

RESEARCH ARTICLE

Short-Term Reservoir Inflow Prediction Using Weather Forecast Data and ExtraTrees Regressor for Hydroelectric Power Plant Operations

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Abstract

Accurate short-term inflow forecasting is essential for optimizing hydroelectric power plant (HPP) operations, where water availability is highly sensitive to dynamic weather conditions. This study proposes a machine learning-based inflow prediction framework that integrates real-time weather forecast data using the ExtraTrees Regressor algorithm. The model was trained on four years of historical hydrological and meteorological data and tested using independent forecast-based weather inputs. The results demonstrate strong predictive performance, achieving a coefficient of determination (R^2) of 0.8243 and a root mean squared error (RMSE) of 26.83 m³/s. By enabling one-hour-ahead inflow forecasts, the proposed approach supports proactive reservoir control, enhances turbine scheduling, and reduces the risk of overflow, thereby not only protecting reservoir integrity but also minimizing potential energy production losses due to unutilized water. This work highlights the potential of transitioning from intuition-based to real-time, data-driven strategies in modern hydropower operations.

Keywords: inflow prediction, extratrees regressor, hydroelectric power, machine learning, weather forecast integration.

I. INTRODUCTION

Hydroelectric power plants (HPPs) play a vital role in supporting global renewable energy goals due to their capacity for clean and flexible electricity generation. However, the effectiveness of HPP operations is fundamentally tied to the availability and predictability of water inflow, which is highly sensitive to dynamic and sometimes extreme weather patterns [1]. In particular, short-term fluctuations in inflow can pose significant challenges for reservoir management and turbine scheduling. Overestimations may lead to uncontrolled water spillage, while underestimations can result in insufficient reservoir levels, both of which reduce energy efficiency and pose operational risks [2].

Despite the availability of meteorological data and hydrological monitoring systems, decision-making in many HPPs remains largely intuition-driven. Operators often rely on experiential knowledge and general weather forecasts to guide daily dispatch strategies [3]. However, as climate patterns grow increasingly unpredictable, the limitations of such subjective methods have become more apparent.

In response to these challenges, recent studies have explored the use of data-driven approaches, including statistical and machine learning methods for more accurate inflow forecasting. Techniques such as ensemble learning, deep learning, and hybrid modeling have shown promising results in capturing nonlinear hydrological behavior [4], [5]. Furthermore, the integration of weather forecast data into inflow models has gained attention as a means of improving prediction accuracy and operational applicability [3].

This study proposes a short-term inflow prediction framework that leverages forecasted weather variables as input features to a machine learning model, specifically the ExtraTrees Regressor. The model is trained on four years of historical hydro-meteorological data and validated using independent short-term weather forecasts. Unlike conventional hydrological models, the proposed approach requires minimal calibration, offers fast computation, and is tailored for real-time applications. The resulting inflow estimates can support proactive turbine scheduling and reservoir control in run-of-river hydroelectric systems, reducing the risk of overflow or emergency water releases and maximizing HPP energy production.

II. LITERATURE REVIEW

Numerous studies have demonstrated the potential of machine learning and statistical models in improving inflow forecasting accuracy. Traditional hydrological models, such as GR4J and HBV-Light, have been widely used for streamflow simulation but often require extensive calibration and are sensitive to input uncertainties [6]. Recent research has shifted towards integrating meteorological forecasts into data-driven frameworks to enhance responsiveness and reduce uncertainty [7].

Wagner et al. [6] investigated the use of medium-range ensemble precipitation forecasts to improve inflow predictions in alpine catchments, demonstrating that ensemble inputs can enhance forecasting skill. However, their framework primarily focused on flood scenarios rather than operational hydroelectric scheduling. Similarly, Meydani et al. [8] showed that combining downscaled numerical weather prediction (NWP) models with rainfall–

runoff simulations could improve daily inflow forecasts. Nonetheless, this approach remains computationally intensive and is not directly suited for real-time applications in power plant operations.

