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Forecasting Remittance Inflow in Nepal Using the Box–Jenkins ARIMA Model

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ABSTRACT– The remittance, defined as a portion of household income sent by individuals from their earnings in foreign economies, constitutes a substantial aspect of Nepal's current financial landscape. This research endeavors to identify an appropriate ARIMA model to forecast the remittance inflow in Nepal from 1990/91 to 2021/22. The Box-Jenkins methodology serves as the framework for modeling and forecasting the annual remittance inflow, with EViews 12 software employed for comprehensive data analysis. Various ARIMA models were evaluated to capture nuances in annual remittance trends. The investigation identified the ARIMA (1,1,1) model as the most suitable for forecasting Nepal's remittance inflow. This finding provides essential insights for policymakers, economists, and stakeholders, facilitating informed decision-making and future economic planning in the country.

KEYWORDS – ***ARIMA, Box-Jenkins Methodology, Forecasting, Remittance inflow***

1. INTRODUCTION

Remittance refers to the portion of household income that individuals send back from foreign economies, typically earned during their temporary or permanent residence in those economies (IMF, 2009). This encompasses both monetary and non-monetary transactions made by individuals in foreign countries. Estimating the precise amount of remittances received by a country is challenging, given that a substantial portion of these transactions might occur through unofficial channels (Metzger et al., 2019; Ratha & Mohapatra, 2007).

Remittances, recognized as a crucial element in the economic growth of developing nations, have gained substantial worldwide focus in recent years. This heightened attention stems from the remarkable growth and impact of remittances globally, particularly their inflow and influence on developing and less developed countries. Not only has the size of remittances consistently increased, but they also stand as one of the principal sources of financial influx into these developing nations. In certain countries, remittances even surpass the volumes received from traditional sources like official aid and private capital flows (Adedokun, 2013; Aggarwal & Peria, 2006; Nyamongo et al., 2012; Pandikasala et al., 2022). Globally, the officially documented international remittances amounted to $672.46 billion in 2021, reflecting a 2.18% increase compared to the figures from 2020. Most of these funds were directed towards development, as outlined in the World Bank's 2021 reports (Nijbroek, 2022).

Nepal is widely recognized as a prominent destination for remittances, signifying a substantial inflow of money sent from individuals residing in various corners of the globe (Sherpa, 2022). This remittance inflow has played a substantial role in the economy, with a noticeable flow beginning in the 1990s and a remarkable growth since 2002. By 2020, Nepal had secured the fifth position globally in terms of the remittance-to-GDP ratio, as highlighted in the World Bank's 2021 report (Gautam, 2021). Nepal, among the developing nations in South Asia, receives substantial remittances due to the significant number of economically active individuals it sends abroad for employment (Acharya & Paudel, 2021). As per the results of the 2021 Census, there are over 2.1 million Nepali citizens residing outside the country, which accounts for 7.4 percent of the national population (NSO, 2023). In the past, India was the main destination for Nepalese migrants, and the majority of remittances came from there (Basnet, 2014; Pant, 2011). Presently, a greater share of remittances originates from nations other than India. Nepal receives its most substantial remittance volumes from countries like Malaysia and several Gulf nations, including Qatar, Saudi Arabia, and the UAE, as reported by the Ministry of Finance, Government of Nepal, in 2022 (Dhakal & Paudel, 2023). In 2021, Nepal received remittances amounting to $8.2 billion, constituting 22.61% of the country's GDP (World Bank, 2022). From 2005 onwards, Nepal has received a higher amount of foreign exchange from remittances compared to the combined sum generated from exports and foreign direct investment, as indicated by the World Bank reports released in 2022 (Dhakal & Paudel, 2023).

In Nepal, remittance-receiving families mainly use remittances for consumption purposes (Bhandari, 2020; Mishra et al., 2022; Thapa & Acharya, 2017). If accomplished with clear plans, remittances can act as substances for development. On the other hand, a lack of preparation for the use of remittances can have adverse effects as shown by several macro-indicators such as relative wages and prices, market segmentation, government spending, investment and money supply, factor productivity, competitiveness, inflation, and exchange rates (Sapkota, 2018; Sigdel, 2022) emphasized the lack of adequate priority to remittances in the national policies of Nepal even when remittance was just burgeoning. Bastagli et al. (2019); and Hagen-Zanker (2014) recognized potential products and policies to influence the productive use of remittances in Nepal. Nalane et al. (2012) suggested that the government should plan schemes and policies to channel remittance into productive projects. Numerous other studies have also suggested to application of remittance for the economic development of Nepal (Nepal et al., 2020; Pant, 2011; Thagunna & Acharya, 2013; Uprety, 2017).

