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Modelling and Forecasting the Value of Special Drawing Rights: An ARIMA Approach

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ABSTRACT

In 1969, the International Monetary Fund (IMF) introduced Special Drawing Rights (SDR) as a financial instrument to supplement currency reserves of member states. SDR allow members to draw money in a currency of their choosing. 2025 IMF data valued SDR held by member states at over USD 660 billion. SDR are, thus, a critical financial indicator of significant potential impact on global economic stability. This study analysed SDR prices from November 2015 to October 2025. The Minimal Information Criterion and the Bayesian Information Criterion were applied to compare ARIMA models, and the ARIMA (1,1,0) emerged as the best fit. Model diagnostics confirmed that no validity assumptions were violated. Observed values were regressed against fitted values. The R^2 value was over 90%, indicating a very strong linear relationship, which is very plausible. The model was then used to forecast SDR prices for the months from November 2025 to April 2026. The findings revealed a slight decline in SDR prices in the forecasted period. These insights have a significant impact on IMF member states, investors and international economic policy makers.

Keywords: Special drawing rights (SDR), autoregressive moving average (ARIMA), time series analysis, forecasting.

INTRODUCTION

Background

The International Monetary Fund (IMF) develops and oversees Special Drawing Rights (SDRs), which serve as reserve assets that support member states' currency holdings [1]. SDR were established in 1969 [2]. SDR can be used to draw other currencies, they can function as a currency or a flexible investment instrument, allowing member states to manage their foreign currency needs and stabilise their economies [3]. SDRs function as an international reserve asset that countries can use in global transactions [4]. Their allocation has contributed to economic stability by boosting member states' reserve positions [5]. According to the IMF [6], as of 31 October 2025 there were over 660 billion united states dollars (USD) worth of SDR held by member states. This significant amount highlights the importance of SDR as a crucial and influential financial asset for member states and other investors. SDR are thus a crucial financial indicator that can impact global economic stability. In times of disaster, numerous countries have utilised SDRs to support their health and social spending requirements [7].

Predicting future time-series values is important in many fields [8]. In finance, forecasting supports key decision-making because markets are volatile and uncertain [9]. For investors, anticipating currency

price movements is crucial for both speculation and managing exchange-rate risk [10]. Time series data contains the operational rules governing the system, it is in research and analysis that we seek to unlock this information and use it to forecast [11]. Accurate forecasting of financial indicators is necessary for strategic planning of policy makers [12].
It is important to understand how SDR prices fluctuate over time. Money markets help regulators ensure liquidity in economies through the monetary policy [13]. In this study, SDR prices were observed for the period from November 2015 to October 2025. A model was then developed and used to forecast the prices in the period from November 2025 to April 2026. The aim of the study was to develop a robust model that represents and accurately forecast SDR values. These forecasts have significant implications for the global economy, as they provide critical insights for member states, investors and other international policy makers. Financial time series forecasting is vital to the global economy because it helps predict economic gains and supports national economic development [14]. Effective forecasting focuses on identifying significant patterns and relationships in past data rather than simply repeating historical events [15].

Aim

This research sought to model and forecast the value of special drawing right (SDR) in united states dollars (USD).

Objectives

This study sought to:

- Identify a suitable parameter range for an $ARIMA(p, d, q)$ model.
- Use the chosen parameter range to select the best fitting model using minimal information criteria.
- Forecast the value of special drawing rights (SDR) for the months from November 2025 to April 2026.

MATERIALS & METHODS

The Autoregressive Integrated Moving Average (ARIMA) model strategy is used in this study. Analysis and creation of graphs tables was done in the Minitab 22 software environment.

ARIMA Model

ARIMA models are widely used due to their accuracy in predicting financial indicators [16]. ARIMA has a capability of high capacity for short-term forecasting [17]. In time-series analysis, an ARIMA model combines autoregressive and moving-average components along with differencing [18]. The ARIMA model is formally stated:
Z_t is an $ARIMA(p, d, q)$ process if
$Y_t = \nabla^{d} Z_t$, the result after differencing the time series d times,
(where ∇ is the differencing operator such that $\nabla Z_t = Z_t - Z_{t-1}$,)
is such that:

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q}, \qquad (1)$$

where $\phi_1, \phi_2, \ldots, \phi_p, \theta_1, \theta_2, \ldots, \theta_q$ are constants, and
ϵ_t is a random process with a mean of zero and constant variance.

Bayesian Information Criterion

The Bayesian Information Criterion (BIC) is a statistic used to select a model that best fits the data while having the minimal complexity [19]. BIC is calculated using equation (2):

$$BIC = -2\ln(\rho) + \tau ln(n), \qquad (2)$$

where:
ρ = likelihood of the model,
τ = number of parameters in the model, and
n = number of observations.

Minimal Information Criteria Selection

The Minimal Information Criteria (MINIC) is a method used to identify the best fitting statistical model among a given set. MINIC identifies the model that best fits the data with the minimal necessary complexity [20]. The Bayesian Information Criterion (BIC) can be used in MINIC selection.

