Comparison of Inflow Forecasting Methods in Optimizing Operation and Maintenance Pattern Study Case: Bakaru Hydropower Plant

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Abstract. Hydropower is an exceptionally reliable and environmentally friendly power generation technology in today's energy landscape. Its eco-friendliness significantly aids in reducing greenhouse gas emissions. However, maintaining the reliability and performance of hydropower plants is paramount to ensuring a stable electricity supply. One of the crucial factors influencing the effectiveness of operation and maintenance planning for hydropower plants is the availability of water inflow. To achieve optimal performance and reliability, it's essential to have a clear understanding of how much water the plant can harness for energy generation. The primary objective of this paper is to conduct a comprehensive and in-depth exploration of various methodologies for forecasting water inflow, with a particular focus on empirical forecasting methods. These forecasting methods are essential in enhancing the planning and execution of operation and maintenance activities in water resource management and hydropower generation. In order to illustrate the practical use of these methodologies, the paper presents a case study on inflow forecasting for the Bakaru Hydropower Plant. This case study utilizes empirical methods such as Multiple Linear Regression (MLR), Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Seasonal Autoregressive Integrated Moving Average (SARIMA) to predict water inflow patterns. The results of the case study indicate that the most effective method for information forecasting at the Bakaru Hydroelectric Power Plant is the Artificial Neural Network (ANN) method, with an R-squared value of 0.39 and a Root Mean Square Error (RMSE) of 25.15.

Keywords: *Inflow Forecasting, Run of River, Numerical, Empirical, ANN, SVM, MLR, SARIMA*

1 Introduction

Hydropower plants are exceptionally reliable and environmentally friendly power generators. Unlike fossil fuel power plants, which generate greenhouse gases and harmful pollutants, hydropower plants generate electricity with zero or almost zero emissions (Demirbas, 2009). In Indonesia, a country with many water

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resources, hydropower has been widely utilized to meet its energy needs, which are increasing daily. Likewise, many other countries worldwide have widely used hydropower for electrical energy sources. It contributed approximately 16% of global electricity (Almulla et al., 2023). Figure 1 shows the world's electricity generation by fuel type in 2016.

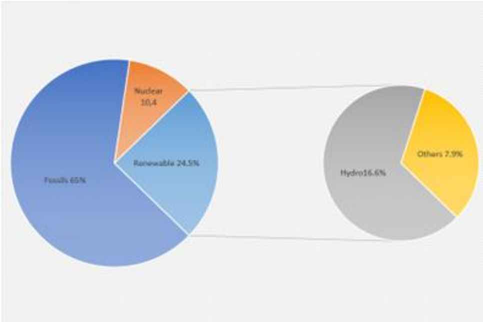


Figure 1. The world's electricity generation by fuel type (Killingtveit, 2020).

Maintaining the reliability of hydropower plants has become one of the most essential roles in supplying sustainable energy. Hydropower plants are expected to operate efficiently and reliably, significantly impacting the global electricity grid. However, the pattern of maintenance is not optimal in some hydropower plants. Maintenance is primarily based on working hours regardless of seasonal conditions when maintenance must be carried out. Inflow forecasting still does not have an influential role in maintenance planning.

The timing of maintenance at hydropower is an important point, as it can impact the overall system's performance and reliability. Inflow forecasting can play an essential role in maintenance planning. Adopting advanced forecasting techniques and real-time monitoring can ensure that maintenance activities are carried out at the most appropriate time, minimize the impact on electricity production, and improve the overall reliability of hydropower plants. This approach is critical as we prioritize sustainable and reliable energy sources in a changing world.

Several studies have examined the role that effective inflow forecasting can play in operation and maintenance patterns. Here are some examples of studies that have been conducted: The Sirikit Dam of the Chao Phraya River, which provides hydropower and irrigation facilities (Meema et al., 2021), Boryeong Dam, which supplies a significant power that provides 25% of South Korea's electricity (Lee et al., 2020), Dukan Reservoir in Iraq which supply hydropower plants (Saab et al., 2022), The River Uruguay at Machadinho (Collischonn et al., 2005), 23 dams located in various climate zones of the contiguous U.S. (CONUS) operated for multiple purposes such as hydropower generation (Ahmad and Hossain, 2019), etc.

Currently, in Indonesia, most hydropower plants rely on historical data averaging discharge from the past 5 or 10 years to plan their operational and maintenance schedule. Unfortunately, many possess comprehensive data that could significantly enhance inflow forecasting accuracy. Numerical data processing can offer a much more effective forecasting inflow when compared to relying on historical data averages.

