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Modeling of Hydro Level and Hydroelectric Power in Kothmale Reservoir, Sri Lanka

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Abstract

The Kotmale Reservoir, located in the Kotmale area of the Nuwara Eliya District, Central Province, Sri Lanka (7°03′39″ N, 80°35′50″ E), supplies water to the Kotmale Hydropower Station (7°07′41″ N, 80°34′42″ E). The power station has three 67 MW turbines with a total installed capacity of 201 MW, making it the second-largest hydroelectric power station in Sri Lanka.

This study aimed to examine the relationship between daily water releases for hydropower generation and daily energy production. Daily operational data were obtained from the Mahaweli Authority of Sri Lanka. The main variables analyzed were daily release volume (million cubic meters, MCM) and daily energy generation (GWh).

Regression analysis was employed to investigate the relationship between these variables. The results indicated a strong positive correlation between release volume and energy generation, showing that higher water releases result in greater electricity production. The fitted regression model is $\log_{10} \text{ENERGY} = 0.075 + [0.918 \times \log_{10} \text{RELEASES}]$.

The regression coefficient (0.918) demonstrates a strong positive association between water releases and energy generation. The findings confirm that daily water releases for hydropower generation are a significant predictor of daily energy output at the Kotmale Hydropower Station, highlighting the importance of reservoir operation in optimizing hydroelectric power production.

Keywords: Kotmale Reservoir, Hydroelectric Power Generation, Regression Analysis, Water Release, Energy Prediction

1. Introduction

The **Kotmale Reservoir**, located in the Kotmale area of the Nuwara Eliya District, Central Province, Sri Lanka (7°03′39″ N, 80°35′50″ E), is one of the country's major hydropower resources. The Kotmale Hydropower Station (7°07′41″ N, 80°34′42″ E) consists of three 67 MW turbines with a total installed capacity of 201 MW, making it the second-largest hydroelectric power station in Sri Lanka. Construction of the dam commenced in August 1979 and was completed in February 1985, while the final generating unit was commissioned in 1988. The embankment dam, built across the Kotmale Oya, has a height of 87 m, a length of 600 m, and three spillways. The facility is jointly operated by the Mahaweli Authority of Sri Lanka and the Ceylon Electricity Board (CEB).

The main objective of this study is to develop a model for forecasting hydroelectric power generation for the subsequent year. Accurate forecasts can support reservoir operation, improve energy planning, and contribute to reducing power shortages in Sri Lanka. In addition, the study investigates the relationship between reservoir conditions and hydroelectric power generation, providing useful information for developing effective hydropower management and energy policies.

1.1 Objectives

The specific objective of this study is to develop an appropriate regression model to predict the relationship between reservoir water level and hydroelectric power generation.

2. Literature Survey

Several researchers have applied regression analysis to investigate hydrological processes and hydroelectric power generation. These studies provide a theoretical and methodological foundation for modelling the relationship between reservoir variables and energy production.

Abeykoon and Peiris (2018) [1] modelled and forecasted rainfall in the Kotmale Reservoir catchment area, Sri Lanka, using time series techniques. Their findings demonstrated the importance of statistical modelling in predicting hydrological variables, providing useful guidance for reservoir-related studies.

Xuefei, Van Gelder, and Vrijling (2010) [20] analysed hydrological data before and after dam construction in China using statistical methods to detect trends and changes in streamflow. Their study highlighted the value of quantitative approaches for understanding hydrological behaviour and supporting reservoir management.

Lima, Lall, and Troy (2014) [13] applied multiple regression models to examine the relationship between hydrological variables and hydropower generation. The study found that reservoir inflow and water availability were significant predictors of electricity generation, demonstrating the usefulness of regression analysis for hydropower forecasting.

Shrestha, Ahmad, and Johnson (2018) [16] developed multiple linear regression models to estimate hydropower generation using reservoir inflow and operational variables. Their results showed that regression models can accurately explain variations in power generation and provide reliable forecasts for reservoir operation.

Overall, previous studies demonstrate that regression analysis is an effective statistical tool for modelling relationships between hydrological variables and hydroelectric power generation. However, limited research has specifically examined the relationship between daily water releases and daily energy generation at the Kotmale Reservoir. Therefore, the present study applies regression analysis to develop a predictive model for hydroelectric power generation using operational data from the Kotmale Hydropower Station.

