Available online at www.HEFJournal.org

ISSN: 2785-2997

Journal of Human, Earth, and Future

Vol. 5, No. 4, December, 2024

Real Time Operation Simulation Model with Early Release Reservoir Storage

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Received 09 July 2024; Revised 12 November 2024; Accepted 17 November 2024; Published 01 December 2024

Abstract

This research intends to build an optimal curve model of reservoir water level fluctuation for real-time water supply operation and to build an information system of gate opening operation due to the real-time release of reservoir storage by considering water demand and flood capacity in the downstream. The proposed methodology combines the update of an optimized rule curve forecast based on 10-dayly inflows projected for the next three months and the optimization of early release volumes based on hourly reservoir routing inflows over the upcoming two days. The water balance simulation is conducted to optimize the irrigation water release-to-demand ratio (K Factor) by considering both deterministic and stochastic inflow scenarios. Real-time reservoir routing simulation is performed to optimize gate openings with the constraint of maintaining the end-of-period water level in line with the updated ten-daily rule curve forecast. This research is conducted in the Dodokan Watershed with the cascade reservoir of Batujai and Pengga. Simulations indicate that optimized gate openings—two gates at 0.4 m and two at 0.2 m for Batujai (with an inflow of 638.7 m³/s) and 0.3 m on Pengga's sixth gate (with an inflow of 616.3 m³/s)—effectively prevent downstream flooding, maintaining reservoir levels within safe limits under High Flood Water Levels (HFLW) and ensuring water supply continuity. With an average K factor effectiveness of 83% for stochastic inflow prediction and 79% for deterministic inflow prediction, the optimized model adjusts spillway operations in real time, ensuring enhanced flood control and operational safety by aligning with real-time rule curves.

Keywords: Flood; Simulation; Optimization; Real Time; Batujai; Pengga.

1. Introduction

Climate change has a significant impact on the water source in Indonesia due to the increasing frequency of floods and droughts. The similar thing happens in the region of Nusa Tenggara Barat Province, which is in the eastern part of Indonesia that has a dry climate. In the rainy season (January-February-March), it tends to get wet; however, in the dry season (June-July-August), it tends to get dry with increasing frequency [1]. Hydrologically, water availability is influenced by global and local climate conditions. This phenomenon of global climate is an interaction of very complex atmospheric circulation that gives an impact to climate change. Meanwhile, the local climate phenomenon like ENSO (El Niño and La Niña) will also influence the season length and water availability change [2]. Dam, as the multi-function infrastructure that functioned as a water supply for raw water, irrigation, and energy, is also hoped to be able to control the flood in the downstream [3].

The system management of multi-reservoirs is difficult because there are the problems of dimension, non-linearity, and conflict of different aims. The optimal operation of a multi-reservoir operation system generally involves the optimization and simulation model that can give the quantitative information for increasing water management operation [4-6].

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http://dx.doi.org/10. 28991/HEF-2024-05-04-03

In Indonesia, based on the decision of Kimpraswil Ministry No. 360/KPTS/M/2004, in operation, a dam is required to have the reservoir rule curve to maintain the continued volume of the reservoir at the end of the period. In general, dam operation staff in the Dam Management Unit (UPB) operate the dam release based on the reservoir water level elevation curve (MAW) or storage volume per period in the Annual Plan of Reservoir Operation (RTOW). RTOW is arranged every year based on the prediction of certain period inflow-demand-based (weekly/ten-daily/monthly). In the case of dam storage, it is dominantly utilized for irrigation, so the K-factor in irrigation that refers to the ratio between water supply and water demand is very important [7]. RTOW utilizes "rule curves" or fixed time-based constraints to establish the ideal water level, often neglecting current weather and hydrological conditions. This approach restricts flexibility and reduces the ability of reservoir operators to make real-time, data-driven decisions, which could result in a loss of reservoir benefits [8].

The main challenge in reservoir management for flood control is integrating river flow forecasts into optimization models. The obstacle in utilizing these forecasts is the lack of acceptance among practitioners, especially in real-time operations on multi-reservoir systems. The incompleteness of existing optimization models often causes this. [9]. Reservoirs, with their inherent storage capacity, play a critical role in water resource management, yet the advent of non-stationary runoff patterns has introduced uncertainties into their operations, especially in large reservoir systems. These changes bring challenges in ensuring safe operation and achieving design benefits under altered runoff conditions [10-12]. Addressing these impacts requires either enhancing hydrological forecasting technologies to reduce water inflow uncertainty or developing adaptive operational strategies to dynamically adjust management practices based on changing conditions [13].

Research has explored adaptive strategies at both macro and micro levels [14]. At the macro level, proposed frameworks for adaptive water management and decision support systems [15]. A stochastic simulation method was proposed at the micro level for risk analysis of flood control reservoir operation [7]. Specific examples include recommending "*Multi-objective Model Predictive Control for Real-Time Operation of a Multi-Reservoir System Implementation"* that integrates genetic algorithms and multi-criteria decision-making for optimized reservoir management [16]. However, this approach faces challenges in computational efficiency and relies heavily on deterministic inflow forecasts, which may limit its effectiveness in real-world applications. Another example study proposes an optimization model for managing flood risks via pre-storm releases, creating reservoir space in advance to reduce downstream flood damage. The model balances hydrological and engineering failure uncertainties in flood forecasting, though limitations remain in accurately predicting storm probabilities and handling trade-offs with water supply storage. Another paper recommends future research to enhance real-time multi-reservoir operation by incorporating stochastic optimization for inflow uncertainty and improving computational efficiency through advanced algorithms. Current weaknesses include high computational demands and reliance on subjective decision-making criteria, which can limit adaptability in fast-changing conditions [17, 18]. Specifically, to optimize the spillway run-off and K-factor (release/demand-supply) for irrigation in real time has not known the availability.

Rainfall forecasting plays a crucial role in water resource management, especially in the context of reservoir operations. In this case, the Annual Plan for Reservoir Operation (RTOW) is essential for regulating outflows in accordance with reservoir inflow conditions. It is recommended that, when creating the reservoir rule curve, the input should be based on updated rainfall predictions [19, 20]. Today, meteorology experts utilize several future weather prediction models for accurate rainfall estimation. The Weather Channel (TWC), part of The Weather Company, uses a comprehensive array of data sources and technologies to predict satellite rainfall data accurately. A recent study found that TWC was about 3.5 times more accurate than other providers between 2017 and 2021 (*https://forecastwatch.com/*). On the other hand, the Meteorology, Climatology, and Geophysics Agency (BMKG) routinely publishes a 3-day climate forecast as well as rainy season characteristics (SMH) for the next 3-month forecast. For operational needs in the field, it is recommended to refer to the new information published by BMKG annually, which updates previous predictions. The SMH analysis is based on observational data from BMKG stations, utilizing both rainfall stations and the Global Satellite Mapping of Precipitation (GSMaP). Based on the latest rainfall and climate forecast information from these data sources, ten-day period inflows and instantaneous inflows can be forecasted, accounting for stochastic variations due to extreme random rainfall conditions.

This research aims to develop an optimal reservoir water level fluctuation model and an information system for real-time gate operation, accounting for both irrigation water release-to-demand ratio (K Factor) and downstream flood capacity. By incorporating stochastic and deterministic inflow scenarios, the study introduces a novel approach for real-time water supply operations. Water balance simulations optimize the K Factor, and real-time reservoir routing simulations are conducted to manage gate openings, ensuring end-of-period water levels align with the updated ten-daily rule curve forecast.

2. Material and Methods

2.1. Research Location

This research is conducted in cascade dam reservoirs of Batujai and Pengga in the Dodokan watershed (567 km²), a river region of Lombok (National Strategy) that consists of 8 meeting points of rivers. The Batujai dam is in Praya city, which is the capital of the Lombok Tengah regency, which serves a 2,860 ha irrigation area and 130 l/s of raw water demand. However, the Pengga dam serves a 3,189 ha irrigation area in part of the Lombok Tengah regency and Lombok Barat, and 200 l/s of raw water. The Batujai dam gets the inflow from 37.15 km² of catchment area, and the Pengga reservoir gets the inflow from 176.37 km² of catchment area and contributions from the Batujai reservoir (Figure 1). River water discharge in the dam downstream is bigger than the available river flow capacity. This condition causes the Gerung district (capital of Lombok Barat regency) to be very vulnerable to the water inundation danger due to the river water overflow, moreover if the seawater level is high tide. Every year, almost 5% of river downstream area experiences flood inundation [20]. Flooding continues to occur despite two cascade dams, which are expected to reduce peak flows in line with the inflowing flood volume. No model has been developed to analyze reservoir releases while accounting for downstream river capacity and local rainfall in the downstream area.

The Batu Jai Dam, with an effective storage capacity of 22,987,050 m³, has a Low Water Level (LWL) elevation of approximately +87.00 meters above sea level (mdpl) and a High Flood Water Level (HFWL) elevation of approximately +97.50 mdpl. For flood control, the dam is equipped with four vertical roller gates of the vertical ogee type, each measuring 3.5 m in width (B) and 11.0 m in height (H). In contrast, the Pengga Dam, with an effective storage capacity of 16,070,000 m³, has an LWL elevation of approximately +44.35 mdpl and an HFWL elevation of approximately +57.50 mdpl. Its spillway is equipped with six radial ogee gates, each with dimensions of 8.5 m in width (B) and 8.7 m in height (H).

