

Article

Model Predictive Control-Based Hydrodynamic Regulation Framework for the Lower Ganjiang River

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Abstract

The Lower Ganjiang River is a multi-branch delta with highly uneven spatial and temporal flow distribution, and conventional static diversion or threshold-based operation fails to stabilise the water level or optimise flow allocation under varying inflows. This study develops a hydrodynamic regulation framework that couples an improved integral time-delay model and model predictive control (MPC). A nonlinear state-space equation is constructed using a quadratic storage–water level relationship and rolling optimisation is solved with CasADi-IPOPT to minimise water-level tracking error, discharge deviation and control effort. The framework is validated offline against MIKE21 simulations for three historical flow scenarios (September 2016, February 2017 and March 2018). Under these scenarios, the Waizhou water level is maintained at 15.5 ± 0.2 m, daily water level variation is limited to ≤ 0.5 m/d, and the diversion ratio deviation is $\leq 5\%$. Compared with the natural state, water level fluctuation is reduced by 21.3% (September 2016 storage scenario). The proposed MPC framework effectively alleviates the spatiotemporal hydrodynamic imbalance of the Lower Ganjiang River, showing satisfactory model accuracy, constraint compliance, and engineering applicability, and offers a promising approach for advanced regulation of complex multi-branch river networks.

Keywords: model predictive control; Lower Ganjiang River; hydrodynamic reconstruction; multi-objective optimization

1. Introduction

River networks provide essential services including water supply, flood control, navigation, and ecosystem support. However, they often suffer from weak hydrodynamics and severe human disturbances, leading to imbalanced spatiotemporal flow patterns. To address this, the concept of “hydrodynamic reconstruction” has been proposed, which refers to the storage and increase in limited water flow energy in a river network area through engineering measures such as sluices, pumping stations, and dredging. Its primary goal is to balance traditional functions such as flood control and water supply with sustainable development requirements like ecological protection and water quality improvement. The core scientific challenge lies in understanding the coupled mechanisms between natural water cycles and engineered intervention systems, thereby rebalancing the regional hydrodynamic regime [1].



Academic Editor: Carlo Gualtieri

Received: 21 May 2026

Revised: 25 June 2026

Accepted: 29 June 2026

Published: 27 July 2026

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Traditional approaches to flow regulation rely on static optimisation or rule-based operation. Static optimisation methods derive fixed diversion ratios or gate schedules from historical data [2–5] but cannot adapt to unforeseen inflow variations. Threshold-based hysteretic control, as currently used at the Nanchang Water Control Project, triggers gate actions only when water levels cross predefined limits (e.g., 15.5 m at Waizhou station). This leads to time lags, water level overshoot, and unbalanced diversion ratios [6].

Model predictive control (MPC) offers a promising alternative by using a process model to predict future system states and solving a rolling optimisation problem at each time step. MPC has been successfully applied to irrigation canals [7], water quality management [8], and long-distance water diversion projects [9]. However, existing MPC studies focus on single channels or simple networks; their application to multi-branch deltaic rivers with pronounced time delays and complex flow partitioning remains underexplored.

The Lower Ganjiang River, which discharges into Poyang Lake through four main branches, suffers from severe hydrodynamic imbalance due to natural topography and sand mining. Previous studies have analysed flow distribution patterns [10], channel evolution [11], and flood control conditions [12] using offline hydrodynamic models, but they have not proposed a predictive regulation framework that can anticipate inflow changes and proactively optimise gate actions.

To address this gap, this paper develops a hydrodynamic regulation framework that couples an improved integral time-delay model with MPC. The key novelty lies in replacing static or reactive rules with a rolling-horizon optimisation that uses inflow forecasts to pre-compensate for time delays. Unlike existing offline optimisation studies, our framework generates control sequences that can be updated when new forecast data become available, thus providing a basis for predictive regulation. The main contributions are: (1) a nonlinear state-space model that captures the storage-water level relationship, (2) a multi-objective MPC formulation that balances water-level stability, diversion ratio accuracy, and control smoothness, and (3) validation against MIKE21 simulations under three historical flow scenarios.

2. Materials and Methods

2.1. Study Area

2.1.1. Nanchang Water Control Project

The Lower Ganjiang River is a multi-branched delta discharging into Poyang Lake (Figure 1). Within the urban area of Nanchang City, the mainstem splits into eastern and western channels, which further divide into the following four branches: West Branch, North Branch, Middle Branch, and South Branch. The Nanchang Water Control Project consists of four independent hubs, one on each branch (Figure 1). Table 1 summarises the key characteristics of each branch, including the hub name, distance from Nanchang City, and typical hydraulic capacity at the target water level (15.5 m).

Table 1. Key characteristics of the four branches and control structures of the Nanchang Water Control Project.

Branch	Control Hub	Distance from Nanchang City (km)	Maximum Discharge Capacity at 15.5 m (m³/s)	Minimum Ecological/Navigation Flow (m³/s)
West Branch	Xiangshan Hub	35	2700	246.5
North Branch	Lianxin Hub	28	300	17.4

Table 1. Cont.

Branch	Control Hub	Distance from Nanchang City (km)	Maximum Discharge Capacity at 15.5 m (m ³ /s)	Minimum Ecological/Navigation Flow (m ³ /s)
Middle Branch	Nanxin Hub	23	1400	140.6
South Branch	Jili Hub	35	400	90.5

Notes: distances are approximate along the channel. Maximum capacities are derived from hydraulic modelling under the target water level (15.5 m at Waizhou). Minimum flows are based on ecological and navigation requirements [6].