ANALYSIS AND RESULTS

Data Source

The data for this study was obtained from the International Monetary Fund (IMF) website in November 2025. SDR price values from November 2015 to October 2025 were used.

The ARIMA Model

To fit an appropriate $ARIMA(p, d, q)$ model, the time series plot of SDR prices (*Figure 1*) was generated to establish stationarity, followed by an autocorrelation and partial autocorrelation plot (*Figure 3*) to estimate an initial parameter range.

Time Series Plot of the price of Special Drawing Rights (SDR) in USD

A month-on-month time series plot was generated for the USD value of SDR for the period from November 2015 to October 2025 (*Figure 1*).

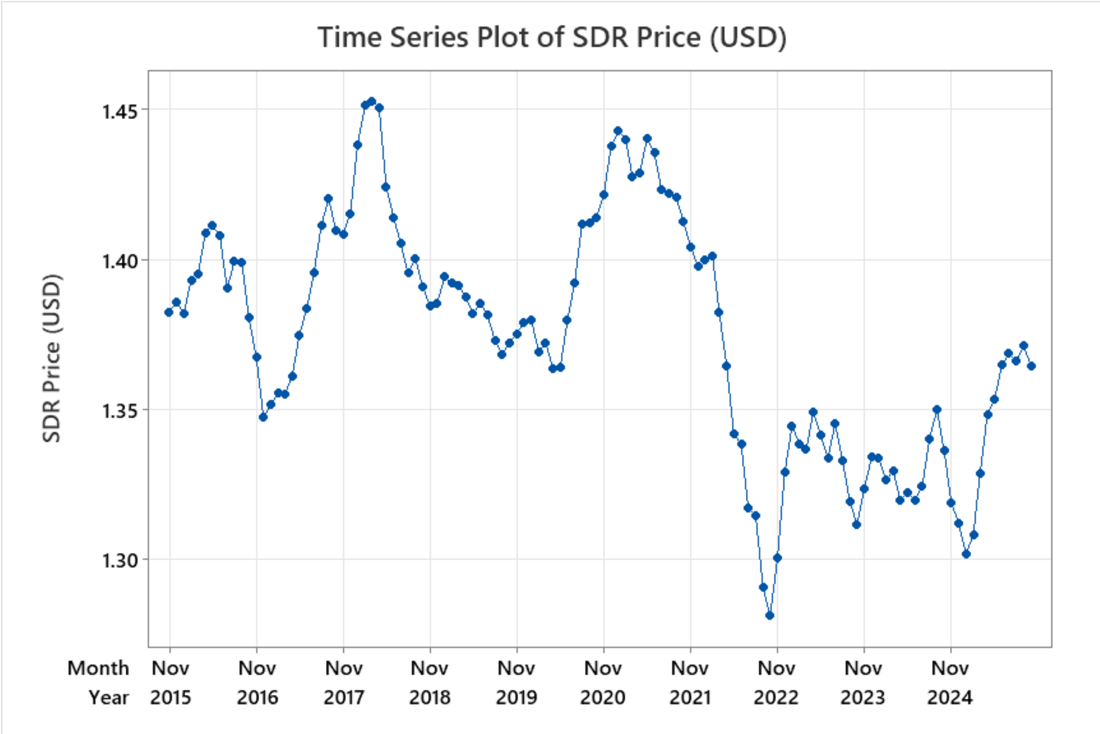


Figure 1: Time series plot of the value of Special Drawing Rights in USD

The time series plot appeared non-stationary. An Augmented Dickey-Fuller test was done to check for stationarity (Table 1).

Table 1: Augmented Dickey-Fuller Test

Null hypothesis:		**Data are non-stationary**
Alternative hypothesis:		Data are stationary
Test Statistic	**P-Value**	**Recommendation**
-2.27665	0.180	Test statistic > critical value of -2.88636.
		Significance level = 0.05
		Fail to reject null hypothesis.
		Consider differencing to make data stationary.

The test statistic was greater than the critical value at the 5% level of significance. The null hypothesis was rejected and it was concluded that the SDR value data was not stationary. It was thus necessary to difference the data.

Time series plot of 1st Differences of SDR value

The data was differenced once, and the time series plot of SDR value differences was generated (*Figure 2*).