Nepal lacks clear policies and effective strategies to manage remittances, posing a challenge in harnessing these substantial financial contributions effectively. This deficiency hampers the redirection of remittances towards avenues that could drive sustained economic growth. Addressing this gap requires prioritized policies maximizing the positive impact of remittances on economic growth. However, implementing these recommendations remains challenging, constraining Nepal's ability to fully utilize remittance inflows for long-term economic progress. The ARIMA model, particularly the Box-Jenkins methodology, emerges as a potential solution by capturing patterns and guiding policy decisions to optimize remittance utilization for Nepal's sustainable economic development.

2. MATERIALS AND METHODS

For this study, a cross-sectional analysis spanning 32 years of remittance inflow data in Nepal from 1990/91 to 2021/22 was conducted to model and forecast using the Box-Jenkins method. EViews 12 software and MS Excel were employed for the data analysis. The research utilized the Autoregressive Integrated Moving Average (ARIMA) model, comprising three components: AR (Ratha et al.) for lag observations, for nonseasonal observation differences, and MA (Hossain et al.) representing the moving average window size. An ARIMA model is denoted as (p,d,q), highlighting the occurrence of each function in the model. Zero values are valid. Initially, for time series modeling, the data must be stationary. Stationarity implies consistent fluctuations around a mean. To achieve this, if the data isn't stationary, a differencing process is applied. If the first-order differences remain non-stationary, second-order differences are used to attain stationarity (Ma et al., 2018; Reisen, 1994). The ARIMA model aims to forecast a series, following the Box-Jenkins methodology's four stages: identification, estimation, diagnostics, and forecasting. This systematic approach is employed to ensure effective modeling and prediction of time series data (Makridakis & Hibon, 1997).

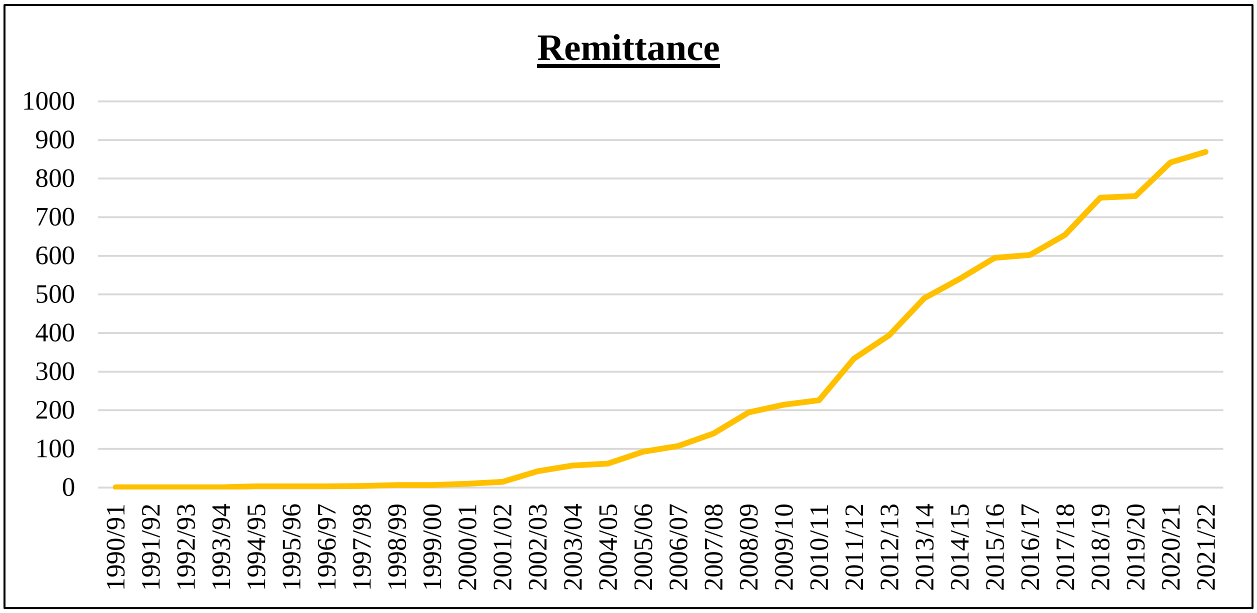


Figure 1. Annual Remittance flow of Nepal, 1990/91-2020/21 (in billions of NRS)

