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Volumetric Inflow Estimation in a Hydropower Dam Using Autoregressive Integrated Moving Average (ARIMA) Modelling and Altimetric Lake Levels

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Background: Several models have been developed for inflow forecasting in reservoirs based on local parameters which may not include an implicit system characteristic like seasonality. Autoregressive integrated moving average (ARIMA) models can be developed to cater for the presence of seasonal and non-seasonal behavior of natural water systems.
Aims: The present study aims to estimate Volumetric Inflow in a Hydropower Dam using Autoregressive Integrated Moving Average (ARIMA) Modelling and Altimetric Lake Levels.
Study Design: The study was conducted in the Kainji reservoir, West Africa located along the Niger River. This study combines satellite-altimetry-based rating curves with reservoir inflow models that capture the seasonality of upstream characteristics.
Results and Discussion: Seasonal multiplicative ARIMA models were developed based on 27-year inflow records and used to forecast seven subsequent years. Reservoir levels measured by satellite radar altimeters were matched with actual inflows to generate rating curves from which future inflows may then be estimated. The model with the best forecasts relative to actual inflow - a seasonal multiplicative ARIMA $(2,1,1) \times (2,1,2)_{12}$ model – was adopted.

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Conclusion: Strong agreements between all three inflow series (actual, model-based, and satellite-based rating curve) suggest that reservoir inflow models can be combined with satellite altimetric for reservoir inflow estimation.

Keywords: Inflow modelling; ARIMA; satellite altimetry; Kainji dam; Niger River.

1. INTRODUCTION

A wide variety of modelling techniques have been used for predicting hydrological parameters in natural water resources systems [1-3]. Where regional or local water systems are of interest, smaller-scale models have been created which better represent the behavior of the systems they were created for [4,5]. Sometimes, the model or methodology may not be admissible beyond a specified region or guiding assumptions, quickly lose validity under changing climatic conditions, or need frequent revalidation when changes arise in the hydrology of an adjoining region which directly impacts it. This is the case in the proposed study area, the Kainji-Jebba dual reservoir system (Fig. 1) in West Africa which is heavily impacted by dams upstream [6-9]. Flooding and droughts are prevalent due to anthropogenic factors like poor operational policies and speculative information about upstream usage, and natural factors like climate change and shrinking water levels [10,11]. Therefore, a reliable means of predicting inflow will be beneficial for planning by stakeholders in this heavily dammed transboundary river.

Some work on river and reservoir inflow modelling and prediction have either substantially depended on mathematical models or some combination of the system's hydrological parameters with a mathematical model [3,12-14]. Other studies have been done specifically in reservoirs with similar geographical, climatic and hydrological conditions as the study area [15,16]. But this study relies on and combines field data with autoregressive integrated moving average (ARIMA) inflow models that capture the seasonal behavior of the water system. Water levels from satellite altimetry were then correlated with actual inflows to generate rating curves from which futuristic estimates of inflow can be made. Although ARIMA models have been used to predict hydro-meteorological parameters [17-19], this study specifically created and compared ARIMA inflow model results with satellite-altimetry-based rating curves for possible use in remotely determining reservoir inflows.

Fig. 1. Niger River Basin showing Kainji reservoir and other dam sites as red triangles [6]

1.1 Study Area

The study area is the Kainji reservoir (Table 1) in West Africa. It is located along the Niger River. The 4,200 km river flows northeast, then southeast, and drains into the Atlantic [20,21]. Along the length of the river are other dams (Fig. 1) used for hydropower, flood control, water supply, and irrigation [22,23]. Monthly storage depends mainly on river inflow as contribution from its catchment accounts for less than 10% of direct inflow [20]. Outflow from the Kainji reservoir is the primary inflow to the Jebba reservoir (Fig. 1) located downstream of the Kainji dam [21,22].

Table 1. Characteristics of Kainji Reservoir

Characteristics of Kainji Reservoir	
Latitude	9°50' N
Longitude	4°40'E
Maximum Capacity (km^3)	15
Minimum Capacity (km^3)	3.5
Maximum surface area (km^2)	1270
Length (km)	135
Maximum Width (km)	30
Maximum Elevation (m.a.s.l.)	141.9

2. METHODOLOGY

***In situ* inflow selection and rating curve generation:** Reservoir inflow volumes and average daily river discharge were collected for a 27-year period (1970-1996) from multiple gauging stations. The station chosen for this study is at the inlet of the reservoir and coincident with the coordinates of satellite altimeter tracks over the reservoir (Fig. 3). This allowed for spatial and temporal comparison of in situ, model-based, and rating-curve-based flows.