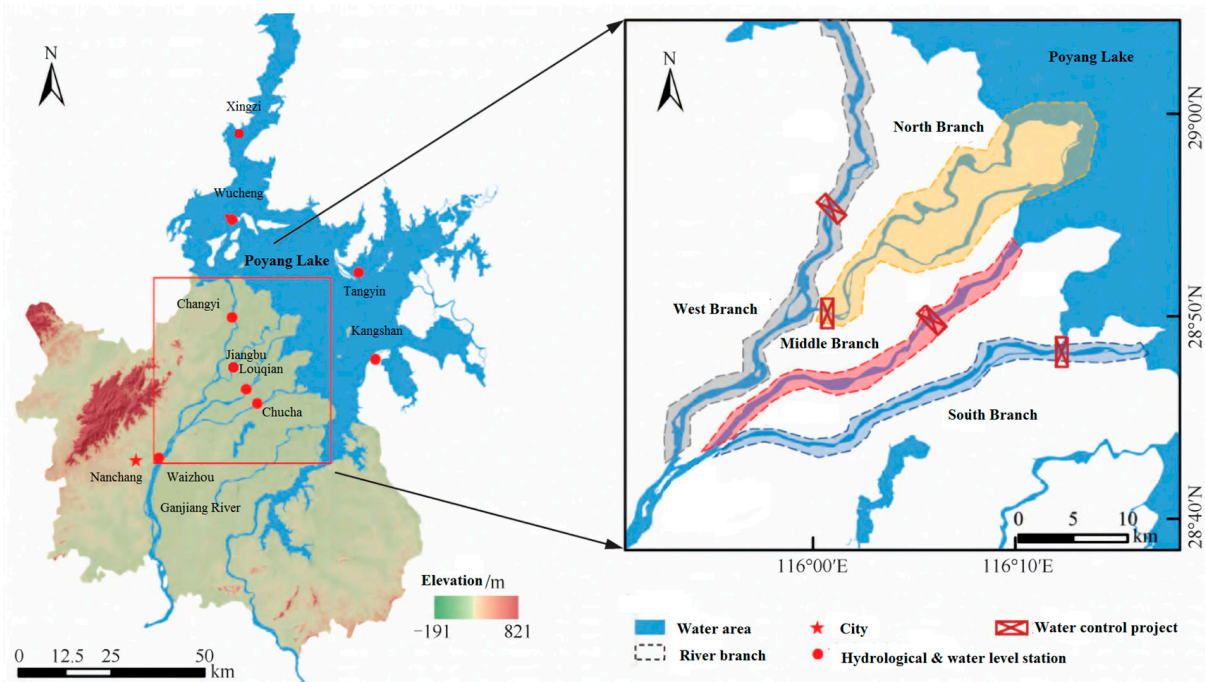


Figure 1. Layout of the Nanchang Water Control Project of the Ganjiang River.

2.1.2. Current Operation Strategy and Limitations

The Nanchang Water Control Project follows a rule-based operation strategy of seasonal regulation. This strategy conserves water during the flood season (April–July) and releases it during the dry season (August–March) to balance river discharge between wet and dry periods. The strategy is summarised in Table 2 and Figure 2. Key water level references are: Waizhou station (primary control) with a threshold of 15.5 m, and Xingzi station (secondary, at Poyang Lake) with a threshold of 13.11 m.

Table 2. Operation strategy at the Nanchang Water Control Project.

Period	Time Range	Primary Objective	Control Logic	Key Constraints
Flood season	April–July	Flood safety	All gates fully opened; natural flood discharge is maintained with no active regulation.	None
Dry season	August–March of the following year	Water level stabilisation, flow distribution optimisation, and ecological water supplementation	Hierarchical regulation based on the following two criteria: (1) Waizhou water level; (2) Xingzi water level	Daily drawdown ≤0.5 m/d; minimum total release ≥495 m ³ /s