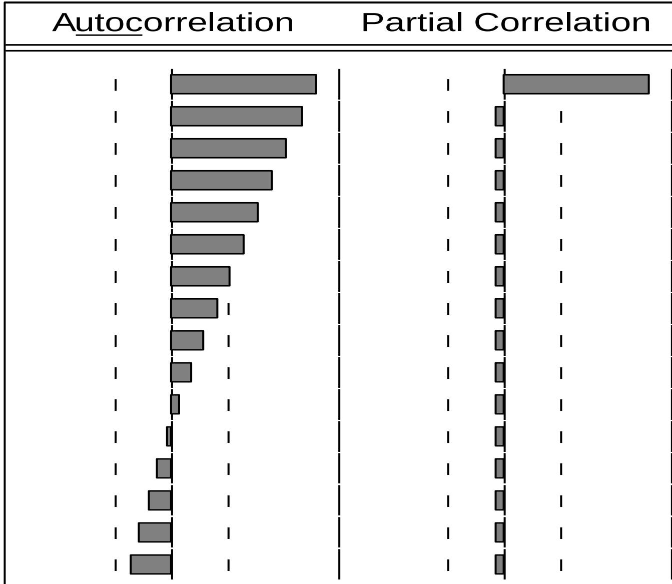
3. RESULTS AND DISCUSSIONS

3.1 Identification of Stationery

Figure 1 presents a graphical representation depicting Nepal's annual remittance inflow (measured in billions of NRS) from 1990/91 to 2020/21. The graph showcased a consistent and continuous rise in remittance inflow throughout these years, signaling a positive and upward trend in remittances for Nepal during this period.

Figure 2 displays a correlogram representing the yearly remittance inflow in Nepal. The analysis focused on the Auto Correlation

Function (ACF) and Partial Auto Correlation Function (PACF) up to 16 lags. Based on the findings from the figure, it can be inferred that the autocorrelation coefficients begin at a high level and gradually decrease, indicating a lack of stationarity in the series. Additionally, the Ljung-Box Q-statistic yielded a value smaller than 0.05, suggesting that we cannot dismiss the null hypothesis, indicating non-stationarity in the remittance inflow series (Hassani & Yeganegi, 2020). To further confirm this, an Augmented Dickey-Fuller (ADF) unit root test was conducted.



	AC	PAC	Q-Stat	Prob
1	0.906	0.906	28.824	0.000
2	0.813	-0.047	52.788	0.000
3	0.720	-0.047	72.248	0.000
4	0.629	-0.048	87.605	0.000
5	0.539	-0.048	99.294	0.000
6	0.450	-0.048	107.78	0.000
7	0.364	-0.048	113.56	0.000
8	0.281	-0.048	117.13	0.000
9	0.200	-0.049	119.03	0.000
10	0.123	-0.048	119.77	0.000
11	0.049	-0.048	119.90	0.000
12	-0.020	-0.048	119.92	0.000
13	-0.085	-0.047	120.34	0.000
14	-0.146	-0.047	121.62	0.000
15	-0.201	-0.046	124.21	0.000
16	-0.251	-0.044	128.48	0.000

Figure 2. Correlogram of annual Remittance inflow of Nepal, 1990/91-2021/22

Table 1. ADF Unit root test result of annual remittance inflow of Nepal

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		3.447712	1.0000
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	
*MacKinnon (1996) one-sided p-values.			

Table 1 presents the outcomes of the ADF unit root test, indicating that the remittance inflow series is non-stationary (p-value>0.05). The null hypothesis of the ADF test is that the time series data contains a unit root, implying it's non-stationary and needs differencing to achieve stationarity (Cavaliere & Taylor, 2007; Cheung & Lai, 1995). This suggests that there isn't sufficient evidence to reject the null hypothesis of a unit root. Hence, it is necessary to transform the series into first or second differences to achieve stationarity (Cavaliere & Taylor, 2007).

Kathford Journal of Engineering and Management,
ISSN: 2661-6106.

VOL. 3 ISSUE 1 JUNE 2023, pp. 72-86

A log transformation was applied to the original remittance series by taking the natural logarithm (Ln) of the remittance values. This transformation aimed to assess whether using the natural logarithm of the remittance series (Ln(remittance)) would result in achieving stationarity (DeJong et al., 1992).

Figure 3 displays the trend line for the Ln(remittance) series of Nepal after applying the logarithm. Even with the logarithmic transformation, the trend continued to rise, suggesting that the Ln(remittance) series remained non-stationary (Velasco, 1999b).