Meanwhile, deep learning-based methods have gained popularity for their ability to model nonlinear relationships in hydrological time series. Wang et al. [9] proposed an optimal deep learning framework for inflow prediction using multiple neural network architectures, including CNN and LSTM. Although the results indicated high accuracy, the model required substantial training time and did not explicitly address short-term operational decision-making. Furthermore, Fortin et al. [10] compared two conceptual hydrological models for streamflow simulation, highlighting the trade-off between model complexity and forecasting performance.

These findings underscore the need for inflow prediction methods that are both accurate and computationally efficient. Despite recent advancements, a research gap remains in the integration of real-time, short-term weather forecast data into lightweight ensemble-based models such as the ExtraTrees Regressor—particularly in the context of near-term turbine dispatch decisions in run-of-river hydroelectric systems. This study aims to address this gap by proposing a machine learning-based inflow prediction model trained on historical hydro-meteorological data and validated using independent short-term weather forecasts. The objective is to equip operators with timely and actionable insights for optimizing reservoir inflow utilization and minimizing unplanned spillage events.

III. METHODS

This section outlines the methodological framework employed in developing a short-term inflow prediction model for hydroelectric reservoir operations. The research began with the collection of historical hydrological and meteorological datasets, which served as the foundation for training the predictive model. Hydrological data—specifically inflow measurements—were obtained from reservoir telemetry stations, while meteorological parameters such as temperature, humidity, cloud cover, and wind speed were sourced from publicly accessible weather platforms.

To address the inherent nonlinearities and complex interactions between weather conditions and inflow patterns, a machine learning approach was adopted. Previous studies have highlighted the effectiveness of ensemble learning methods in hydrological forecasting under dynamic weather conditions [13], [14]. Moreover, the integration of forecasted meteorological data into inflow prediction frameworks has been recommended as a future direction for enhancing operational decision-making [12].

In line with these insights, this study employs the ExtraTrees Regressor, a tree-based ensemble algorithm known for its robustness and ability to handle high-dimensional, nonlinear data relationships. Although this specific algorithm has not been widely applied in prior inflow prediction studies, its selection in this research fills a methodological gap and contributes novel insights to the hydrological forecasting domain.

A. Methodological Framework

The overall methodological framework is illustrated in the flowchart presented in Figure 1. The process begins with data collection, followed by preprocessing steps including data cleaning, synchronization, and feature engineering. The ExtraTrees Regressor model is then trained on the prepared dataset. Predictions are generated using the testing dataset, and the results are evaluated using standard performance metrics.

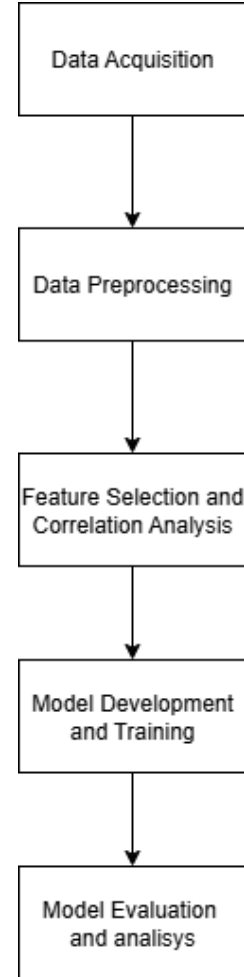


Fig. 1. Methodological Framework

B. Data Sources and Description

This study employs two primary sources of data to support the development of the short-term reservoir inflow prediction model. The first is historical inflow data obtained from hydrological telemetry stations operated by the local reservoir management authority. These stations continuously monitor real-time water level and flow data upstream of the reservoir, providing accurate records of inflow rates critical for model training and validation.

