The Indonesian Journal of Computer Science
www.ijcs.net
Volume 14, Issue 3, June 2025
https://doi.org/10.33022/ijcs.v14i3.4889

Optimizing Water and Energy Resources: Forecasting Kariba Dam Water Levels Using the ARIMA Model Amid Load Shedding Challenges in Zambia

Julius Zulu[1], Gardner Mwansa[2]
julius.zulu@bed-rock.org author[1], gmmwansa@gmail.com[2]
[1]The Bed-Rock Research Consultancy, Department of Research Services, Lusaka, Zambia
[2]Walter Sisulu University, Department of Information Technology, South Africa

Article Information

Received : 23 May 2025
Revised : 1 Jun 2025
Accepted : 16 Jun 2025

Keywords

Forecasting, Kariba Dam, Water Levels, Load Shedding

Abstract

The Kariba Dam is a critical source of hydroelectric power for Zambia, but fluctuating water levels have led to recurrent load shedding, impacting economic productivity and daily life. Effective forecasting of water levels using the ARIMA model can help optimize resource management, improve energy planning, and mitigate the adverse effects of power shortages. The study aimed to forecast water levels at Kariba Dam from 2022 to 2035 using the Autoregressive Integrated Moving Average (ARIMA) model. Utilizing historical data from 1924 to 2021, the Box–Jenkins modeling approach was employed to develop the most suitable predictive model for capturing the stochastic variations in water levels at Kariba Dam. The best-fitting ARIMA (6,1,3) model was selected based on statistical criteria, including log likelihood, Sigma, and Akaike and Bayesian information criteria, ensuring robustness and accuracy. The results indicate a fluctuating trend in water levels with a slight overall increase of 4.56% over the forecast period. These findings have significant implications for water resource management, hydropower generation, and climate resilience planning. The study highlights the importance of adaptive strategies to mitigate potential risks associated with water level variability, ensuring sustainable energy production and transboundary water governance for Zambia.

A. Introduction

The Kariba Dam, situated on the Zambezi River between Zambia and Zimbabwe, is one of the largest man-made reservoirs in the world. It plays a pivotal role in hydroelectric power generation, providing electricity to both countries and supporting regional economic activities. However, the dam's water levels have been subject to significant fluctuations in recent years, driven by a combination of climatic and anthropogenic factors. These fluctuations have profound implications for energy production, water resource management, and socio-economic stability in the region [1].

Zambia, in particular, has been heavily impacted by the variability in water levels at Kariba Dam. The country relies on hydroelectric power for over 80% of its electricity generation, making it highly vulnerable to changes in water availability [2]. In recent years, prolonged droughts and increased water usage have led to reduced water levels in the dam, resulting in insufficient power generation capacity. This has forced the Zambia Electricity Supply Corporation (ZESCO) to implement frequent load shedding, a measure that involves rotating power outages to manage electricity demand [3]. Load shedding has had severe socio-economic consequences, including disruptions to industrial operations, reduced productivity, and diminished quality of life for households [4].

The relationship between water levels at Kariba Dam and load shedding in Zambia is complex and multifaceted. On one hand, low water levels directly reduce the dam's power generation capacity, necessitating load shedding. On the other hand, load shedding can indirectly influence water usage patterns, as industries and households may resort to alternative water sources or reduce consumption during power outages [5]. Despite this interplay, existing studies on water level forecasting at Kariba Dam have largely focused on climatic factors such as rainfall and evaporation, with limited consideration of the impact of load shedding [6]. This represents a significant gap in the literature, as load shedding is both a consequence and a driver of water level variability.

Accurate forecasting of water levels at Kariba Dam is essential for effective reservoir management and energy planning. Traditional forecasting methods, such as statistical models and machine learning algorithms, have been employed to predict water levels based on historical data and climatic variables [7]. However, these methods often fail to account for the dynamic interactions between water levels, energy demand, and load shedding. The Autoregressive Integrated Moving Average (ARIMA) model, a widely used time-series forecasting tool, offers a promising approach to address this limitation. By incorporating load shedding data as an exogenous variable, the ARIMA model can provide more accurate and comprehensive forecasts of water levels at Kariba Dam [9].

This study aims to fill the research gap by developing an ARIMA-based forecasting model that integrates load shedding data to predict water levels at Kariba Dam. The objectives of the study are threefold: (1) to analyze the historical trends and drivers of water level fluctuations at Kariba Dam, (2) to incorporate load shedding data into the ARIMA model as a key variable, and (3) to provide actionable insights for policymakers to optimize water and energy resource management. By addressing these objectives, the study seeks to contribute to sustainable resource management and mitigate the socio-economic impacts of load shedding in Zambia.

While several studies have explored the factors influencing water levels at Kariba Dam, there is a notable gap in the literature regarding the integration of load shedding data into predictive models. Existing studies primarily focus on climatic factors, such as rainfall and evaporation, but fail to account for the direct and indirect impacts of load shedding on water usage and reservoir management. Additionally, the application of advanced time-series forecasting models, such as ARIMA, to predict water levels at Kariba Dam remains underexplored. This study addresses these gaps by:

1. Incorporating load shedding data as a key variable in the ARIMA model.
2. Providing a comprehensive analysis of the interplay between energy demand, water usage, and reservoir levels.
3. Offering a predictive framework that can inform policy decisions and improve water and energy management strategies

B. Methodology

1. Data Description

The secondary data utilized in this article was gathered from the Western Power Data (https://observablehq.com/@westernpower/kariba). The data covers the period 1924 to 2021, thereby giving a total of 97 observations. Zulu, Mwansa, Wakumelo recommends at least 30 observations [9]. Many others would recommend at least 100 observations. The data collected was called into STATA version 14.2 to forecast water levels at Kariba Dam in Zambia from 2021 to 2035. The first data set is used for model estimation and the second set for forecasting and model validation.