According to Table 2, both the ACF and PACF of the Ln(Remittance) series exhibited a consistent pattern, demonstrating p-values exceeding 0.05. This pattern closely resembled the characters observed in the original level remittance series. Additionally, Table 2, presenting the results of the ADF unit root test, confirmed the absence of significant evidence to reject the

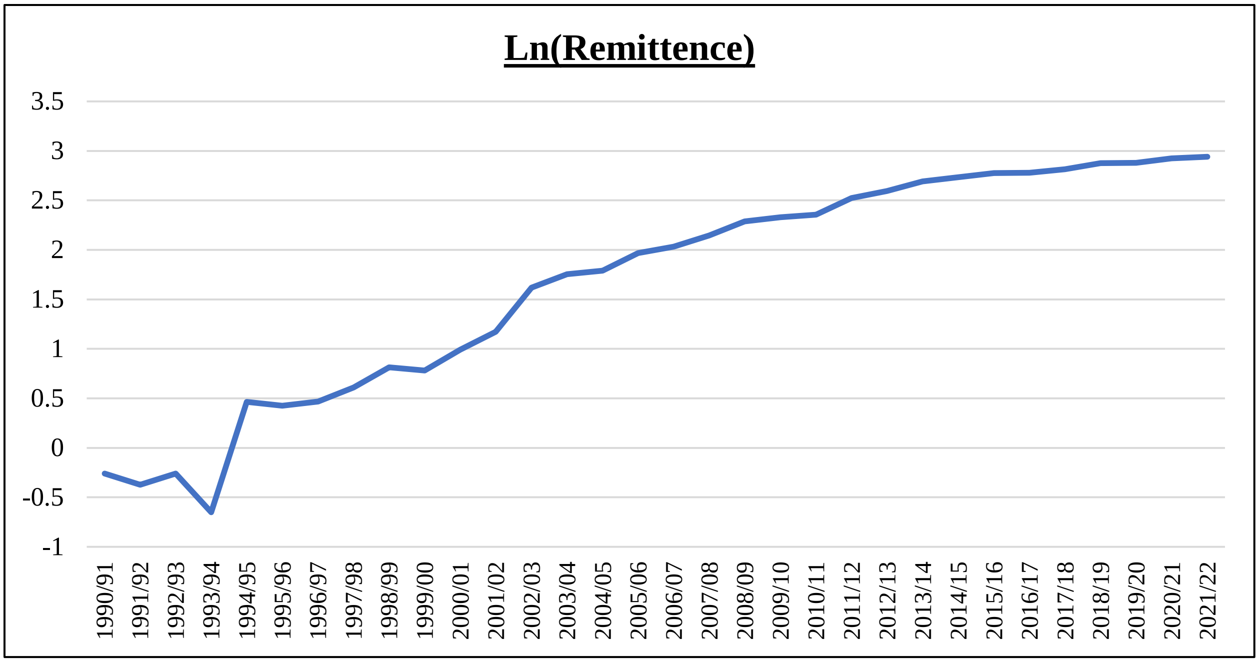


Figure 3. The trend line of the Ln(Remittance) series

Table 2. ADF Unit root test result of Ln(remittance)difference of Ln(Remittance)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.303730	0.6151
Test critical values:	1% level	-3.661661	
	5% level	-2.960411	
	10% level	-2.619160	

*MacKinnon (1996) one-sided p-values.

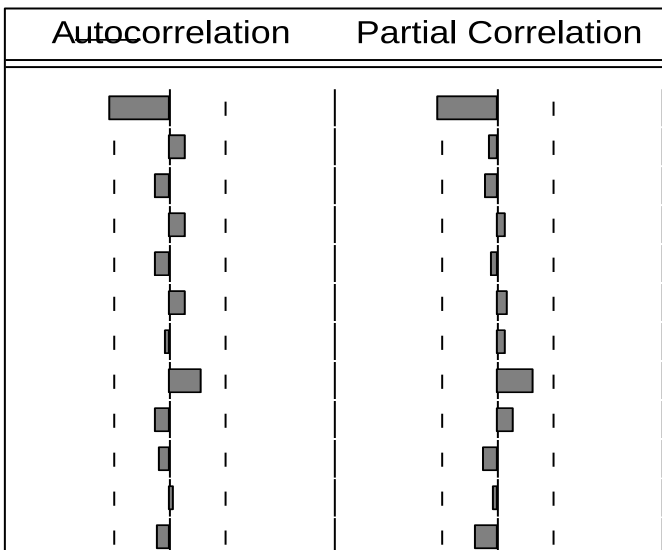
null hypothesis of a unit root existing within the Ln(remittance) series (Hall, 1994).

Hence, in the following stage, the autocorrelation and partial autocorrelation functions using the first difference operator of Ln(remittance) series have been inspected to approve the stationarity in the first difference log Remittance series, D(Ln(Remittance)).

The findings presented in Figure 4, depicting the correlogram of the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) of the Differenced Ln(remittance) series, indicate that 11 out of 12 correlations fall within the 95 percent confidence intervals up to the specified 24 lags (though only 12 lags are reported here). This observation strongly suggests that the first difference of the Ln(remittance) series has achieved stationarity (Ramsey, 1974).

Table 3. ADF Unit root test result of the first difference of Ln(Remittance) series

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.056973	0.0000
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	
*MacKinnon (1996) one-sided p-values.			