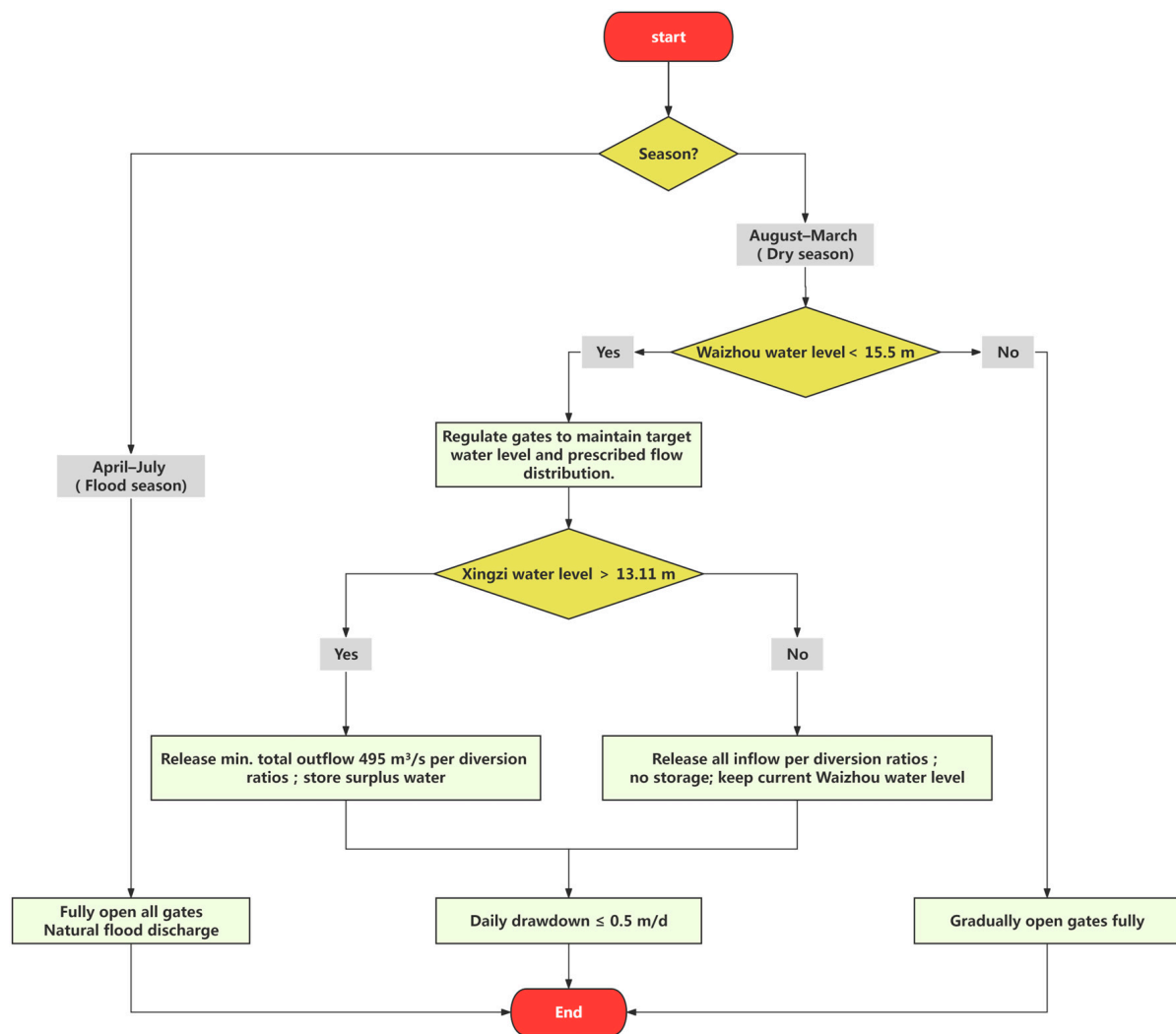


Figure 2. Simplified flowchart of the operation strategy at the Nanchang Water Control Project.

Despite its clear logic, the rule-based strategy suffers from the following three major drawbacks:

- (1) Time lag and overshoot. Thresholds trigger actions only after the water level crosses 15.5 m. Due to flow propagation delays (2–4 h from Waizhou to downstream branches), gate responses lag behind actual water-level changes, causing overshoot (sharp rise and then sudden drop) and oscillations, which endanger bank slopes.
- (2) Reactive rather than predictive. The strategy cannot anticipate rapid inflow increases. When a flood wave approaches, the gates do not act until the water level exceeds 15.5 m, forcing a rapid rise and potentially exceeding safe limits.
- (3) Poor multi-objective coordination. Water level is the only feedback variable. The strategy does not systematically optimise diversion ratios or minimise gate movements, leading to frequent adjustments and accelerated equipment wear.

A PID (proportional–integral–derivative) controller could in principle improve water level tracking by continuously adjusting gate openings. However, river systems exhibit long and variable time delays. In a delayed system, the controller’s corrective action reaches the control point only after the delay period. This lag causes the integral term to accumulate error unnecessarily, leading to oscillations or even instability. While advanced PID variants (e.g., Smith predictor) can compensate for moderate delays, the strongly nonlinear storage–water level relationship and the need to coordinate four branches with different delay times

make PID impractical. Model predictive control (MPC) inherently handles delays by using a predictive model to forecast future responses and optimise control actions over a rolling horizon, thus pre-compensating for time lags while respecting multiple constraints.

2.2. Data Sources and Processing

The hydrological data used in this study were obtained from the Jiangxi Provincial Hydrological Monitoring Centre (JXHMC), the official authority responsible for hydrological monitoring throughout the Ganjiang River Basin and the Poyang Lake region. The dataset includes hourly water level (m) and discharge (m^3/s) records from Waizhou station (the primary control point for the Nanchang Water Control Project) and from the following four downstream branch stations: Changyi (West Branch), Jiangbu (North Branch), Louqian (Middle Branch), and Chucha (South Branch). All raw data were provided in tab-separated text format, with a temporal resolution of 1 h for the years 2016–2018. Monthly and long-term averages were subsequently derived from these hourly records.

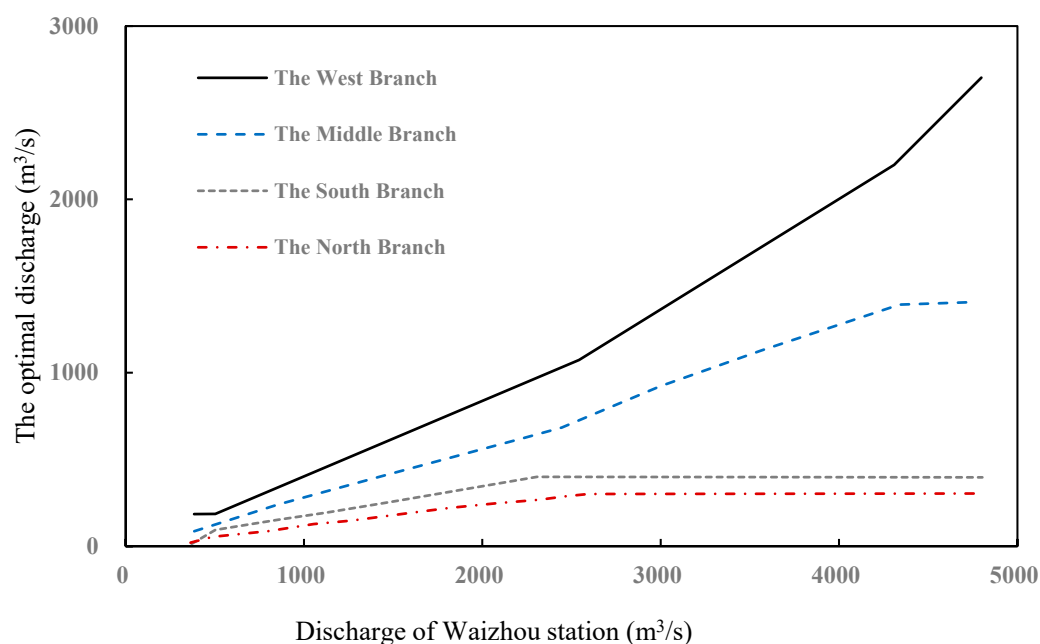
Prior to analysis, all raw data underwent a multi-step quality control procedure. Records flagged by the JXHMC as instrument malfunction or transmission error were removed based on the quality assurance annotations provided by the monitoring centre. Missing values were filled by linear interpolation. Outlier detection was performed using the 3σ (three-standard-deviation) method. After automatic detection, all candidate outliers were manually checked against historical flood and drought records to distinguish measurement errors from true extreme events.