2. ARIMA

The Auto-Regressive Integrated Moving Average (ARIMA) model is a combination of the Auto-Regressive (AR) and Moving Average (MA) models, with data that has been differentiated n times. This model, also known as the Box-Jenkins model, was developed by George Box and Gwilyn Jenkinson and is used to analyze and predict time series data [8]. For time series data, the ARIMA model is self-regresses with error correction via the moving average method. Regression is performed in the AR model between a variable at a specific time and the variable itself in the past (lag). The MA model is one of several analytical methods for determining the moving average of a variable over a given time period [10].

ARIMA (p, d, q) is a model in which p is the AR order value, d is the number of data differencing processes until the data reaches the stationary condition, and q is the MA order. In general, the AR model is as shown in equation (1) below:

$$y_t = \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t_p} + e_t \qquad [1]$$

With description:

- y_t: variable value at time t
- α_1: AR coefficient; i : 1,2,….p;

- e_t : error value at time t
- p : order AR

In equation (1), the AR model depends on the value of previous observations.
The MA model, in general, is in equation (2) below.

$$y_t = e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \qquad [2]$$

With description:

- y_t : variable value at time t
- θ_1: MA coefficient; i : 1,2,….q;
- e_t : error value at time t
- q : order MA

The MA model is influenced by the current error value and the error value with a certain weight in the past, as shown in equation (2).

We get the ARIMA model in general from the AR model in equation (1) and the MA model in equation (2), with parameter descriptions in equations (2) and (3) as before.

$$yt = \alpha_1 \gamma_{t-1} + \cdots + \alpha_p \gamma_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-i} \qquad [3]$$

The description is the same as the equation (1) and (2). In equations (3), the current value depends on or is influenced by several previous values, including the current error value and several previous error values. The ARIMA method has the following stages: stationary test, AR and MA value determination, and the best model [11], [12].

2.1. Stationary Test

One of the requirements for using the ARIMA method is that the time series data be in a stationary state. The term “stationary” refers to the absence of a trend of data growth or decline [8]. If the data is not in a stationary state, the differencing process can be used.

There are several methods for determining whether a time series data set is stationary, including summary statistics and statistical tests. Summary statistics, such as the average and variance of time series data, are used to determine whether or not there is a significant change in the average and variance values within a given time range. Other methods include statistical tests, which are used to determine stationary conditions in time series data. The Augmented Dickey-Fuller Test is a statistical test frequently used to determine stationary conditions (ADF test).

The ADF test is a statistical test that is also known as a unit root test. The unit root test is used to determine how strongly a time series data contains an element of trend. The p-value indicates the outcome of the ADF test. The p-value represents the probability that the data series is not stationary. If the p-value is 0.9622, the data series is 96.22 percent nonstationary. Stationary data series can also be identified by comparing the test-statistic value to the critical value (1 percent). If the test-statistic value exceeds the critical value (1%), the data series is not stationary, and vice versa [11], [12].

If the data is not in a stationary state, the differencing process can be used to convert the time series data to a stationary state. The process of differencing is carried out in the same manner as in equation (4).

$$\nabla \quad d_{yt} = y_t - y_{t-1} \qquad [4]$$

With description:

- y_t : current value
- y_{t-i} : previous value
- $\nabla \quad d_{yt}$: differencing results
- d : value of order differencing

As in the equation, each value in the time series data is carried out by a differencing process (4). The differencing process can be repeated multiple times until the time series data becomes stationary. The order differencing value is represented by the number of differencing processes performed. The variable commonly used to indicate order differencing [11], [12].

2.2. Determination of AR and MA Value

Once the time series data has reached a stationary state, the initial estimated values of AR and MA can be determined. The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) values can be used to calculate AR and MA values. ACF and PACF graphs can be created visually to help determine the AR and MA values.

The ACF formula is:

$$r_k = \frac{\sum_{t=1}^{n-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{n}(x_t - \bar{x})^2} \qquad [5]$$

With description:

- r_k : autocorrelation coefficient on lag-k
- k : time difference
- n : number of observations
- k : average observation
- x_t : observation at time t
- x_{t+k} : observations at time $t + k$, $k = 1,2,3,$ ...

The PAC formula is:

$$\pi_k = \begin{cases} 1, k = 0 \\ r_1, k = 1 \\ \frac{r_k - \sum_{t=1}^{k-1} \pi_{k-1,t} \times r_{k-t}}{1 - \sum_{t=1}^{k-1} \pi_{k-1,t} \times r_{k-t}} \end{cases} \qquad [6]$$

With description:

- π_k : partial autocorrelation coefficient on lag-k
- r_k : autocorrelation coefficient on lag-k

The value π_k, t, is obtained through equation (7)

$$\pi_k, t = \pi_{k-1,t} - \pi_k \pi_{k-1,k-t} \quad [7]$$

With description:

- $\pi_{k,k} = \pi_k$

The significant limit formula is:

$$v = \pm \frac{1.96}{\sqrt{N}} \quad [8]$$

With description:

- v : critical value or significant value
- N : the amount of observation data used

The AR and MA values are determined by the number of lags that are outside the significant limit. For example, in Figure 1 of the ACF graph, there are three significant lags (outside the significant limit), so the initial MA value is three, whereas the initial AR value from the PACF graph is one. The amount of lag that is significant for the AR order value is typically used for variables and to indicate the MA order [1], [12].

2.3. Determination of the Best Model

After determining the initial estimated values, these values can be used to generate several possible ARIMA model order estimates. As a result, several ARIMA model order combinations can be created, and each order model can be compared to determine the best ARIMA model order [11], [12]. The best order model is one that produces a model with the smallest error in its prediction results. The Root Mean Squared Error (RMSE) value can be used to evaluate the error.

The equation shows the Advances in Engineering Research, volume 207 300 formula for calculating the RMSE value (9).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N} (y_t - \widehat{y_t})}{N}} \quad [9]$$

With description:

- y_t : actual time series value at time
- $\widehat{y_t}$: the predicted value at time
- N : amount of data used for prediction evaluation

The RMSE value indicates the model's accuracy in predicting the actual value. The lower the RMSE value (close to zero) is, the more accurate the prediction model's predictions, and vice versa [11], [12].