3. Materials and Methods

This study employed secondary data obtained from the Mahaweli Authority of Sri Lanka. The dataset comprised daily observations recorded at the Kotmale Hydropower Station. The analysis focused on two variables: daily release volume for power generation, measured in million cubic meters (MCM), and daily energy generation, measured in gigawatt-hours (GWh).

Prior to analysis, the dataset was examined for completeness, consistency, and missing values to ensure data quality. Descriptive statistics were computed to summarize the characteristics of the variables, while Pearson's correlation analysis was performed to assess the strength and direction of the relationship between daily water releases and energy generation.

Regression analysis was then employed to develop a predictive model for hydroelectric power generation. Several functional forms, including linear, logarithmic, exponential, and power regression models, were evaluated to identify the most appropriate relationship between the variables. Model performance was assessed using the Akaike Information Criterion (AIC), where the model with the lowest AIC value was selected as the best-fitting model. In addition, the coefficient of determination (R^2), residual analysis, and the statistical significance of the regression coefficients were used to evaluate the adequacy of the selected model.

All statistical analyses and model development were performed using R software, which provides comprehensive packages for data analysis, regression modelling, model selection, and diagnostic evaluation.

4. Results and Discussion

4.1 Descriptive Statistics of Variables

Table 4.1: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
RELEASES	2.09	1.58	0	12.84
ENERGY	1.11	0.85	0	4.86

According to the Table 4.1 means and variance of all variables are highly changed with the time (day).

4.2 Pearson's product-moment correlation

Hypothesis:

H_0: True correlation is equal to Zero.

H_1: True correlation is not equal to Zero.

Table 4.2: Pearson's product-moment correlation

Data	t	df	P-Value	Correlation	95% Confidence Interval	
					Lower Level	Upper Level
RELEASES and ENERGY	376.98	52	$< 2.2 \times 10^{-16}$	0.958	0.957	0.959
lg(RELEASES) and lg(ENERGY)	393.85	12540	$< 2.2 \times 10^{-16}$	0.961	0.928	0.975

P-value < 0.05, H_0 is rejected at 5% significance level, then the data correlation is not equal to zero.

All independent variables are strongly intercorrelated, indicating a positive correlation. Positive correlation indicates significant interdependence between variables.

4.3 Regression Analysis

Table 4.3: Coefficients Estimates for the Regression model

lg(ENERGY) ~ lg(RELEASES)					
Coefficients	**Estimate**	**Standard Error**	**t value**	**P-Value**	**Result (5% Significance Level**
Intercept	0.075	0.0022	34.13	$<2x10^{-16}$	Reject H_0
lg(RELEASES)	0.918	0.0023	393.85	$<2x10^{-16}$	Reject H_0

Table 4.4: Estimates for Regression model

Residual standard error: 0.1279 on 12540 degrees of freedom Multiple R-squared: 0.9252, Adjusted R-squared: 0.9252 F-statistic: $1.551x10^{+05}$ on 1 and 12540 DF, p-value: $< 2.2x10^{-16}$ AIC:-15985.75

4.4 Model selection

This study used the Akaike Information Criterion (AIC) and R-squared value to select the best fitted model. This process provides an opportunity to get the best estimated model through the selection of backward forward direction model. Minimum AIC and Maximum R-squared values found from below model.

$$\log_{10} \text{ENERGY} = 0.075 + [0.918 \times \log_{10} \text{RELEASES}]$$

4.5 Regression model accuracy

Table 4.5: Descriptive statistics for model Residuals

Min	1Q	Mean	Variation	Median	3Q	Max
-1.72	-0.04	0.01	0.03	1.65	-1.72	-0.04

4.6 Check the Residuals distribution

Hypothesis:

H_0: Residuals are normal.

H_1: Residuals are not normal.

Shapiro-Wilk normality test is used to test the residuals normality (Table 4.6).

Table 4.6: Anderson-Darling normality test

Anderson-Darling normality test
A = 1625.4, p-value $< 2.2 x10^{-16}$

P value < 0.05, H_0 is rejected at 5% significance level. Therefore, residuals are not normally distributed at 5% significance level.