Hence, a Comparison of inflow forecasting in optimizing operation and maintenance patterns is necessary. The purpose of this research was to compare several methods in inflow forecasting. In this study, three distinct methods will be applied, namely Multi Linear regression (MLR), Support Vector Machine (SVM), and Artificial Neural Network (ANN). This study will be conducted at Bakaru Hydropower Plant and will encompass the application of all three methods.

This study aims to identify and compare the effectiveness of each method in predicting water inflows to hydropower. Thus, these results will help hydropower plants like Bakaru Hydropower to improve their operational planning and maintenance.

2 Inflow Forecasting Methods

2.1 Multi Linear Regression (MLR)

Regression analysis is a statistical method to predict and estimate the correlation between variables with a cause-and-effect connection. Univariate regression is a regression model that analyses the relationship between one dependent and independent variable. In comparison, a regression model with one dependent variable and more than one independent variable is called multiple linear regression (Uyanık and Güler, 2013). The numerical method of forecasting inflow includes multiple linear regression, which is the simplest machine learning model. The general equation of MLR is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{1}$$

Where Y is the dependent variable, β_0 is intercept, X_i are independents variable, β_i are parameters, and ε is error. Some conditions that must be met to perform MLR analysis are normal distribution, linearity, absence of outliers, and there is no double relationship between independent variables (Büyüköztürk, 2002).

2.2 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a machine learning model included in a supervised learning algorithm; SVM can be used for classification and regression functions. SVM was invented in 1991 by French researcher Isabelle Guyon. The working principle of SVM is to predict two possible groups from the given data and determine which is different from the other (Wee et al., 2021). The advantages of SVM are that it can provide clear decision boundaries, handle non-linear data, and have wide applications, including text classification, image classification, and regression prediction (Wee et al., 2021). Figure 2 shows the general flow chart of SVM.

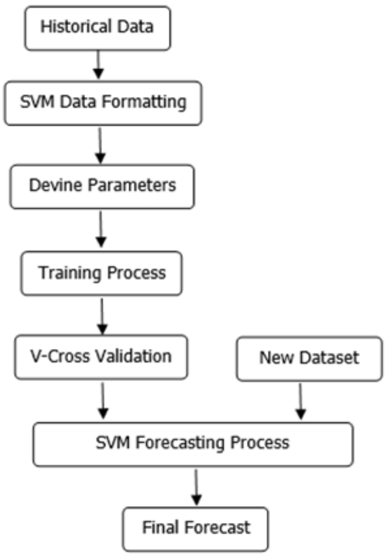


Figure 2 General Flowchart of SVM

2.3 Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are computational models inspired by the structure and function of the human brain (Haykin, 1994). They are used in machine learning and are very effective in classification, regression, and pattern recognition. Neural networks consist of interconnected processing elements with quality connections adjusted during training. The study used an advanced neural network with a backpropagation learning algorithm. Its basic unit is a processing node that behaves like a neuron, which sums weighted inputs and passes them through the activation function. The nodes form a layer with no connections within that layer. The input layer distributes the data, followed by the hidden and output layers (Taghi Sattari et al., 2012). Figure 3 shows a general model for artificial neural networks.

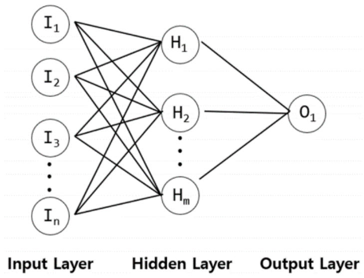


Figure 3. General artificial neural networks model

Since being introduced by McCullough and Pitts in 1943, the concept of neurons has continued to evolve into much more detailed and realistic models, both of neurons and larger systems within the brain, giving rise to the modern field of computational neuroscience (Chukwuemeka Nwobi-Okoye et al., 2013a).

2.4 Autoregression Integrated Moving Average (ARIMA)

Time Series prediction is a method aimed at extracting inter-implicit relationships in a time series and investigating changes in principle based on previous observations. Thousands of models have emerged from the perspective and idea of flexible model ideas. ARIMA is one of the most fundamental models in time series prediction (Yitong Li et al., 2023).

The ARIMA model is a method of time series analysis based on stochastic theory proposed by Box and Jenkins in 1970. A time series is a group of stochastic variables that change with time and exhibit some regularity, allowing for predicting future patterns (Wen et al., 2023).