	AC	PAC	Q-Stat	Prob
1	-0.382	-0.382	4.9761	0.026
2	0.101	-0.053	5.3347	0.069
3	-0.087	-0.078	5.6095	0.132
4	0.104	0.056	6.0170	0.198
5	-0.090	-0.033	6.3329	0.275
6	0.100	0.060	6.7394	0.346
7	-0.031	0.041	6.7805	0.452
8	0.199	0.229	8.5432	0.382
9	-0.095	0.093	8.9616	0.441
10	-0.062	-0.096	9.1499	0.518
11	0.031	-0.021	9.1994	0.603
12	-0.081	-0.135	9.5540	0.655

Figure 4. Correlogram of the first difference of Ln(Remittance) series

Table 3 showcases the Augmented Dickey-Fuller (ADF) test outcomes applied to the first Ln(Remittance) difference series. The lag length was selected using the Akaike Information Criterion (AIC) to determine

Kathford Journal of Engineering and Management,
ISSN: 2661-6106.

VOL. 3 ISSUE 1 JUNE 2023, pp. 72-86

stationarity. The table reports test statistic and their corresponding p-values. The results strongly reject the null hypothesis of a unit root at a 1 percent significance level ($p < 0.01$), affirming that the first difference of the logarithm of the Remittance series is stationary. Hence, it implies that the preferred differencing level is identified as d = 1 (Velasco, 1999a).

The potential AR and MA orders were established by analyzing the ACFs and PACFs of the first difference of the log GDP series in Figure 4, calculated for 24 lags. In Figure 4, the ACF of D(LnRemittance) indicates notable autocorrelation at lag 1 and displays a decay pattern following an exponential trend with a damped sine-wave shape beyond lag 1. Particularly, a substantial negative spike is evident at lag 1 in the ACF, suggesting that the correlation between successive observation pairs in the initial period exceeds the expected zero sampling error. However, all subsequent autocorrelations fall within the 95 percent confidence limit. Hence, this suggests a potential order of 1 for the moving average process (i.e., q = 1).

Figure 4 showcases the Partial Autocorrelation Functions (PACFs) concerning the initial difference in the logarithm of the Remittance series. Notably, the partial autocorrelation recorded at lag 1 stands at -0.382, significantly different from zero. Furthermore, there's a notable negative spike specifically at lag 1, whereas all other partial autocorrelations remain within the 95 percent confidence limit. This observation indicates a possible order of 1 for the autoregressive process (p = 1).

The pattern observed in Figure 4, where both the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) display similar trends, indicates an ARIMA process. This pattern aligns with autoregressive and moving average processes ranging from the lowest order,0, to the highest order, 1.

In the Box-Jenkins method, determining the preliminary values for the autoregressive, differencing, and moving average parameters involves a subjective evaluation. These initial orders serve as starting points and are subject to adjustment. Consequently, a series of ARIMA (p, d, q) models are examined, exploring different combinations of p and q values. This iterative approach aims to pinpoint the most fitting model that delivers enhanced precision in predictions and analytical outcomes.

3.2 Estimation of the model

This study determines the optimal ARIMA model by considering various metrics such as volatility, regression's standard error, adjusted R-square, Akaike Information Criterion (AIC), and Schwarz Information Criterion (SIC) (Depken et al.). The model's effectiveness is gauged by its volatility, measured through Sigma square (SIGMASQ), where a lower Sigma square signifies a more efficient predictive capacity. Additionally, the superior model is characterized by a higher adjusted R-square (Adj. R^2) and lower values for the standard error of the regression, AIC, and SIC (Cheung & Lai, 1993; Reddy, 2019).

The research assessed various models with autoregressive and moving average orders to find the best fit. The correlogram of the D(LnGDP) series indicates the need to consider both lagged variables and lagged errors during estimation. Table 4 displays the outcomes of the estimated ARIMA models, helping to select the best models based on SIGMASQ, Adj. R2, SER, AIC, and SIC. Table 4 provides confirmation that among various models, the ARIMA(1, 1, 1) model stands out as the superior choice based on metrics such as SIGMASQ, Adj. R^2, SER, AIC, and SIC.