The data were organised into three subsets according to their specific purposes in model development and validation.

- (1) Subset 1—Model calibration (2018 hourly data). The full year of 2018 (hourly records) was used to calibrate the integral time-delay model and to estimate the storage–water level relationship. From this subset, the flood wave propagation time from Waizhou station to each downstream branch was calculated using the peak time difference method based on hourly water level data. Table 3 presents the resulting propagation times for each month of 2018.
- (2) Subset 2—Validation scenarios (historical flood events). Three historical flood events from 2016 to 2018 (after the commissioning of the Xiajiang Hydropower Station) were selected as independent validation cases to test the predictive performance of the calibrated MPC framework. These events span a wide range of flow fluctuation amplitudes, as summarised in Table 4.
- (3) Subset 3—Determination of optimal diversion ratios (long-term data). The optimal relationship between the Waizhou discharge and the branch discharges (shown in Figure 3) was adopted from Zhang et al. (2025) [6]. In that study, a two-dimensional hydrodynamic model (MIKE21) was calibrated and validated against observed water levels and velocities in the Lower Ganjiang River. Using this model, the authors simulated flow velocities under different inflow rates and historical diversion ratios. They found that when the Nanchang Water Control Project impounds to the target water level of 15.5 m at Waizhou, the branch flow velocity is approximately linear with the branch discharge. Based on this linear relationship, a linear programming problem was formulated to maximise the minimum flow velocity among the four branches (max–min criterion), subject to the maximum discharge capacity and minimum ecological/navigation flow constraints of each branch (see Section 2.1.2, Table 2 for these numerical values). The resulting optimal branch discharges (Figure 3) are therefore model outputs from the validated MIKE21 simulations processed through linear programming, i.e., a calibrated optimal control relationship, not raw observations.

Table 3. Flood wave propagation times across tributaries in the Ganjiang Estuary (2018).

Month	Waizhou Water Level (m)	Waizhou Flow (m ³ /s)	Propagation Time (Flood/Dry Season, Waizhou Tributary) (h)			
			West Branch (50 km from Waizhou)	North Branch (32 km from Waizhou)	Middle Branch (34 km from Waizhou)	South Branch (34 km from Waizhou)
1	12.91	2270	4	2	2	2
2	10.35	751	15	6	3	3
3	12.90	2050	4	2	2	2
4	11.23	972	10	5	3	3
5	13.77	2460	4	2	2	2
6	17.52	9110	2	1	1	2
7	16.47	6700	3	2	1	1
8	14.58	1620	−2	−1	0	0
9	11.57	1060	14	6	2	2
10	11.58	1270	5	3	2	1
11	14.53	3790	4	2	2	2
12	12.95	2240	4	2	2	2

**Figure 3.** Relationship between Waizhou discharge and the optimal discharge of each branch.**Table 4.** Validation scenarios.

Scenario	Time Period	Maximum Flow (m ³ /s)	Minimum Flow (m ³ /s)	Flow Variation (m ³ /s)
Scenario 1	September 2016	4200	773	3427
Scenario 2	March 2018	2050	789	1261
Scenario 3	February 2017	1110	682	428

2.3. Model and Algorithm

2.3.1. Improved Integral Delay Prediction Model

The classical integral time-delay model was proposed by Schuurmans et al. [13]. It establishes an explicit equation between the water level deviation at the control point and the inflow/outflow variations in a canal pool:

$$\frac{dh(t)}{dt} = \frac{1}{A_d} [q_{in}(t - \tau_d) - q_{out}(t)] \quad (1)$$

where h is the water level (m), q_{in} is inflow (m^3/s), q_{out} is outflow (m^3/s), A_d is the backwater area (m^2), and τ_d is the flow time delay (s). A_d and τ_d are generally derived via formulaic calculation [13], hydrodynamic model fitting [14], or field measurements. In canal hydrodynamic scheduling studies, these two parameters vary slightly and are commonly treated as constants to reduce model complexity, retaining the linear form of the equation [15].

However, in natural river systems, the relationship between water level and storage is nonlinear. When inflow fluctuates rapidly, the linear approximation introduces biases in predicting the dynamic water-level response. These biases propagate through the rolling optimisation process, leading to control actions that deviate from the global optimum. To address this issue, we incorporate an explicit storage–water level relationship and formulate a nonlinear state equation using an implicit function:

$$\frac{dV(t)}{dt} = q_{in}(t - \tau_d) - q_{out}(t) \quad (2)$$

$$h(t) = aV(t)^2 + bV(t) + c \quad (3)$$

where V is (m^3); the coefficients a , b , and c are obtained by quadratic fitting of the storage–water level curve.

2.3.2. State-Space Equation for Predictive Control

Discretising Equation (2) with a control interval $T_s(\text{s})$ gives the storage update equation:

$$V(k+1) = V(k) + T_s [q_{in}(k - k_d) - q_{out}(k)] \quad (4)$$

where T_s is the discretization time step (s), k is the discrete time index, and $k_d = \tau_d/T_s$ is the integer delay step.