In this case study, the type of ARIMA used will be SARIMA. The general equation is:

$$\Delta^d y_t = \theta_0 + \sum_{i=1}^{p} \varphi_i \, \Delta^d \, y_{t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{2}$$

Where:
ε_t= the series y_t after d-order differencing
φ_i and θ_j= parameters to be estimated
p and q = the orders.

3 Case Study: Bakaru Hydropower Plant

3.1 Bakaru Hydropower

Bakaru is a hydropower plant with a run-of-river type, which deflects water in the river to generate electrical energy. Although included in the run-of-river category, the Bakaru hydropower plant has a small dam with an initial capacity of about 6,900,000 cubic meters. Bakaru dam is essential in regulating inflow and water usage in the Bakaru hydropower plant. Overall, the Bakaru hydropower plant has a unique configuration, combining the characteristics of a run-of-river and large dam-type power plants.

The Mamasa River Basin (DAS) is located to the north of Mount Paraleang in Polumasu, passing through Pinrang City and merging into the Saddang River, covering an area of approximately 1200 km2 along the total length of the Mamasa River, which is about 126 km. Figure 4 shows the DAS of the Mamasa River that is used to generate electricity at Bakaru Hydropower.

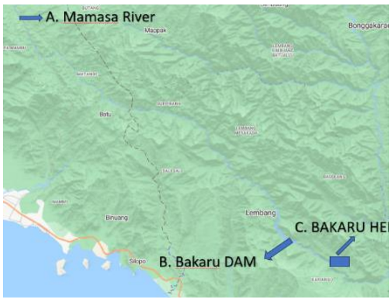


Figure 4 DAS Mamasa (A-B)

Bakaru Hydropower has a capacity of 126 MW, making it one of Sulawesi's largest renewable energy power plants. In the operational and maintenance planning at Bakaru Hydropower, they still rely on working hours and average data from the actual inflow over the past five years. This leads to inefficiencies in the operational planning and maintenance at Bakaru Hydropower. This becomes a significant disadvantage for the electrical system in Sulawesi.

3.2 Data Collection

The data used for this case study is obtained from the evaluation and reporting of the hydrology of the dam and the Bakaru Hydropower. The data consists of actual inflow, power load, and dam elevation. The compiled data spans from January 2013 to 2022. Other than that data, it will also be supported by rainfall data obtained from BMKG (Meteorology, Climatology, and Geophysics Agency). The available rainfall data also spans from January 2013 to December 2022.

3.3 Inflow Forecasting and Analysis

3.3.1 Data Precipitation

Data precipitation is carried out by importing libraries and data, brief exploratory data analysis, and seeing feature correlations without time considerations. Brief exploratory data analysis is carried out in several stages to produce a summary statistics dataset as shown in Tables 1 and 2 below:

Table 1 Weekly data summary statistics

	Load (MW)	Inflow (M^3/s)	Elevation (mdpl)	Rainfall (mm)
Count	480	480	480	480
Mean	98.51	64.03	615.29	338.85
Std	27.95	37.1	0.66	229.74
Min	0	10.92	609.23	0
25%	82.56	36.03	615.29	166.75
50%	107.67	55.22	615.42	329.5
75%	121.66	87.23	615.48	494.25
Max	126	181.62	61.7	1200

Table 2 Monthly data summary statistics

	Load (MW)	Inflow (M^3/s)	Elevation (mdpl)	Rainfall (mm)
Count	120	120	120	120
Mean	98.69	62.2	615.3	339.63
Std	26.27	31.6	0.42	216.36
Min	0.12	12.89	611.26	0
25%	86.67	37.99	615.3	190.75
50%	106.3	59.22	615.41	339
75%	118.04	76.63	615.46	477.5
Max	126	139.62	615.53	962

After that, a scatter plot and heatmap were used to see feature correlations without time considerations. The results are shown in Figure 5 below:

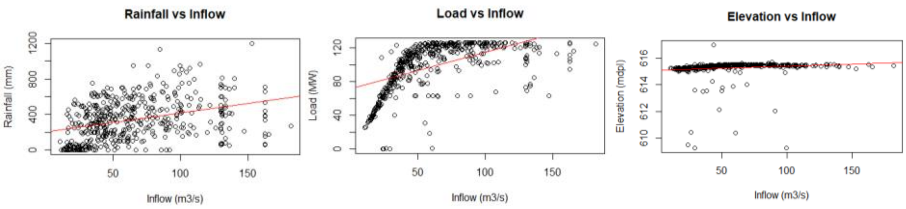


Figure 5 Scatter plot of features

Table 3 shows the obtained p-values for each predictor:

Table 3 P-values of the predictors

Predictors	P-Value
Rainfall	2.285e-06
Load	1.277e-14
Elevation	0.0007497

3.3.2 MLR and SVR

The initial steps in MLR and SVR are to separate between the dependent variable/variable to be predicted (y) and the independent variable (X). Because we do not consider the time series here, the X is Load (MW), Elevation (mdpl), and Rainfall (mm). At the same time, the y is the data to be predicted, namely Inflow (m^3/s).