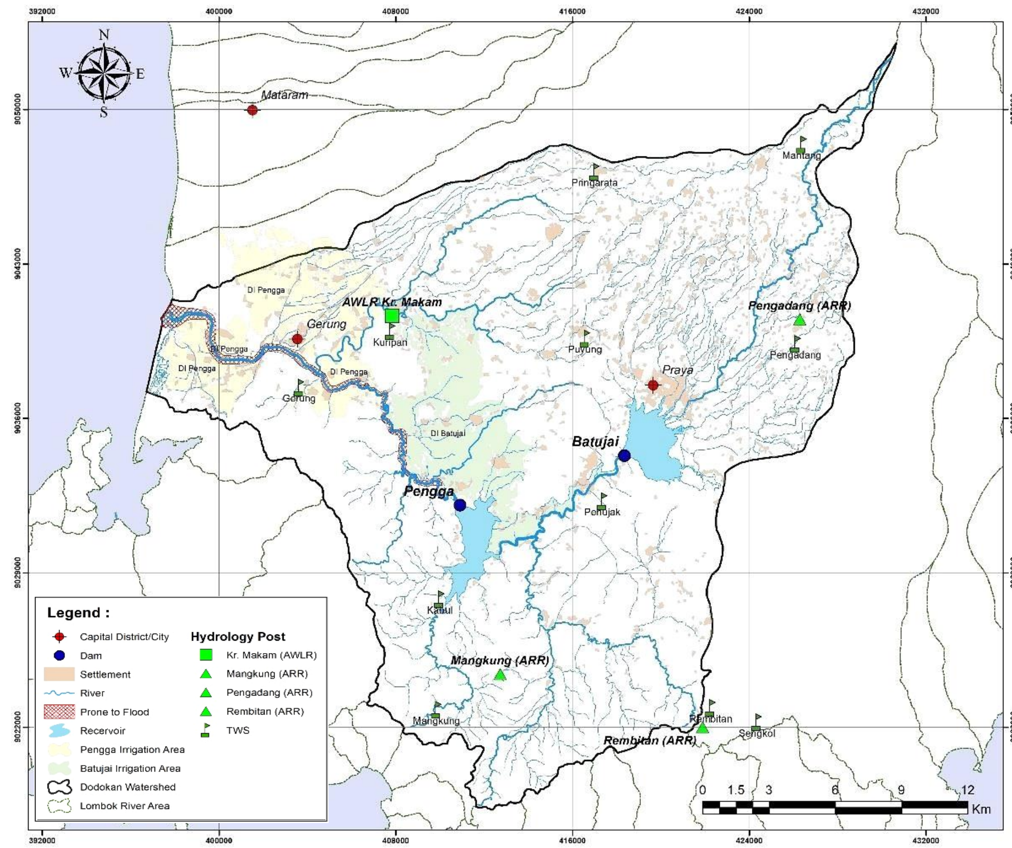


Figure 1. Location Map of Batujai-Pengga Reservoir in Dodokan Watershed

2.2. The Arrangement of Reservoir Operation Pattern

Based on the decision of Kimpraswil Ministry No 360/KPTS/M/2004, in operation is required to have a rule curve reservoir to maintain that the end volume is under the end volume threshold (V_{rule}). The reservoir operation pattern (POW) is the base scheme of reservoir operation, and the building and implementation refer to RTOW. It discusses the procedures of reservoir outflow in accordance with the conditions of volume and/or reservoir water elevation, water demand, and river capacity in the dam downstream. According to the decision, there are three methods for designing reservoir operation patterns: conventional, simulation, and optimization. In the simulation method, reservoir operation is modeled based on inflow data for wet, normal, and dry conditions to determine operational thresholds. These thresholds guide outflow management to prevent critical storage conditions and ensure adequate water levels at the end of the operational period.

The reservoir stores or releases water is based on the decision that is made by the system operator. Long-term operations require historical data series, while real-time operations rely on current inflow-demand data, initial volume, and end-of-period volume thresholds. Rule curves can be developed through non-linear optimization-simulation functions based on inflow, demand, and volume [21]. Real-time operations focus on optimizing the current reservoir system, with optimization techniques generally using forecast or interpolated data as input. Decision-making strategy is crucial and can be enhanced by combining real-time optimization into two model types: a long-term and a short-term daily model. The proposed methodology combines the update of an optimized rule curve forecast based on 10-day inflows projected for the next three months and the optimization of early release volumes based on hourly reservoir routing inflows over the upcoming two days. The method of mass balance can be applied in the analysis of surface flow, crop water requirement, operation of reservoirs and weirs, flood routing, and water balance in watersheds [22] and water allocation models [23]. The water balance simulation is conducted to optimize the irrigation water release-to-demand ratio (K Factor) by considering both deterministic and stochastic inflow scenarios. Real-time reservoir routing simulation is performed to optimize gate openings with the constraint of maintaining the end-of-period water level in line with the updated ten-daily rule curve forecast. Figure 2 presents the water balance sketch for the cascade reservoir. The basic equation of reservoir storage simulation analysis uses the mass balance [24] and generally can be written as follows:

$$I - O = \Delta V \quad (1)$$

where I = inflow/input, O = outflow/output, and ΔV = volume change during Δt period.

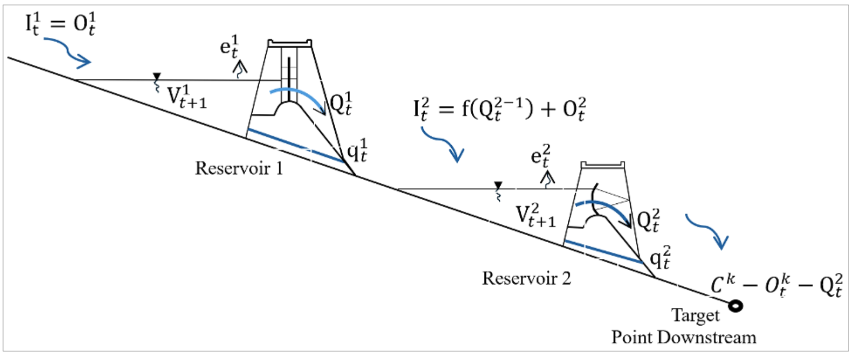


Figure 2. Water Balance Sketch in a Cascade Reservoir

The reservoir routing model is constructed based on the water balance equation [25-28] and can be written as follows:

$$V_{t+1}^k = V_t^k + (I_t^k - Q_t^k) \Delta t - e_t^k \quad (2)$$

$$I_t^k = f(Q_t^{k-1}) + O_t^k \quad (3)$$

Where:

Δt = time interval.

V_t^k= storage values at time t of the kth reservoir (k=1, 2).

k = number of reservoirs.

I_t^k = inflow of the kth reservoir during the time period Δt.

Q_t^k = release of the kth reservoir during time period Δt.

e_t^k = water volume losses (m^3) from the kth reservoir, such as evaporation and seepage during time period Δt.

F(-) = is the channel flood routing functional between the upstream and downstream reservoir

O_t^k = the interval inflow between the reservoir target point.

2.3. Methodology

The process begins with preparing the RTOW, which is simulated annually by the dam management unit (typically in September each year) to update the real-time operational rule curve. The RTOW is developed based on rainfall conditions forecasted by BMKG. Inflow is calculated based on dependable historical discharge (deterministic inflow) and rainfall transformation analysis predicted stochastically into streamflow using a calibrated HEC-HMS Hydrology Model (stochastic inflow). The RTOW simulation sets the target end volume to ensure readiness for the next operational period. This rule curve relies on the mass balance equation between inflow and reservoir release used to meet water demand, with the objectives to (i) maintain an end volume close to the start of the year and (ii) prevent significant declines in the K-factor curve (release-to-demand ratio) across periods. The reservoir rule curve is determined through non-linear optimization simulation [9]. The entire simulation process uses Microsoft Excel and VBA scripting for iterative calculations. The simulation-optimization boundaries for determining the RTOW are as follows:

1. The time interval (Δt) follows a ten-day irrigation approach: ten-daily-I spans days 1-10, ten-daily-II covers days 11-20, and ten-daily-III runs from day 21 to the end of the month. This results in 36 ten-day periods per year, allowing the impact of discharge changes due to channel flood routing between reservoirs to be disregarded.
2. The prediction of operation initial volume (V_0^k) is based on the end volume of the previous hydrological year (September) and considers volume allocation for irrigation after meeting allocations for household water supply, urban/village needs, and river/ecosystem maintenance.
3. Stochastic inflow (I_t^k) is generated by transforming a calibrated HEC-HMS model using ten-day predicted rainfall inputs analyzed with the Thomas-Fiering model. This analysis is based on statistical parameters from historical rainfall data across ARR locations (Batujai, Pengga, Pengadang, Rembitan, Mangkung, Kabul, Kuripan, Jurang Sate, Lingkok Lime), with a three-month rainfall prediction boundary for district areas corresponding to ARR locations, as per SMH guidelines. The inflow prediction for the subsequent nine months is based on BMKG's annual SMH forecast.
4. Deterministic inflow (I_t^k) is based on the probability of monthly dependable discharge, determined by ranking ten-day gauged inflow data for each period at Batujai and Pengga dams from October 2013 to September 2022. Ten-day predicted inflow is matched as follows: a normal year corresponds to the 50% dependable discharge, an above-normal SMH (AN) is matched with a wet year (20% dependable discharge), and a below-normal SMH corresponds to a dry year (80% dependable discharge).
5. The irrigation water requirements for paddy, corn, and soybean are calculated using the KP-1 method and supporting KP guidelines (2013 revised edition), following crop intensity and planting patterns agreed upon by water users as outlined in the Planting Arrangement Plan Document (RTT).
6. Optimization of water using with the indicator of K-factor (FK) that is uneven proportional between periods [16] and minimal of 30%, and the fluctuation of K-factor between reservoirs in the same period $[FK_t^k - FK_{t-1}^k] \leq 30\ \%$
7. Reservoir operation attends as follows: i) minimum of operation level elevation (LWL), ii) effective storage, and iii) RRV (Reliability, Resiliency, and Vulnerability) must be 1-1-0 [7].
8. Water losses (e_t^k) calculates the possibility of evaporation is 0.1% of the available volume.