Table 4: Test Results of ARIMA (p, d, q) Model Fitting

	SIGMASQ	Adj. R^2	SER	AIC	SIC
ARIMA (1,1,1)	762.1415	0.19863	29.58127	9.057688	9.935719
ARIMA (0,1,1)	993.6638	-0.00753	33.16817	9.934012	10.07278
ARIMA (1,1,0)	945.5722	0.04123	32.25558	9.886657	10.02543

denoted as ARIMA (1,1,1) and can be expressed as:

$$D(LnRemittance) = 26.48631 + 0.929509D(LnRemittance_{t-1}) - 0.695296\varepsilon_{t-1} + \varepsilon_t$$

3.3 Diagnostic Checking

Before using the final model for forecasting, it's crucial to conduct various diagnostic tests to confirm its goodness of fit. A key assumption for selecting the most accurate model is that residuals are akin to white noise and are uncorrelated. Hence, evaluating the Box-Jenkins model involves inspecting these residuals. If the residuals are randomly distributed, autocorrelations and partial autocorrelations statistically amount to zero. If not, it suggests an incorrect model fit.

The research investigates autocorrelation and partial autocorrelation of residuals at

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	26.48631	29.37635	0.901620	0.3752
AR(1)	0.929509	0.134943	6.888165	0.0000
MA(1)	-0.695296	0.235301	-2.954918	0.0064
SIGMASQ	762.1415	197.3112	3.862637	0.0006

R-squared	0.278743	Mean dependent var	28.00007
Adjusted R-squared	0.198603	S.D. dependent var	33.04403
S.E. of regression	29.58127	Akaike info criterion	9.750688
Sum squared resid	23626.39	Schwarz criterion	9.935719
Log likelihood	-147.1357	Hannan-Quinn criter.	9.811003
F-statistic	3.478214	Durbin-Watson stat	2.350398
Prob(F-statistic)	0.029572		

Inverted AR Roots	.93
Inverted MA Roots	.70

Table 5. Estimation Model ARIMA (1,1,1)

The outcomes displayed in Table 5 confirm the statistical significance of both coefficients of AR and MA at a 1% significance level. With roots measuring 0.92 and 0.69 within the unit circle, it signifies stationarity and inevitability. The selected model, as outlined in Table 4, is

defined

lag intervals to assess autocorrelation. It focuses on examining the residual autocorrelations using Ljung-Box Q statistic tests for serial autocorrelation across 24 lags. Figures 5 and 6 illustrate the correlogram of residuals and squared residuals, showcasing autocorrelations and

Kathford Journal of Engineering and Management,
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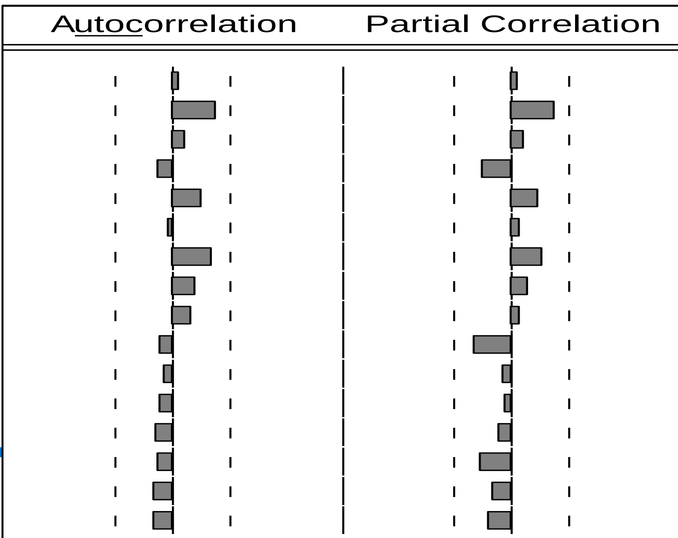
VOL. 3 ISSUE 1 JUNE 2023, pp. 72-86

partial autocorrelations of the ARIMA (1,1,1) model, accompanied by their respective p-values.

Table 5 indicates that the appropriate model is (1,1,1). A flat correlogram is an ideal outcome. If any lag appears significant, the model should be re-evaluated. The residual values' correlogram appears flat, indicating they fall within the standard error bounds (95% CI). This suggests that all essential information has been apprehended. Consequently, this model will be utilized for forecasting purposes.



	AC	PAC	Q-Stat	Prob
1	0.035	0.035	0.0429	0.836
2	0.258	0.257	2.3865	0.303
3	0.081	0.069	2.6243	0.453
4	-0.092	-0.173	2.9445	0.567
5	0.176	0.158	4.1676	0.526
6	-0.020	0.041	4.1834	0.652
7	0.244	0.192	6.7189	0.459
8	0.141	0.102	7.6005	0.473
9	0.117	0.046	8.2342	0.511
10	-0.077	-0.226	8.5222	0.578
11	-0.045	-0.046	8.6269	0.656
12	-0.071	-0.037	8.9012	0.711
13	-0.102	-0.077	9.4887	0.735
14	-0.095	-0.195	10.033	0.760
15	-0.112	-0.109	10.831	0.765
16	-0.108	-0.132	11.628	0.769