After that, X and y will be divided into four variables, namely X_train, X_test, y_train, y_test.

The ratio of the number of data trains and tests is 80%: 20% with random_state = 42. From the intercept and slopes results obtained from the algorithm above, this MLR model has the following linear regression formula:

$$Y = 60.93 + 19.49\,x1 - 1.08\ \ x2 + 2.27\,x3 \tag{3}$$

After that, we evaluate performance using R-squared (R^2) and Root Mean Square Error (RMSE). Table 4 shows the results:

Table 4 MLR and SVR performance

	MLR Monthly	MLR Weekly	SVR Monthly	SVR Weekly
R-Squared	0.33	0.26	0.11	0.24
RMSE	26.78	27.63	30.83	27.94

3.3.3 Artificial Neural Networks (ANN)

The initial steps in ANN are the same as those in MLR and SVM. After splitting data, define the number of hidden units used, along with the number of hidden units used for each layer: Layer 1 = 160, layer 2 = 480, layer 3 = 256.The learning rate used is 0.01. Then, define the loss function to be used. Because this is related to regression, the loss function used is Mean Squared Logarithmic Error with Adam optimizer. Then, do ANN training with epochs = 10, batch size = 64, and validation split = 0.2.

3.3.3.1 Mean Square Logarithmic Error

Plot means squared logarithmic error with epochs. The smaller the model, the better the epoch order, then calculate the R-squared and RMSE. Figure 6 shows mean squared logarithmic error for monthly and weekly datasheet.

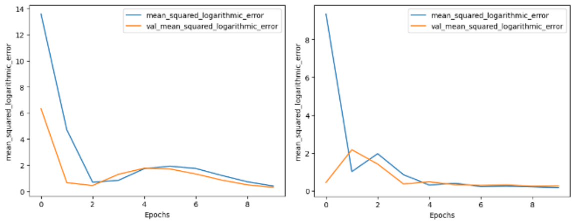


Figure 6 Mean squared logarithmic error (monthly and weekly datasheet)

3.3.3.2 Model performance test

Table 5 below shows the model performance test from monthly and weekly datasheet.

Table 5 Model performance test

	Monthly	Weekly
R-Squared	-0.65	0.38
RMSE	42.10	25.33

3.3.4 Seasonal Autoregression Integrated Moving Average (SARIMA)

3.3.4.1 Stationarity testing for ARIMA parameters (p, d, q)

Figure 7 below shows stationary test for ARIMA with monthly and weekly datasheet.

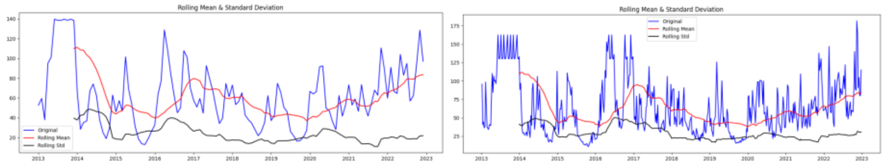


Figure 7 Stationarity test for ARIMA (monthly and weekly datasheet)

Both monthly and weekly datasheet has a Critical value (5%) > Test statistic, dan p-value < 0.05; this means that Time Series Inflow is stationery and time series modelling can be done.

3.3.4.2 ACF and PACF testing for ARIMA parameters (p, d, q)

The ARIMA model is a combination of 3 models: AR (p): Auto-Regressive, I (d): Integrated, and MA (q): Moving Average, where (p, d, q) is known as the order in the ARIMA model. The value of this parameter is based on the model mentioned above. p: Number of terms on auto-regressive, d: The number of differentials needed to make a time series stationery, q: The number of lagged forecast errors in prediction calculations.