The constraints for simulation optimization in determining the Real-Time (RT) Rule Curve (RC) are aligned with the RTOW, with the following condition adjustments:

- Real-time updates to reservoir water level (MAW).
- Ten-day updates for stochastic and deterministic inflow data based on changes in SMH constraints for the 3-month forecast, with the remaining period assumed constant according to the RTOW.

By modifying Equations 2 and 3, where the reservoir spillway outflow [29] is determined by gate opening, the water balance equation is obtained as follows:

$$V_{t+1}^k = V_t^k + (I_t^k - (co^k W^k T^k \sqrt{2g.f(B_t^k.H_t^k)})) \triangle t \tag{4}$$

and Equation 3.

The information system for gate opening, based on real-time reservoir storage releases, considers downstream water demand and flood capacity, with a user-friendly interface implemented in Microsoft Excel. Reservoir routing simulations are conducted using the HEC-HMS model, which can be automated through a combination of VBA in Excel and programming languages such as Python and Jython. Data import and export in CSV format to the HEC-DSS HMS file dataset [18] are managed using Jython scripts through a batch file that communicates with the Jython programming language. The constraints for optimizing spillway gate opening are as follows:

1. Reservoir storage limits:

$$V_{min}^k < V_{t+1}^k \leq V_{max}^k$$

With V_{min}^k *and* V_{max}^k these represent the minimum and maximum allowable storage levels for the Kth reservoir at time t+1, corresponding to the ten-day real-time rule curve basis.

2. Release capacity limits:

$$Q_t^k \leq Q_{max}^k (C^k - O_t^k) \text{ With k = 2 (Pengga dam)}$$

where; Q_t^k = The maximum discharge of the Pengga Dam occurs when the river downstream reaches its bank-full capacity at time t, C = Bank Full River Capacity, and O_t^k = interflow between the Reservoir and the target point of river downstream.

Flow chart study is presented in Figure 3.

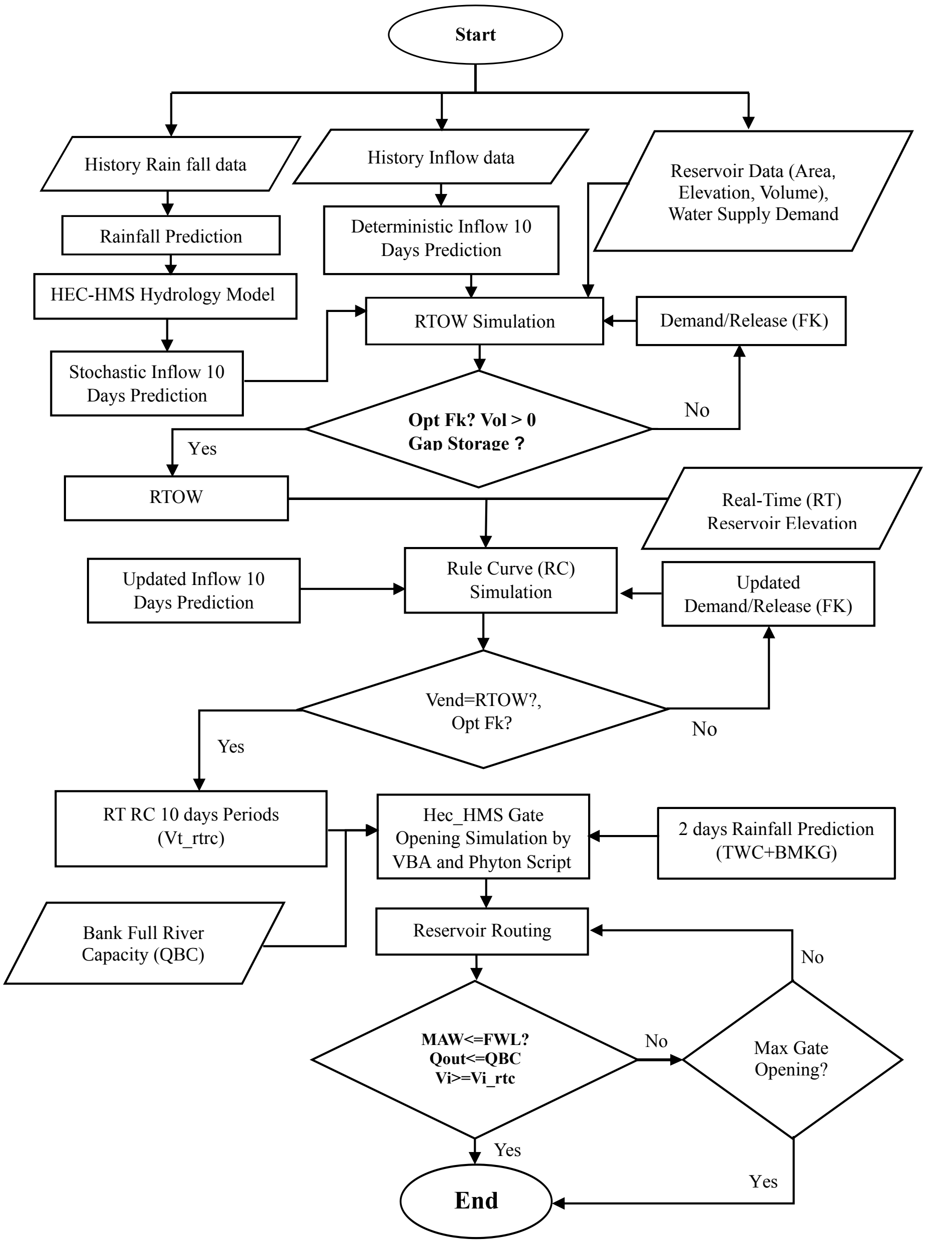


Figure 3. Flow Chart of the Simulation-Optimization Model for Rule Curve Updates and Reservoir Routing

3. Results and Discussion

3.1. Inflow Reservoir

Inflow forecasting for reservoirs is a key component for reservoir operation, water resources management, and inter-regional water transfer [30]. In this paper, forecasting ten-daily stochastic flow for water availability analysis using the continuous hydrology model by HEC-HMS, with the model input being a 3-month rainfall prediction. Continuous hydrologic modeling synthesizes hydrologic processes and phenomena (i.e., synthetic responses of the basin to several rain events and their cumulative effects) over a longer time that includes both wet and dry conditions [11, 31]. To improve the accuracy of rainfall prediction, a modified Thomas-Fiering model can be applied by adding relevant exogenous variables to the 16th rainfall data at 8 rainfall stations in the Dodokan watershed. This modification allows the model to consider external factors that affect rain patterns, making the prediction results more representative. With this approach, the model can accommodate complex climatic variations in a baseline time frame, often influenced by changes in the external environment and weather factors [30]. The prediction of 10-day rain is forecasted by the robust stochastic forecasting of the Thomas Fiering method on time series data in 8 rain posts. This method is applied along with exogenous variables in the form of rainy season properties (SMH) from BMKG predictions. The results of the prediction model produced an average value of RMSE (27.683), a correlation coefficient (0.586) in the calibration process (80% data), and an RMSE value (30.241) and a correlation coefficient (0.838) in the validation process (20% data), which indicates that the model accurately represents a 3-month precipitation prediction [32].

Stochastic inflow was analyzed using the HEC-HMS software. The calibration of the model parameters was conducted by assessing the degree of similarity between the model output and the observational data collected from the AWLR Karang Makam. The calibration result of HEC-HMS modelling shows that the NSE value is 0.42 due to a percent bias of 9.52%; the RMSE is 0.8, which indicates that the model accurately represents the transformation of rainfall into streamflow [32]. Based on the predicted inflow for the hydrological year period (2020 to 2023) calculated every October of the previous year, the inflow of Batujai and Pengga reservoirs was obtained as presented in Table 1. Based on Table 1, it is known that the stochastic inflow data (the average is 1,661 m^3/s) has more variation of fluctuation than the deterministic inflow (the average is 1,371 m^3/s), and each standard deviation is 1,367 m^3/s and 1,143 m^3/s.

Table 1. Recapitulation of Statistical Data for Reservoir Inflow Prediction

No.	Reservoir	Period	Deterministic Inflow (m^3/s)				Stochastic Inflow (m^3/s)			
			Min	Average	Max	St Dev	Min	Average	Max	St Dev
1	Batujai	2020/2021	0	1,408	3,619	1,189	511	1,500	5,600	1,280
		2021/2022	0	1,263	3,583	1,073	452	1,778	7,800	1,732
		2022/2023	0	1,568	3,837	1,161	487	1,422	7,500	1,221
2	Pengga	2020/2021	0	1,307	3,689	1,135	221	1,745	4,600	1,408
		2021/2022	0	1,224	3,689	1,117	287	1,991	4,140	1,325
		2022/2023	0	1,453	3,729	1,183	236	1,532	4,870	1,233
		Avg.	**0**	**1,371**	**3,691**	**1,143**	**366**	**1,661**	**5,752**	**1,367**

The rainfall prediction for the next 48 hours provided by the weather forecaster provider TWC is used as an input to the single event base model by HECHMS. The existing rainfall data from April 13, 2023, to April 30, 2024, consists of 9202 hours in 11 sub-districts within the Dodokan watershed and has a low correlation with correlation values (R = 0.34 to 0.38). Previous studies have shown that the SARIMAX model can analyze the direct relationship between rainfall and climate indices, considering lagged effects, which can improve prediction accuracy [22]. This research corrects the existing TWC data using the stochastic SARIMAX regression prediction model, with 80% of the data used for calibration and 20% for validation. The upper and lower bounds of weather forecasts from BMKG at corresponding times are used as exogenous variables. The SARIMAX model performs significantly better than the existing TWC data, with correlations increasing to an average of 0.56 during calibration and 0.53 during validation; the average RMSE values for calibration and validation are 1.131 and 1.875, respectively. There is instilling confidence in the improved prediction accuracy. The Stochastic 2-day inflow prediction was analyzed using the event-based hydrology model by HEC-HMS. The calibration of the model parameters was conducted by assessing the degree of similarity between the model output and the observational data collected from the AWLR Karang Makam. The calibration result of HEC-HMS modelling shows that the NSE value is 0.721 due to a percent bias of 9.30%. The RMSE is 0.50, which indicates that the model accurately represents the transformation of rainfall into streamflow.