The second source is meteorological data retrieved from platform that aggregates weather forecasts and observations from multiple authoritative sources, including NOAA's Integrated Surface Database (ISD). The weather data comprises various atmospheric variables such as temperature, dew point, humidity, cloud cover, wind speed, precipitation, and solar radiation, among others. These data

are available on an hourly basis, aligning well with the temporal resolution required for short-term inflow forecasting.

Prior to modeling, both datasets undergo preprocessing steps to handle missing values, remove outliers, and ensure temporal synchronization between inflow and weather parameters. This preprocessing stage ensures the reliability and consistency of the input features used in the machine learning model.

The selected meteorological and hydrological parameters used as model inputs and target variable are summarized in Table I below.

TABLE 1. PEARSON CORRELATION COEFFICIENTS BETWEEN WEATHER PARAMETERS AND RESERVOIR INFLOW

PARAMETER	CORRELATION COEFFICIENT
CLOUDCOVER	0.2901
WIND DIRECTION	0.2321
PRECIPITATION PROBABILITY	0.2064
PRECIPITATION	0.1988
DEW POINT	0.1539
HUMIDITY	0.0854
TEMPERATURE	0.0164
WIND GUST	-0.1642
WIND SPEED	-0.2259
SEA LEVEL PRESSURE	-0.2273

C. Data Preprocessing

Data preprocessing involved synchronizing the timestamps between inflow measurements and weather data to ensure accurate input-output pairing. Data cleaning was performed by removing invalid entries such as missing values (NaN), negative values, or values outside the expected physical range. Feature engineering included the extraction of temporal features such as year, month, day, and hour from the datetime field. The complete dataset was divided into two subsets: approximately 80% for training and 20% for testing. Normalization was deemed unnecessary due to the robustness of the ExtraTrees algorithm against unscaled features.

D. Features Extraction

To identify the most relevant meteorological parameters influencing reservoir inflow, a correlation analysis was conducted between each weather variable and the inflow target. The results of this analysis are presented in Table X, which ranks the weather parameters based on their Pearson correlation coefficients with inflow.

As shown in the table, cloudcover, elevation, wind direction, precipitation probability, and precipitation exhibit the highest positive correlation with inflow, with cloudcover having the strongest correlation coefficient of 0.29. These parameters are meteorologically consistent with inflow behavior, as increased cloudiness and precipitation levels typically lead to higher surface runoff into the reservoir.

Conversely, variables such as sea level pressure, windspeed, and wind gust show moderate negative correlations, suggesting that higher atmospheric pressure and wind speed are often associated with drier conditions, which may reduce inflow. Time-related features (e.g., hour, month, day, and year) and other weather attributes such as temperature, dew point, and solar radiation exhibit very low correlation values, indicating weak or no linear relationship with the inflow data.

TABEL II WEATHER AND HYDROLOGICAL PARAMETERS WITH UNITS

Parameter	Unit
Cloudcover	% (percentage)
Wind Direction	° (degrees from north)
Precipitation Probability	% (percentage)
Precipitation	mm (millimeters)
Dew Point	°C (degrees Celsius)
Humidity	% (percentage)
Temperature	°C (degrees Celsius)
Wind Gust	km/h or m/s
Wind Speed	km/h or m/s
Inflow	m ³ /s (cubic meters per second)
Elevation	m (meters above sea level)

a.

Based on this analysis, the most influential features were selected for inclusion in the predictive model to improve accuracy and reduce dimensionality, serving as an essential preprocessing step before model training.

E. Data Preprocessing

Data preprocessing involved synchronizing the timestamps between inflow measurements and weather data to ensure accurate input-output pairing. Data cleaning was performed by removing invalid entries such as missing values (NaN), negative values, or values outside the expected physical range. Feature engineering included the extraction of temporal features such as year, month, day, and hour from the datetime field. The complete dataset was divided into two subsets: approximately 80% for training and 20% for testing. Normalization was deemed unnecessary due to the robustness of the ExtraTrees algorithm against unscaled features.

