MA) processes, used to model time series data. The AR part models the relationship between the current value and its previous values, while the MA part captures the relationship between the current value and past forecast errors Box and Jenkins (1970).

$$X_t = c + \alpha_1 X_{t-1} + \dots + \alpha_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \quad (3)$$

This model is a combination of the Auto-regressive model and Moving Average Model.

2.4. Auto-Regressive Integrated Moving Average (ARIMA) Model

ARMA models can be adapted for non-stationary time series by applying differencing, which leads to the ARIMA models. The general non-seasonal form is represented as ARIMA (p, d, q), where p refers to the order of autoregression, d is the degree of differencing, and q is the order of the moving average. For instance, if X_t is a non-stationary series, we first difference X_t to make ΔX_t stationary, resulting in the ARIMA ($p, 1, q$) model.

$$\Delta X_t = c + \alpha_1 \Delta X_{t-1} + \dots + \alpha_p \Delta X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \dots - \theta_q \varepsilon_{t-q} \quad (4)$$

Where $\Delta X_t = X_t - X_{t-1}$. However, if both p and q are equal to zero in equation (4), the model simplifies to a random walk model, which is categorized as ARIMA (0, 1, 0).

3. Review of literature

This literature review combines both empirical and theoretical studies to provide a comprehensive understanding of GDP forecasting and economic growth theories. While theoretical studies provide foundational concepts of economic growth and empirical studies will provide practical applications of GDP forecasting in real-world using ARIMA model.

3.1. Theoretical studies

3.1.1 Classical Economic Growth Theory

This theory developed by early economists such as Adam Smith (1776), David Ricardo (1817), and Thomas Malthus (1), proposes that economic growth arises from the accumulation of capital and labor. However, it argues that growth is ultimately limited by diminishing returns. This theory highlights land, labor, and capital as fundamental inputs, with expansion constrained by factors such as population growth and the finite availability of resources.

3.1.2 Neoclassical Growth Theory

Formulated by Robert Solow and Trevor Swan (1950), this theory highlights technological progress, labor, and capital as primary factors driving economic growth. The Solow-Swan model introduces the idea of a "steady state" and suggests that sustained long-term growth is primarily fueled by external technological advancements rather than solely by increases in capital or labor.

3.1.3 Endogenous Growth Theory

Paul Romer (1980) and Robert Lucas (1990), emphasizes internal economic factors such as human capital, innovation, and knowledge spillovers, which are viewed as endogenous rather than external influences. The theory proposes that sustained economic growth can result from strategic investments in human capital and innovation.

3.1.4 Harrod-Domar Growth Model

Roy Harrod (1939) and Evsey Domar (1946), this model focuses on the link between savings and investment as key drivers of economic growth. It suggests that increased savings lead to greater investment, thereby boosting the growth rate. However, it also underscores possible growth instability arising from mismatches between savings and investment levels.

3.1.5 Schumpeterian Growth Theory

This theory, inspired by Joseph Schumpeter (1942), emphasizes innovation, entrepreneurship, and "creative destruction", the process where new technologies replace outdated ones, as key forces driving economic growth. According to Schumpeterian theory, ongoing innovation is crucial for maintaining long-term growth.

3.1.6 Unified Growth Theory

This modern theory, linked to Oded Galor (2005), seeks to integrate the stages of economic growth within a unified framework, illustrating how economies shift from periods of stagnation to sustained growth. It incorporates elements such as population trends, education, and technological advancement, proposing that societies progress through stages that ultimately foster long-term economic development.

3.1.7 Dependency Theory

Dependency theory proposes that the global economic system facilitates the exploitation of less developed countries by wealthier nations, which, in turn, limits the economic progress of poorer countries. The theory contends that reliance on more affluent nations restricts independent development and constrains growth, Prebisch (1950) & Frank (1967).