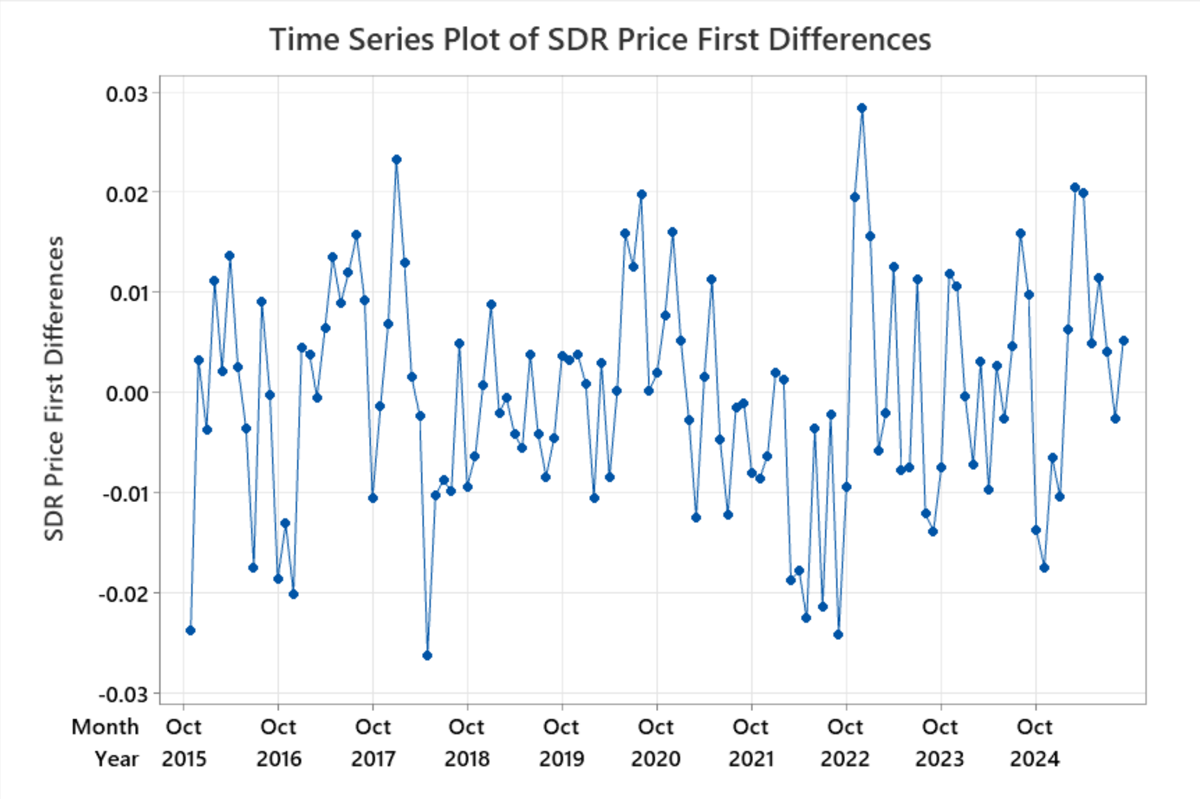


Figure 2: Time series plot of first differences of SDR value in USD

The first differences of the SDR values appeared more stationary than the original SDR values. An Augmented Dickey-Fuller test was done to confirm this observation (Table 2).

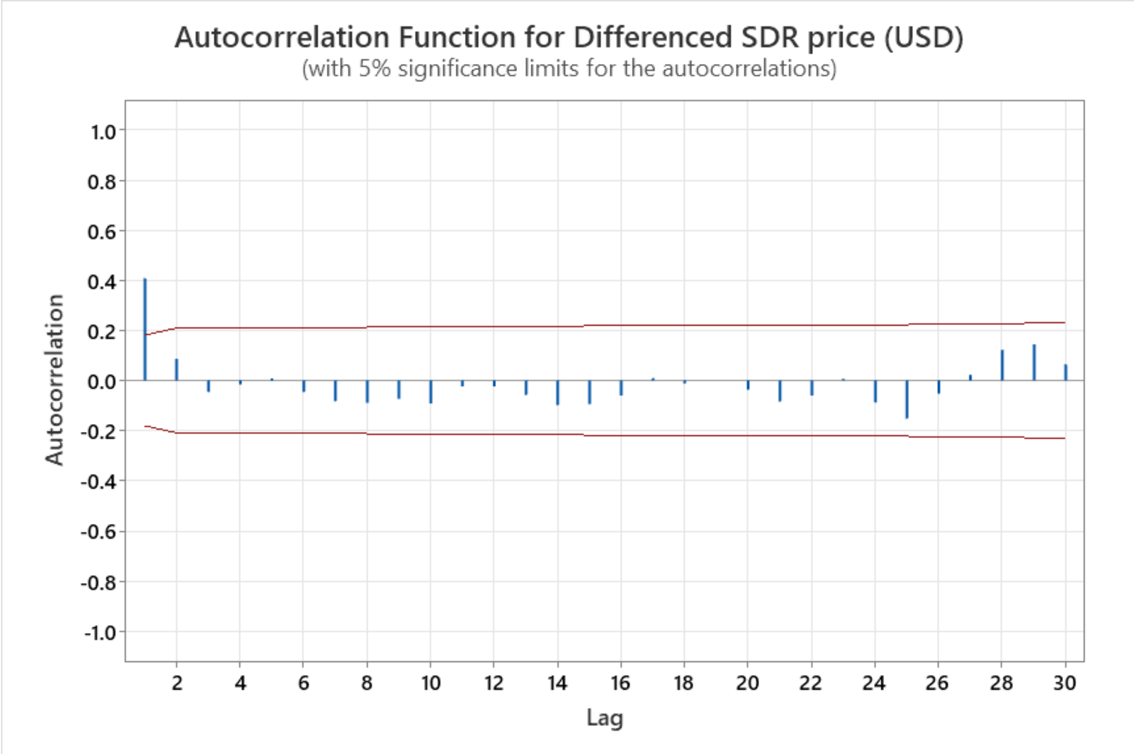
Table 2: Augmented Dickey-Fuller Test

Null hypothesis:		**Data are non-stationary**
Alternative hypothesis:		Data are stationary
Test Statistic	**P-Value**	**Recommendation**
-7.28562	0.000	Test statistic <= critical value of -2.88636.
		Significance level = 0.05
		Reject null hypothesis.
		Data appears to be stationary, not supporting differencing.