IV. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from the implementation of the proposed inflow prediction model. The discussion emphasizes the model's predictive accuracy, robustness under varying hydrometeorological conditions, and its practical implications for operational decision-making in hydroelectric power plant management. Comparative evaluations with other ensemble methods are also provided to demonstrate the superiority and applicability of the ExtraTrees Regressor in real-time forecasting scenarios.

A. Model Performance

To assess the predictive performance of the proposed inflow forecasting model, this study utilizes two commonly adopted evaluation metrics: Root Mean Squared Error (RMSE) and the Coefficient of Determination (R^2). RMSE is chosen for its ability to represent the average magnitude of prediction errors in the same unit as the target variable (m^3/s), which is highly interpretable in hydrological forecasting. It penalizes large errors more severely, making it suitable for evaluating real-world impact where extreme deviations can lead to significant operational consequences.

R^2 is used to indicate the proportion of variance in the observed inflow that can be explained by the model. It reflects how well the model captures underlying patterns and relationships in the data, which is particularly important for inflow prediction where variability is high and influenced by complex weather dynamics. The combination of RMSE and R^2 provides a balanced view of both the model's accuracy and its explanatory power, making them suitable for evaluating inflow prediction performance in hydroelectric operations.

The ExtraTrees Regressor model demonstrated strong predictive performance when evaluated on the test dataset, achieving a Root Mean Squared Error (RMSE) of $26.83 \text{ m}^3/\text{s}$ and a Coefficient of Determination (R^2) of 0.8243. These metrics reflect the model's high accuracy in capturing the complex and nonlinear relationships between meteorological inputs and short-term reservoir inflow. The relatively low RMSE indicates that the deviations between predicted and actual inflow values are minimal, while the R^2 value suggests that over 82% of the variance in the inflow data is effectively explained by the model.

These results emphasize the model's capacity to generalize well under unseen weather scenarios, which is essential for real-time forecasting applications. By accurately representing short-term inflow dynamics, the model provides a reliable foundation for reservoir management strategies such as anticipatory gate operations, turbine dispatch planning, and flood risk mitigation.

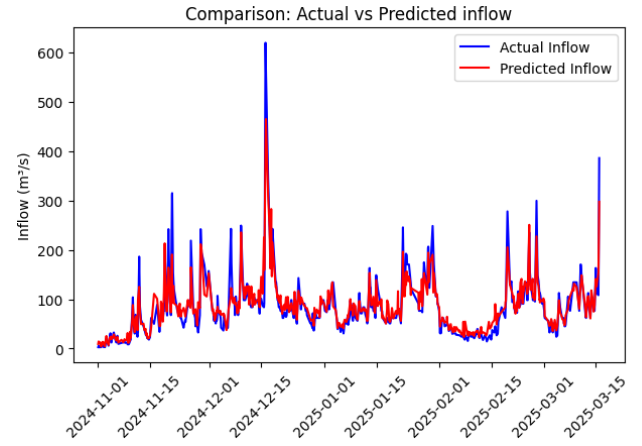


Fig. 2. Comparison Actual vs Predicted Inflow

Figure 2 illustrates the temporal comparison between observed inflow and model predictions over the testing period. The visual representation confirms the model's ability to closely follow actual inflow trends across a range of conditions. Although slight underestimations are observed during certain peak inflow events—likely due to the rarity and sharp magnitude of such events—the model successfully captures the overall pattern and amplitude of fluctuations. This consistency underscores the robustness of the ExtraTrees Regressor in adapting to diverse hydrological behaviors and enhances its suitability for deployment within decision-support systems for hydroelectric operations.