3.2 Empirical Studies

The application of ARIMA models to GDP forecasting originated with the foundational work of box and Jenkins (1970). In the context of Afghanistan this is the first study undertaking GDP modeling using ARIMA. There are used these models for studying GDP in different countries such as; Yao Ma (2024) in his paper, an ARIMA time series models is used to model China's GDP from 1978 to 2022 for empirical analysis. The results of the study show that the predicated GDP values are in a good agreement with the actual values. Therefore, it can be seen China's GDP will still maintain steady growth. Sultan (2023) performed ARIMA (1, 1, 1) model to forecast the United States GDP for 93 years (1929 - 2022). The ARIMA (1, 1, 1) is a good fit to forecast Gross Domestic Product. Lu, S. (2021) examine on GDP forecast analysis combining BP neural network and ARIMA model to predict the non-linear residual of GDP and adds the predicted values of two models to obtain the final predicted value of the model. In the choice of one-way model, this study chooses the differential autoregressive moving average model. The result showed that the forecasting effect of the combined model is better than that of a single model, as well as the combined weight coefficient method proposed in this paper is better than the combined model composed of other weight coefficient methods in the predictions error. The results show that the neural network has strong nonlinear mapping ability and good robustness, can identify and distinguish noisy samples, and is also a better GDP prediction model. Uddin, K., & Tanzim, N. (2021) assists to forecast the GDP for seven years and highlights the indicators affecting the GDP in the context of Bangladesh using ARIMA model. This study reveals a consistent upward trend in Bangladesh's GDP over the years, indicating sustained growth that is likely to continue expanding in the future. Miah an et al. (2019) use data from 1960 to 2017 to forecast the GDP for following 13 years using ARIMA (1, 2, 1) model. It is figured out that the forecast values of GDP in Bangladesh are steadily increasing over the next thirteen years. Abonazel and Abd-Elftah (2019) applied Box-Jenkins approach to find out an appropriate Auto-Regressive Integrated Moving Average (ARIMA) based on the annual data from 1965 to 2016. Therefore, the appropriate ARIMA (1, 2, 1) was build to predict the Egypt GDP. As per the results the Egypt GDP will continue to its upward trend. Agrawal (2018) empirically studied India's GDP modeling and forecasting using ARIMA. The result of study showed non of the ARIMA model proves to be significant than other but the author went ahead with AR(1) and MA(2) in order to predict the evolution of real GDP from quarterly real GDP 1996 to 2017. All forecasting seemed to be approaching in the long run, though in the short run, due to big financial shock in 2008 caused divergence in the system. Suryanto and Hidayat (2017) in their study aimed to forecast Indonesia's GDP using ARIMA model to support governmental economic planning. The findings of model showed that a significant fit for GDP forecasting, and a strong tool for Indonesia's GDP forecasting. Farooqi (2016) utilized ARIMA to forecast the stability of Pakistan's economy and growth of GDP. The model proved effective projection of GDP helping policymakers to set a proportional goal. Yang et al. (2016) applied ARIMA (2, 4, 2) model in the prediction of the growth domestic product from 1978 to 2014 for the following five years. The results indicated a good fit for GDP forecast in short term. Thus, the two years prediction showed upward trend, but the trend showed small rise compared to previous years due to China's economic growth strategies changes and a lot of indicators shaping GDP. Musundi et al. (2016) studied Kenya's annual GDP data for the years of 1960 to 2012 using ARIMA (2, 2, 2) model. The findings indicate that the relative error is around 5%, which is considered fairly accurate. The forecasted values suggest that Kenya's GDP is likely to experience significant growth over the five-year period from 2013 to 2017.

4. Research Methodology

4.1 Pre-Analysis of Data

An annual Growth Domestic Product (GDP) obtained from Statista for the period of 2002 to 2023, in order to find a suitable ARIMA model for forecasting GDP in Afghanistan. Before conducting the Augmented Dickey-Fuller (ADF) test to check the stationarity of GDP, it is essential to first plot the raw data. Visualizing the data allows for an initial assessment of stationarity by observing trends, seasonality, or patterns in the time series.