3.2. Water Demand

The service of dam water demand is irrigation and raw water. The irrigation of water requirements in the Batujai and Pengga irrigation areas is based on the cropping pattern in the document of RAAT-WS Lombok, with the cropping pattern being paddy-paddy/second crop-second crop (300%). The equation that is used to analyze maximum irrigation water requirement ($Q\ D_{max}$) and crop water requirement (NFR) is in accordance with KP-02 (2013). The irrigation water requirement is analyzed based on the rainfall, evapotranspiration, irrigation area, type of crop, group, and efficiency of irrigation, based on the cropping pattern (RTT) in the document of the Annual Water Allocation Plan (RAAT) in BWS Nusa Tenggara I. The efficiency of irrigation is assumed based on the qualitative report by Water Resources Observer that is new/post-rehab (65%), good (55%-65%), moderate (45%-55%), and bad (35%-45%) [16]. The efficiency of irrigation water use is low, which is about 50% compared to 80% in developed countries [33]. Table 2 presents irrigation water requirements that are supplied by both dams.

Table 2. Irrigation Water Requirement

No.	Reservoir	Water Requirement			
		NFR Max (l/s/ha)	Max (l/s)	Min (l/s)	Mean (l/s)
1	Batujai	1.23	4,469	0	2,081
2	Pengga	1.21	1,852	0	1,010

In addition to irrigation, water demand includes raw water supply, hydroelectric power generation (PLTMH), and river maintenance flow. Raw water supply is provided at a constant rate, and PLTMH operations follow the local irrigation pattern. For the Batujai Dam, raw water demand is 130 l/s, while for the Pengga Dam, raw water operations are planned to start in 2024, with a target of 150 l/s for the Mandalika Main Economic Region. River maintenance flow, intended to sustain the river ecosystem, is calculated as 5% [7] of the available inflow.

3.3. Simulation of Annual Plan of Reservoir Operations (RTOW)

The simulation of the plan in the scheme of RTOW arrangement in the conditions of deterministic inflow (statis) and stochastic inflow (dynamic) produces the results as presented in Table 3 and Figures 4 and 5.

Table 3. Recapitulation of Simulation Results for the Annual Plan Reservoir Operations (RTOW)

No.	Reservoir	Period	Inflow Deterministic			Inflow Stochastic		
			K Factor	% of Reservoir Volume	Gap* (m)	K Factor	% of Reservoir Volume	Gap* (m)
1	Batujai	2020 Oct I – 2020 Dec III	20-25%	6-47%	0.06-3,98 (Avg 1.88)	30-50%	16-42%	0.14-1.36 (Avg 0.93)
		2021 Oct I – 2021 Dec III	25-30%	8-34%	0.13-2.62 (Avg 1.30)	52-100%	10-33%	0.06-2.19 (Avg 1.48)
		2022 Oct I – 2023 Dec III	30-45%	8-51%	0.06-2.00 (Avg 1.16)	30-45%	30-45%	0.04-1.18 (Avg 0.68)
		2020 Oct I - 2021 Sept III	25-100%	20-100%	0.00-0.51 (Avg: 0.21)	60-100%	40-100%	0.00-0.72 (Avg: 0.032)
		2021 Oct I - 2022 Sept III	45-100%	29-100%	0.02-0.53 (Avg: 0.22)	50-100%	50-100%	0.02-1.06 (Avg: 0.35)
		2022 Oct I - 2023 Sept III	30-100%	31-100%	0.02-0.50 (Avg: 0.20)	35-100%	30-100%	0.00-1.26 (Avg: 0.27)
2	Pengga	2020 Oct I – 2020 Dec III	32-70%	13-42%	0.06-3.98 (Avg 1.88)	32-70%	34-100%	0.00-2.49 (Avg: 0.60)
		2021 Oct I – 2021 Dec III	100%	27-55%	0.13-2.62 (Avg.1.30)	100%	54-100%	0.02-0.98 (Avg 0.49)
		2022 Oct I – 2023 Dec III	35-100%	41-80%	0.25-1.85 (Avg 1.27)	35-100%	46-100%	0.00-1.33 (Avg 0.42)
		2020 Oct I - 2021 Sept III	25-100%	20-100%	0.01-2.15 (Avg: 0.52)	60-100%	40-100%	0.02-2.40 (Avg: 0.45)
		2021 Oct I - 2022 Sept III	45-100%	55-100%	0.01-0.80 (Avg: 0.21)	50-100%	50-100%	0.02-1.90 (Avg: 0.35)
		2022 Oct I - 2023 Sept III	50-100%	42-100%	0.01-1.31 (Avg: 0.21)	30-100%	60-100%	0.03-0.70 (Avg: 0.25)

Based on Figures 4 and 5, which show the trend of reservoir water levels from the RTOW simulation analysis, it is observed that, in the ten-day period of October 1, 2020, the initial reservoir water levels are 90.09 mdpl and 54.45 mdpl for the Batujai and Pengga dams, respectively. At the end of the hydrological year simulation in September III 2021, the RTOW simulation with stochastic inflow results in final reservoir levels of 90.14 mdpl for Batujai and 53.80 mdpl for Pengga, while deterministic inflow results in 90.07 mdpl and 52.51 mdpl, respectively. These end values ensure storage availability for the next hydrological year, achieving 100% reliability, 100% resiliency, and 0% vulnerability while optimizing water supply in each period. However, the range of K-factor per period is 25% < FK < 100% for deterministic inflow and 60% < FK < 100% for stochastic inflow, as shown in Table 3. A similar pattern is observed in the subsequent hydrological year, as presented in Table 3. Reviewing the entire hydrological year, a significant gap persists between the actual reservoir water level and the optimal water level from the RTOW, based on both stochastic and deterministic inflows. Given that both inflow scenarios rely on SMH predictions for the next 3 months, Table 3 compares the K-factor, reservoir fill percentage, and the deviation from actual water levels for the period from October I to December III (9 periods) each year. During this period, stochastic inflow better reflects fluctuations in reservoir water levels, as shown by higher K-factor values, a greater reservoir fill percentage, and a smaller gap between RTOW MAW and actual MAW in each period. After the initial three-month period (post-December III), larger deviations are mainly due to underestimated rainfall predictions, resulting from the unpredictability of global climate phenomena, such as La Niña, and local climate effects that are challenging to forecast as early as September, when RTOW planning is conducted.

Based on the maximum, minimum, and average data from the RTOW simulation results for annual operations, the following are observed: (i) the K-factor ranges from 20-100% for both deterministic and stochastic inflows, (ii) the reservoir fill percentage ranges from 20-100% with deterministic inflow and 40-100% with stochastic inflow, and (iii) the average gap to actual conditions is between 0.20-0.52 m with deterministic inflow and 0.27-0.45 m with stochastic inflow. This indicates that the simulation using stochastic inflow achieves a higher level of accuracy than with dependable (deterministic) inflow, which tends to remain constant.

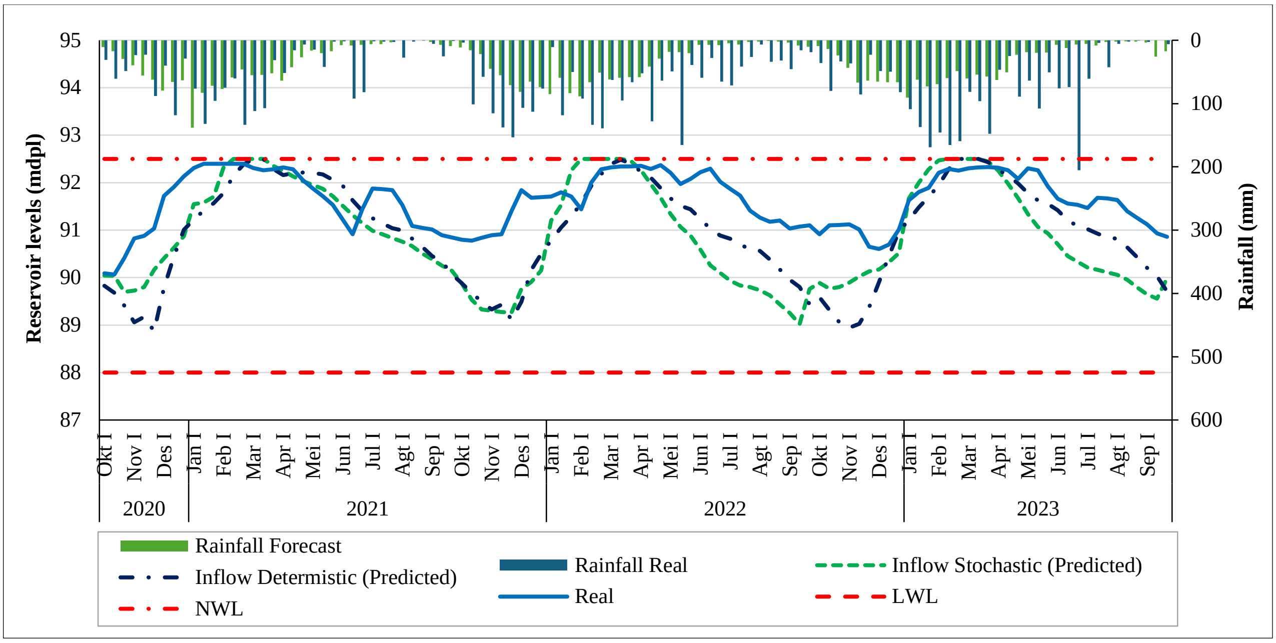


Figure 4 Comparison of Deterministic, Stochastic, and Real RTOW Batujai reservoir