ARIMA model sequence selection criteria: p: The lag value when the Partial Autocorrelation (PACF) graph is truncated or drops close to 0 for the first time; d: The number of times differentiation is performed to create a stationary time series, q: The lag value when the Autocorrelation (ACF) chart crosses the upper confidence for the first time. The result of ACF and PACF testing shown in Figure 8 below:

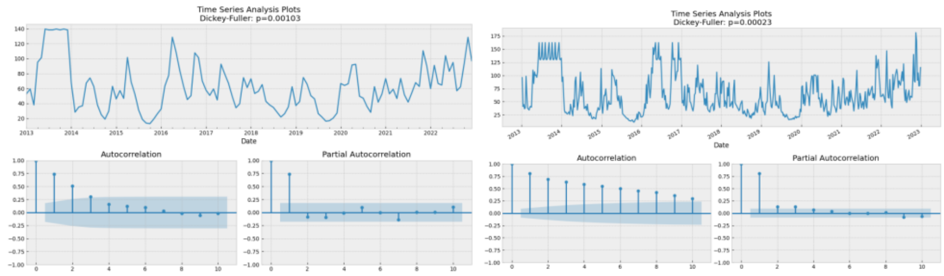


Figure 8 Time series analysis plot for ARIMA (monthly and weekly datasheet)

From both charts above, because ACF Tails Off and PACF Cuts Off after lag to 1, parameter p is 1, and parameter q is 0. So, it can be concluded the parameters p, d, and q obtained are the same for both datasheets:

p = 1 (PACF chart cuts off after lag to 1) and d = 0 (Because from the beginning, the inflow is stationary without even differential transformations)

q = 0 (ACF Tails Off Chart)

3.3.4.3 ACF and PACF testing for seasonal parameters (P, D, Q, S)

The result of ACF and PACF testing for seasonal parameters are shown in Figure 9 below:

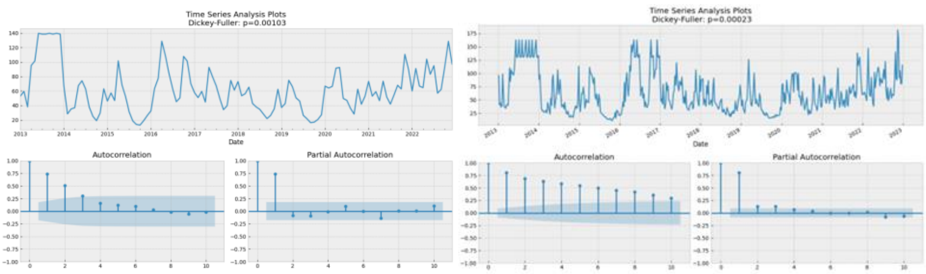


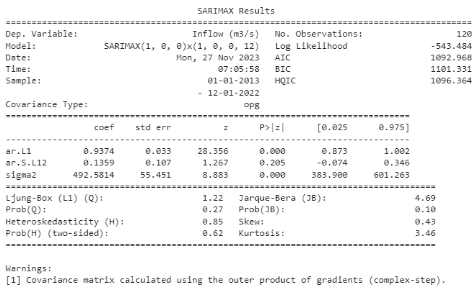
Figure 9 Time series plot for seasonal (monthly and weekly datasheet)

From both charts above, because ACF Tails Off and PACF Cuts Off after lag to 1, parameter p is 1, and parameter q is 0.

3.3.4.4 SARIMA result

The results of SARIMA model for monthly and weekly datasheet are shown in Table 6 below.

Table 6 SARIMA results for monthly and weekly datasheet



```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                       Inflow (m3/s)   No. Observations:                  120
Model:             SARIMAX(1, 0, 0)x(1, 0, 0, 12)   Log Likelihood                -543.484
Date:                             Mon, 27 Nov 2023   AIC                           1092.968
Time:                                     07:05:58   BIC                           1101.331
Sample:                                 01-01-2013   HQIC                          1096.364
                                      - 12-01-2022
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9374      0.033     28.356      0.000       0.873       1.002
ar.S.L12       0.1359      0.107      1.267      0.205      -0.074       0.346
sigma2       492.5814     55.451      8.883      0.000     383.900     601.263
===================================================================================
Ljung-Box (L1) (Q):                   1.22   Jarque-Bera (JB):                 4.69
Prob(Q):                              0.27   Prob(JB):                         0.10
Heteroskedasticity (H):               0.85   Skew:                             0.43
Prob(H) (two-sided):                  0.62   Kurtosis:                         3.46
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
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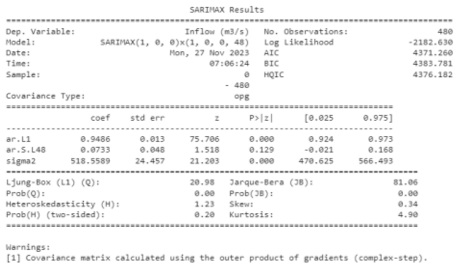