Figure 6: Correlogram of Residuals (Autocorrelation test)

5. Ljung-Box test for squared residuals for ARIMA (1,1,1)

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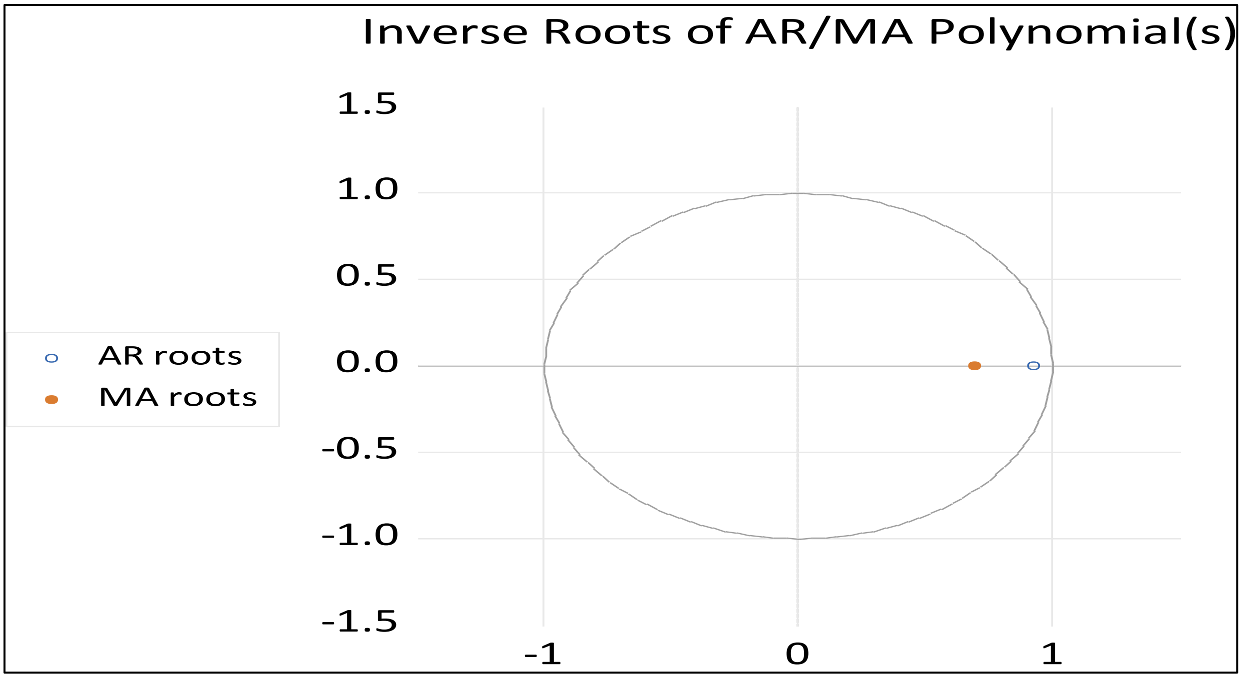

Figure 7. Inverse Roots of AR/MA Polynomials

Table 6 displays the results of the Ljung-Box test performed on squared residuals, a method frequently employed to evaluate autocorrelation. The utilization of the Ljung-Box Q statistic indicates that the autocorrelations and partial autocorrelations of residuals at various lags do not show significant deviations from zero. This indicates that all fluctuations fall within the 95 percent confidence interval, signifying that the residuals follow a random pattern (Safi & Al-Reqep, 2014). Consequently, this suggests that the model adequately fits the data.

Figure 7 displays the inverse roots of the AR (autoregressive) and MA (moving average) characteristic polynomials, evaluating the stability of the selected ARIMA (1,1,1) model. These roots are instrumental in determining the model's stability; when values fall below one and are within the unit circle, it indicates stability. If the roots surpass one or exist outside the circle, it invalidates the impulse response standard errors. Figure 7 confirms the stability of the ARIMA model, showcasing inverse roots within the unit circle, denoting values below unity. When both AR and MA roots align in the same direction within the circle, it further emphasizes the model's stability, implying consistent and predictable patterns within remittance series data (Pesaran, 2007).