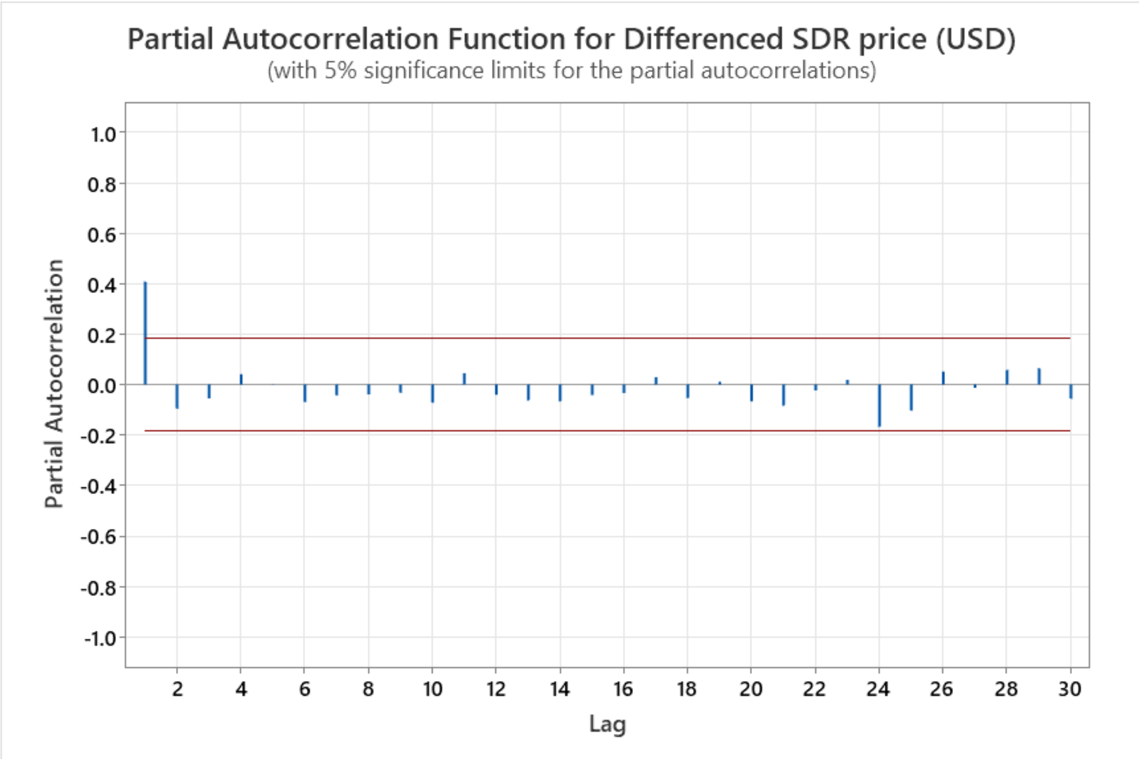
The test statistic was less than the critical value at the 5% level of significance. The null hypothesis was, therefore, rejected and it was concluded that the data was stationary. The data had been differenced once for it to be stationary. Thus, in the $ARIMA(p, d, q)$ model, $d = 1$.

Autocorrelation and partial autocorrelation plots

Autocorrelation and partial autocorrelation plots of differenced SDR prices were generated for the period from November 2015 to October 2025 (*Figure 3)*.



(a)



(b)

Figure 3: (a) Autocorrelation plot of differenced SDR price. (b) Partial autocorrelation plot of difference SDR price.

The ACF and PACF plots of differenced data (*Figure 3*) both had a significant spike at lag 1 and then decayed exponentially after the first lag, indicating that the *ARIMA (p, d, q)* parameters were likely in the neighbourhood of $(p, d, q) = (1,1,1)$.

Model Selection

Minimal Information Criteria (MINIC) selection was used to identify the optimal values of p and q.

The parameters, p and q, were tested in the ranges:

$0 \leq p \leq 3,$
$0 \leq q \leq 3.$

Table 3 below shows the resulting Bayesian Information Criteria (BIC) values.