```
                                     SARIMAX Results
==========================================================================================
Dep. Variable:                       Inflow (m3/s)   No. Observations:                  480
Model:             SARIMAX(1, 0, 0)x(1, 0, 0, 48)   Log Likelihood               -2182.630
Date:                             Mon, 27 Nov 2023   AIC                           4371.260
Time:                                     07:06:24   BIC                           4383.781
Sample:                                          0   HQIC                          4376.182
                                             - 480
Covariance Type:                               opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.9486      0.013     75.706      0.000       0.924       0.973
ar.S.L48       0.0733      0.048      1.518      0.129      -0.021       0.168
sigma2       518.5589     24.457     21.203      0.000     470.625     566.493
===================================================================================
Ljung-Box (L1) (Q):                  20.98   Jarque-Bera (JB):                81.06
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               1.23   Skew:                             0.34
Prob(H) (two-sided):                  0.20   Kurtosis:                         4.90
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

3.3.4.5 Prediction

Figure 10 shows the prediction with monthly and weekly datasheets.

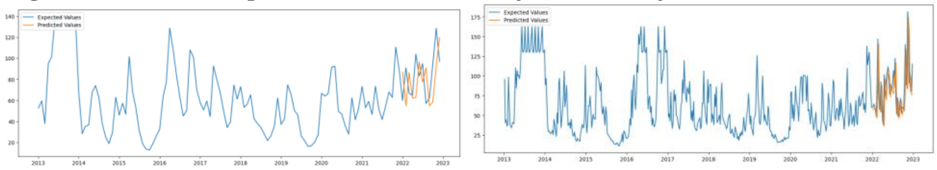

Figure 10 SARIMA prediction with monthly and weekly datasheet

The model performance test from the prediction shown in Table 7 below:

Table 7 Model prediction performance test

	Monthly	**Weekly**
R-Squared	-0.68	-0.07
RMSE	27.22	31.57

4 Conclusion

From the results of a case study conducted at the Bakaru hydropower plant, an ANN-Weekly model with the largest R^2 and the smallest RMSE was obtained. The order of test performance of all tested models can be seen in the following Table 8:

Table 8 Performance table of inflow forecasting methods

Model	R-Squared	RMSE
ANN – Weekly	0.39	25.15
MLR – Monthly	0.33	26.78
MLR – Weekly	0.26	27.63
SVR – Weekly	0.25	27.84
SVR – Monthly	0.12	30.83
SARIMA – Weekly	-0.07	31.57
ANN – Monthly	-0.68	27.22
SARIMA – Monthly	-0.88	44.98

This study has overlooked factors such as sedimentation and the water level within the watershed due to limitations in available data. Consequently, for future research endeavors, it is advisable to gather additional data that is anticipated to correlate with the inflow discharge. This comprehensive data collection can potentially enrich the understanding of the dynamics associated with water flow and its influencing factors within the studied area.

4.1.1.1 MLR and SVR:

Monthly data shows better model performance compared to weekly data, with the monthly MLR (Multiple Linear Regression) model providing the best results in both cases. However, the model performance results using R Squared are closer to 0 than to 1, indicating that the models are still not effective at explaining the data's variability. This is likely due to the influence of time series elements affecting the four features, meaning that standard machine learning models like linear regression are not sufficient to capture the underlying patterns. Time series-based models, such as ARIMA, may be more suitable for handling time dependencies that conventional models cannot address.

4.1.1.2 ANN

Weekly data performs significantly better than monthly data, with the ANN (Artificial Neural Network) model outperforming both the MLR (Multiple Linear Regression) and SVM (Support Vector Machine) models. This suggests that the weekly data, with its higher frequency and potentially more detailed patterns, allows the ANN to capture complex relationships more effectively than the other models.

4.1.1.3 SARIMA

Monthly data performs slightly better than weekly data, but the performance of the SARIMA model is generally lower than that of the MLR, SVM, and ANN models. This indicates that while SARIMA is designed for time series data, it may not capture the underlying patterns as effectively as the other machine learning models in this particular case.

5 Acknowledgement

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