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Research Management Cell, Pokhara Multiple Campus, Pokhara, Nepal
Email: research.intelligencepmcrmc021@gmail.com
URL: www.pmcpokhara.edu.np

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Autoregressive Integrated Moving Average Predictive Modelling for Per Capita GDP of Nepal

[1]Dipendra Bahadur Chand

Abstract

A nation's Gross Domestic Product (GDP) is an important index that reflects the health and performance of an economy and its aggregate income. In this paper, annual data of Nepal's GDP for the period 1960 – 2022 is used to forecast the GDP of Nepal through Autoregressive Integrated Moving Average (ARIMA) modelling techniques. We seek to make accurate long-term predictions for the period 2023 – 2037 to gain insights into the future expected trajectory of economic growth in Nepal. In the present empirical study, stationarity at the second-order differencing with the ARIMA (2, 2, 1) model is identified to predict the GDP of Nepal for the next 15 years. The finding shows that the forecast values of Nepal's GDP will be $1384.426 per capita in 2023 and $2180.822per capita in 2037. Our study provides skeletal guidance for government bodies and investors who rely on planning and strategizing resources on accurate predictions of GDP per capita. By accurately predicting GDP per capita, administrators in investment and policy making can make informed economic decisions that may steer economic growth, stability, and development in an optimum direction.

Keywords
GDP
ARIMA
Forecasting
Nepal
Box- Jenkins approach
R Studio

GROSS DEMESTIC PRODUCT (GDP) is a strategic component in measuring National Income and Product Accounts. GDP represents the total value of final goods and services. GDP assessment is based on the quantum of consumption and investment by households and businesses in addition to the governmental expenditure and net exports. GDP is, therefore, crucial in maintaining a healthy economy as it embodies all financial transactions, including banking aspects. Planning and decision-making for the entire economy is thus conditioned on accurate information with respect of all the three stakeholders in the economic transactions, namely, households,

1. Assistant Professor, Department of Management, Farwestern University Mahendranagar. Email: dipendrachand27@gmail.com

businesses and government, which GDP is capable of delivering. We thus have an estimated nominal GDP (NGDP) which is used for the purpose of future planning by the finance ministry of the country. The real GDP (RGDP) is obtained after adjusting the estimated NGDP for inflation. The latter is also known as observed GDP in actual real-time. However, all budget planning and projections utilize the former, i.e., NGDP, whereas RGDP directly impacts the common citizen. Therefore, fluctuations in the level of GDP covariates are important in determining the gap between NGDP and RGDP. The effective mathematical relationship is represented as NGDP – inflation rate = RGDP.

GDP computation is based on the principle of averages, which has an upward bias. Therefore, GDP does not capture income, expenditure, or production changes at the regional level. For instance, if a large group of people experience declining income at a time when its complement group in the same population is smaller but experiences upwardly rising incomes, then GDP registers rise. To overcome this upward bias to a sufficiently large extent, in this paper, we focus on the concept of GDP per capita, which gives a more realistic picture of a nation's economic health. GDP measures an economy's current market value for all products and services generated during the assessment period. This value encompasses spending and costs on personal consumption, government purchases, inventories, and the foreign trade balance. Thus, the total capital at stake and covered under the GDP envelope of a specific period can be viewed through (i) production undertaken, (ii) income generated and (iii) expenditure accrued for the same period.

Several research studies have been designed on the temporal data template where study units are macroeconomic units like countries or sub-regions like states, districts, or countries. In the present paper, we employ Autoregressive Integrated Moving Average (ARIMA) model proposed by Box and Jenkins (1970) for understanding the GDP movement with time. Past studies have used predictive ARIMA modelling for GDP of different countries. For instance, Kiriakidis and Kargas (2013) used predictive ARIMA model for predicting GDP of Greece, while correctly predicting recession in the near future. The RGDP in Greece for the period 2015-2017 was forecast by Dritsaki (2015) using an ARIMA (1, 1, 1) model based on data for the period of 1980-2013 which correctly indicated a gradual rise in GDP. Wabomba et al. (2016) projected Kenya's GDP from 2013-2017 using an ARIMA (2, 2, 2) model based on data for period of 1960-2012. Predicted estimates correctly indicated that Kenya's GDP will expand faster over the next five years, from 2013-2017. Agrawal (2018) estimated RGDP in India using publicly available quarterly RGDP data from Quarter 2 of 1996 to Quarter 2 of 2017 using ARIMA model. Abonazel et al. (2019) used an ARIMA (1, 2, 1) model over the period 1965-2016 to correctly forecast the rise in GDP for Egypt during for the period 2017-2026 and Eissa (2020) forecasted the GDP per capita for Egypt and Saudi Arabia, from 2019-2030 using the ARIMA (1, 1, 2) and ARIMA (1, 1, 1) models respectively based on data from the period 1968-2018. Their study showed that both Egypt's and Saudi Arabia's GDP per capita would continue to rise. In order to forecast the GDP and consumer `price index (CPI) for the Jordanian economy between 2020 and 2022, Ghazo (2021) employed ARIMA (3, 1, 1) model for GDP and ARIMA (1, 1, 0) model for CPI respectively, based on sample data from the period 19762019. They rightly anticipated stagflation for the Jordanian economy as a result of the predicted shrinkage in GDP and first rise in CPI. In order to escape the stagflationary cycle and achieve more stable CPI, this study provided inputs to the economic policy makers to develop sensible measures for boosting GDP and fending off inflationary forces. Mohamed (2022) used an ARIMA (5, 1, 2) model for the period between 1960-2022 to forecast trajectory of GDP in Somalia for the next fourteen quarters. In order to forecast the quarterly GDP of Philippines, Polintan et al. (2023) used data from 2018-2022 through an ARIMA (1, 2, 1) model for forecasting GDP in the Philippines, for 2022-2029 and predicted a steady growth trajectory. Lngale and Senan (2023) used predictive ARIMA (0, 2, 1) model for predicting GDP of India, pertaining to the period 1960-2020 and predicted a steady growth trajectory. Tolulope et al. (2023) used an ARIMA (2, 1, 2) model for predicting the Nigerian GDP using both in sample and out of sample prediction method, based on data for the period of 19602020 which correctly indicated a gradual rise in GDP. Urruttia (2019) used an ARIMA (1, 1, 1) model over the period from the first quarter of 1990 to the fourth quarter of 2017 with a total of 112 observations for forecasting future GDP. Remittance income in Nepal vis- a vis GDP has between studied by Gaudel (2006). Srivastava and Chaudhary (2007) looked in to role of remittance in economic development of Nepal. Energy – GDP dependence in Nepal is focus of work under taken by Asghar (2008). Dahal (2010) studied role of GDP on educational enrolment and teaching strength in the school system of Nepal. GDP and oil consumption relations are analyzed by Bhusal (2010). Thagunna and Acharya (2013) assessed investment, saving, exports and imports as determinants of GDP. Chaudhary and Xiumin (2018) analysed determinants of inflation in Nepal. Interrelations between foreign trade and GDP of Nepal are investigated by Prajuli (2021). The present paper is the first study where a self-regressed Bayesian investigation on GDP is made with identification of a unique TS statistical model to project future pattern of GDP in Nepal. One step ahead prediction for the year 2022 is validated by the recent World Bank report. Information about GDP can be quite advantageous for the business and economy, particularly for investors, business people and the governmental units aiming for cost effectiveness and maximizing profit in addition to guiding the government for framing future economic policies and in planning and control of various economic measures.