Figure 1: GDP Plot

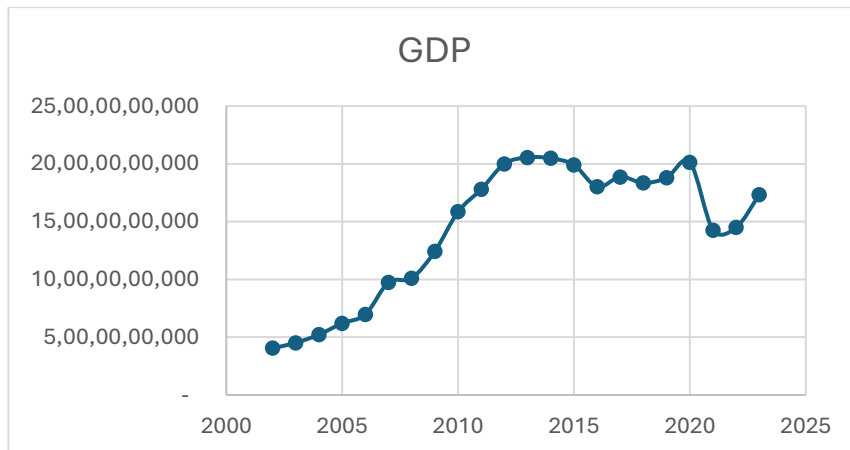
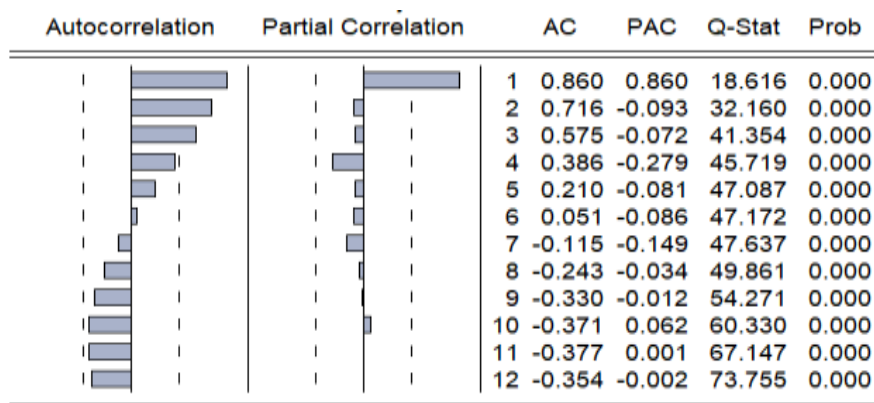


Figure 2: ACF & PCF Plot



The figure 1 & 2 indicate that the data is not stationary, the ADF test can then be performed to statistically confirm the visual observation.