TABEL III COMPARISON OF ENSEMBLE MODELS FOR INFLOW PREDICTION

Parameter	R^2	RMSE (m^3/s)
Extra Trees Regressor	0.8243	26.83
Random Forest Regressor	0.7473	32.17
Gradient Boosting Regressor	0.2064	47.64
Light Gradient Boosting Machine	0.7	35.07

In order to validate the model's performance, the ExtraTrees Regressor was compared against several other widely used ensemble learning algorithms, including Random Forest, Gradient Boosting, LightGBM, and AdaBoost. As summarized in **Table III**, ExtraTrees achieved the highest predictive accuracy among all ensemble models tested, with the lowest RMSE ($26.83 \text{ m}^3/\text{s}$) and the highest R^2 value (0.8243). In contrast, the Random Forest Regressor yielded a slightly lower R^2 of 0.7473 and a higher RMSE of $32.17 \text{ m}^3/\text{s}$, while boosting-based methods such as LightGBM and Gradient Boosting Regressor performed less favorably, especially under rapidly changing inflow conditions. AdaBoost Regressor, in particular, recorded significantly lower predictive reliability, with a negative R^2 value (-0.5649), indicating poor generalization.

These comparative results further strengthen the selection of ExtraTrees Regressor as the preferred model for short-term inflow prediction in hydroelectric contexts. Its combination of high accuracy and robustness across varying hydrometeorological conditions makes it a promising

candidate for integration into operational forecasting systems. Furthermore, the model's efficiency in training and prediction time enhances its practicality for near real-time deployment in hydropower scheduling and water release decision-making processes.

B. Impact of Forecasted Weather

The integration of forecasted weather data into the testing phase is essential for replicating realistic operating conditions, ensuring that the model reflects the actual environment in which hydropower plant decisions are made. Instead of relying on historical weather records, the model utilizes near-future meteorological forecasts, enabling one-hour-ahead inflow predictions that align with operational timeframes. This approach increases the practical applicability of the model by equipping operators with timely information, which supports anticipatory actions such as early water release planning, reservoir level regulation, and turbine operation optimization [13], [2].

This forecast-based framework marks a notable shift from conventional inflow prediction methods, which are often retrospective and limited to post-event analysis. While traditional models can effectively capture historical inflow dynamics, they lack predictive responsiveness and adaptability to real-time hydrometeorological variability [3]. By leveraging real-time weather forecasts—including anticipated rainfall, temperature, humidity, and wind conditions—the proposed model closes the gap between data analysis and operational decision-making. As a result, it provides not only reliable short-term predictions but also operationally relevant insights that enhance the readiness and responsiveness of hydroelectric power systems. This proactive capability positions the model as a valuable component within intelligent decision-support systems designed for modern reservoir and turbine management [4].

C. Operational Implication

Accurate short-term inflow predictions are fundamental for optimizing the operations of hydroelectric power plants (HEPPs), particularly those with daily storage or run-of-river configurations where inflow variability directly impacts dispatch planning, turbine scheduling, and gate management. In these systems, real-time inflow fluctuations can cause rapid changes in reservoir levels, necessitating quick and informed operational responses. With reliable hourly forecasts derived from weather data and machine learning models, operators are better equipped to anticipate hydrological events and implement proactive control strategies.

The proposed flowchart for HEPP operation, as shown in Fig. 3, illustrates a structured process in which inflow prediction data is central to decision-making. The process begins by estimating the current water storage using the height–volume (HV) curve, followed by calculating the turbine outflow based on the current operating efficiency. A key decision node then evaluates whether the forecasted inflow exceeds the maximum permissible outflow. If this condition is met, water is discharged at the allowable maximum to prevent overspill.