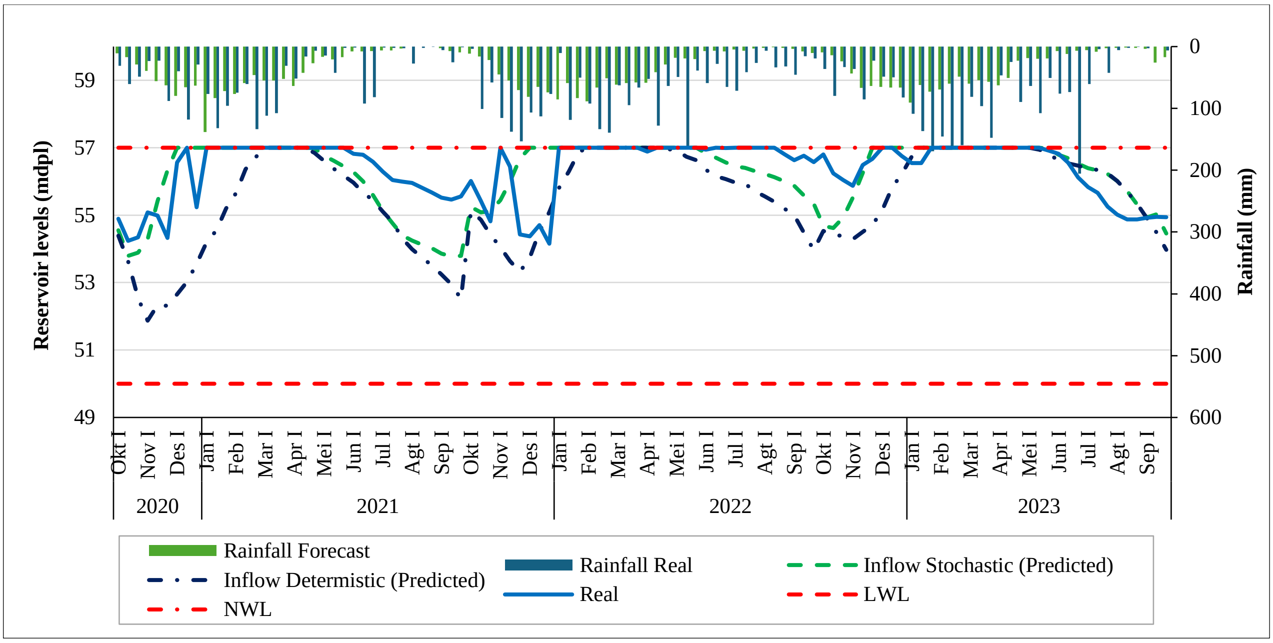


Figure 5. Comparison of Deterministic, Stochastic, and Real RTOW Pengga Reservoir

3.4. Rule Curve Simulation with Real Time Implementation

The rule of simulation-optimization in determining Real-Time (RT) Rule-Curve (RC) follows the RTOW with the condition adjustment as follows: a) to be carried out, the input updating of reservoir real water level (MAW) that happens every period; b) updating the stochastic and deterministic inflow every period/month in accordance with the constraint chain of SMH-BMKG; c) the requirement of fluctuation constraint or difference of K-factor between reservoirs is not calculated. Figures 6 and 7 present the Rule Curve of Real-Time Implementation in the Batujai and Pengga reservoirs, the implementation of simulation in 2020/2021, 2021/2022, and 2022/2023, and Table 4 presents the recapitulation of simulation results.

Table 4. Recapitulation of Simulation Result Comparison in the Implementation of Real Time Rule Curve (RC)

Scenario Inflow Prediction	Year of 2020/2021				Year of 2021/2022				Year of 2022/2023			
	Correlation		RMSE		Correlation		RMSE		Correlation		RMSE	
	Batujai	Pengga	Batujai	Pengga	Batujai	Pengga	Batujai	Pengga	Batujai	Pengga	Batujai	Pengga
Deterministic	98.9%	94.6%	0.33	0.47	94.0%	71.4%	0.33	0.73	93.2%	97.3%	0.43	0.36
Stochastic	99.3%	98.6%	0.25	0.17	94.8%	99.3%	0.44	0.29	94.6%	98.7%	0.31	0.26

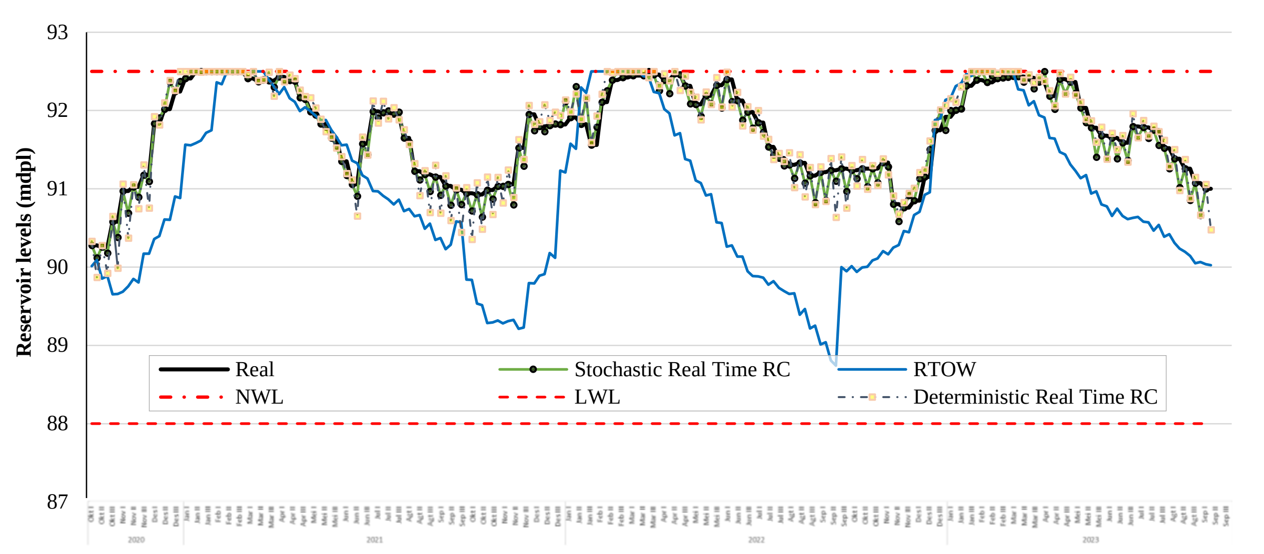


Figure 6. Rule Curve of Real Time Implementation in Batujai Reservoir

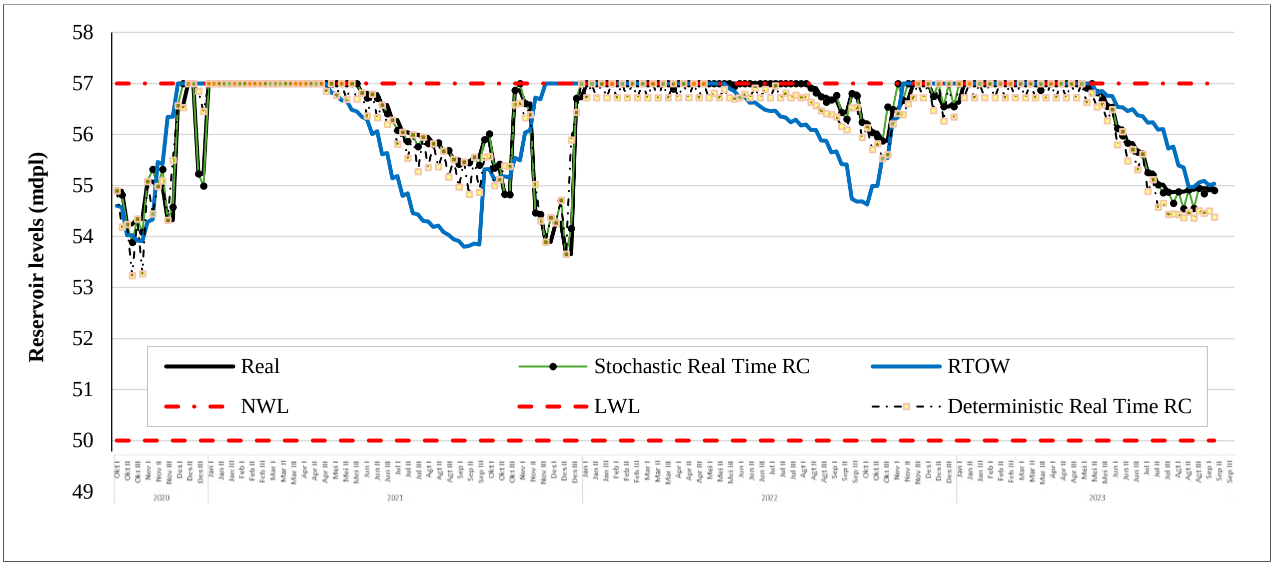


Figure 7. Rule Curve of Real Time Implementation in Pengga Reservoir

Table 4 compares the implementation results of the real-time rule curve. The correlation values and RMSE for reservoir water level observations (simulation vs. actual MAW) show that simulations based on stochastic inflow provide higher correlation and better RMSE than deterministic inflow over the entire period for both the Batujai and Pengga dams.