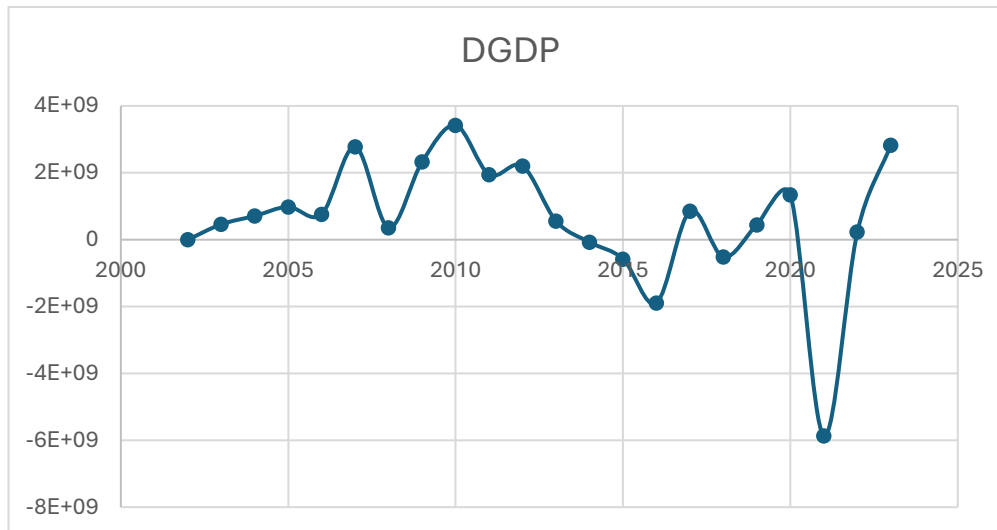
Table 1. Augmented Dickey Fuller Test

Null Hypothesis: GDP has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC, maxlag=4)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.787004	0.3761
Test critical values	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

Developed by Author based on Statista Data

In (Table 1) the Augmented Dickey-Fuller test statistic shows -1.787004 with P-value of 0.3761 which is not statistically significant at 1%, 5%, & 10% level. Therefore, we accept the null hypothesis, and our data has a unit root test (series of GDP is no stationary) at level and intercept. To address this, we will difference the GDP data to achieve stationarity.

Figure 3: DGDP Plot



After differencing the data, the plot (Figure 3) visually indicates that the GDP series has become stationary, as evident by the absence of trends or patterns in the differenced data. To statistically confirm this observation, the Augmented Dickey-Fuller (ADF) test is performed on the differenced series. This ensures that the stationarity of the data is verified through both visual inspection and robust statistical evidence.

Table 2. Augmented Dicky Fuller Test

Null Hypothesis: D(GDP) has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic – based on SIC, maxlag=4)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.566073	0.0166
Test critical values	1% level	-3.808546	
	5% level	-3.020686	
	10% level	-2.650414	

Developed by Author based on Statista Data

In (Table 2), we reject the null hypothesis at 1st difference, as the result of Augmented Dickey-Fuller test statistic shows significant at 1%, 5%, & 10% level with the P-value of 0.0166, which is smaller than 0.05%, rejecting the initial hypothesis and accepting the alternative hypothesis.

Table 3. OLS Regression Analysis for Differenced GDP

Variable	Coefficient	Std. Error	t-statistic	Prob.
C	6.2E+08	4.29E+08	1.474231	0.1560
R-squared	0.000000		Mean dependent var	6.32E+08
Adjusted R-squared	0.000000		S.D. dependent var	1.96E+09
S.E. of regression	1.96E+09		Akaike info criterion	45.68180
Sum squared resid	7.72E+10		Schwarz criterion	45.73154
Log likelihood	-478.6589		Hannan-Quinn criter.	45.69259
Durbin-Watson stat	1.678895			

Developed by Author based on Statista Data

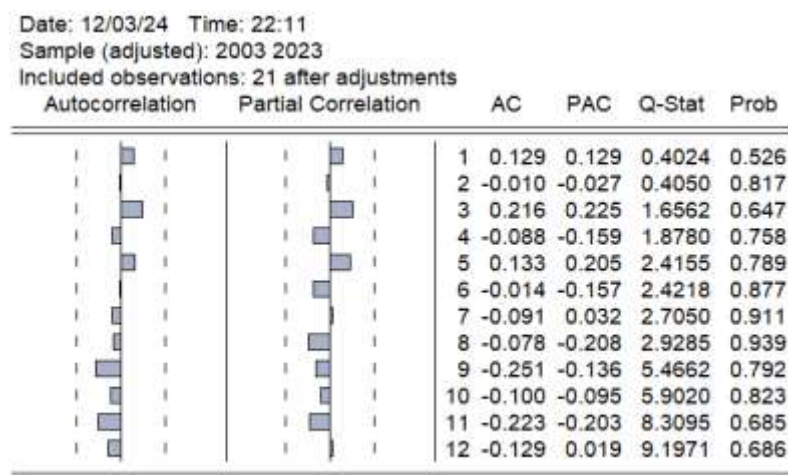
To validate the stationarity of the differenced GDP series ($d(\text{GDP})$), an Ordinary Least Squares (OLS) regression was performed using the formula $d(\text{GDP}) = c$, where c is the constant term. The results are presented in Table 3.