The Study Region

The Federal Democratic Republic of Nepal is a landlocked country in South Asia sharing its boundaries with India and Tibet. World Bank 2022 report the total GDP (hence froth, GDP) of Nepal to be 36.29 billion USD with 122 billion USD Purchasing Power Parity (PPP). GDP per capita is placed at 1,230 USD and PPP at 4,190 USD for the year 2021. GDP growth rate for Nepal is 2.7% while GDP of Nepal represents 0.02% of the world economy for the year 2021. The main economic sectors in Nepal are agricultural, hydro-power, natural resources, tourism and handicrafts. These sectors have a significant impact on Nepal economy in terms of their contribution to the GDP. Empirical research conducted by Nepal Rastra Bank (NRB) in the year 2020 concluded tourism to be a crucial economic sector for both the short-run and the long- run economic growth of Nepal. The NRB report indicated a significant relationship between tourism industry and the county's economic growth which is one of the fasted growing industries in the country. More than a million indigenous people are engaged in the tourism industry for their livelihood. Tourism accounts for 7.9% of the total GDP while 65% of the population is engaged in agricultural activities contributing to 31.7% of GDP. About 20% of the area is cultivable, another 40.7 % is forested and the remaining land is mountainous. Thus, Nepal's GDP is heavily dependent on remittance. According to the Central Bureau of Statistics Nepal (2022) report, Nepal has received remittance amounting to Nepalese Rupees (NRs.) 875 billion in the financial year 2019-20, which translates into a remittance to GDP ratio of 23.23%. Nepal is primarily a remittance-based country with remittance inflow amounting to more than a quarter of the country's GDP. Nepal's total labour force in the year 2020 was 16,016,900 with sectoral distribution by occupation as 43% in agriculture 21% in industry and share of services at 35%. The inflation rate in Nepal was recorded at 6% and the unemployment rate at 1.4%. Nepal's total exports were reported to be worth 918 million USD in the year 2020, its main exports being carpets, textiles, pulses, tea, etc. Its main export partners are India, USA, Japan, Malaysia, Singapore, Germany, and Bangladesh. Total imports for the same period were recorded at 10 billion USD with prominent import goods being petroleum, electrical goods, machinery, gold, etc. Its principal import partners are India and China.

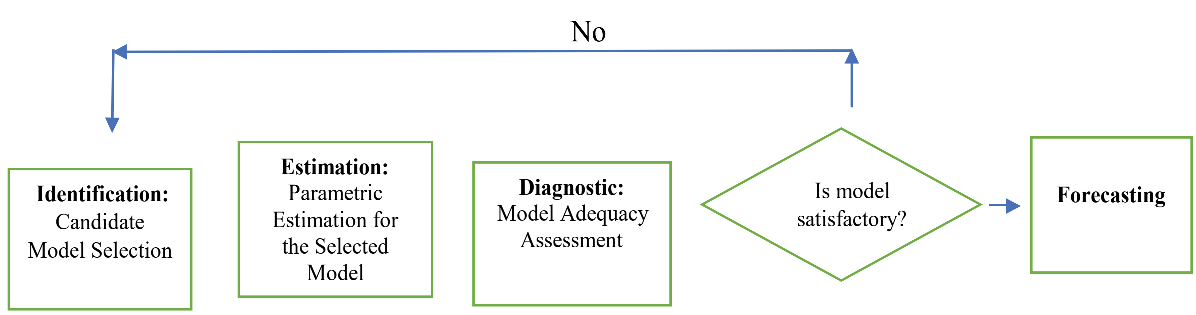
In this paper, we estimate and predict the GDP per capita of Nepal for next one and half decade by using ARIMA time series model. Section 2 describes model determination methodology used in the present work. Section 3 enumerates the models and the model adequacy measures. Section 4 focusses on data description and its analysis. Conclusion and recommendations are summarised in section 5.