Referring to the simulation results in Figure 6, the Batujai reservoir simulation with stochastic inflow achieves an optimal FK value of 100% in each period of 2021/2022 and 2022/2023. However, with deterministic inflow, the FK still requires adjustments of 50% and 45% for one period each, specifically in the ten-day periods of October II and November III. Overall, the average optimization result for the K factor simulation across all periods with stochastic inflow predictions is 66%, while with deterministic inflow predictions it is 50%. In the K factor optimization simulation using actual inflow data, the result is 78%. This indicates that real inflow data provides the highest optimization level for the irrigation water release-to-demand ratio, serving as a benchmark at 100% effectiveness. Relative to this, the stochastic forecast achieves approximately 84.62% effectiveness, and the deterministic forecast reaches about 64.10% effectiveness. This suggests that while actual inflow data is ideal, stochastic inflow predictions are preferable over deterministic ones for more effective reservoir management, as they more closely align with real inflow conditions.

According to the results in Figure 7, the Pengga reservoir simulation shows a significant drop in water level from +56.44 mdpl in November II to +54.46 mdpl in November III for the 2021/2022 hydrological year. This is due to the peak irrigation demand during this period (1,851.83 l/s) and outflow through the spillway gate, recorded on November 12, 13, 14, 16, 17, 22, 23, 24, and 25, with each release measuring 46.0 m³/s. Based on real-time simulations with both stochastic and deterministic inflow inputs, FK remains at 100%, indicating that the water level decrease remains safe for meeting irrigation needs. The average optimization result for the K factor simulation across all periods in Pengga Reservoir with stochastic inflow predictions is 83%, while with deterministic inflow predictions it is 79%. In the K factor optimization simulation using actual inflow data, the result is 87%, which serves as a benchmark at 100% effectiveness for the irrigation water release-to-demand ratio. Relative to this, the stochastic forecast achieves approximately 95.4% effectiveness, and the deterministic forecast reaches about 90.8% effectiveness. This indicates that while actual inflow data yields the highest optimization level, stochastic inflow predictions are preferable over deterministic ones for effective reservoir management, as they more closely align with real inflow conditions

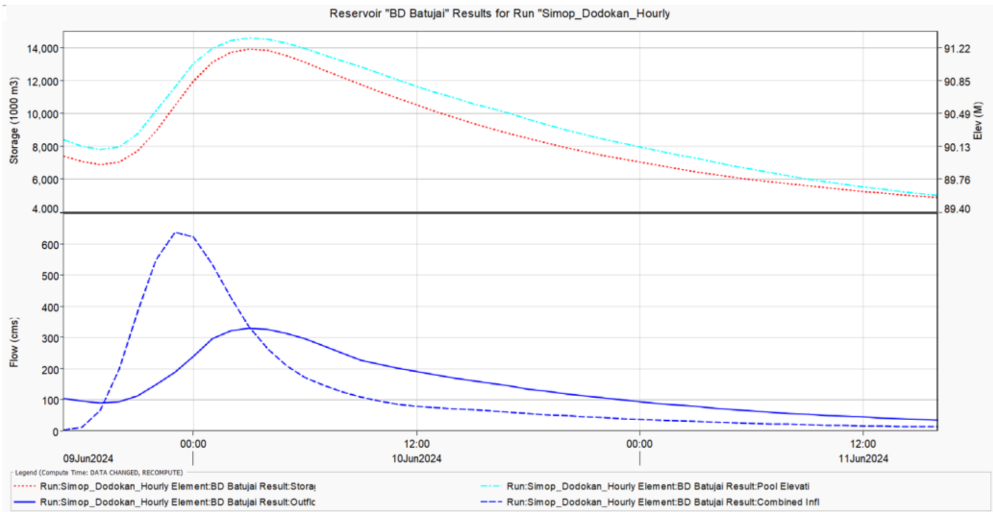
3.5. Result Analysis of Model

3.5.1. Optimization Condition of Gate Opening for Controlling Flood in Downstream

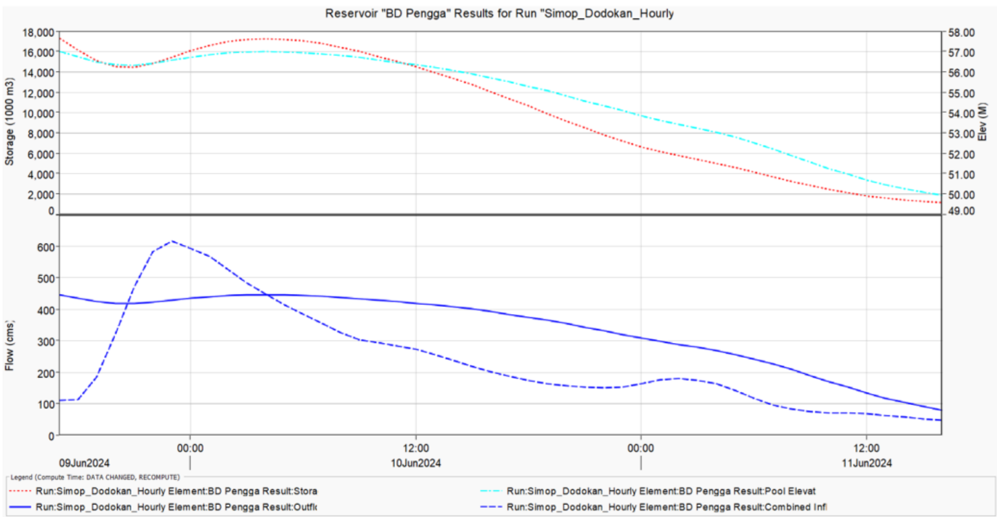
According to daily records from the Batujai and Pengga stations, significant rainfall events included 114 mm on November 25, 2017, in the Batujai Catchment Area, and 139 mm on March 26, 2017, in the Pengga Catchment Area. However, rainfall in the downstream catchment areas was uneven, with a maximum of 36.55 mm recorded in the same month at the Kuripan station. Assuming rainfall occurs alongside the initial MAW levels, averaging +90.2 m for Batujai and +57.0 m for Pengga reservoirs in November, and based on staff reports, during peak rainfall, the spillway gates were once fully opened to heights of 2.0 m at Batujai Dam and 1.0 m at Pengga Dam. Using this information, a simulation was conducted to evaluate the model's effectiveness in optimizing gate openings for both spillways.

Condition Before Optimization

Based on rainfall data converted into hourly inflow, the Batujai Reservoir recorded an inflow of 638.7 m³/s. With gate openings, an outflow of 330.5 m³/s was achieved, resulting in a maximum water elevation of +91.3 m, which remains safely below the maximum Full Water Level (FWL). In contrast, the Pengga Dam registered an inflow of 616.3 m³/s with a water elevation of +57.0 m. A gate opening of 0.5 m produced an outflow of 446.8 m³/s from the Pengga Dam. Figure 8 shows the hydrographs for Batujai and Pengga reservoirs and the location of the downstream flood review point.



(a)



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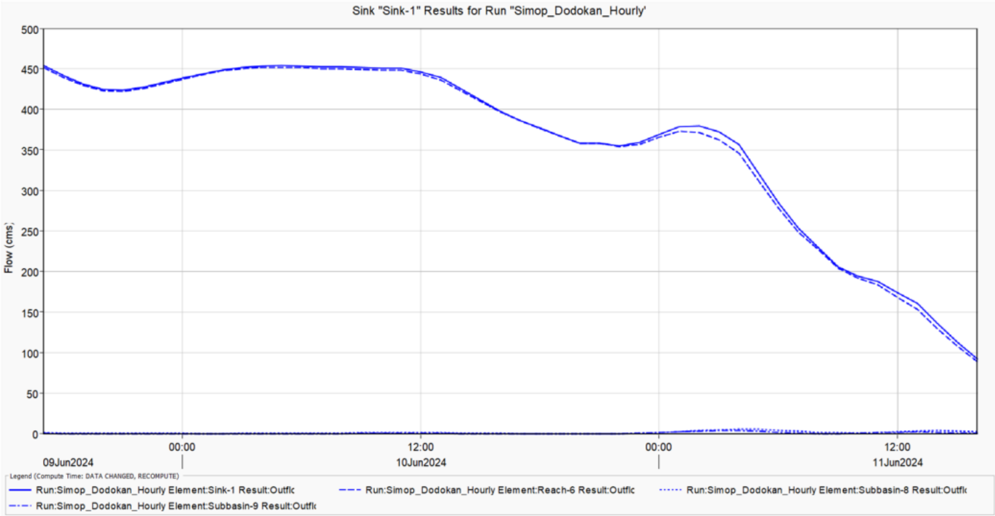


(c)

Figure 8. Discharge Hydrograph Due to the Gate Opening: a) Batujai; b) Pengga; c) Downstream

Based on Figure 8, the reservoir volume is rapidly reduced by 100 m³/s, and the reservoir water level decreases by 10 cm within the first three hours with a 1-meter opening of the fourth spillway gate. This water release causes an immediate reduction in storage at the downstream Pengga Dam, where the spillway gate is opened to an average height of 0.5 m, resulting in an initial outflow of 446.8 m³/s in the first hour (Figure 8(b)). The outflow then fluctuates, decreasing and later rising again at the twelfth hour to align with the inflow recession of the hydrograph. According to the inflow data in Figure 8(c), the river discharge hydrograph reaches 454.5 m³/s at the review point in Gerung district. Since the river's capacity in this area is 350 m³/s, flooding occurs. The hydrograph also shows a reduction in flood discharge downstream as it follows the Pengga Dam's outflow pattern, but at the 34th hour, the river flood hydrograph increases again due to additional inflow from tributaries downstream of the Pengga Dam. Table 5 presents the estimated outflow based on gate opening measurements.