The OLS regression indicates that the constant term (C) is not statistically significant, with a p -value of 0.156, suggesting no significant trend in the differenced GDP series. The R-squared and Adjusted R-squared values are both 0, confirming that the model does not explain any variation in the differenced series. Furthermore, the Durbin-Watson statistic of 1.68 indicates no strong autocorrelation in the residuals, supporting the assumption of stationarity. These findings validate the application of the ARIMA model, as stationarity is a prerequisite for its use.

4.2 Empirical Analysis

4.2.1 Model Identification

The model identification and ordering of the ARIMA (p, I, q) is essential stage to create a model, as per preliminary analysis that the ARIMA (p, I, q) has chosen to forecast Afghanistan DGD series. To verify the ARIMA (p, I, q) model, the Autocorrelation Function (ACF) and Partial Autocorrelation function (PACF) are considered to help in developing ARIMA Model.



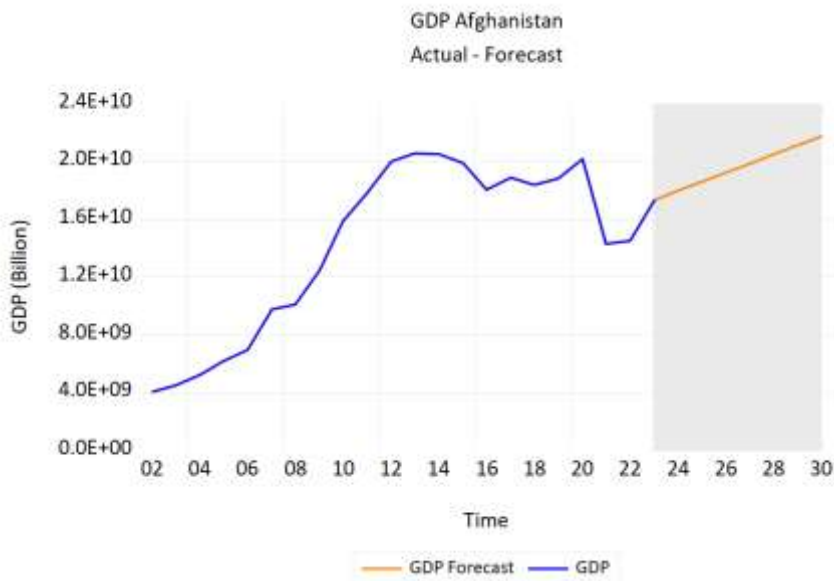
Through the ARIMA model parameter selection process, the candidate ARIMA (0, 1, 0) model was identified for this study. This model was chosen based on an analysis of the data to determine the optimal orders of autoregression (p), differencing (I), and moving average (q).

4.2.2 Result of Forecasting Using ARIMA (p, d, q) Model

The present study is based on annual data, covering the period from 2002 to 2023, having a total number of 21 observations. The ARIMA model, short for Auto-Regressive Integrated Moving Average, is a popular statistical method for time series analysis and forecasting. In the ARIMA model, the predicted value of a variable is derived as a "linear combination of its previous values and past errors Hanke and Wichern (2005). These composite structural models are highly effective and well-suited for generating short-term forecasts Pai and Shenglin (2005). After determining the most appropriate model based on historical data, such as selecting ARIMA (0, 1, 0) for its simplicity and fit, the series can be forecasted using this model. This process ensures that the forecast captures the underlying patterns and trends in the data while minimizing errors. By applying ARIMA (0, 1, 0), we focus on the integrated component, addressing non-stationarity and leveraging a random walk with drift to generate accurate future predictions.