Inflow modeling: A basic ARIMA (p, d, q) model (Box et al., 2007) was used in forecasting. This may be written as:

$$z_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \cdots + \varphi_3 z_{t-p} + \propto_t - \theta_1 z_{t-1} - \theta_2 z_{t-2} - \cdots \theta_3 z_{t-q} \quad (1)$$

A seasonal ARIMA model was then used to combine both seasonal and non-seasonal patterns in reservoir inflow into one single multiplicative model that may be summarily expressed as ARIMA (p, d, q) × (P, D, Q)s. This is a basic ARIMA (p,d,q) model whose residuals were further modelled by an ARIMA(P,D,Q)s structure with linear operators (P,D,Q). Here, p = non-seasonal AR (or autoregressive) order, d = non-seasonal differencing, q = non-seasonal MA (or moving average) order, P = seasonal AR order, D = seasonal differencing, Q = seasonal MA order, and S or s = time span of repeating seasonal pattern. A seasonal multiplicative model provides the benefit of catering for seasonality in reservoir inflows given that typical inflow and storage series for this reservoir suggest a return to about the same level yearly [11,20,23]. Seasonality in a time series refers to a regular, repetitive pattern of changes over a given time of S or s periods. The term s is the number of time periods before which the pattern is seen again. Time series of inflow (Figure 3) for this reservoir appear to exhibit some seasonal patterns in monthly datasets where high values occur in rainy months and lower values occur in other dry months. Therefore s = 12, that is, the period of seasonal behavior of inflows to the reservoir. Without differencing operations, the seasonal multiplicative ARIMA model used for the inflow time series [24] was expressed as follows:

$$\text{Seasonal AR: } \varphi(B^S) = 1 - \varphi_1 B^S - \ldots - \varphi_P B^{PS} \quad (2)$$

$$\text{Seasonal MA: } \theta(B^S) = 1 + \theta_1 B^S + \ldots + \theta_Q B^{QS} \quad (3)$$

While the inflows follow a given pattern yearly, the random presence of high inflows in some years suggests some non-seasonality which is better investigated by a different method of de-seasonalizing and modeling using differencing techniques [1]. Non-seasonal behavior of the system was then modeled thus:

$$\text{AR: } \varphi(B) = 1 - \varphi_1 B - \ldots - \varphi_p B^p \quad (4)$$

$$\text{MA: } \theta(B) = 1 + \theta_1 B + \ldots + \theta_q B^q \quad (5)$$

The trends of autocorrelation functions (ACF) and partial autocorrelation functions (PACF) were used to determine the significance of non-seasonal behavior on the series [24]. Steps for determining the most appropriate multiplicative model were performed. This involved the determination of model parameters and an iterative process of fitting, forecasting, and comparing different model results.

3. RESULTS AND DISCUSSION

Three multiplicative ARIMA (p,d,q) x (P,D,Q) models appeared most suitable for inflow volume prediction based on relative errors between measured and forecasted flows. These were ARIMA (101) x $(011)_{12}$, ARIMA (111) x $(212)_{12}$, and ARIMA (2,1,1) x $(2,1,2)_{12}$ seasonal multiplicative models (Fig. 4 and Table 2).

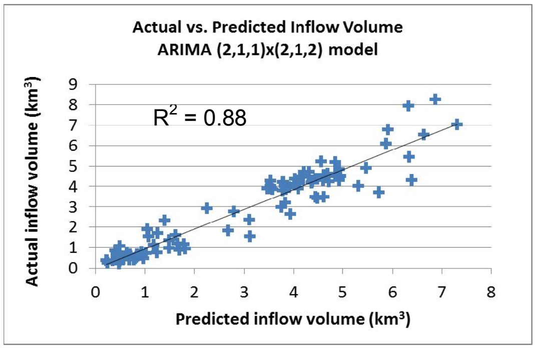

Fig. 2. Actual vs. predicted inflow volume for ARIMA (2,1,1) x $(2,1,2)_{12}$ model

Possible reasons for such differences lie in the varied ability of each model to capture true seasonal behavior of the system and in the comparison of only monthly average values in Table 2. The ARIMA (2,1,1) x $(2,1,2)_{12}$ gave the lowest relative errors and highest determination coefficient (Fig. 2 and Table 2) for the seven-year forecasted period. Supplementary analysis of these model results was done using a rating curve developed for the inlet of the reservoir. The ACFs and PACFs also showed evidence of randomness about zero and decay within the first five lags. A rating curve generated for the inlet of the reservoir (Fig. 3) resulted in a high determination coefficient of 0.98. Inflows estimated using this rating curve showed low relative errors (Table 2). The in-situ inflow data used for this study (1970 – 2003) was the only period made available by the local government. Therefore, the models were partly based on this data and compared with modelled results for the last seven years (1997-2003) of actual data. The model's validity beyond the stated period may then be investigated when additional inflow records are made available.