Table 3: Model Selection

Model (d = 1)	BIC
p = 0, q = 0	-726.04
p = 0, q = 1	-740.31
p = 0, q = 2	-738.41
p = 0, q = 3	-733.96
p = 1, q = 0	-741.62
p = 1, q = 1	-737.48
p = 1, q = 2	-731.71
p = 1, q = 3	-732.55
p = 2, q = 0	-737.77
p = 2, q = 1	-736.65
p = 2, q = 2	-729.28
p = 2, q = 3	-727.19
p = 3, q = 0	-733.62
p = 3, q = 1	-729.11
p = 3, q = 2	-724.63
p = 3, q = 3	-723.21

The parameter combination $p = 1$ and $q = 0$ minimised the BIC. Thus, the selected model was $ARIMA(1,1,0)$.

Final Parameter Estimates

Table 4 and Table 5 show the final parameter estimates and statistics for the residual sum of squares.

Table 4: **Final Estimates of Parameters**

Type	Coef	SE Coef	T-Value	P-Value
AR 1	0.4064	0.0844	4.82	0.000
Constant	-0.000235	0.000930	-0.25	0.801

Table 5: Statistics for Residual Sums of Squares

DF	SS	MS
117	0.0120445	0.0001029

Model Validation

Residual Analysis

The model was assessed using residual analysis plots:

In *Figure 4*: Autocorrelation function and partial autocorrelation function plots.

In *Figure 5*: Normal probability plot, the scatter plot of residuals against fitted values, histogram of residuals and time series plot of residuals.

The residual ACF and PACF (*Figure 4(a) and (b)*). had no significant spike, it was thus concluded that the selected parameters were sufficient to produce a suitable model. On visual inspection of the normal probability plot (*Figure 5(a)*)., it was observed that the points followed a straight line, implying that the residuals were normally distributed. The scatterplot of residuals against fitted values (*Figure 5(b)*) showed no pattern. It was then concluded that the residuals were randomly distributed as required for an accurate model. The histogram of residuals (*Figure 5(c)*) shows that the normality assumption in not violated. From *Figure 5(d),* the errors are randomly scattered about a mean of zero.

It was concluded that the $ARIMA(1,1,0)$ model used, correctly simulates the SDR price, and thus, can be used to make predictions of the future value of SDR.

Regression Analysis

A regression model was fitted to the fitted SDR values against the observed SDR values. The resulting statistics were shown in Equation (3) and Tables 6-8.

Table 6: Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.0135	0.0317	0.43	0.671	
SDR Price (USD)	0.9902	0.0230	42.96	0.000	1.00

Table 7: Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.0099387	94.04%	93.99%	93.80%

Table 8: Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	1	0.18231	0.182309	1845.66	0.000
SDR Price (USD)	1	0.18231	0.182309	1845.66	0.000
Error	117	0.01156	0.000099		
Total	118	0.19387			

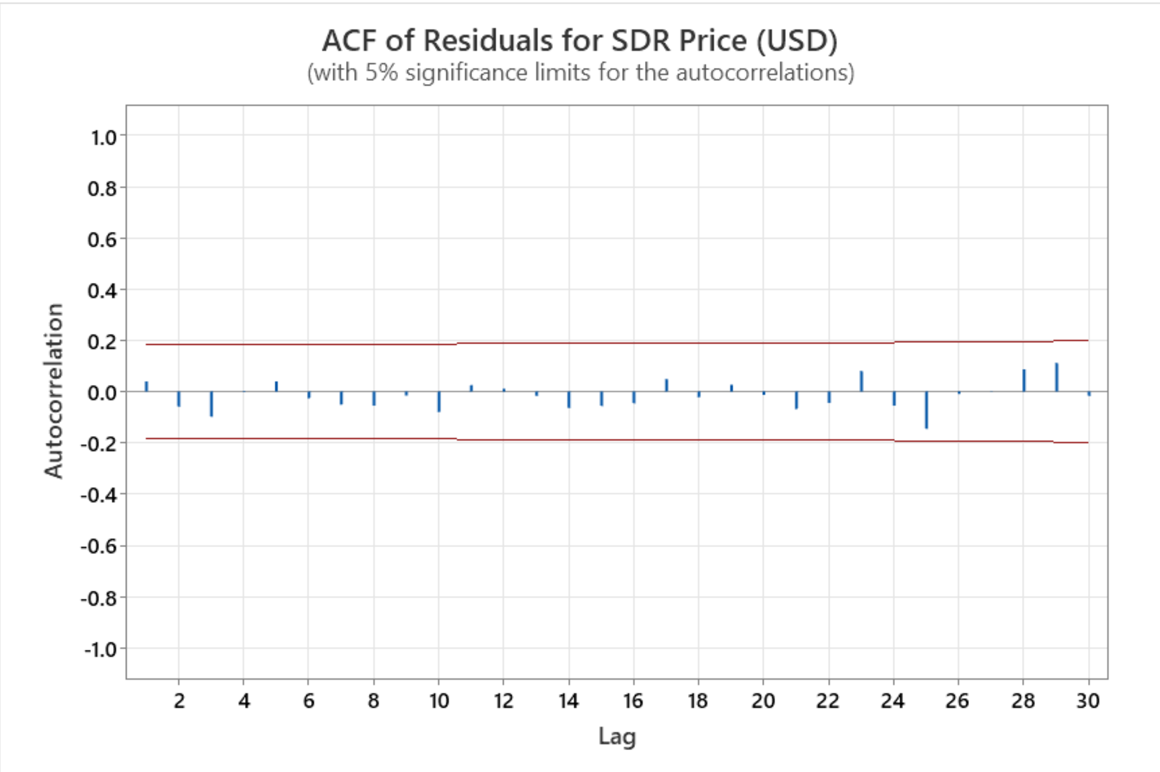
Regression Equation

Fitted values = 0.0135 + 0.9902 SDR Price (USD) (3)