In time-delay system discretisation, τ_d is typically converted to an integer step, k_d . When τ_d is not an integer multiple of T_s , the conventional approach is to round up as follows: $k_d = n + 1$ ($n < \tau_d/T_s \leq n + 1$, $n \in \mathbb{N}$). This approximation is acceptable when $T_s \ll \tau_d$. However, in large-river regulation projects such as the Nanchang Water Control Project, the control cycle is often long and can be comparable to or even larger than the flow propagation delay τ_d . In the extreme case $T_s > \tau_d$, we have $n = 0$ and $k_d = 1$. The delay effect then partially spans across control cycles, causing prediction distortion and systematic controller bias.

Therefore, we set the control step T_s as an integer multiple of τ_d and the prediction step equal to τ_d . The choice of a fixed delay $\tau_d \approx 2$ h is based on the dominant propagation time during the dry season (August–March), which is the period of active gate regulation. As shown in Table 3, during dry months (February, September, and October), the propagation times for the three eastern branches are 2–3 h, and for the West Branch they are 5–15 h. The 2 h value was selected because it represents the shortest characteristic delay of the system; using a longer delay (e.g., 15 h) would require a much longer prediction horizon and significantly increase computational cost without improving control performance, as the water level response at Waizhou is most sensitive to the nearest branches. Moreover, the negative values in August are due to backwater effects from Poyang Lake, which occur only during the high-water season when the gates are fully open and no active control is applied. Therefore, these anomalous values do not affect the MPC performance during the regulated dry season. With $\tau_d \approx 2$ h, we take $T_s = 2$ h and consequently $k_d = 1$. This aligns

the prediction granularity with the physical time delay and eliminates cross-cycle aliasing. The system operates on the following three time scales:

State update interval = $T_s = 2$ h (equals τ_d);

Control cycle = $T_c = 12$ h (gates operation interval). The control actions (branch discharges) are kept constant over each T_c period, i.e., for $T_c/T_s = 6$ consecutive state updates;

Prediction horizon = 48 h (4 control cycles).

With $T_s = \tau_d$ and $k_d = 1$, the state equation simplifies to:

$$V(k+1) = V(k) + \tau_d[q_{in}(k-1) - q_{out}(k)] \quad (5)$$

The water level is then computed directly from the storage using Equation (3):

$$h(k) = aV(k)^2 + bV(k) + c \quad (6)$$

2.3.3. Objective Function

The general form of the MPC objective function is:

$$J = \sum_{k=1}^N \ell[x(k), u(k)] \quad (7)$$

where J is the objective function to be minimised, N the prediction horizon, and $\ell[x(k), u(k)]$ the stage cost. For the Nanchang Water Control Project, whose primary goal is to maintain the Waizhou water level at $h_{ref} = 15.5$ m, the stage cost consists of three penalization terms.

(1) Water-level tracking error

$$\ell_{tracking}(k) = \|h(k - k_d) - h_{ref}\|_Q^2 \quad (8)$$

where $h(k)$ is the predicted water level at time step k and Q is a diagonal positive-definite weighting matrix that adjusts the tracking accuracy. This term drives the system to stabilise the water level at the target value.

(2) Control input increment penalty

Define the vector of control increments as

$$\Delta \mathbf{q}_{out}(k) = [\Delta q_1(k), \Delta q_2(k), \Delta q_3(k), \Delta q_4(k)]^T \in \mathbf{R}^4 \quad (9)$$

With $\Delta q_i(k) = q_i(k) - q_i(k-1)$ for the four branches (West, North, Middle, and South). The penalty is

$$\ell_{input}(k) = \|\Delta \mathbf{q}_{out}(k)\|_{R_{\Delta u}}^2 \quad (10)$$

where $R_{\Delta u} = \text{diag}(R_{\Delta u,1}, R_{\Delta u,2}, R_{\Delta u,3}, \text{ and } R_{\Delta u,4})$ is a diagonal positive-definite weighting matrix. Penalising abrupt changes reduces gate operation frequency and amplitude, thereby extending equipment lifetime and ensuring smooth regulation.

(3) Discharge deviation from optimal distribution

Define the vector of branch discharges

$$\mathbf{q}(k) = [q_1(k), q_2(k), q_3(k), q_4(k)]^T \quad (11)$$

and the corresponding optimal discharge vector (obtained from the pre-computed relationship; see Figure 3)

$$q_{opt}(k) = [q_{opt,1}(k), q_{opt,2}(k), q_{opt,3}(k), q_{opt,4}(k)]^T \quad (12)$$

The deviation penalty is

$$\ell_{opt}(k) = \|q_{opt}(k) - q(k)\|_{R_u}^2 \quad (13)$$

where $R_u = \text{diag}(R_{u,1}, R_{u,2}, R_{u,3}, \text{ and } R_{u,4})$ is a diagonal positive-definite weighting matrix. This term enforces that the actual flow distribution stays close to the optimal one while the water level is being regulated.

The total stage cost is the sum of the following three components:

$$\ell[x(k), u(k)] = \ell_{tracking}(k) + \ell_{input}(k) + \ell_{opt}(k) \quad (14)$$

By substituting (14) into (7), the original multi-objective problem (stable water level, optimal flow distribution, and smooth control actions) is converted into a single-objective optimisation that can be solved efficiently. The resulting optimal control sequence $q(k)$ (or equivalently the branch discharges) is computed in a rolling-horizon fashion.

2.3.4. Constraints

The optimisation problem is subject to the following constraints at each time step k .

(1) Branch discharge limits

Let $q(k)$ denote the vector of branch discharges (West, North, Middle, and South). The lower and upper bounds are given by:

$$q_{i,min} \leq q_i(k) \leq q_{i,max} \quad (15)$$

where the inequalities are interpreted component-wise. From Section 2.1.2, Table 1:

$$q_{i,min} = [246.5, 17.4, 140.6, 90.5] \text{ m}^3/\text{s}, q_{i,max} = [2700, 300, 1400, 400] \text{ m}^3/\text{s} \quad (16)$$

These limits reflect the maximum discharge capacity at the target water level (15.5 m) and the minimum ecological/navigation flow requirements.