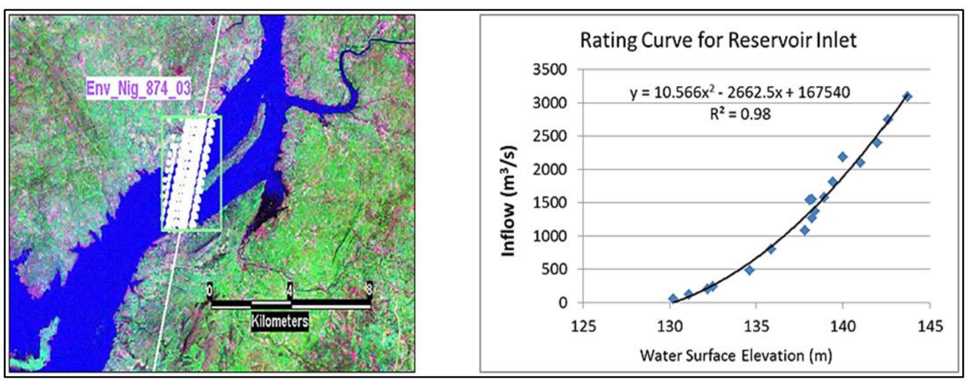

Fig. 3. Left (Satellite image of reservoir inlet, usda.gov) and Right (Reservoir inlet rating curve)

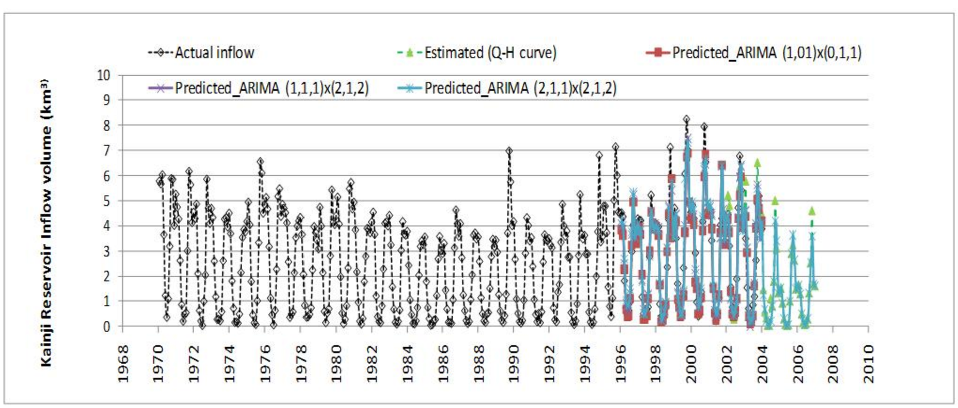

Fig. 4. Time series of reservoir inflow volume

Table 2. Monthly average reservoir inflow over the seven-year period tested (1997-2003)

Actual inflow at Kainji dam (m^3/s)	7-year averages for each month (1997-2003)	Predicted inflow ARIMA (211)x(212) (m^3/s)	Predicted inflow ARIMA (111)x(212) (m^3/s)	Predicted inflow ARIMA (101)x(011) (m^3/s)	Estimated from Q-H rating curve (m^3/s)	Relative Error in ARIMA (211)x(212)	Relative Error in ARIMA (111)x(212)	Relative Error in ARIMA (101)x(011)	Relative Error in Q-H rating curve estimate
1674	Jan	1691.39	1719.86	1732.97	1632.96	0.0104	0.0274	0.0352	0.0245
1409	Feb	1500.98	1510.37	1603.56	1371.06	0.0653	0.0719	0.1381	0.0269
602	Mar	555.04	681.66	624.20	624.29	0.0780	0.1323	0.0369	0.0370
201	Apr	215.97	233.87	285.70	197.64	0.0745	0.1635	0.4214	0.0167
82	May	100.03	110.71	119.58	86.87	0.2199	0.3502	0.4583	0.0594
196	Jun	185.82	219.45	234.61	189.53	0.0520	0.1197	0.1970	0.0330
421	Jul	456.18	544.09	515.06	435.05	0.0836	0.2924	0.2234	0.0334
1502	Aug	1388.28	1472.11	1421.43	1466.45	0.0757	0.0199	0.0536	0.0237
1653	Sep	1666.23	1992.89	2047.09	1616.95	0.0080	0.2056	0.2384	0.0218
1633	Oct	1665.63	1747.78	1787.88	1599.00	0.0200	0.0703	0.0948	0.0208
1506	Nov	1261.78	1295.71	1301.76	1466.22	0.1622	0.1396	0.1356	0.0264
1581	Dec	1593.99	1588.23	1645.18	1562.85	0.0082	0.0046	0.0406	0.0115
					Average relative error	0.0715	0.1331	0.1728	0.0279

4. CONCLUSION

The in-situ inflow data used for this study (1970 – 2003) and the modeling exercise yielded results that demonstrate their suitability for forecasting reservoir inflows. This suggests that the seasonal behavior of the system was adequately represented by the models for the period evaluated. The potential also exists for applying other predictive tools like artificial neural networking and support vector machines for forecasting hydrological parameters of such natural water systems for use in making water management decisions.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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