C. Results and Discussions

This section presents the analysis and discussions of the study. To present the findings, we followed the Box-Jenkins (B-J) four steps namely model identification, model estimation, diagnostic checking and forecasting [8].

1. Model Identification

The first stage involves checking the stationarity of the series through visual examination and formal statistical tools. A point to be noted at this point is that stationarity is a prerequisite for applying Box-Jenkins method. For the current study stationarity will be checked through time series plot of Zambia's foreign debt along with scatter plot, time series plot, series Corelogram-Autocorrelation Function (ACF) plot, and Partial Autocorrelation Function (PACF) plot.

In order to forecast water levels at Kariba Dam from 2021 to 2036, the scatter plot of the time series data against time periods from 1924 to 2021 is given in Fig. 1.

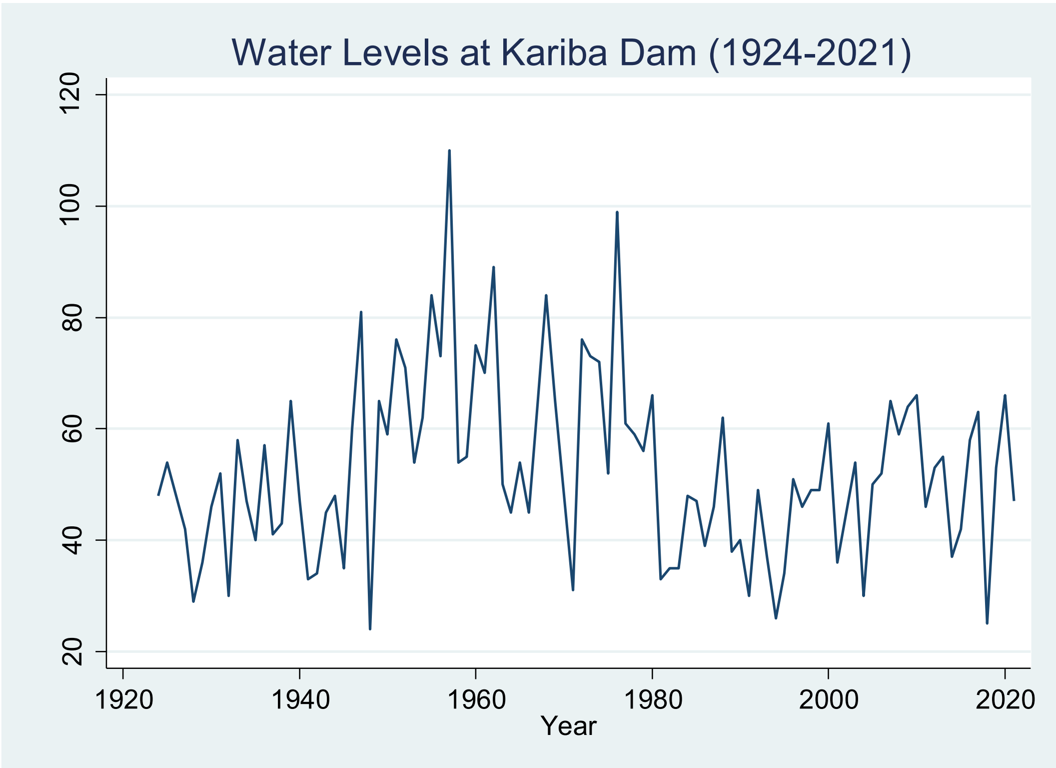

Figure 1. The scatter plot of the time series data against time periods

Fig. 1 shows that during the water levels at Kariba Dam from 1924 to 2021 exhibit significant fluctuations, influenced by various environmental and human factors. In the early years (1924–1950s), water levels showed moderate variability with a gradual increase, peaking notably in the late 1950s and early 1960s, likely due to high rainfall and reservoir filling after the dam's construction. Another peak occurred in the early 1980s, followed by a period of more pronounced fluctuations and periodic declines. From the 2000s onwards, the water levels remained highly variable, with fewer extreme highs compared to earlier decades. These trends can be attributed to rainfall variability, hydroelectric power usage, climate change effects, and upstream activities affecting the Zambezi River basin. The observed fluctuations underscore the importance of sustainable water management, as Kariba Dam serves as a critical water source for Zambia and Zimbabwe, supporting energy production and livelihoods.

In order to verify whether the data is stationary, time series plot has been plotted, and it is shown in Fig. 2.