(2) Total discharge balance

The sum of branch discharges must equal the total inflow at Waizhou station:

$$\sum_i^4 q_i(k) = q_{in}(k) \quad (17)$$

where $q_{in}(k)$ is the observed or forecasted inflow. This constraint ensures mass conservation over the control horizon.

(3) Water-level change rate

To protect bank stability and prevent rapid drawdown, the daily water-level variation is limited to 0.5 m. In the discrete-time setting with step $T_s = 2$ h, this is enforced as

$$|h(k) - h(k-1)| \leq 0.5 \times \frac{T_s}{24} = 0.0417 \text{ m} \quad (18)$$

per time step. This ensures that the cumulative change over any 24 h period (12 consecutive steps) does not exceed 0.5 m. The constraint is applied as 12 inequality constraints over the 48 h prediction horizon (one for each overlapping 24 h window).

2.4. Model Solution and Sensitivity Analysis

The nonlinear MPC problem formulated in Sections 2.3.2–2.3.4 is solved using the CasADi framework [16] for symbolic modelling and automatic differentiation, interfaced with the IPOPT interior-point nonlinear programming solver [17].

2.4.1. Computational Environment and Problem Size

The MPC controller was implemented in Python 3.11.7 on a computer with an AMD Ryzen 7 7735H processor (3.20 GHz), 16 GB RAM, running Windows 10 Professional. At each rolling optimisation call, the decision variables are the branch discharges for the four branches over the prediction horizon. With a control cycle $T_C = 12$ h and a prediction horizon of 48 h, the horizon contains 4 control blocks. Thus, the number of decision variables is $4 \times 4 = 16$ (all continuous). The constraints include: (i) discharge bounds for each branch at each control block—16 double-sided inequality constraints; (ii) daily water-level change limits—12 inequality constraints (one per each 12 h step within the 48 h horizon, to ensure that any 24 h variation does not exceed 0.5 m). No hard constraint is imposed on the control increment; instead, a quadratic penalty term is added to the objective function to smooth gate adjustments. Hence, a single optimisation involves 16 decision variables and 28 inequality constraints.

Based on the simulation of the September 2016 inflow sequence (30-day simulation, approximately 60 optimisation calls), the average solution time was 0.17 s per call, with a minimum of 0.11 s and a maximum of 0.21 s. This is far below the state-update interval (2 h), confirming that the computational overhead is acceptable for online implementation.

2.4.2. Solver Settings and Initialization

IPOPT implements a primal-dual interior-point method with a filter line-search strategy to ensure global convergence. The convergence criteria are based on the Karush–Kuhn–Tucker (KKT) optimality residuals. Convergence tolerances are set to 1×10^{-8} for optimality and 1×10^{-6} for constraint violation; maximum iterations are 500.

A hybrid cold-start/hot-start strategy is employed. For the first optimisation step (cold start), no prior control sequence is available. An initial guess is generated based on the measured inflow at Waizhou, using historical average diversion ratios (West: $\approx 41\%$, North: 12%, Middle: 29%, and South: 18%), and then clamped to the feasible discharge bounds of each branch. For all subsequent rolling steps (hot start), the optimal control sequence obtained from the previous optimisation is shifted forward in time, and the already executed control action is discarded. This warm-starting drastically reduces the number of iterations required and guarantees real-time feasibility.

2.4.3. Weight Determination and Sensitivity Analysis

The weights Q , R_u and $R_{\Delta u}$ correspond to water-level tracking accuracy, diversion ratio rationality, and smoothness of gate adjustments, respectively. With water-level control as the highest priority, Q was set relatively large. Through trial-and-error on three typical hydrographs, the baseline values were set to $Q = 0.01$, $R_u = 0.05$, and $R_{\Delta u} = 0.005$.

A sensitivity analysis was performed by varying each weight by factors of 2^{-3} to 2^3 around the baseline, using the September 2016 inflow scenario. The following three metrics were evaluated: water level RMSE, discharge error D_{err} , and control effort C_{effort} . The results are plotted in Figure 4 (sensitivity curves). The analysis shows that increasing Q improves water-level tracking but at the cost of higher control effort and slightly larger diversion

error. Increasing R_u reduces D_{err} but may worsen the water-level RMSE. Increasing $R_{\Delta u}$ smoothes gate movements (lower C_{effort}) while making the water-level response slightly slower. No single set of weights is dominant for all objectives; the choice depends on the operator's priority. Importantly, the solution time remained nearly constant (≈ 0.17 s) across all sensitivity runs, as the problem size does not change. The sensitivity analysis provides quantitative support for the baseline weights and can guide adaptive weight tuning in future implementations.