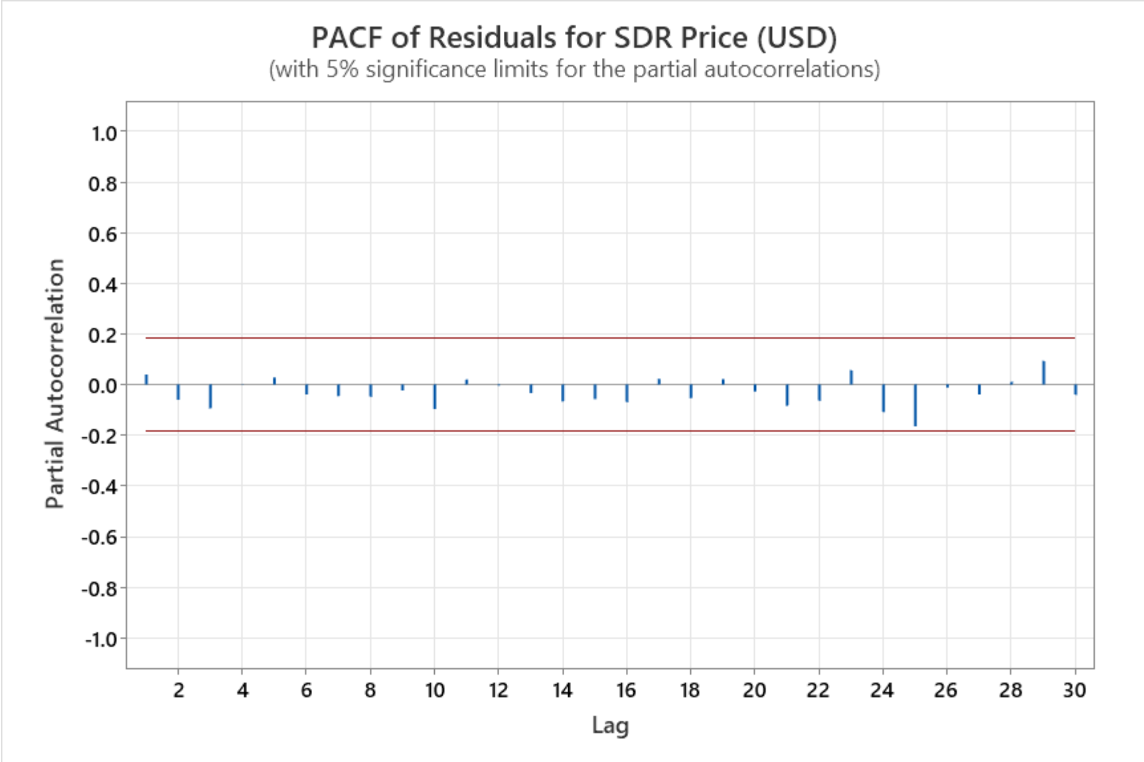
DISCUSSION

The regression coefficient was very close to 1 (Equation 3), showing that the fitted values were approximately equal to the observed values with high accuracy. The p-values in Table 8 showed that the regression coefficient was statistically significant. The R^2 value of 94% (Table 7) showed that the observed values were good predictors of the fitted values. In the regression line and scatter plot of fitted values against observed values (*Figure 6*), the points were closely aligned to the regression line, confirming that the fitted values were approximately equal to the observed values with a high degree of accuracy.

Residual Analysis Plots



(a)



(b)