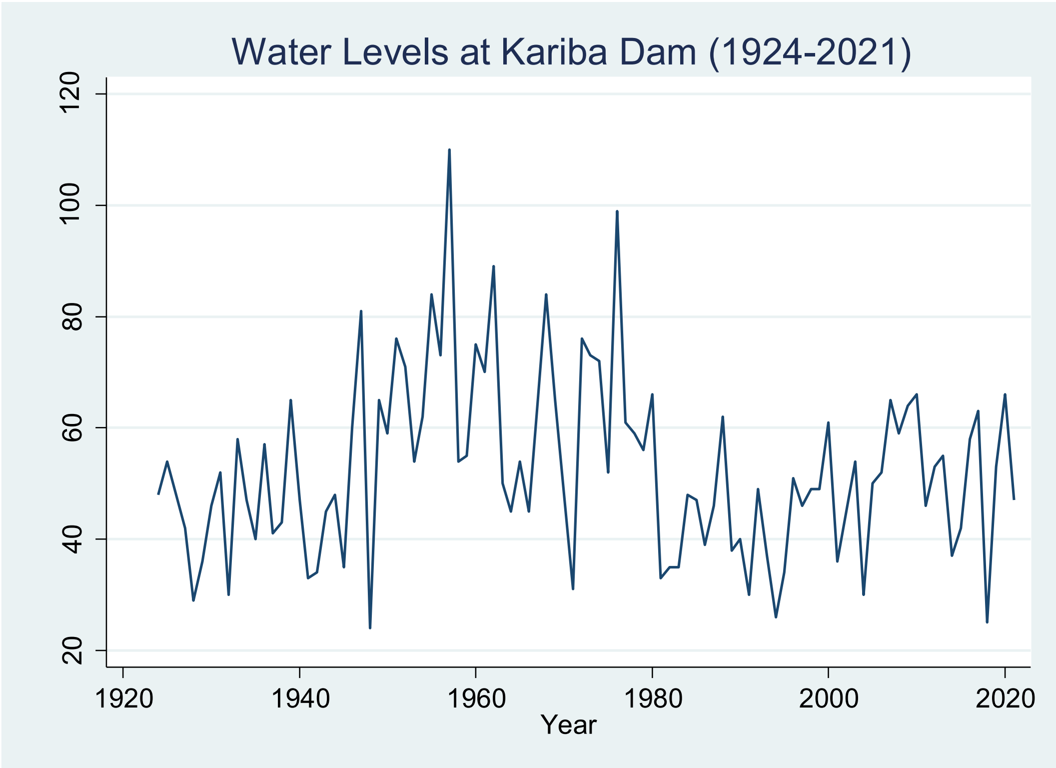

Figure 2. Stationary test using graphical method

Fig. 2 shows that the water level data at Kariba Dam appears to be non-stationary due to visible long-term trends, changing variability, and possible cyclical patterns. The graph shows fluctuations with significant peaks in the 1950s–1980s, followed by varying levels in recent years, indicating that the mean is not constant over time. Additionally, the magnitude of changes differs across periods, suggesting that the variance is also not stable. The repeated rise and fall of water levels imply potential seasonality or cyclicality, which further supports non-stationarity. To confirm this visual stationarity check, formal tests like the Augmented Dickey-Fuller (ADF) test or Philips Perron (PP) test were performed at 5% level of significance as shown in Table I:

Table 1. Formal stationary tests using both ADF and PP tests

Augmented Dickey–Fuller (ADF) Test				
	Statistics.	1% Critical Value	*5% Critical Value*	*10% Critical Value*
Z(t)	*-7.208*	*-4.047*	*-3.453*	*-3.152*
MacKinnon appropriate p-value for z(t)=0.0000				
Water	*Coef.*	*Std.Err*	*t*	$P > \|t\|$
L1.	*.3002953*	*.0983496*	*-7.11*	*0.000*
Trend	*-.021885*	*.0566675*	*-0.39*	*0.700*
Constant	*37.95886*	*6.181228*	*6.14*	*0.000*
Phillips-Perron (PP) Test				
Z(t)	*-8.401*	*-5.123*	*-4.344*	*-4.001*
MacKinnon appropriate p-value for z(t)=0.0000				
Water	*Coef.*	*Std.Err*	*t*	$P > \|t\|$
L1.	*.4341072*	*.0613604*	*-5.71*	*0.000*
Trend	*-.001357*	*.0233502*	*-0.64*	*0.240*
Constant	*44.95886*	*4.151322*	*9.02*	*0.000*

Note: *critical value α **1%*****, **critical value*** α **5%*****, *** critical value*** α **10%**

Table I indicates that the time series data is stationary, as evidenced by the calculated t-statistics for both the Augmented Dickey–Fuller (ADF) test (-3.453) and the Phillips–Perron (PP) test (-4.297), which exceed the critical values at the 5% significance level. This conclusion is further supported by the MacKinnon p-values for both tests, which are less than $0.05\ (p < 0.05)$, confirming statistical significance. According to Zulu, Mwansa, and Wakumelo [9], as well as Febriyanti et al. [13], data is considered stationary when the MacKinnon p-value is less than the chosen level of significance.

Furthermore, the study conducted autocorrelation (ACF) and partial autocorrelation (PACF) analyses at the first differences, as shown in Fig. 3. and Fig. 4. below. The visual inspection of the correlogram (ACF/PACF functions) facilitates the determination of whether the data set follows a pure autoregressive (AR) process, a pure moving average (MA) process, or a mixed ARMA process [9].