Methodology

Time series models are characterized by the clustering effect or serial correlation in time. In the present paper, we employ ARIMA modelling to estimate and forecast Nepal's GDP. ARIMA modelling addresses such issues of dependent errors by introducing time lagged dependent variable and past error terms on the determinant side of the time series model. ARIMA model consists of AR, I, and MA segments where AR indicate the autoregressive part, I indicate integration i.e., the order of differencing in the observed series to achieve stationarity and MA indicate the moving average component in the model. The four stages of the iterative ARIMA model fitting process are Identification, estimation, diagnostic checking, and time series forecasting. (Figure 1).

Figure 1

Iterative ModellingProgression for a Stationary Variable in Box



It employs a general technique for choosing a possible model from a large class of models. The chosen model is then evaluated to see if it can accurately explain the series using the historical data. Auto-correlation function (ACF) and partial auto-correlation function (PACF) are used to select one or more ARIMA models that seem appropriate during the identification stage. The next stage involves estimating the parameters of a specific Box-Jenkins model (1970) for a given time series. This step verifies the parsimony in terms of the number of model parameters or lack of over-specification by determining whether, in addition to the residuals being uncorrelated, the chosen least amount of squared residuals are found in the AR and/or MA parameters. A critical and sensitive aspect of an ARIMA model is parsimony. An over-parameterized model cannot predict as efficiently as a sparse model. Model diagnostics and testing is carried out in the third step. The underlying presumption is that the error terms, ε_t, behave in a manner consistent with that of a stationary, unchanging process. If the residuals are drawn from a fixed distribution with constant mean and variance, they should be white noise. The most adequate Box-Jenkins model fulfils these prerequisites for the residual distribution. The best model needs to be decided based on these four paradigms. Thus, testing of the residuals would lead to a better suitable model. A graphical technique called a quantile-quantile (Q-Q) plot compares the distributional similarities of two datasets. In the context of ARIMA models, a Q-Q plot is often used to check whether the model's residuals follow a normal distribution.

The Model and Forecast

1. Autoregressive Model

With the intent to estimate the coefficients β_(j,) j = 1,2, …,p, an AR process for the univariate model is the one that shows a changing variable regressed on its own lagged values. AR model of order p, or AR (p), is expressed as,

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t \qquad (1)$$

ACF gives a correlation coefficient between the dependent variable and the same variable with different lags, but the effect of shorter lags is not kept constant, meaning that the effect of shorter lag is remained in the autocorrelation function. The correlation between y_t and y_(t-2) includes the correlation effect between y_t and y_(t-1). On the other hand, PACF gives a correlation coefficient between the dependent variable and its lag values while keeping the effect of shorter lags constant. The correlation between y_t and y_(t-2) does not include the effect of correlation between y_t and y_(t-1).

2. Moving Average Model

Let ε_t (t = 1,2,…) be a white noise process, with t standing for a series of independent and identically distributed (iid) random variables expecting ε_t is zero and variance of ε_t is σ^2. After that, the qth order MA model, which accounts for the relationship between an observation and a residual error, is expressed as

$$y = \alpha \quad \theta\ \varepsilon_{-1} + \theta\ \varepsilon_{-2} + \cdots + \theta\ \varepsilon_{-q} \quad \varepsilon \qquad (2)$$

represents the impact of past errors on the response variable. Estimated coefficients θ_(j,) j = 1,2, … ,q, accounting for short-term memory help in forecasting.

3. Autoregressive Moving Average Model

The model AR, coupled with the MA modelling strategy is called Autoregressive Moving Average (ARMA) models intended for stationary data series. ARMA (p, q) model is expressed as:

$$y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q\ \varepsilon_{t-q} + \varepsilon_t \qquad (3)$$

An amalgam of the AR and MA models is represented by (3). In this instance, the greatest order of p or q cannot be provided merely by ACF or PACF.

4. Autoregressive Integrated Moving Average Model

The extension of ARMA model is ARIMA model which enable to transform data by differencing to make data stationary. ARIMA model can be written as ARIMA (p, d, q), where p is the order of AR term, d is the number of differencing required to make series stationery and q is the order of MA term. For example, if y_it is a non-stationary series, we will take a first-difference of y_t to make Δy_t= stationary, and then the ARIMA (p, 1, q) model is expressed as:

$$\Delta y_t = \alpha + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (4)$$

Where Δ y_t= y_t- y_(t-1), then d = 1, which implies a one-time differencing step. The model transforms into a random walk model, categorized as ARIMA (0.1,0), if p = q = 0.

Table 1
ARIMA (p, d, q) Model for d = 0, 1, 2

d	0	1	2
Model	$y_t = Y_t$	$y_t = Y_t - Y_{t-1}$	$y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2})$

5. Model Adequacy Measures

Before employing a model for predicting, diagnostic testing must be done on it. The residuals that remain after the model has been fitted are deemed sufficient if they are just white noise, and the residuals' ACF and PACF patterns may provide insight into how the model might be improved. Akaike (1973) developed a numerical score that can be used to identify the best model from among several candidate models for a specific data set. Akaike information criterion (AIC) results are helpful compared to other AIC scores for the same data set. A smaller AIC score indicates a better empirical fit. Estimated log-likelihood (L) is used to compute AIC as,

$$AIC = - 2(L + s) \quad (5)$$

Such that s is the number of variables in the model plus the intercept term. Schwarz (1978) developed an alternative model comparison score known as Bayesian (Schwarz) information criterion BIC (or SIC) as an asymptotic approximation to the transformation of the Bayesian posterior probability of a candidate model expressed as,

$$BIC \text{ or } SIC = - 2L + s \log(n) \quad (6)$$

L is the maximum likelihood of the model, s is the number of parameters in the model, and n is the sample size. Like AIC, BIC also balances the goodness of fit and model complexity. However, BIC places a higher penalty on model complexity compared to AIC because it includes a term that depends on the sample size (s log(n)). As with AIC, the goal is to minimize the BIC value to select the best model.