Figure 3 illustrates the comparison between the predicted GDP values and the actual GDP values for Afghanistan. The blue line represents the actual values, while the orange line depicts the predicted values. The figure demonstrates that the model's predicted values closely align with the actual GDP values, effectively capturing the overall trend of Afghanistan's GDP. Furthermore, it indicates that Afghanistan's GDP is projected to grow steadily over the next six years.

Figure 4: Comparison of Afghanistan's GDP, Actual vs Forecasted Values



Afghanistan's GDP for the period 2024 to 2030 has been forecasted using the prediction functions of EViews 10 (student version). The projected GDP values for the next six years are as follows: \$1.8 billion in 2024, \$1.86 billion in 2025, \$1.92 billion in 2026, \$1.99 billion in 2027, \$2.05 billion in 2028, \$2.11 billion in 2029, and \$2.18 billion in 2030.

Conclusion

This study has employed the ARIMA model to empirically analyze and forecast Afghanistan's GDP from 2024 to 2030. By utilizing historical GDP data and adopting a rigorous time-series modeling approach, the research aimed to provide a reliable outlook on Afghanistan's economic trajectory. The results indicate that while the ARIMA model offers robust short-term predictions, the economic environment in Afghanistan is highly susceptible to external and internal shocks. This includes political instability, security concerns, and fluctuations in international aid, all of which contribute to the uncertainty surrounding long-term economic growth.

The model's projections highlight a modest growth trend, suggesting that Afghanistan's economy has the potential for gradual recovery and expansion if favorable conditions prevail. However, the findings underline the importance of addressing the underlying challenges that impede sustainable economic development in Afghanistan.

Based on the empirical findings of this study, the following recommendations are proposed to advance Afghanistan's economic development.

Firstly, Robust institutions are essential for fostering economic growth. The government should prioritize building transparent and accountable institutions to attract both domestic and foreign investment. This includes streamlining regulatory frameworks and combating corruption to enhance investor confidence.

Secondly, improving infrastructure is critical for economic development. Investments in transportation, energy, and communication networks can facilitate trade, reduce production costs, and integrate Afghanistan into regional and global markets.

Thirdly, As a predominantly agrarian economy, Afghanistan should focus on modernizing its agricultural sector. Introducing advanced farming techniques, improving irrigation systems, and providing access to credit for farmers can significantly boost productivity and rural incomes.

Fourthly, Political and security stability are prerequisites for economic development. Efforts should be made to achieve long-lasting peace through dialogue and international cooperation, ensuring a conducive environment for economic activities.

By addressing these challenges and implementing the above recommendations, Afghanistan can overcome its economic development hurdles and pave the way for a brighter and more prosperous future. The findings of this study underscore

the importance of comprehensive policy interventions that align with the country's socio-economic realities. While the ARIMA model provides a useful tool for GDP forecasting, the ultimate trajectory of Afghanistan's economy will depend on the successful execution of these strategies.