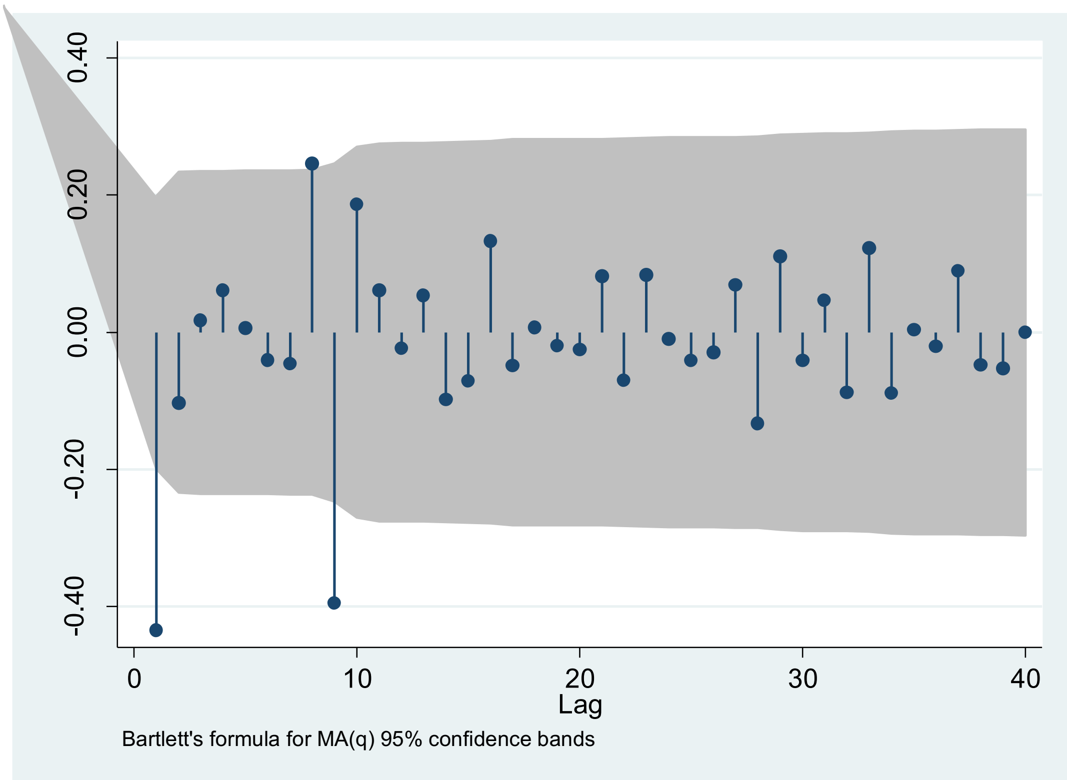

Figure 3. Plot of ACF of the first difference data

Fig. 3 shows that the first-differenced data exhibits three statistically significant spikes in the autocorrelation function, indicating that a moving average (MA) component of order 3 (MA (3)) is appropriate. This conclusion is supported by the fact that only three spikes are statistically significant at the 95% confidence level for the time-series data.

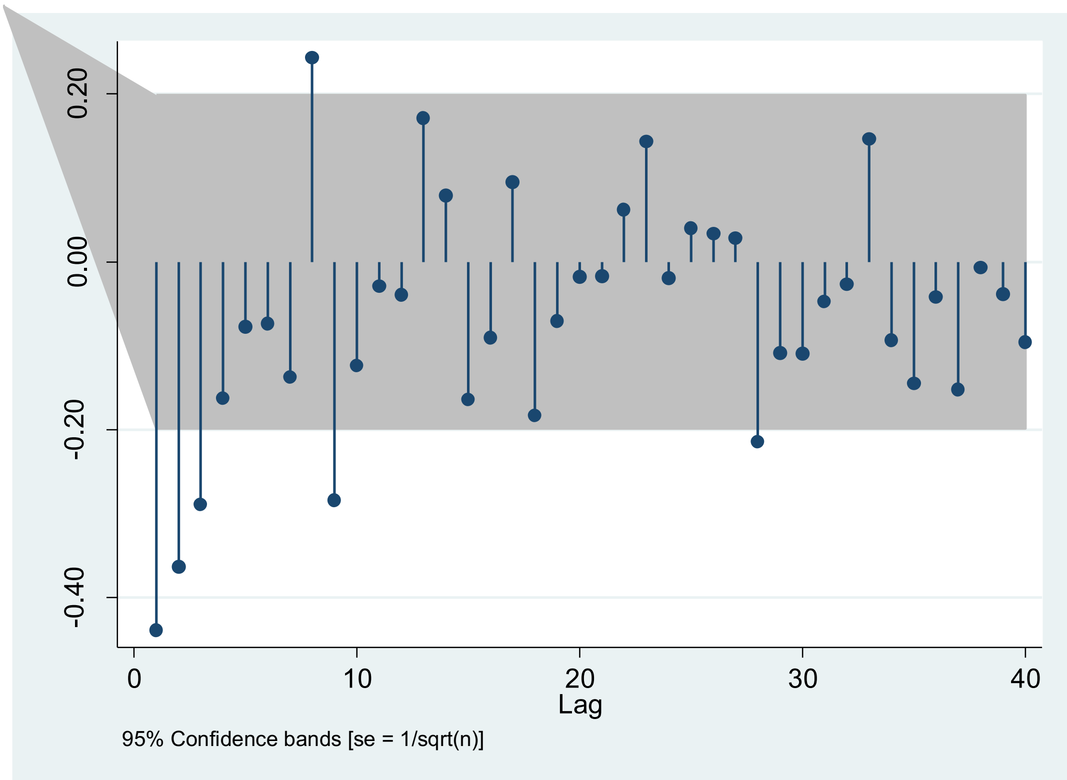

Figure 4. Plot of PACF of the first difference data

Fig. 4 reveal that the partial autocorrelation function (PACF) of the first-differenced data exhibits six statistically significant spikes, corresponding to AR (1) through AR (6). In line with the principle of parsimony, this suggests the inclusion of up to six autoregressive (AR) lags. Additionally, the autocorrelation function (ACF) indicates one significant moving average (MA) lag. Based on these findings, the candidate ARIMA models considered in this study include ARIMA (1,1,3), ARIMA (2,1,3), ARIMA (3,1,3), ARIMA (4,1,3), ARIMA (5,1,3), AND ARIMA (6,1,3) components.

2. Model Estimation

This section presents the estimation of multiple models to identify the most suitable one for forecasting the water levels at Kariba Dam based on a set of criteria proposed by Box et al. [14]. These criteria include parameter significance, log-likelihood values, sigma (error variance), and the Akaike and Bayesian Information Criteria (AIC and BIC). Table II below summarizes the results of the evaluated candidate models.

Table 2. Model Section Process

Model Selection Criteria					
Models	Sigma	Loglikelihood	AIC	BIC	Best Model
ARIMA (1,1,3)	15.00678	-400.8453	813.6906	829.1388	
ARIMA (2,1,3)	14.87952	-400.0708	814.1415	832.1645	
ARIMA (3,1,3)	14.55415	-399.4177	812.8354	830.8583	
ARIMA (4,1,3)	14.66604	-399.5785	817.157	840.3294	
ARIMA (5,1,3)	14.89624	-400.1801	818.3603	841.5527	

ARIMA (6,1,3)	14.14577	-397.2715	816.543	844.8648	
Best Model	ARIMA (6,1,3)	ARIMA (6,1,3)	ARIMA (3,1,3)	ARIMA (1,1,3)	ARIMA (6,1,3)

The results presented in Table II suggest that the ARIMA (6,1,3) model is the most appropriate for forecasting water levels at Kariba Dam. This model was selected based on its superior statistical performance, including the highest number of significant parameters, the lowest log-likelihood and sigma values, as well as the minimum Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values [15]. Prior to confirming ARIMA (6,1,3) for forecasting purposes, diagnostic tests were conducted to validate its suitability.