6. Forecasting

Box-Jenkin's time series model method applies only to stationary and invertible time series. Lidiema (2017), Dritsakis and Klazoglou (2019). Future value forecasting can begin once the requirements have been met through procedures like differencing. We can utilize the chosen ARIMA model to predict when it meets the requirements of a stationary univariate process. Further, diagnostic checking is done to verify the forecasting accuracy of the ARIMA model.

7. Forecasting Accuracy

We now present different measures listed to determine the accuracy of a prediction model.

(i) Mean Absolute Error

The mean absolute difference between a dataset's actual (observed) values and the model's predicted values is computed using the Mean Absolute Error (MAE) algorithm. The absolute rather than squared differences make MAE more robust to the outliers. The formula to calculate the MAE is,

$$M\ A\ E\ \ \frac{1}{n}\,\sigma^{n}_{=1} ȁ y - y_i\, ȁ \tag{7}$$

Where n is the total number of observations, y_(i)is the actual value of time series in data point i, and y _i denotes forecasted value of time series data point i.

(ii) Root Mean Square Error

Root Mean Square Error (RMSE) is a popular accuracy measure in regression analysis based on the difference between a dataset's actual (observed) values and the model's predicted values. Lower RMSE indicates the alignment of the model's predictions with the actual data. The formula to calculate the RMSE is,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}}, \tag{8}$$

However, due to the squaring of deviations, RMSE gives underweight to the outliers and may not be suitable for all types of datasets. Depending on the specific problem and characteristics of the data, we can use metrics such as Mean Absolute Error (MAE) or R-squared (coefficient of determination) may also be used in conjunction with RMSE to gain a more comprehensive understanding of the model's performance.

(iii) Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is used to measure the percentage variation between a dataset's actual (observed) values and the model's predicted values, and it is useful to understand the relative size of the errors compared to the actual values. The formula to calculate the MAPE is,

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \cdot 100\% \tag{9}$$

However, it needs to be more well-defined when the actual values are zero or near zero, which can result in non-sensical very large MAPE values.

(iv) Mean Percentage Error

Mean Percentage Error (MPE) is instead of taking the absolute percentage difference like in MADE consider the signed percentage difference. Therefore, accounting for both the (positive and negative) magnitude of the errors. The formula to calculate the MPE is,

$$MPE = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - \hat{y}_i}{y_i} \right)^2 \times 100 \qquad (10)$$

Such that, lower values of MPE indicate better forecast accuracy. A value of zero MPE would imply that the forecasted values match the actual values perfectly. However, MPE can have some limitations, such as the potential for the errors to cancel each other out, leading to an artificially low MPE even if the model's performance is unsatisfactory.

(v) Mean Absolute Scaled Error

Mean Absolute Scaled Error (MASE) measures the performance of a model relative to the performance of a naive or benchmark model. The MASE provides a more interpretable measure of forecast accuracy than metrics like Mean Absolute Error (MAE), especially when dealing with time series data and comparing different forecasting models. It provides insights into whether a model provides meaningful improvements over a basic, naive forecasting approach. The formula to calculate the MASE is,

$$MASE = \frac{\frac{1}{J} \sum_{j=T+1}^{T+J} |y_i - \hat{y}_i|}{\frac{1}{T-1} \sum_{i=2}^{T} |y_i - y_{i-1}|} \qquad (11)$$

where n is the length of the series and m is its frequency, i.e., m=1 for yearly data, m=4 for quarterly, m=12 for monthly, etc.

MASE measures how well the model performs relative to the naive model's forecast errors taken as a benchmark. A value of MASE less than 1 indicates that the model performs better than the naive model regarding absolute forecast errors, while a value greater than 1 shows worse performance than the naive model.

Data and Analysis

For modelling and forecasting non-seasonal time series data of the annual GDP of Nepal, we have obtained data from the website of World Bank for the period 1960 – 2022. This implies that we have 63 observations of GDP, based on this data, we have proposed the ARIMA (2, 2, 1) model to forecast the GDP of Nepal for the next fifteen years (2023 – 2037).

1. Model Identification for GDP

Progression of GDP per capita of Nepal is graphed in Figure 2. A steady long-term rise is observed during 1960 – 2022. Beyond 2010 the rate of upward trend increases sharply. The time series may be quickly and easily determined to be unstable because of the GDP of Nepal's clearly marked increasing trend. Autocorrelation Function (ACF) (Figure 3) and Partial Autocorrelation Function (PACF) (Figure 4) are studied further to understand genesis of data structure. It is evident from the PACF that a single prominence indicates the fictitious primary value of n=1 when it crosses the confidence intervals. Furthermore, at ACF 11 heights, the same issue occurs. According to the ACF plot, the autocorrelations in the observed series is very high, and positive. A slow decay in ACF suggests that there may be changes in both the mean and the variability over time for this series. The arithmetic mean may be moving upward, with rising variability. Variability can be managed by calculating the natural logarithm of the given data, and the mean trend can be eliminated by differencing once or twice as needed to achieve stationarity in the original observed series. An instantaneous nonlinear transformation applied to the optimal forecast of a variable may not produce the transformed variable's ideal forecast (Granger and Newbold, 1976). In particular, using the exponential function to forecasts for the original variable when excellent forecasts of the logs are available may not always be the best course of action. Therefore, we further employ the differencing process on the untransformed actual data series.

