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

Dipendra Bahadur Chand

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 differing 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 $2180.822 per 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.

GROSS DOMESTIC 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,
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 countries 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, Gazo (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
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and the remaining land is mountainous. Thus, Nepal’s GDP is heavily dependent on remittance.

Data and Analysis

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 handi-
crafts. 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 fastest 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 activi-
ties 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 agricul-
ture 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 focuses 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 Modelling Progression for a Stationary Variable in Box*

![Diagram of Iterative Modelling Progression](image)

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, $\varepsilon \_t$, behave in a manner consistent with that of a

| Identification: Candidate Model Selection |
| Estimation: Parametric Estimation for the Selected Model |
| Diagnostic: Model Adequacy Assessment |
| Is model satisfactory? |
| Forecasting |
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 fulfills 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,

\[ y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t \]  

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

\[ y = \alpha + \theta \varepsilon_{t-1} + \theta \varepsilon_{t-2} + \cdots + \theta \varepsilon_{-q} + \varepsilon \]  

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:

\[ y_t = \alpha + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \]  

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 \( \Delta y_t = \text{stationary} \), and then the ARIMA (p, 1, q) model is expressed as:

\[
\Delta y_t = \alpha + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_q \epsilon_{t-q} + \epsilon_t
\] (4)

Where \( \Delta y_t = y_t - y_{t-1} \), 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 \( d = 0, 1, 2 \)

<table>
<thead>
<tr>
<th>p</th>
<th>0</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>( y_t = Y_t )</td>
<td>( y_t = Y_t - Y_{t-1} )</td>
<td>( y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) )</td>
</tr>
</tbody>
</table>

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,

\[
\text{AIC} = -2(L + s)
\] (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,

\[
\text{BIC or SIC} = -2L + s \log(n)
\] (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-Jenkins's time series model method applies only to stationary and invertible time series. Lidiema (2017), Dritsakis and Klaezoglou (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,

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \]

Where \( n \) is the total number of observations, \( y_i \) is the actual value of time series in data point \( i \), and \( \hat{y}_i \) 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,

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y(i) - \hat{y}(i))^2}{N}} \]

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,

\[ MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \]
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 MAE consider the signed percentage difference. Therefore, accounting for both the (positive and negative) magnitude of the errors. The formula to calculate the MPE is,

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

$$MASE = \frac{1}{m} \sum_{j=1}^{T} \left| \frac{\sum_{i=T+j}^{T+m} y_i - \hat{y}_i}{m} \right|$$

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*

![Graph showing GDP data from 1960 to 2021](image)

**Figure 3**
*Autocorrelation function Graphs of the GDP Series*

![Graph showing autocorrelation function](image)
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>
<thead>
<tr>
<th>((p, d, q))</th>
<th>Model-I</th>
<th>Model-II</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2,2,2)</td>
<td>620.3456</td>
<td>691.683</td>
</tr>
<tr>
<td>(0,2,0)</td>
<td>646.7677</td>
<td>724.934</td>
</tr>
<tr>
<td>(1,2,0)</td>
<td>644.8669</td>
<td>722.6668</td>
</tr>
<tr>
<td>(0,2,1)</td>
<td>624.1036</td>
<td>697.3245</td>
</tr>
<tr>
<td>(1,2,1)</td>
<td>625.2472</td>
<td>698.4418</td>
</tr>
<tr>
<td><strong>(2,2,1)</strong></td>
<td><strong>618.3642</strong></td>
<td><strong>689.7005</strong></td>
</tr>
<tr>
<td>(1,2,2)</td>
<td>624.3858</td>
<td>697.0097</td>
</tr>
<tr>
<td>(2,2,0)</td>
<td>629.1622</td>
<td>703.1548</td>
</tr>
<tr>
<td>(3,2,1)</td>
<td>620.3479</td>
<td>691.6844</td>
</tr>
<tr>
<td>(3,2,0)</td>
<td>624.4103</td>
<td>697.2054</td>
</tr>
<tr>
<td>(3,2,2)</td>
<td>621.3597</td>
<td>692.8173</td>
</tr>
</tbody>
</table>

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.
The golden ratio corresponds to a line segment state-of-the-art golden ratio based on its mathematical structures and their constructional properties, beauty perspective, and construction design is somewhat lacking. This paper covers the investigation to the ACF plot, the autocorrelations in the observed series is very high, and positive. A slow cross of the confidence intervals. Furthermore, at ACF 11 heights, the same issue occurs. According to Akhtaruzzaman & Shafie, 2011, 2.2 The golden ratio corresponds to an equilateral triangle the golden gnomon and the golden triangle, respectively, Akhtaruzzaman & Shafie, 2011. Note that, such a cut BP in ∆ABC is the golden cut where triangles ∆ABP and ∆BCP are discovered, its parameters determined, and its diagnostics examined. Table 5 provides the GDP from the viewpoint of sample-based information, of AIC and BIC, Model I is a better representative of GDP for Nepal. The best fitted ARIMA model has been used to obtain forecast values for next one and half years 2023 – 2030 in the original time series data base. The same R program is now re-run for the robustness of the model-based prediction we next include the first eight predicted values for the forecasts of GDP and oil consumption relations are analyzed by Bhusal (2010). Thagunna and Acharya (2013) studied role of GDP on educational enrolment and teaching strength in the school system of Nepal. The Federal Democratic Republic of Nepal is a landlocked country in South Asia sharing some limitations, such as the potential for the errors to cancel each other out, leading to an artificially high AIC value, which correctly indicated a gradual rise in GDP. Wabomba et al. (2016) projected Kenya’s GDP for the period 2015-2017 was forecast predicting recession in the near future. The RGDP in Greece for the period 2015-2017 was forecast and Kargas (2013) used predictive ARIMA model for predicting GDP of Greece, while correctly forecasting future pattern of GDP in Somalia for the next fourteen quarters. In order to forecast the quarterly GDP trajectory of GDP in Somalia for the next fourteen quarters. In order to forecast the quarterly GDP.
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*