3.4 Forecasting

The selection of appropriate forecasting methods heavily relies on the available data (Koutsandreas et al., 2022). The primary aim of forecasting is to anticipate forthcoming values within a time series (Shumway & Stoffer, 2011). This study specifically employed past values of the time series to forecast its future values, a method commonly referred to as Univariate Time Series Forecasting. ARIMA serves as a forecasting algorithm founded on the

Kathford Journal of Engineering and Management,
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VOL. 3 ISSUE 1 JUNE 2023, pp. 72-86

concept that information contained within previous time series values alone can be utilized to predict future values (Prabhakaran et al., 2018). Considering the analyses from earlier sections, the study concluded that the ARIMA (1, 1, 1) model stands as the most suitable for forecasting remittances.

the symmetric Mean Absolute Percentage Error (sMAPE) is a metric utilized to evaluate forecast accuracy, calculating the average percentage difference between predicted and actual values while considering their absolute difference. A sMAPE value of 4.03% suggests that, on average, the ARIMA model's predictions

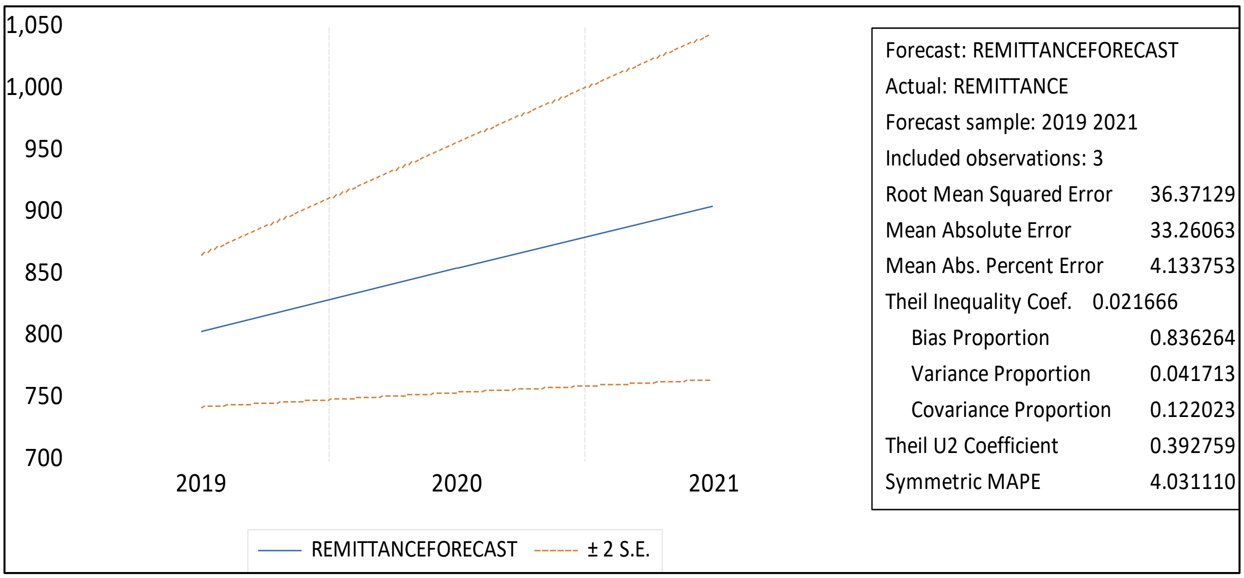

Figure 8. In-Sample Forecast of Remittance Inflow

The forecast graph is shown below;
Figure 8 illustrates the in-sample forecast of remittance inflow from 1990/91 to 2020/21. The predicted values of Ln(remittance) fall within a range of plus-minus two estimated standard errors.
This indicates a reasonably reliable prediction interval, reflecting the model's confidence in forecasting the values (Henderson et al., 2012). Similarly, a Theil Inequality Coefficient of 0.00216, closely approaching zero, indicates a minimal level of inequality between the predicted and actual values. This suggests a high level of accuracy in the forecasting model, reflecting a well-fitted and reliable predictive performance (Leuthold, 1975). Additionally,

deviate by approximately 4.03% from the actual observed values. This value indicates a relatively low level of error in the ARIMA model's forecasts, implying that its predictions closely align with the actual outcomes (Karthika et al., 2017; Mohamed et al., 2010).
In conclusion, considering all these parameters together, they collectively support the validity of the chosen ARIMA (1, 1, 1) model for forecasting remittance inflow in Nepal.

4. CONCLUSIONS

This study extensively examined the remittance inflow data in Nepal through the application of the Box-Jenkins ARIMA methodology, spanning from 1990/91 to 2021/22. The investigation involved series stationarity checks, transformation procedures, and model parameter identification through correlograms and unit root tests. The ARIMA (1, 1, 1) model emerged as the best fit. Diagnostic tests validated the model's goodness of fit, confirming its appropriateness for forecasting. The analysis displayed consistent trends in remittance inflows, and the ARIMA model predictions closely aligned with observed values, signifying accurate forecasts.

ARIMA, especially in the Box-Jenkins approach, relies on sizable datasets (typically over 50 observations) for accurate time series analysis. Insufficient data can weaken model reliability. Future research might explore ways to adapt ARIMA for smaller datasets or combine it with other methods for better predictions with limited data.

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