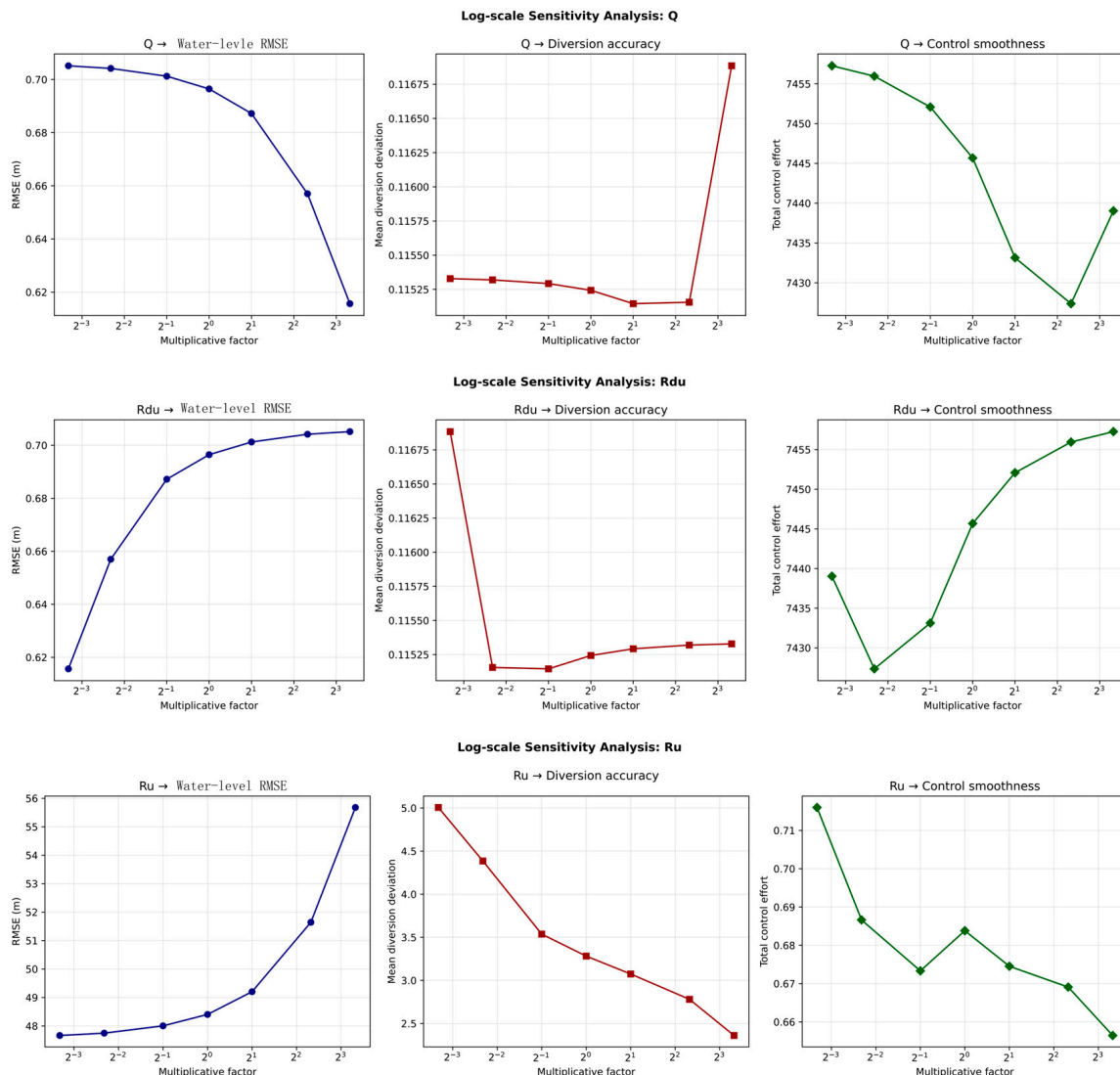


Figure 4. Sensitivity analysis of weighting coefficients.

The baseline weights ($Q = 0.01$, $R_u = 0.05$, and $R_{\Delta u} = 0.005$) achieve a balanced trade-off as follows: water level RMSE ≤ 0.1 m, diversion error $\leq 5\%$, and moderate control effort. The controller is not overly sensitive to $\pm 20\%$ variations in the weights, and the computational cost remains low. Therefore, the empirical tuning is acceptable for the purpose of this study. For applications with different priorities (e.g., strictly smooth gate operations or extremely high water-level precision), the weights can be adjusted according to the sensitivity trends reported above.

2.5. Model Validation

The proposed MPC framework was validated using the high-fidelity hydrodynamic model MIKE21, which was independently calibrated and validated against observed wa-

ter levels in the Lower Ganjiang River. The MIKE21 model was built for the Lower Ganjiang River using 2018 topographic data and unstructured meshes (35–70 m resolution). It solves the two-dimensional shallow water equations. The model was calibrated against 2018 hourly water-level data from five stations (Waizhou, Nanchang, Changyi, Louqian, and Chucha). Calibration focused on Manning’s roughness coefficients (final range $n = 0.033\text{--}0.045$) and eddy viscosity. The model performance was evaluated using the correlation coefficient r and NSE. For all stations, $r > 0.95$ and $NSE > 0.94$, indicating excellent agreement. The MAE ranged from 0.02 m to 0.20 m, the RMSE from 0.20 m to 0.34 m, and the RRE was below 5%. Hence, the MIKE21 model is sufficiently accurate to serve as a benchmark for validating the MPC framework.

For three historical validation scenarios (September 2016, March 2018, and February 2017), the MPC controller generated optimal control sequences (branch discharges) using the improved integral time-delay model. These sequences were then imposed as boundary conditions in the MIKE21 model, and the resulting water levels at Waizhou were simulated. Natural (unregulated) water levels were also simulated for comparison (Figure 5). Table 5 summarises the agreement between the MPC-predicted water levels and the MIKE21 simulations, including the mean absolute error (MAE), root mean square error (RMSE), maximum absolute error, and the Nash–Sutcliffe efficiency (NSE).

Table 5. Validation metrics of MPC offline-optimised water level against MIKE21 simulation.