Figure 4: (a) ACF of residuals for SDR price (b) PACF of residuals for SDR price

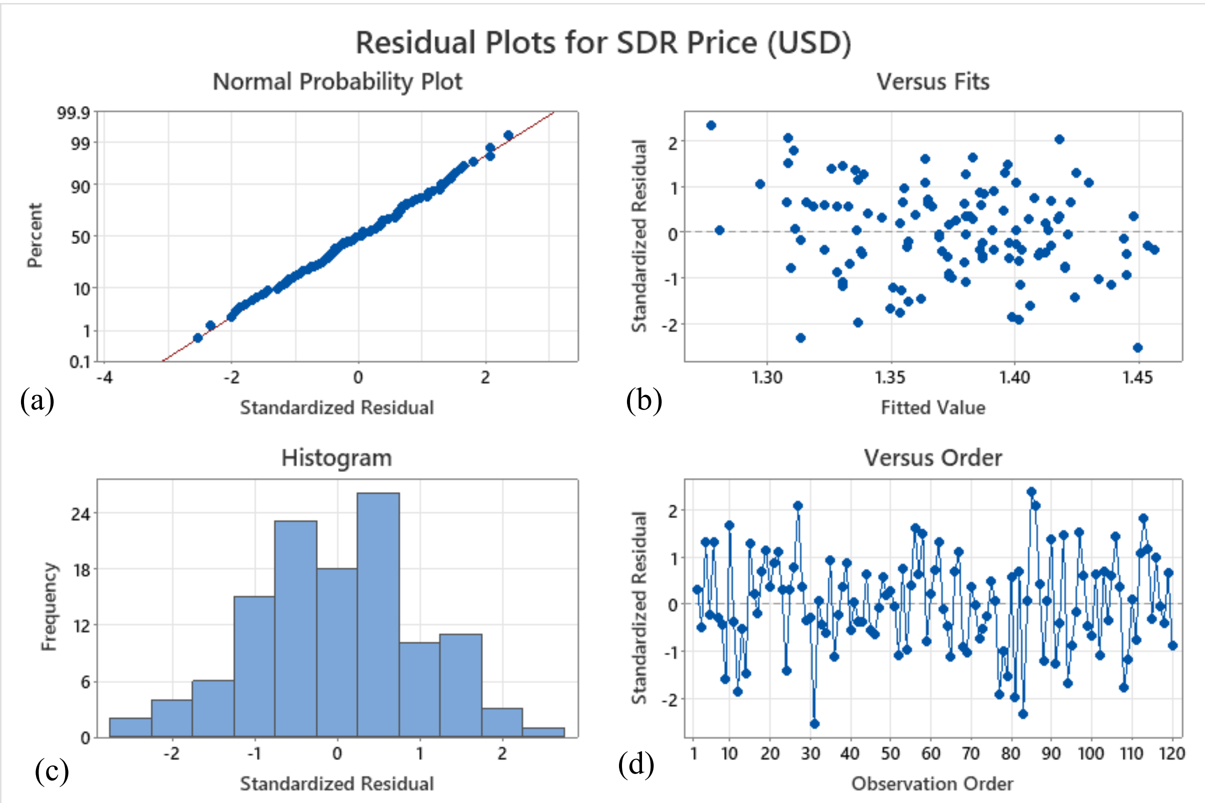


Figure 5: (a)Normal probability plot (b) Scatter plot of residuals against fitted values (c)Histogram of residuals (d) Time series plot of residuals

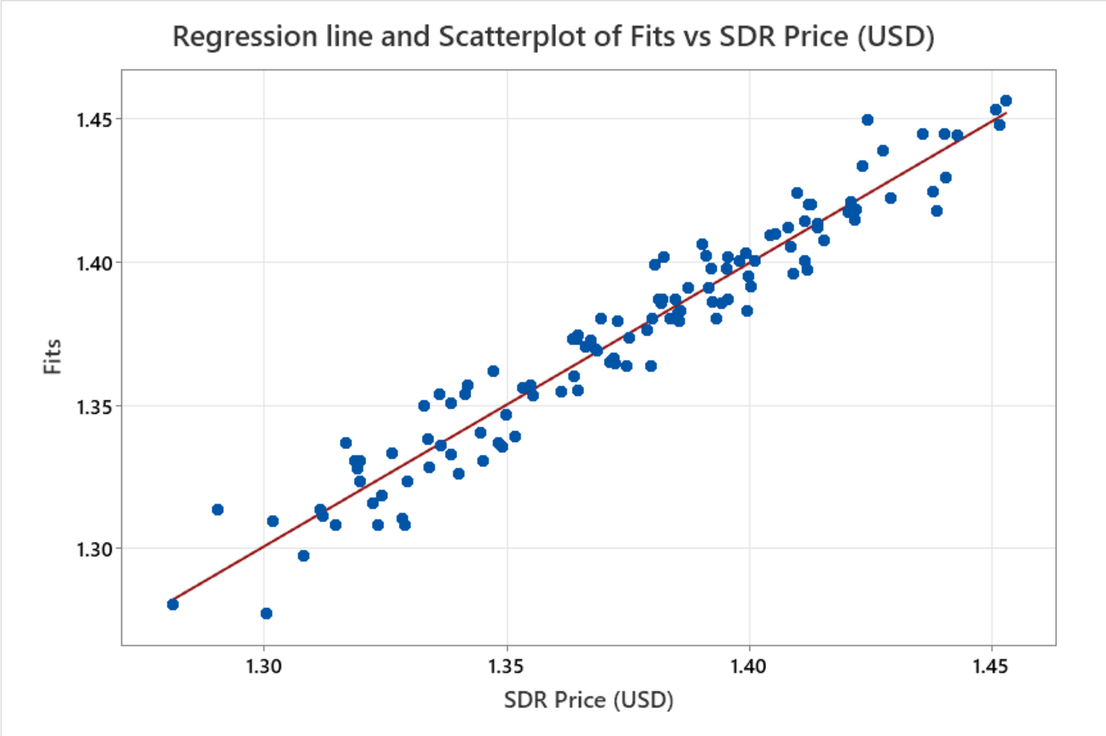


Figure 6: Regression line and scatter plot of fitted SDR values against observed SDR values.