3. Model Diagnostics

In Section 3.3, the study identified ARIMA (6,1,3) as the most appropriate model for forecasting water levels at Kariba Dam. To objectively justify this model selection, diagnostic tests were conducted to assess whether the model residuals exhibit white noise characteristics and whether both the autoregressive (AR) and moving average (MA) processes are covariance stationary. The results of these tests are illustrated in Fig. 5.

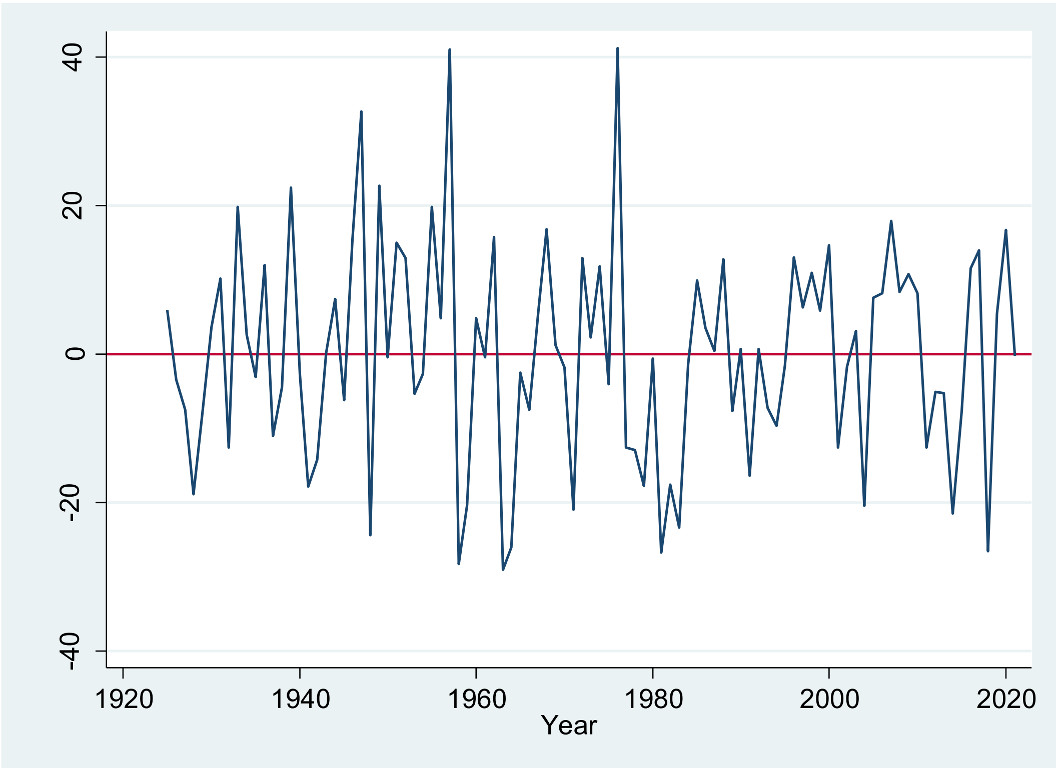

Figure 5. White noise test for time series residuals

As shown in Fig. 5, the residuals fluctuate consistently around the mean $(\mu = 0)$, indicating that they exhibit white noise properties and that the series follows a stable univariate process. In addition to this visual inspection, the study also conducted a formal Portmanteau test for white noise, the results of which are presented in Table III.

Table 3. Portmanteau Test for white noise

Portmanteau (Q)	**statistic**	**=**	**33.3578**
Prob > chi2(15)	=	0.7619	

The results in Table III indicate that the residuals exhibit white noise characteristics, as the p-value is 0.7619, which is greater than the 0.05 significance level. Consequently, the null hypothesis cannot be rejected. According to Zulu and Mwansa [15], when the p-value obtained from the Portmanteau test exceeds the chosen significance level, the alternative hypothesis is rejected in favor of the null hypothesis, confirming the presence of white noise. Furthermore, to verify that the AR and MA processes are covariance stationary, the study conducted stationarity and invariability tests, the results of which are presented in Fig. 6.