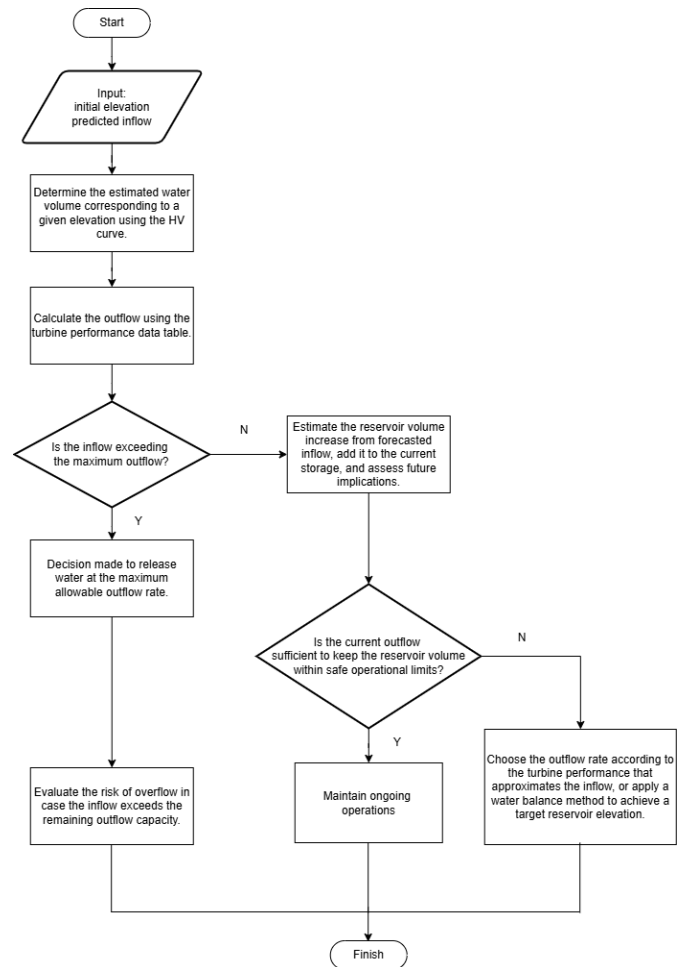


Fig. 3. Proposed unit operation scheme driven by inflow prediction data

Otherwise, the inflow forecast is used to estimate future volume increase, which is added to the current storage to evaluate whether the planned outflow is sufficient to maintain reservoir safety. If not, the operator assisted by predictive tools selects the optimal discharge level by either matching inflow with turbine performance characteristics or applying a water balance approach to achieve a target elevation.

This approach is validated in the simulation results shown in Fig. 4, where early release actions are taken in anticipation of high inflow events, as guided by the forecast data. The system initiates controlled outflows before the peak inflow period, demonstrating how inflow predictions support preemptive reservoir management. Such anticipatory actions help reduce unnecessary spillage and allow for more efficient water utilization, ultimately contributing to the optimization of energy production by minimizing lost generation opportunities.

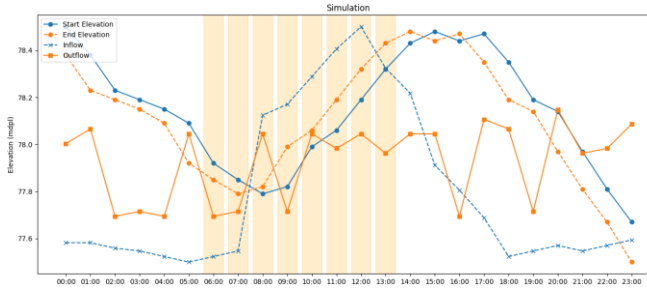


Fig. 4. Simulation result based on proposed unit operation scheme

Importantly, plant operators are no longer solely reactive in their role. They now actively leverage historical hydrological patterns, real-time telemetry, and inflow predictions to determine operational setpoints that maximize energy production while maintaining compliance with environmental and structural constraints. By utilizing forecast data, operators can pre-emptively schedule unit loading, coordinate gate operations, and even simulate different operational scenarios to assess their outcomes. This data-centric approach transforms reservoir management from a rule-based routine into a responsive and dynamic process.