Forecasting

The $ARIMA(1,1,0)$ model was used to predict the price of Special Drawing Rights over the six-month period from November 2025 to April 2026. The results are shown in Table 8.

Table 8: Predicted SDR price in USD

Month	Predicted SDR price (USD)	Observed SDR price (USD)
Nov 2024	1.35	1.34
Dec 2024	1.33	1.32
Jan 2025	1.31	1.31
Feb 2025	1.31	1.30
Mar 2025	1.30	1.31
Apr 2025	1.31	1.33
May 2025	1.34	1.35
Jun 2025	1.36	1.35
Jul 2025	1.35	1.36
Aug 2025	1.37	1.37
Sep 2025	1.37	1.37
Oct 2025	1.36	1.37
Nov 2025	1.37	
Dec 2025	1.37	
Jan 2026	1.37	
Feb 2026	1.37	
Mar 2026	1.37	
Apr 2026	1.37	

Time Series Plot of Observed SDR prices and ARIMA Predicted SDR prices

A time series plot of observed SDR prices and ARIMA predicted SDR values was generated (*Figure 7)*.

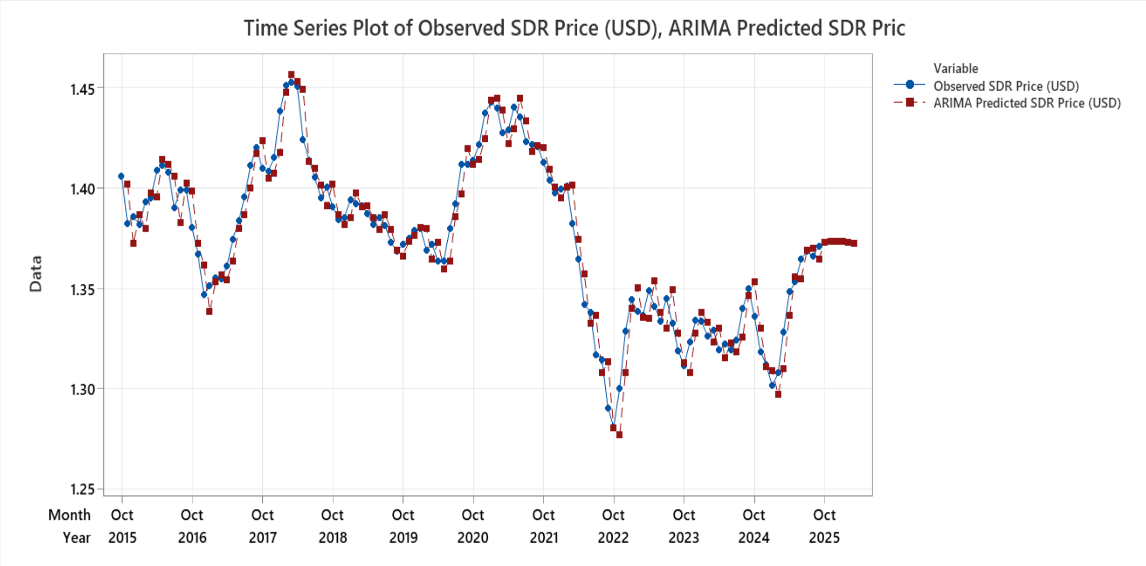


Figure 7: Time series plot of observed SDR prices and ARIMA predicted SDR prices

From *Figure 7* the predicted SDR prices were closely aligned with the observed SDR prices, indicating that the model was a good fit for the data.

DISCUSSION AND CONCLUSION

The $ARIMA(1,1,0)$ model successfully replicated SDR price movements over the period from November 2015 to October 2025. This enabled the researchers to generate reliable forecasts for the period from November 2025 to April 2026. Residual analysis confirmed the randomness of errors. This implied that chosen model was a good fit for the data. Normality of residuals implied that the predictions made by the model were reliable and it could be used to forecast reliably. The analytic approach of the research, including stationarity testing and model validation demonstrated the dependability of the results. There was a close alignment between the observed SDR prices and the SDR prices predicated by the model. This offered confidence for investors and other stakeholders to rely on the predictions of future SDR prices.

The data on SDR price observations was non-stationary. This implied the presence of external economic influences affecting SDR price changes. This suggested that the factors affecting SDR price movements have systematic trends, which were addressed when the data was differenced. The selection of the $ARIMA(1,1,0)$ indicated the influence of immediate and past values on SDR price variations.

Future SDR price forecasts indicate a slight decline over the months from November 2025 to April 2026. It is recommended for Investors and other stakeholders to monitor the economic indicators that might affect these outcomes.

Further research can be done using alternate methods such as machine learning algorithms so as to improve the accuracy of future price predictions. Future researchers could also investigate the evolution of economic factors affecting SDR price fluctuations such as global liquidity, currency policy shifts or geopolitical developments

Declaration by Authors

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