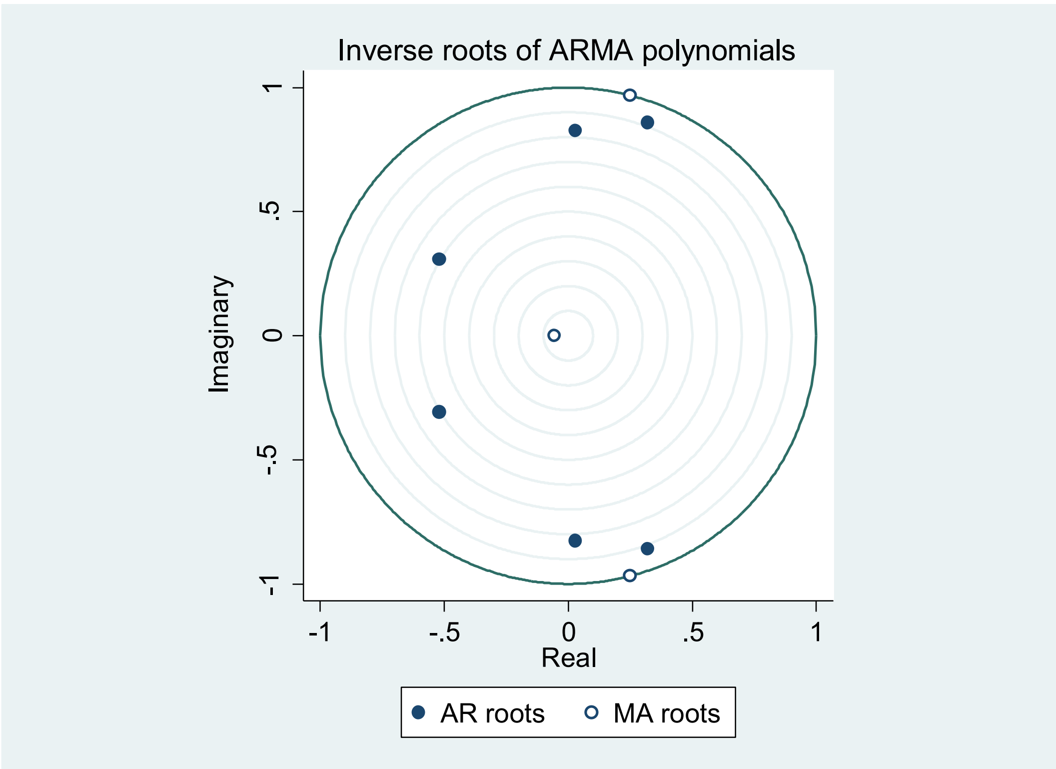

Figure 6. Covariance stationery test for both AR and MA components

Fig. 6 illustrates that the inverse roots of the ARMA polynomials confirm the stability and invertibility of the estimated ARMA (6,1,3) model. In the plot, all autoregressive (AR) roots (represented by blue dots) and moving average (MA) roots (represented by white dots) lie within and along the unit circle, indicating that the model meets the necessary conditions for stationarity and invertibility [15], [12], [9]. The presence of AR roots within the unit circle confirms that the autoregressive component is stable and does not exhibit explosive behavior. Likewise, the MA roots falling within and along the unit circle suggest that the moving average component is invertible, allowing past forecast errors to be effectively incorporated into future predictions. As none of the roots lie outside the unit circle, the ARMA (6,1,3) model is both correctly specified and appropriate for forecasting purposes.

4. Model Forecasting

As the final step in the ARIMA modeling process, this section applies the ARIMA (6,1,3) model identified in Section 3.1 and validated in Section 3.2 to forecast water levels at Kariba Dam over a thirteen-year horizon. Fig. 7 below presents the out-of-sample forecasting results for the period 2022 to 2035.

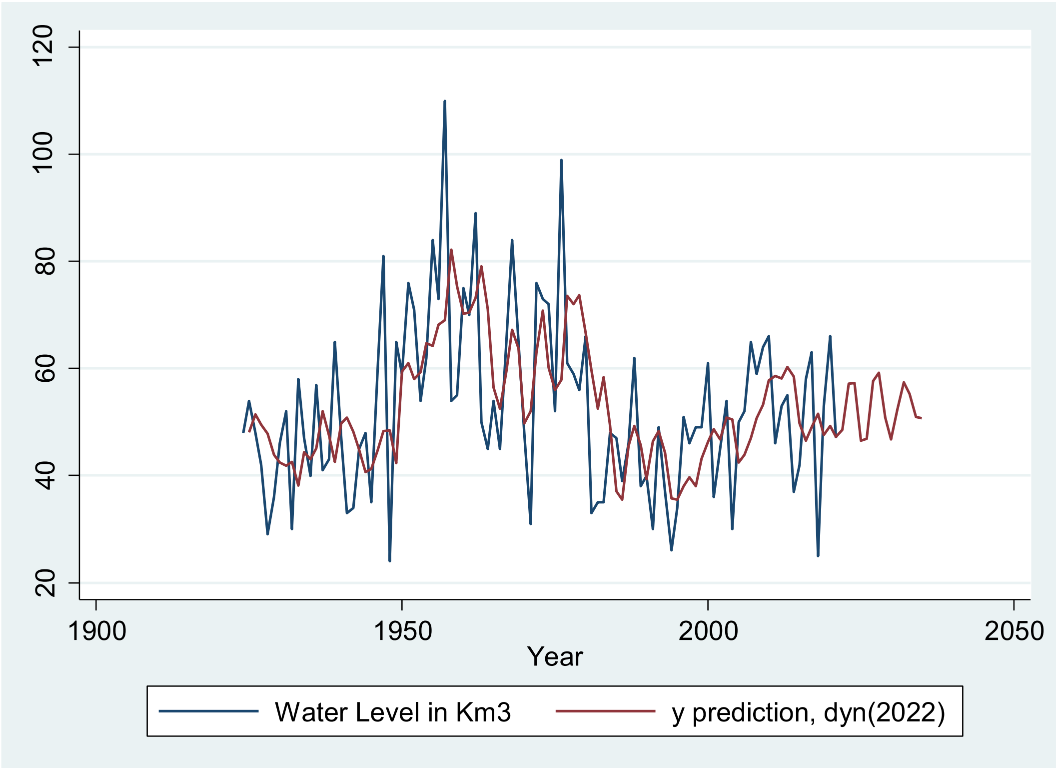

Figure 7. Plot of forecasted water levels at Kariba Dam

Results from Fig. 7 shows that the forecasted water levels at Kariba Dam from 2022 to 2035 exhibit a fluctuating trend with periodic increases and decreases rather than a consistent upward or downward pattern. The water level starts at 48.54 km^3 in 2022, followed by an increase in 2023 (57.21 km^3) and 2024 (57.36 km^3), indicating a short-term rise. However, a decline occurs in 2025 (46.57 km^3) and 2026 (46.92 km^3) before another increase in 2027 (57.65 km^3) and 2028 (59.27 km^3), marking one of the highest points in the forecast. This cyclical pattern continues with alternating peaks and dips, such as a drop in 2030 (46.77 km^3) and subsequent rises in 2031 (52.39 km^3) and 2032 (57.40 km^3). Towards the end of the forecast period, the water levels remain relatively stable, fluctuating around 50-55 km^3 between 2033 and 2035. The trend suggests periodic variations influenced by climatic factors, inflow variations, and water usage patterns. However, in 15 years, the water level at Kariba Dam on average is expected to increase by approximately 4.56% from 2022 to 2035. The fluctuations indicate the need for adaptive water management strategies to ensure stability in water supply and hydroelectric power generation.