<table>
<thead>
<tr>
<th>Model Process</th>
<th>I</th>
<th>II</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AR₁</td>
<td>AR₂</td>
</tr>
<tr>
<td>Coefficients</td>
<td>0.0665</td>
<td>-0.4065</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.1333</td>
<td>0.1264</td>
</tr>
<tr>
<td>AIC</td>
<td>618.36</td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>626.81</td>
<td></td>
</tr>
</tbody>
</table>

**Table 4**

*Model Comparison Measures*

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th>MAE</th>
<th>MPE</th>
<th>MAPE</th>
<th>MASE</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>34.98561</td>
<td>20.4341</td>
<td>1.276214</td>
<td>6.908845</td>
<td>0.8097521</td>
</tr>
<tr>
<td>II</td>
<td>32.95309</td>
<td>18.13002</td>
<td>1.138476</td>
<td>6.129198</td>
<td>0.6330358</td>
</tr>
</tbody>
</table>

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
The GDP Data During 1960 to 2021

Figure 2

Forecast. If not, then the model needs improving. In this research, the ACF graph (Figure 5) and Q-Q Plot of the Residual Series Autocorrelation Function Graphs of the Residual Series

Based on GDP time chronological data for the period 1960 – 2022, we have considered ten

2.1 The golden ratio corresponds to isosceles triangles

Akhtaruzzaman & Shafie, 2011.

Table 5

Forecasted of GDP for Nepal

<table>
<thead>
<tr>
<th>Year</th>
<th>Forecasted GDP per capita</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model -I</td>
<td>Model-II</td>
</tr>
<tr>
<td></td>
<td>Lower limit</td>
<td>Upper limit</td>
</tr>
<tr>
<td></td>
<td>Lower limit</td>
<td>Upper limit</td>
</tr>
<tr>
<td>2023</td>
<td>1384.426</td>
<td>1312.961</td>
</tr>
<tr>
<td>2024</td>
<td>1421.475</td>
<td>1304.142</td>
</tr>
<tr>
<td>2025</td>
<td>1481.899</td>
<td>1338.590</td>
</tr>
<tr>
<td>2026</td>
<td>1548.280</td>
<td>1379.252</td>
</tr>
<tr>
<td>2027</td>
<td>1605.555</td>
<td>1403.154</td>
</tr>
<tr>
<td>2028</td>
<td>1659.803</td>
<td>1421.051</td>
</tr>
<tr>
<td>2029</td>
<td>1717.551</td>
<td>1442.946</td>
</tr>
<tr>
<td>2030</td>
<td>1776.762</td>
<td>1465.340</td>
</tr>
<tr>
<td>2031</td>
<td>1834.648</td>
<td>1834.645</td>
</tr>
<tr>
<td>2032</td>
<td>1891.851</td>
<td>1891.843</td>
</tr>
<tr>
<td>2033</td>
<td>1949.547</td>
<td>1949.538</td>
</tr>
<tr>
<td>2035</td>
<td>2065.381</td>
<td>2065.370</td>
</tr>
<tr>
<td>2036</td>
<td>2123.070</td>
<td>2123.056</td>
</tr>
<tr>
<td>2037</td>
<td>2180.822</td>
<td>2180.806</td>
</tr>
</tbody>
</table>
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 $2180.822 per 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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The golden ratio corresponds to a line segment both in plane geometry and in solid geometry. Finally, Section 4 focuses on data description and its analysis. Conclusion and recommendations are provided in the last section. The study region is covered under the GDP envelope of a specific period, which can be viewed through (i) production and (ii) expenditures on personal consumption. GDP measures an economy’s current market value for all products and services generated. A large group of people experiencing declining income at a time when its complement is increasing can result in stagflation. Information about GDP can be quite advantageous for evidence-informed decision-making. However, one must be always aware that any model is based prediction enables planners to address specific economic challenges such as resource allocation.

Our study discovers that the proposed ARIMA models are useful for future GDP per capita forecasting. The best-fitted ARIMA model has been used to obtain forecast values for the next one and half years. The analysis of time series: 12 provides the total value of final goods and services. GDP assessment represents the sample data from the period 1976-2019. They correctly anticipated stagflation for the Jordanian economy between 2020 and 2022, Ghazo (2021) employed ARIMA models for forecasting GDP of Greece, while correctly discovering, its parameters determined, and its diagnostics examined. Table 5 provides the GDP for the considered time series.

References


The golden ratio corresponds to internal division.

The arithmetic mean may be moving upward, with rising variability. Variability can be decay in ACF suggests that there may be changes in both the mean and the variability over time for

The Golden Ratio corresponds to the external division of a line segment.

Akhtaruzzaman & Shafie, 2011.

Figure 4