FIgure 2

The GDP Data During 1960 to 2021

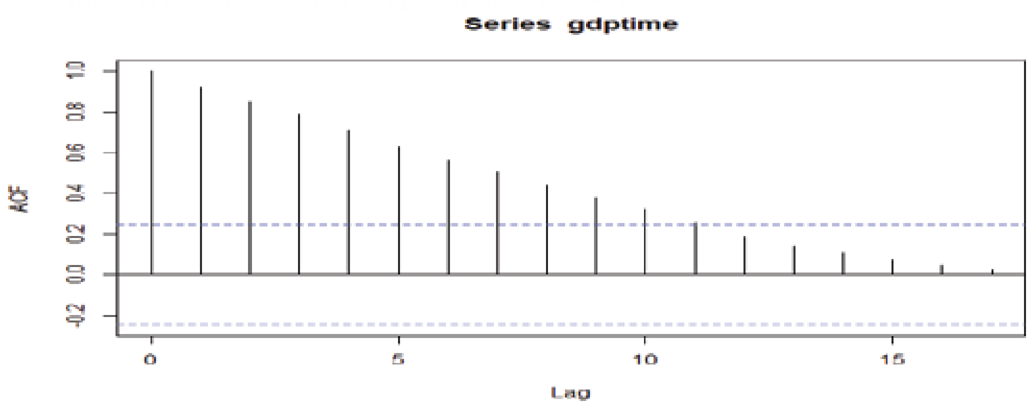


Figure 3

AAutocorrelation function Graphs of the GDP Series

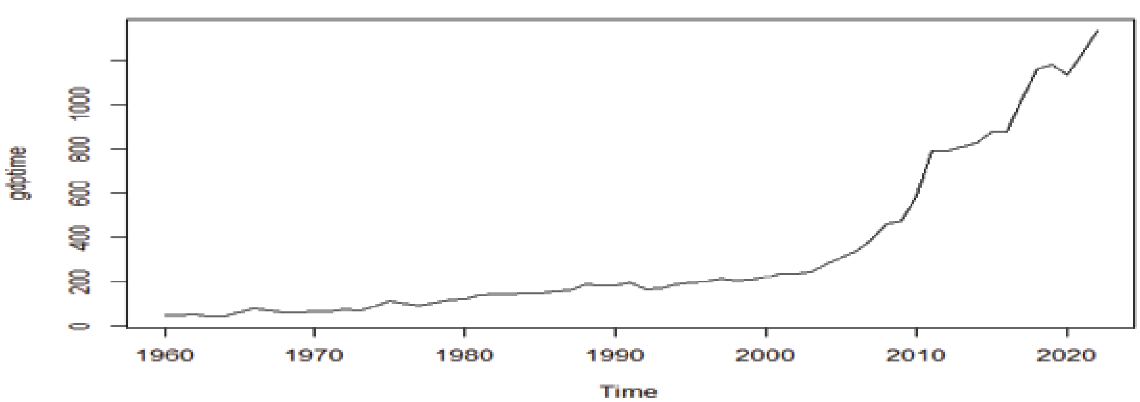
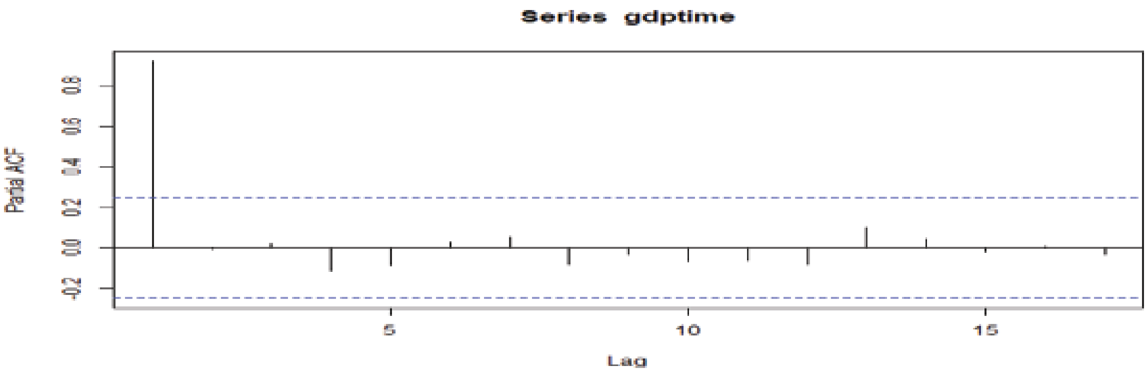


Figure 4

Partial Autocorrelation Function Graphs of the GDP Series



2. Diagnostics and Estimation for GDP

Based on GDP time chronological data for the period 1960 – 2022, we have considered ten tentative ARIMA (p, d, q) models (Table 2) and estimate the parameters using R interface. The model with minimum AIC is deemed to fit best and will be referred to as Model I, henceforth.

Table 2
Tentative ARIMA (p, d, q) Models of GDP for Nepal

(*p, d, q*)	Model-I	Model-II
(2,2,2)	620.3456	691.683
(0,2,0)	646.7677	724.934
(1,2,0)	644.8669	722.6668
(0,2,1)	624.1036	697.3245
(1,2,1)	625.2472	698.4418
(2,2,1)	**618.3642**	**689.7005**
(1,2,2)	624.3858	697.0097
(2,2,0)	629.1622	703.1548
(3,2,1)	620.3479	691.6844
(3,2,0)	624.4103	697.2054
(3,2,2)	621.3597	692.8173

The applicability test assesses the error or residual sequence of the fitted data for consistency. If a white noise sequence for residuals is obtained, then the model I is considered suitable for forecast. If not, then the model needs improving. In this research, the ACF graph (Figure 5) and PACF graph (Figure 6) of residual sequence are exhibit white noise process. Hence, ARIMA (2,2,1) well fits (Table 2) the considered time series GDP data from Nepal.