Several studies have highlighted the critical role of accurate inflow forecasting in enhancing hydropower efficiency. Gragne et al. [1] demonstrated that improved real-time inflow forecasting leads to better operational decision-making and more efficient use of available water resources. Geheyen [11] further emphasized that robust flow prediction enables operators to avoid unnecessary spillage and improve turbine dispatch planning, particularly during periods of hydrological uncertainty. These findings underscore that reliable inflow prediction is not only a technical asset but a strategic requirement for modern hydropower plant operations.

D. Comparison With Previous Work

Previous studies have commonly employed various machine learning algorithms for inflow forecasting, predominantly using historical datasets. For instance, Wu et al. [7] applied deep learning models like RNN and LSTM, achieving promising accuracy in historical inflow prediction. Similarly, Salinas et al. [12] utilized ensemble learning techniques for flood forecasting, demonstrating the potential of ensemble approaches to enhance prediction accuracy. Additionally, Meema et al. [2] integrated ensemble precipitation forecasts for medium-range inflow predictions, indicating the operational advantages of incorporating weather forecasts. However, these studies typically lacked real-time weather forecast integration for short-term operational predictions. This research builds upon these prior works by explicitly incorporating hourly forecasted meteorological parameters, thereby improving the practicality and immediacy of operational decision-making in hydroelectric power plant management.

V. CONCLUSION

This study has successfully demonstrated the capability of a data-driven forecasting approach using the ExtraTrees Regressor algorithm for short-term reservoir inflow

prediction at hydroelectric power plants. Hourly forecasted meteorological parameters were utilized as input features, enabling the model to achieve a high predictive performance with a Root Mean Squared Error (RMSE) of 26.83 m³/s and a Coefficient of Determination (R^2) of 0.8243. The strong performance indicates that short-term inflow fluctuations influenced by weather dynamics were effectively captured. By addressing the limitations of conventional rule-based or intuition-driven management strategies, the proposed model is positioned to support improved responsiveness and minimize the risks associated with uncontrolled spillway releases [1].

In comparison with other ensemble and non-ensemble methods, the ExtraTrees Regressor was shown to outperform alternatives such as Random Forest, Gradient Boosting, and LightGBM, particularly in terms of error metrics and execution time, as presented in Table III. Its relatively low computational demand and resistance to overfitting make it suitable for real-time operational environments. The model's consistent tracking of both stable and peak inflow events confirms its robustness under diverse hydrological conditions, thereby validating its applicability in decision-support tools for turbine dispatch and flood risk mitigation [13].

This study acknowledges several limitations that may affect the generalizability of the results. The model was trained and tested using a dataset spanning four years, with 80% used for training and 20% reserved for testing. This data split was chosen to reduce the risk of overfitting while still providing sufficient historical variation for model learning. Moreover, the test data was selected from the rainy season, when inflow is highly sensitive to rapidly changing weather conditions. This choice was intentional to evaluate the model's robustness under high variability. However, inflow patterns during dry seasons are typically more stable and can be more accurately interpreted through water level (WL) station readings. As such, model performance under dry-season conditions was not explicitly evaluated, which may limit the conclusions regarding year-round applicability.

For future work, it is suggested that the predictive model be integrated into an optimization-based reservoir operation framework to support hydroelectric energy production planning. The model itself should also be further enhanced by expanding the training and testing datasets to include longer historical periods and multiple hydrological cycles across both wet and dry seasons. This would allow the model to generalize better across seasonal patterns and increase its robustness under diverse climatic scenarios. By linking inflow forecasts with turbine scheduling algorithms, optimal dispatch strategies could be generated dynamically to maximize energy output while satisfying reservoir constraints and operational priorities. This concept has been explored in prior studies, where forecast-driven optimization models were used to enhance hydropower efficiency and water use planning [19]. Further enhancements may be achieved by employing multi-objective optimization techniques, such as evolutionary algorithms or reinforcement learning, which can account for trade-offs among energy production, flood control, and water conservation goals. The development of such an integrated decision-support system would transform the forecasting model into a core component of predictive operational management in hydroelectric power systems.

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