Table 5. Outflow Based on the Estimation of Gate Opening

No.	Reservoir	Initial Elevation (m)	RTOW (m)	Before Optimized			
				Gate Open	End Rsv Elev (m)	Outflow (m^3/s)	Downstream (m^3/s)
1	Batujai	90.20	89.5	4x2 m	91.3	330.5	-
2	Pengga	57.00	53.9	6x0.5 m	57	446.8	454.5

Condition After Optimization

Due to the constraint of the annual plan water level of reservoir operation (RTOW) and rule curve of real time as presented in Figure 9 in Batujai and Pengga reservoir, the model of automatic gate opening carried out the simulation-optimization with MAW constraint that is as the interpolation result of real time rule curve due to the period that is accordance with ten-daily period when the model is run. However, the value of optimal real time rule curve currently is in the elevation of +92.1 m for Batujai reservoir and +57.0 m for Pengga reservoir, however the value of RTOW in this period is each of 55.4 m (Figure 9). The model will optimize the gate opening to produce outflow with the constraint of maximal storage elevation for dam safety that is in HFLW (High Flood Water Level): in elevation of +97.5 m in Batujai dam and +57.5 m for Pengga reservoir and produces water level in reservoir is minimal that is similar with optimal elevation based on the simulation of real time rule curve. Another constraint requires that the reservoir water level at the end of the period must meet or exceed the RTOW level, and that discharge from the Pengga Dam downstream remains within safe, non-flooding limits. Based on these constraints, the model optimizes gate openings to achieve effective regulation and maintain optimal reservoir water levels in the inundation area, forecasting conditions for the next two day.

Based on the simulation and optimization of gate openings using a VBA Script algorithm to automate the HEC-HMS program, an iterative gate opening adjustment of 0.1 m identified the most effective opening level that meets all constraints without causing downstream flooding, as shown in Table 6.

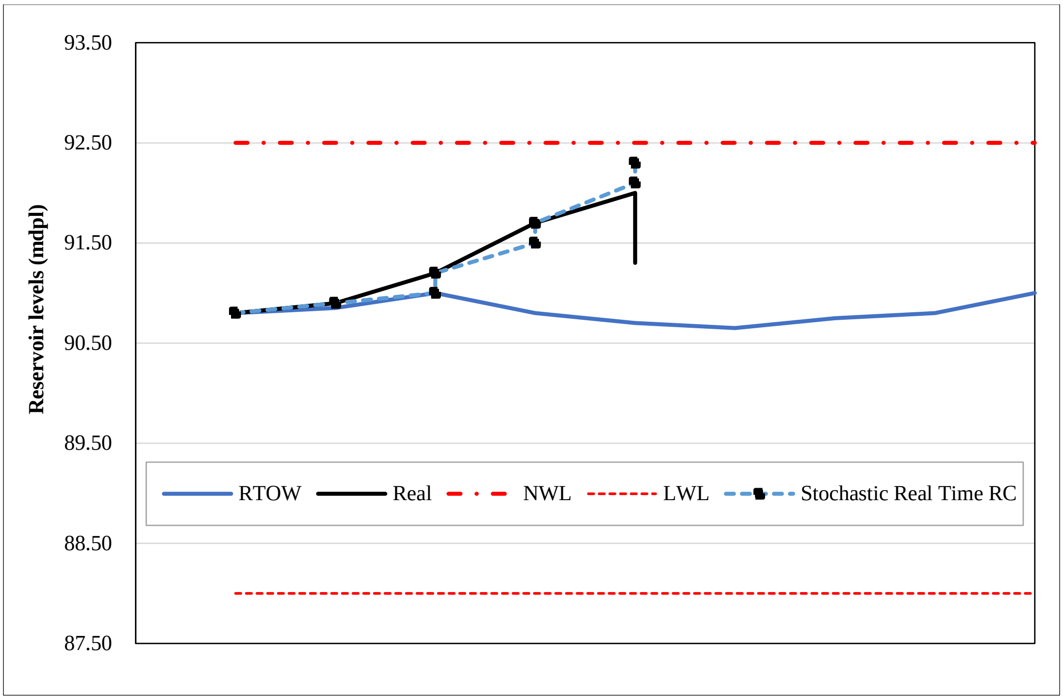


Figure 9. Real Time Rule Curve of Batujai

Table 6. Outflow and Optimal Gate Opening

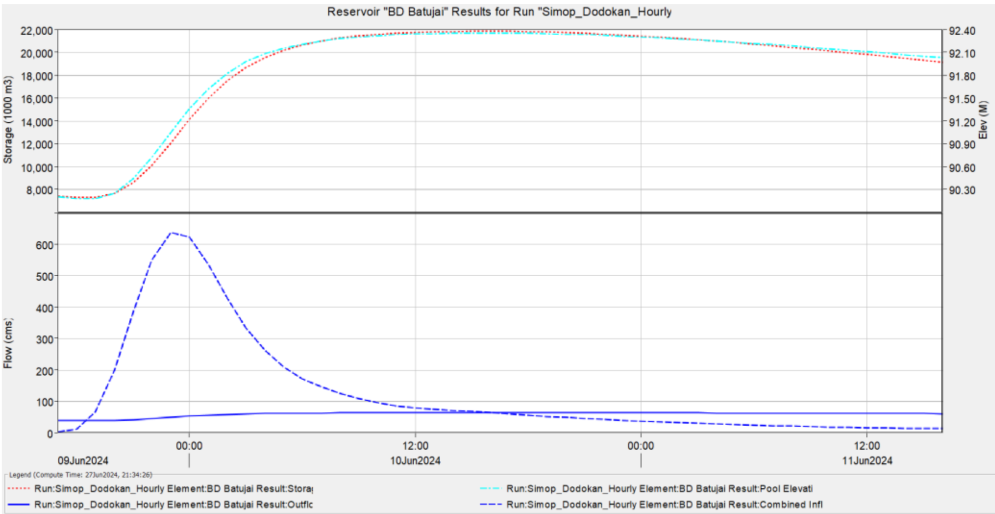
No.	Reservoir	Initial Elevation (m)	RTOW (m)	After Optimization				
				Gate Open	Real Time RC (m)	End Rsv. Elev (m)	Outflow (m^3/dt)	Downstream (m^3/dt)
1	Batujai	90.20	89.5	2×0.4 m, 2×0.2 m	92.1	92.3	64.2	-
2	Pengga	57.01	53.9	6×0.3 m	57	57	312.5	320.1

Table 6 shows that varying the gate openings—specifically, setting two gates to 0.4 m and two gates to 0.2 m at the Batujai Dam, along with a 0.3 m opening on the sixth gate at the Pengga Dam—can effectively prevent downstream flooding. Additionally, the reservoir water level is maintained at 92.3 m, safely below the High Flood Water Level (FWL) of 97.5 m, and above the recommended rule curve and RTOW levels, ensuring continuity in the water supply. Figure 10 shows the discharge hydrograph following the optimized gate openings.

Based on a comprehensive review of dam spillway discharge at Batujai Dam, both with historical rainfall data (January 18, 2021, and February 27, 2021) and TWC's two-day rainfall forecast (March 25 and March 27, 2023), it is evident that actual discharges consistently exceeded the optimized recommendations. Key observations include:

- On January 18, 2021, Batujai's actual outflow reached 32.64 m³/s, significantly higher than the optimized 5.75 m³/s, resulting in an end elevation lower than expected.
- On February 27, 2021, the actual outflow was 64.56 m³/s, compared to the optimized 28.9 m³/s, leading to a lower-than-target end elevation.
- On March 25, 2023, Batujai's actual discharge was 10.79 m³/s, more than double the optimized 5.78 m³/s, causing the end elevation to remain at the initial 92.40 m instead of reaching the optimized 92.85 m.
- On March 27, 2023, the actual outflow spiked to 86.36 m³/s, far exceeding the optimized 5.598 m³/s, which resulted in an end elevation of 92.34 m, lower than the target of 92.66 m.

These findings highlight a trend of over-operation of the spillway gates, suggesting that actual discharges were consistently higher than necessary across multiple scenarios. To improve reservoir management and maintain target water levels, adjustments to gate operations are recommended to better align with optimized discharge levels, thereby avoiding unnecessary water release and enhancing operational efficiency.