Figure 5
Autocorrelation Function Graphs of the Residual Series

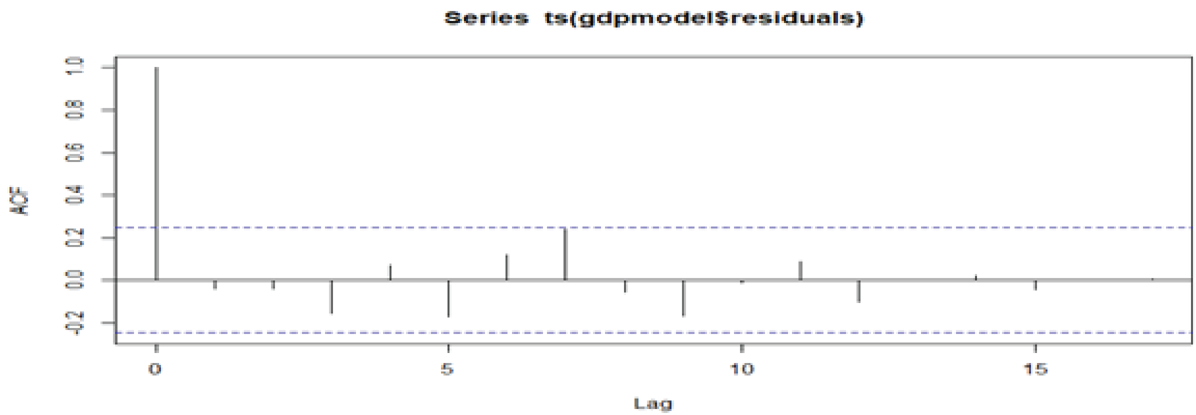


Figure 6
Partial Autocorrelation Function Graphs of the Residual Series

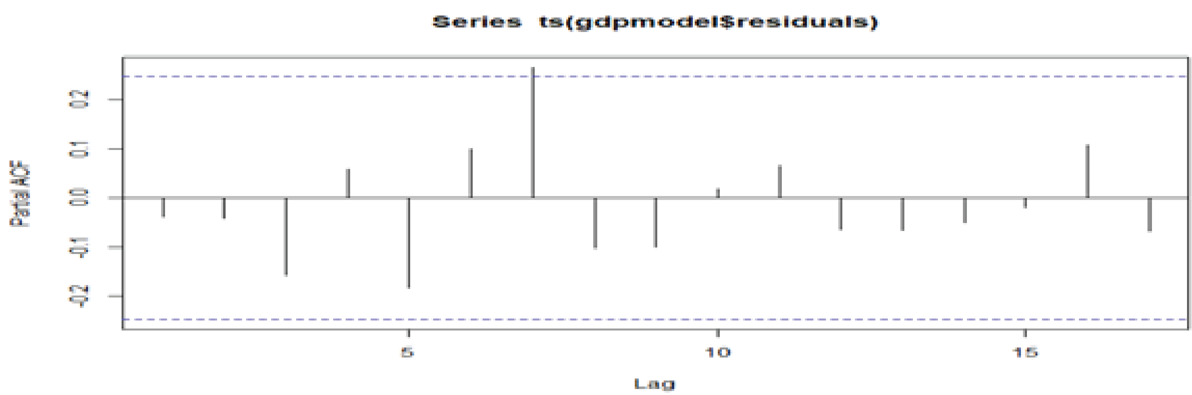


Figure 7
Q-Q Plot of the Residual Series

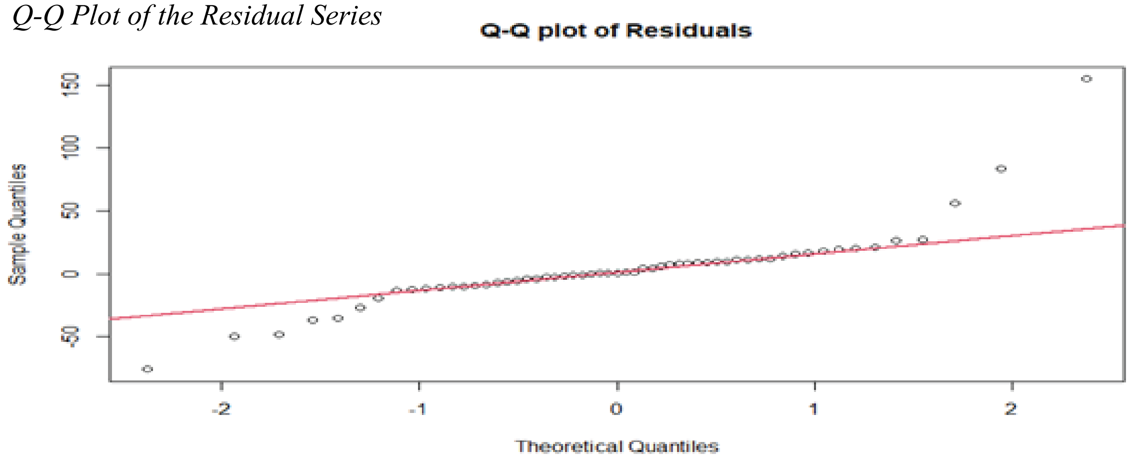


Figure 7, illustrates the normal Q-Q plot, the maximum points seem to falls on or near the line. So, it can be said that the model residuals are normally distributed which is one of the assumptions of linear regression.