The following Fig 4.1 Normal Probability plot for model residuals.

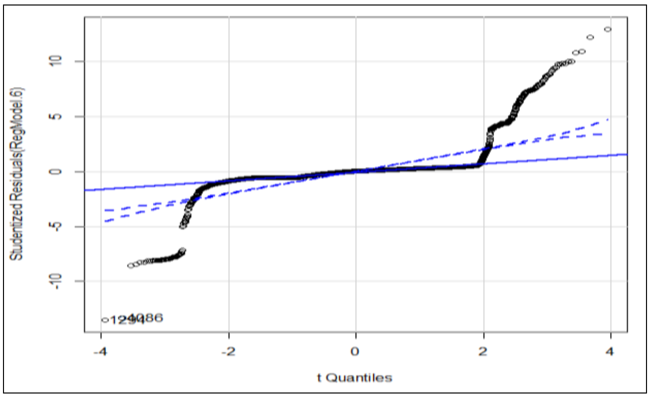

Fig 4.1: Normal Probability plot for model residuals

A residual analysis was used to find out whether the all model are wrong or not. According to the current study, there is a random trend pattern and the model has a constant variance of residuals, and therefore variables are independent. Fig 4.1, illustrates the residual behavior.

4.7 Check the residuals variance

Hypothesis:

H_0: Residuals have constant variance.

H_1: Residuals have not constant variance.

Non-constant Variance Score Test is used to test whether the residuals have constant variance.

Table 4.7: Non-constant Variance Score Test for model residuals

Non-constant Variance Score Test
Chi-square = 831.9805, df = 1, p-value $< 2.22x10^{-16}$

P value < 0.05, H_0 is rejected at 5% significance level. Therefore residuals do not show constant variance at 5% significance level.

4.8 Check the residuals independent.

Durbin Watson Test is used to test the independency.

Hypothesis:

H_0: Residuals are uncorrelated (Autocorrelation is zero).

H_1: Residuals are correlated (Autocorrelation is not zero).

Table 4.8: Test the serial correlation - Durbin-Watson test

Durbin-Watson Test
DW = 0.828, p-value $< 2.2x10^{-16}$

P value < 0.05, H_0 is rejected at 5% significance level. Therefore, residuals have an autocorrelation at 5% significance level. Then residuals are correlated.

4.9 Model Validation

The Model Validation technique is applied, hence to verify whether there is any difference between actual and estimated value of Energy.

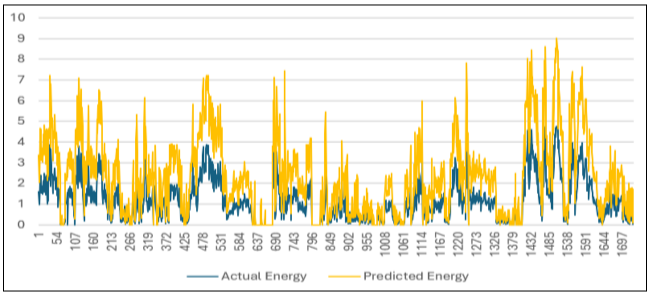

Fig 4.2: Validates the results

As indicated in the Fig 4.2, the predicted and the Actual Energy are overlapping and almost same pattern according to the current study. This reveals the estimated model is adequate the utilized sample.

5. Conclusions

This study examined the relationship between daily water releases and hydroelectric power generation at the Kotmale Reservoir using regression analysis. The results revealed a strong positive relationship between release volume and energy generation, indicating that water releases are a significant predictor of hydroelectric power output.

The best-fitting regression model was selected based on the minimum Akaike Information Criterion (AIC) and is expressed as:

$$\log_{10} \text{ENERGY} = 0.075 + [0.918 \times \log_{10} \text{RELEASES}]$$

With a coefficient of determination of (R^2 = 92.52%). The high R^2 value indicates that the model explains a substantial proportion of the variation in daily energy generation.

The findings demonstrate that the proposed regression model can be used to estimate future hydroelectric energy generation when the daily release volume is known. Therefore, the model provides a practical tool for reservoir operation, hydropower planning, and decision-making, contributing to more efficient water resource management and electricity generation in Sri Lanka.

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