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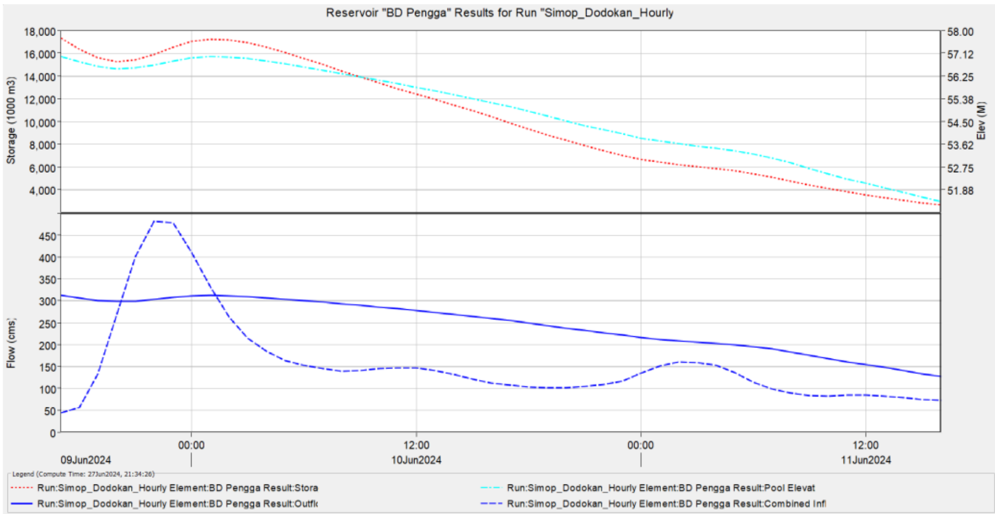

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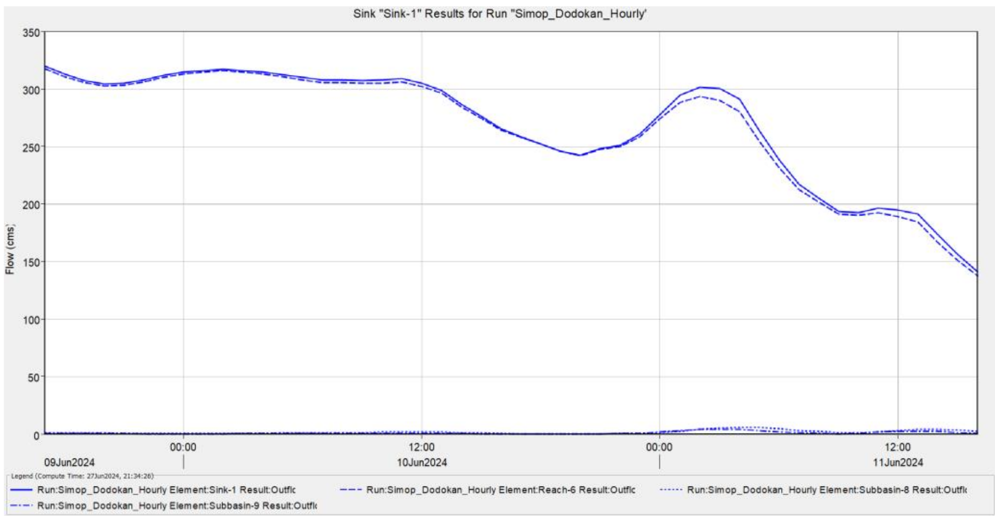

(c)

Figure 10. Discharge Hydrograph after Gate Opening Optimization: a) Batujai; b) Pengga; c) Downstream

3.5.2. Information of Early Warning to the Dam Safety

To determine the dam's flood discharge limits before overtopping, the model was run with scaled-up rainfall inputs, starting from the initial water level elevation as previously described. The optimal maximum gate opening was reached when rainfall was scaled up by a factor of 3.24 (approximately 450 mm), with all gates fully open. Under these conditions, the resulting MAW elevations were +94.0 mdpl at Batujai (approximately at the dam crest) and +57.0 mdpl at Pengga (FWL), with downstream flood discharge reaching 1,532.5 m³/s. Figures 11 and 12 present the inflow and outflow hydrographs just before the Batujai Dam reaches overtopping.

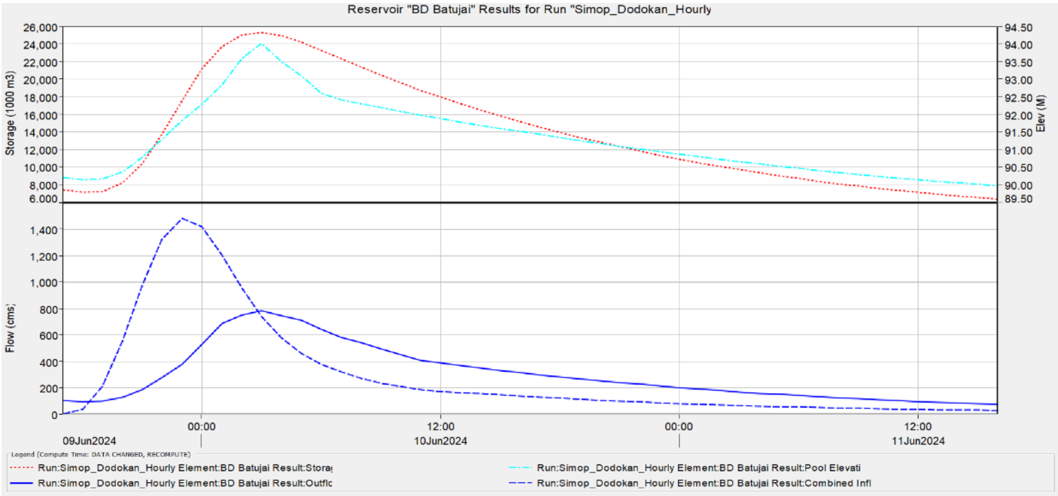

Figure 11. Discharge Hydrograph in Batujai Dam in the Scale up Rainfall Condition Flood

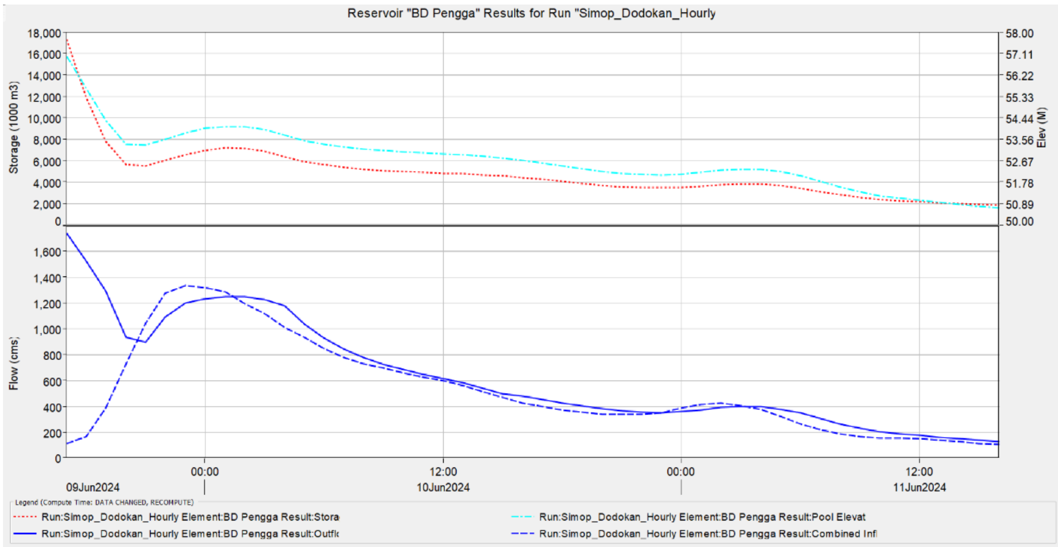

Figure 12. Discharge Hydrograph in Pengga Dam in the Scale Up Rainfall Condition Flood

4. Conclusion

Based on the analysis, the following conclusions are drawn: The Rule Curve model for per-period reservoir storage, optimized for the K-factor and reservoir fill, demonstrates that stochastic inflows provide significantly higher accuracy than deterministic (static) inflows in rule curve design. Beginning each hydrological year, simulations incorporating the RTOW and real-time updates to actual reservoir levels (MAW) and periodic stochastic inflow projections achieve improved correlation and RMSE values. This responsiveness enhances predictive accuracy for the Batujai and Pengga reservoirs, underscoring the advantage of stochastic inflows in rule curve application. The reservoir information system, combining the rule curve with ten-day period simulations and real-time hourly routing in HEC-HMS (supported by VBA, Python, and Jython), optimally adjusts spillway openings, preventing downstream flooding while maintaining reservoir storage. The optimized settings—two gates at 0.4 m and two at 0.2 m for Batujai (inflow of 638.7 m^3/s) and 0.3 m on the sixth gate at Pengga (inflow of 616.3 m^3/s)—effectively keep reservoir levels within safe High Flood Water Level (HFLW) limits and ensure water supply continuity. The model's early release strategy, aligned with the real-time rule curve, enables the Batujai and Pengga dams to handle extreme inflows effectively. Batujai, under initial MAW flood season conditions, can manage inflows up to 3.24 times the maximum monthly rainfall (~450 mm), ensuring water levels remain within design safety thresholds. The model enhances adaptive spillway operations by optimizing the irrigation water release-to-demand ratio (K Factor) to 83% with stochastic and 79% with deterministic inflows, balancing flood control and operational safety through alignment with real-time rule curves. In summary, this study recommends the adoption of stochastic inflow predictions in rule curve modeling. This approach provides more accurate reservoir level projections, improves real-time operational control, and supports a robust strategy for flood mitigation and water supply management in the Dodokan watershed.

5. Declarations

5.1. Author Contributions

Conceptualization, I.W.A. and P.T.J.; methodology, I.W.A.; validation, I.W.A.; formal analysis, I.W.A.; investigation, I.W.A. and P.T.J.; resources, I.W.A. and L.M.L.; data curation, I.W.A. and R.A.; writing—original draft preparation, I.W.A. and P.T.J.; writing— review and editing, L.M.L. and R.A.; visualization, L.M.L. and R.A. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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