Table 3

Estimated Coefficients and Model Adequacy Criterion

Model	I			II		
Process	AR_1	AR_2	MA_1	AR_1	AR_2	MA_1
Coefficients	0.0665	-0.4065	-0.7644	0.0664	-0.4081	-0.7655
Standard Error	0.1333	0.1264	0.0911	0.1216	0.1143	0.0842
AIC		618.36			689.70	
BIC		626.81			698.64	

Table 4

Model Comparison Measures

Model	RMSE	MAE	MPE	MAPE	MASE
I	34.98561	20.4341	1.276214	6.908845	0.8097521
II	32.95309	18.13002	1.138476	6.129198	0.6330358

Table 3 represents the estimated coefficients and model adequacy criterion for both Model I and Model II. Model II estimates have smaller standard errors (Table 3) with smaller RMSE, MAE, MPE, MAPE and MASE. Table 4 which indicate smaller associated residuals for model fit. However, from the viewpoint of sample-based information, of AIC and BIC, Model I is a better representative for the considered time series.

3. Forecasting of GDP for Nepal

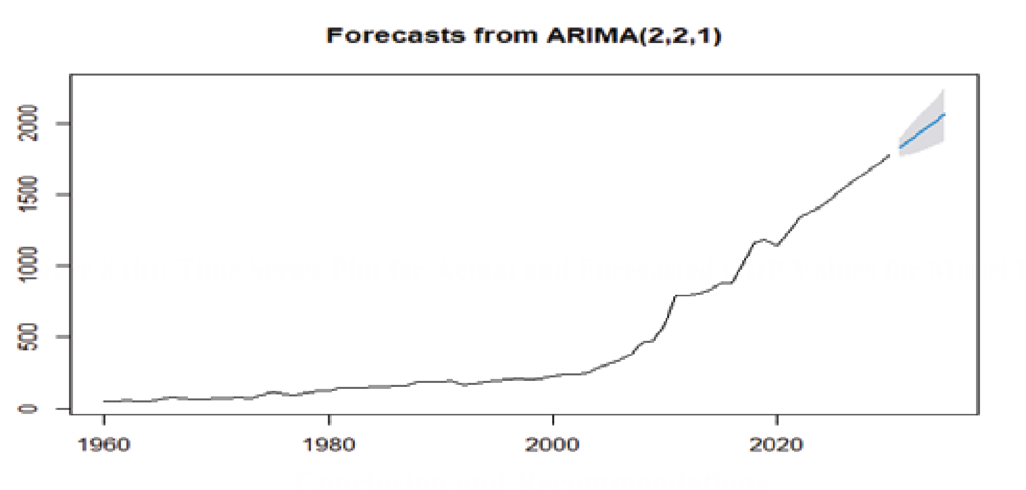
One use of a model is to anticipate the future values of a time series after the model has been discovered, its parameters determined, and its diagnostics examined. Table 5 provides the GDP projections for the time window 2023 – 2037. Figure 8 (a) and Figure 8 (b) shows the trend of the actual and forecasted GDP values with their 95% confidence limits for the years 1960 – 2022, as well as the GDP that would be predicted, based on these 63 years for the next 15 years forecasted values of GDP for the Model I and Model II respectively by using the proposed ARIMA (2, 2, 1) model. The Model I predicted values indicate that the Nepal GDP specific growth run continues. Since the national economy is a complex and dynamic system, and that the outcome is simply a predicted number, therefore in order to prevent the economy from suffering from strong fluctuations, the administrators we should maintain the stability and continuity of microeconomic regulation and control with special attention to the risk of adjustment in economic operation, (Wabomba et al. 2016). We should also adjust the corresponding target value in light of the current situation. Thus, to assess robustness of the model-based prediction we next include the first eight predicted values for the years 2023 – 2030 in the original time series data base. The same R program is now re-run for the composite period 1960 – 2030. Again ARIMA (2, 2, 1) emerges as the best fit model on the basis of AIC from among the eleven considered models. With the new compounded data model (Model II, henceforth). We predict the next seven annual GDP values for the period 2031 – 2037. 95% confidence interval for Model II are found to be shorter (Table 5) thus retrieving that Model II is more efficient for predictive purpose

Table 5
Forecasted of GDP for Nepal

Year	Forecasted GDP per capita		95% Confidence Interval			
	Model -I	Model-II	Model-I		Model-II	
			Lower limit	Upper limit	Lower limit	Upper limit
2023	1384.426		1312.961	1455.891		
2024	1421.475		1304.142	1538.808		
2025	1481.899		1338.590	1625.207		
2026	1548.280		1379.252	1717.308		
2027	1605.555		1403.154	1807.956		
2028	1659.803		1421.051	1898.554		
2029	1717.551		1442.946	1992.155		
2030	1776.762		1465.340	2088.185		
2031	1834.648	1834.645	1484.161	2185.135	1767.657	1901.634
2032	1891.851	1891.843	1500.546	2283.156	1781.928	2001.758
2033	1949.547	1949.538	1516.257	2382.838	1815.423	2083.653
2034	2007.554	2007.545	1531.025	2484.084	1849.483	2165.607
2035	2065.381	2065.370	1544.189	2586.573	1876.158	2254.582
2036	2123.070	2123.056	1555.862	2690.278	1899.910	2346.202
2037	2180.822	2180.806	1566.364	2795.281	1924.230	2437.382

Figure 8 (b)

Time Series Plot for Actual and Forecasted GDP Values for Model II



Our study discovers that the proposed ARIMA models are useful for future GDP per capita of Nepal. For the development and assessment of different ARIMA models, we have used annual data from 1960 – 2022 and found that the ARIMA (2, 2, 1) model as the most appropriate one. Our findings are in line with earlier research, which discovered that ARIMA models as effective tools of forecasting economic indicators like GDP. Our present study makes a practical contribution by providing in-depth explanations of how ARIMA models might be used to predict Nepal's per-capita GDP. The best fitted ARIMA model has been used to obtain forecast values for next one and half decade. The finding shows that the forecast values of Nepal's GDP will be $1384.426 per capita in 2023 and $2180.822per capita in 2037. The results show that Nepal a growing GDP substantially, however, this growth is not sufficient. So, it is suggested to the policy maker to invest more on areas of infrastructure development, research and development, and facilitate to establishing more startups with focus on green investment and sustainability.