Reference

- 1- Box, G. E. P. and Jenkins, G. (1970), *Time Series Analysis, Forecasting and Control*, San Francisco, CA: Holden Day.
- 2- Smith, A (1776). *An Inquiry into the Nature and causes of the Wealth of Nations*. London: W. Strahan and T. Cadell.
- 3- Ricardo, D. (1817). *On the Principles of Political Economy and Taxation*. London: John Murray.
- 4- Malthus, T. R. (1798). *An Essay on the Principle of Population*. London: J. Johnson.
- 5- Solow, R. M. (1956). "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics*, 70(1), 65–94.
- 6- Swan, T. W. (1956). "Economic Growth and Capital Accumulation." *Economic Record*, 32(2), 334–361.
- 7- Romer, P. M. (1986). "Increasing Returns and Long-Run Growth." *Journal of Political Economy*, 94(5), 1002–1037.
- 8- Lucas, R. E. (1988). "On the Mechanics of Economic Development." *Journal of Monetary Economics*, 22(1), 3–42.
- 9- Harrod, R. F. (1939). "An Essay in Dynamic Theory." *The Economic Journal*, 49(193), 14–33.
- 10- Domar, E. D. (1946). "Capital Expansion, Rate of Growth, and Employment." *Econometrica*, 14(2), 137–147.
- 11- Schumpeter, J. A. (1942). *Capitalism, Socialism, and Democracy*. New York: Harper & Brothers.
- 12- Aghion, P., & Howitt, P. (1992). "A Model of Growth through Creative Destruction." *Econometrica*, 60(2), 323–351.
- 13- Galor, O. (2005). "From Stagnation to Growth: Unified Growth Theory." *Handbook of Economic Growth*, 1A, 171–293.
- 14- Galor, O. (2011). *Unified Growth Theory*. Princeton: Princeton University Press.
- 15- Prebisch, R. (1950). *The Economic Development of Latin America and Its Principal Problems*. United Nations Economic Commission for Latin America.
- 16- Frank, A. G. (1967). *Capitalism and Underdevelopment in Latin America: Historical Studies of Chile and Brazil*. New York: Monthly Review Press.
- 17- Box, G. E. P., & Jenkins, G. M. (1970). *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day.
- 18- Ma, Y. (2024). Analysis and Forecasting of GDP Using the ARIMA Model. *Information Systems and Economics*, 5(1), 91-97.
- 19- Nikzad, A. M., & Thippeswamy (2004), E. The Impact of Health Investment on Economic Growth: Empirical Evidence from Afghanistan.
- 20- Sultan, M. A. (2023). Forecasting the GDP in the United States by using ARIMA Model. *Can. J. Bus. Inf. Stud.*, 5(3), 63-69.
- 21- Lu, S. (2021). Research on GDP forecast analysis combining BP neural network and ARIMA model. *Computational Intelligence and Neuroscience*, 2021(1), 1026978.
- 22- Uddin, K., & Tanzim, N. (2021). Forecasting GDP of Bangladesh using ARIMA model. *International Journal of Business and Management*, 16(6), 56-65.
- 23- Miah, M. M., Tabassum, M., & Rana, M. S. (2019). Modelling and forecasting of GDP in Bangladesh: An ARIMA approach. *Journal of mechanics of continua and mathematical science*, 14(3), 150-166.
- 24- Abonazel, M. R., & Abd-Elftah, A. I. (2019). Forecasting Egyptian GDP using ARIMA models. *Reports on Economics and Finance*, 5(1), 35-47.
- 25- Agrawal, V. (2018). GDP modelling and forecasting using ARIMA: an empirical study from India. *Central European University*.

- 26- Suryanto, T., & Hidayat, A. (2017). Using ARIMA model for forecasting GDP Indonesia. *Journal of Economic and Financial Studies*, 5(2), 32-41.
- 27- Farooqi, A. H. (2016). Forecasting GDP growth of Pakistan using ARIMA model. *Journal of Asian Development*, 2(1), 1-15.
- 28- Yang, B., Li, C., Li, M., Pan, K., & Wang, D. (2016, December). Application of ARIMA model in the prediction of the gross domestic product. In *2016 6th international conference on mechatronics, computer and education informationization (MCEI 2016)* (pp. 1258-1262). Atlantis Press.
- 29- Musundi, S. W., M'mukiira, P. M., & Mungai, F. (2016). Modeling and forecasting Kenyan GDP using autoregressive integrated moving average (ARIMA) models.
- 30- Hanke, E. J., & Wichern, W. D. (2005). *Business Forecasting* (8th ed.). USA: Pearson Education Inc.
- 31- Pai, P. F., & Shenglin, C. (2005). A Hybrid ARIMA and Support Vector Machines Model in Stock Price Prediction. *Omega*, 33 (2005), 497-505.