D. Policy Implication

The forecasted water levels at Kariba Dam from 2022 to 2035 have significant policy implications for water resource management, energy production, and climate resilience planning. The slight upward trend, coupled with periodic fluctuations, suggests the need for adaptive water management policies to ensure sustainable usage for hydropower generation, agriculture, and domestic supply. Given the role of Kariba Dam in Zambia and Zimbabwe's electricity supply, policymakers should focus on enhancing energy diversification by integrating alternative renewable sources such as solar and wind to reduce dependence on hydroelectric power, especially during low water level periods. Additionally, climate adaptation policies should emphasize improved forecasting and risk management strategies to mitigate the impact of extreme weather events on water availability. Investment in infrastructure efficiency such as upgrading turbines and optimizing water release schedules can further enhance energy output while maintaining ecological balance. Lastly, transboundary water governance frameworks should be strengthened to promote cooperation between Zambia and Zimbabwe, ensuring equitable water distribution and sustainable management of the dam in the face of climate change and increasing demand.

E. Conclusion

After applying time series modeling techniques, the ARIMA model was utilized to analyze and forecast the water levels at Kariba Dam over the period from 2022 to 2035. The primary objective of this study was to predict future water level variations and identify trends that could inform water resource management and hydropower planning. The best-fitting ARIMA (6,1,3) model was selected based on its ability to capture the stochastic fluctuations in the data, ensuring stability and reliability in the forecasts. The analysis indicates a fluctuating but slightly increasing trend in water levels, with an overall projected rise of approximately 4.56% over the forecast period. This suggests that while variations will persist due to climatic and operational factors, the general water level is expected to remain relatively stable. These findings underscore the importance of adaptive management strategies to ensure sustainable water usage and energy production at Kariba Dam.

F. Recommendations

Based on the study's findings and objectives, here are key recommendations for to address the challenges of water level fluctuations at Kariba Dam and the impact of load shedding in Zambia:

1. Policymakers and Energy Planners

1. Reduce reliance on hydroelectric power by investing in alternative energy sources such as solar, wind, and geothermal energy. This will mitigate the impact of low water levels at Kariba Dam on Zambia's energy supply.
2. Encourage energy efficiency and conservation measures among industries, businesses, and households to reduce electricity demand during peak periods and minimize the need for load shedding.

3. Develop adaptive water release strategies for Kariba Dam that balance power generation, irrigation needs, and ecological requirements, especially during periods of low rainfall.

2. Zambia Electricity Supply Corporation (ZESCO)

1. Use predictive analytics to optimize load shedding schedules, minimizing disruptions to critical sectors such as healthcare, education, and manufacturing.
2. Invest in grid modernization and infrastructure upgrades to reduce transmission losses and improve the reliability of electricity supply.
3. Work with Zimbabwe and other regional stakeholders to develop a coordinated approach to water and energy management at Kariba Dam.

3. Government of Zambia

1. Provide tax breaks, subsidies, and other incentives to attract private sector investment in renewable energy projects.
2. Develop and implement climate adaptation strategies to address the increasing frequency of droughts and their impact on water resources.
3. Allocate funding for research initiatives focused on water and energy management, particularly those addressing the challenges of Kariba Dam.

G. References

[1] J. Mukarati, S. Nkomo, and T. Dube, "Climate variability and water level changes in the Zambezi River Basin: Implications for hydroelectric power generation," Afr. J. Environ. Sci., vol. 8, no. 1, pp. 56–74, 2020.

[2] ZESCO, Annual Energy Report 2021: Hydropower Generation and Challenges. Zambia Electricity Supply Corporation, 2021.

[3] M. Chibamba, T. Banda, and J. Phiri, "Impact of hydroelectric power shortages on economic productivity in Zambia," Energy Policy Res. J., vol. 45, no. 3, pp. 231–245, 2022.

[4] P. Sichone, C. Mwale, and K. Ngoma, "Socio-economic effects of load shedding on households and businesses in Zambia," Zambian Econ. Rev., vol. 15, no. 2, pp. 89–104, 2021.

[5] M. Nyambe, P. Sichone, and R. Banda, "The interplay between load shedding and water consumption patterns in Zambia," J. Energy Water Manag., vol. 10, no. 4, pp. 67–81, 2023.

[6] K. Mubanga, A. Simukonda, and L. Tembo, "Predicting water level variations at Kariba Dam using climatic and hydrological models," J. Hydrol. Water Resour., vol. 12, no. 2, pp. 112–129, 2021.

[7] L. Tembo, B. Phiri, and D. Chileshe, "Application of machine learning techniques in hydrological forecasting: A case study of Kariba Dam," Int. J. Water Resour. Environ. Eng., vol. 27, no. 1, pp. 45–62, 2020.

[8] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, Time Series Analysis: Forecasting and Control, 5th ed. Hoboken, NJ, USA: John Wiley & Sons, 2015.

[9] J. Zulu, G. Mwansa, and M. Wakumelo, "Forecasting price of fuel using time series autoregressive integrated moving average model: A Zambian review

from 1998 to 2022," II Ponte, vol. 78, pp. 101–118, 2022, doi: 10.21506/j.ponte.2022.8.7.
[10] V. Yakovyna and O. Bachkai, "The comparison of Holt-Winters and Box-Jenkins methods for software failures prediction," 2017.
[11] M. I. Fauzan, "Analisis pemrosesan paralel dalam mendukung layanan prediksi cuaca," 2018.
[12] J. Zulu, G. Mwansa, and K. Changwe, "Forecasting inflation rate using the ARIMA model: Zambia's perspective from 2023 to 2043," Int. J. Res. Sci. Innov., vol. 11, no. 12, pp. 698–713, 2025, doi: 10.51244/IJRSI.2024.11120063.
[13] S. Febriyanti, W. A. Pradana, M. J. Saputra, and E. Widodo, "Forecasting the Consumer Price Index in Yogyakarta by Using the Double Exponential Smoothing Method," Parameter: J. Stat., vol. 2, no. 1, pp. 1–7, 2021.
[14] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, Time Series Analysis: Forecasting and Control, 4th ed. Hoboken, NJ, USA: John Wiley & Sons, 2008
[15] J. Zulu and G. Mwansa, "Modelling and forecasting foreign debt using ARIMA model: The Zambian case from 2022 to 2035," Int. J. Res. Innov. Social Sci., vol. 6, no. 11, pp. –, Nov. 2022.