Model II reinforces that short- term prediction of GDP is more precise (Table 5). Model based prediction enable planners to address specific economic challenges such as resource allocation. A robust GDP prediction could guide the government about the expected revenue generation, and expenditure optimization. Business and governments could plan investment, inventory management and volume of production. Statistical prediction thus empowers a decision maker with scope for evidence informed decision- making. However, one must be always aware that any model is sustainable as long as the background conditions such as other influencing market forces remain at the same level.

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References

Abonazel, M.R., & Abd-Elftah, A.I. (2019). Forecasting Egyptian GDP using ARIMAmodels. *Reports on Economics and Finance*, *5*(1), 35-47.

Agrawal, V. (2018). GDP modelling and forecasting using ARIMA: An empirical study from India. *Doctoral Dissertation*, Central European University.

Akaike, H. (1973) . Information theory and an extension of the maximum likelihood principle. *In 2nd International Symposium of Information Theory* , Akademia Kiado, Budapest, 267-281.

Asghar, Z. (2008). Energy-GDP relationship: A causal analysis for the five countries of South Asia. *Applied Econometrics and International Development*, *8*(1), 167-180.

Bhusal, T.P. (2010). Econometric analysis of oil consumption and economic growth in Nepal. *Economic journal of Development Issues*, *11*(2), 135-143.

Box, G. E., & Jenkins, G. (1970). *Time series analysis: Forecasting and control*. Holden-Day, San Francisco.

Chatfield, C. (2016). *The analysis of time series: An Introduction,* CRC Press.

Chaudhary, S.K., & Xiumin, L. (2018). Analysis of the determinants of inflation in Nepal. *American Journal of Economics*, *8*(5), 209-212.

Dahal, M.P. (2010). Higher educational enrolment, school teachers and GDP in Nepal: A aausality analysis. *Economic Journal of Development Issues*, *11&12* (1-2), 69-91.

Dritsaki, C. (2015). Forecasting real GDP rate through econometric models: An empirical study from Greece. *Journal of International Business and Economics*, 3(1), 13-19.

Eissa, N. (2020). Forecasting the GDP per capita for Egypt and Saudi Arabia using ARIMA models. *Research in World Economy*, *11*(1), 247-258.

Gaudel, Y.S. (2006). Remittance income in Nepal: Need for economic development. *Journal of Nepalese Business Studies*, *3*(1), 9-17.

Ghazo, A. (2021). Applying the ARIMA model to the process of forecasting GDP and CPI in the Jordanian economy. *International Journal of Financial Research, 12*(3), 70-77.

Kiriakidis, M., & Kargas, A. (2013). Greek GDP forecast estimates. *Applied Economics Letters*, 20(8), 767-772.

Kumar, N., & Juneja, P. (2015). A review: Analysis and forecasting of GDP by using ANN. *International Journal of Advances in Engineering Research*, *9*(5), 39-43.

Lngale, K.Y. & Senan, R. (2023). Predictive analysis of GDP by using ARIMA approach. *The Pharma Innovation Journal*, *12*(5), 309-315.

MacKinnon, J.G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics*, *11*(6), 601-618.

Mohamed, A. O. (2022). Modeling and forecasting Somali economic growth using ARIMA models. *Forecasting, 4*(4), 1038-1050.

Ning, W., Kuan-jiang, B., & Zhi -fa, Y. (2010). Analysis and forecast of Shaanxi GDP based on the ARIMA model. *Asian Agricultural Research*, *2*(1), 34-41.

Parajuli, R. (2021) A Study on impact of foreign trade in GDP of Nepal. *Interdisciplinary Journal of Management and Social Sciences*, *2*(1), 165-171.

Polintan, S.N., Cabauatan, A.L.L., Nepomuceno, J.P., Mabborang, R.C., & Lagos, J.C. (2023). Forecasting gross domestic product in the Philippines using ARIMA model. *European Journal of Computer Science and Information Technology*, *11*(2), 100-124.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, *6*(2), 461-464.

Srivastava, N.L., & Chaudhary, S.K. (2007) Role of remittance in economic development of Nepal. *Journal of Nepalese Business Studies*, *4*(1), 28-37.

Thagunna, K.S., & Acharya, S. (2013). Empirical analysis of remittance inflow: The case of Nepal. *International Journal of Economics and Financial Issues*, 3(2), 337-344.

Tolulope,J.O., Babyemi, A.W., Shayau, S.A., & Sh ehu, B. (2023). Model for forecasting Nigerian real GDP using ARIMA. *Journal of Mathematical Sciences & Computational Mathematics*, *4*(2), 152-168.

Urrutia, J.D., Abdul, A.M., & Atienza, J.B.E. (2019) Forecasting Philippines imports and exports using Bayesi an artificial neural network and autoregressive integrated moving Average. In *AIP Conference Proceedings*, *2192*(1), p. 090015.

Uwimana, A., Xiuchun, B., & Shuguang, Z. (2018). Modeling and forecasting Africa 's GDP with time series models. *International Jo urnal of Scientific and Research Publications*, *8*(4), 41-46.

Wabomba, M.S., Mutwiri, M.P., & Mungai, F. (2016). Modelling and forecasting Kenyan GDP using ARIMA models. *Science Journal of Applied Mathematics and Statistics* , *4*(2), 64-73.