Scenario	MAE (m)	RMSE (m)	Max Error (m)	NSE
September 2016	0.26	0.34	0.90	0.92
March 2018	0.15	0.19	0.48	0.96
February 2017	0.09	0.12	0.31	0.98

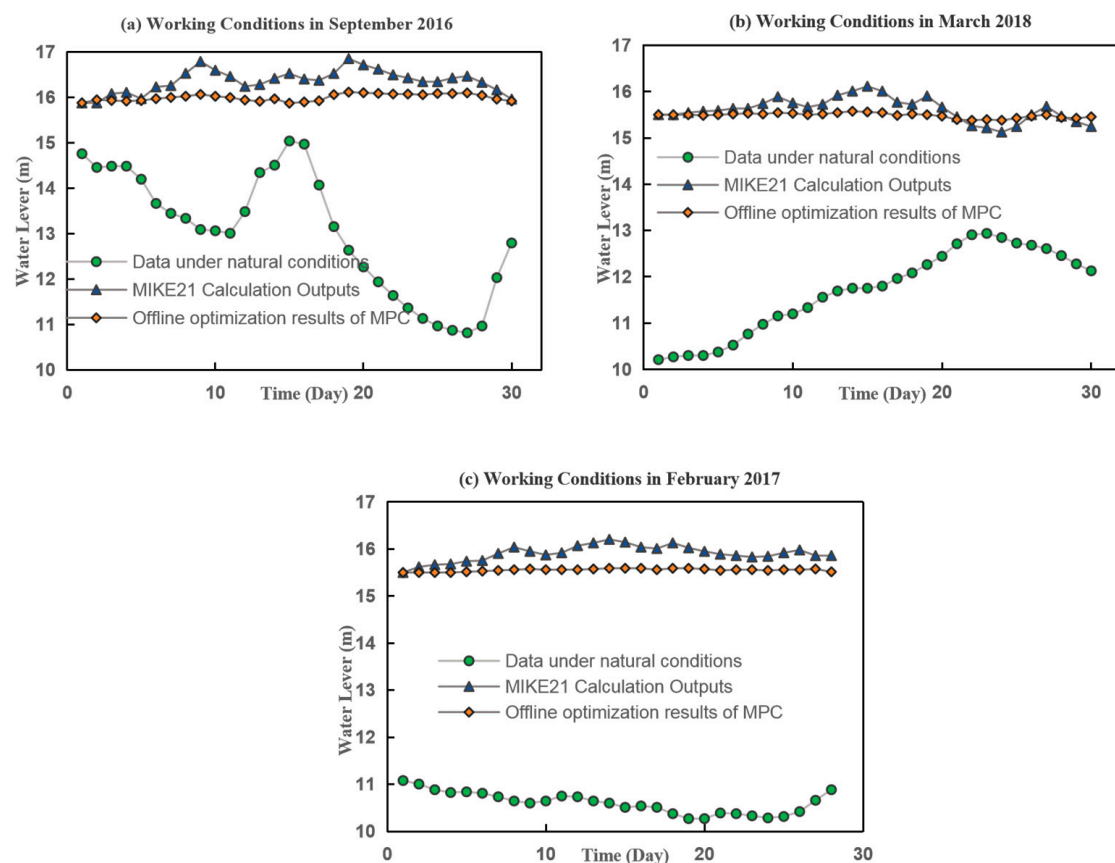


Figure 5. Verification of the MPC scheduling scheme in the MIKE21 hydrodynamic model.

The NSE values >0.92 indicate excellent dynamic trend reproduction. The maximum error (0.90 m) occurs only during the most extreme inflow variation (from $1390 \text{ m}^3/\text{s}$ to $4200 \text{ m}^3/\text{s}$ within 5 days). Under this extreme condition, the simplified integral time-delay model slightly over-predicted the water-level rise compared to the MIKE21 benchmark. However, this error is transient and lasts less than 12 h. From an operational safety perspective, the controller still respects the daily drawdown limit (0.5 m/d), and the high NSE (0.92) confirms that the overall trend and timing are well-captured. The target of $15.5 \pm 0.2 \text{ m}$ applies to normal steady-state regulation; during extreme flood events, larger transient deviations are acceptable as long as safety constraints are met. Therefore, the 0.90 m error does not compromise the practical utility of the framework. The offline optimisation model and MIKE21 exhibit highly consistent water-level trends, both effectively eliminating the drastic water-level fluctuations observed in historical data caused by inflow variability. These results confirm the practical feasibility of the hydrodynamic regulation scheme derived from MPC offline optimisation and lay a foundation for its potential real-time application.

3. Results

The performance of the proposed MPC framework was evaluated under the following three typical hydrological scenarios representing different operational demands: water storage (September 2016), steady-state water level (February 2017), and flood discharge (March 2018). In each scenario, the controller was run in offline optimisation mode using historical inflow data as perfect forecasts. The resulting water levels at Waizhou station and the diversion ratios of the four branches were compared against the natural (unregulated) condition (all gates fully opened). The daily water-level variation was calculated as the maximum daily drawdown observed in the simulation. The diversion ratio deviation was defined as the absolute difference between the actual diversion ratio and the optimal one derived from Zhang et al. [6]. Control effort was measured by the average absolute increment of branch discharges per control cycle, and gate movements were counted when $|\Delta q_i| > 1 \text{ m}^3/\text{s}$ for any branch between two consecutive control cycles (12 h).

3.1. Performance Under Water Storage Scenario

Figure 6 shows the water-level regulation and diversion ratio control during the impoundment phase. Under MPC regulation, the Waizhou water-level variation rate was always controlled within the safe threshold of 0.5 m/d , and the water level rose steadily to the target value of 15.4 m on day 19 and remained within 15.3–15.5 m afterwards. Compared with the natural process (water level plummeting from 12.49 m to 10.80 m over eight days), the peak-to-peak water level fluctuation was reduced by 21.3% (from 1.69 m to 1.33 m). The proactive buffer adjustment during the inflow surge (September 10–15) demonstrates the feedforward predictive capability of MPC. Table 6 summarises the key performance indicators for this scenario.

Table 6. Performance under the water storage scenario (September 2016).

Metric	Natural Condition	MPC Regulation	Improvement/Compliance
Mean water level (m)	12.24	15.42	/
Peak-to-peak fluctuation (m)	1.69	1.33	21.3% reduction
Maximum daily drawdown (m/d)	1.12	0.48	≤ 0.5 (compliant)
Max diversion ratio deviation (%)	38.2	4.7	$\leq 5\%$ (compliant)
Average control increment (m^3/s per 12 h)	/	24.6	/
Gate movements (count)	/	14	/

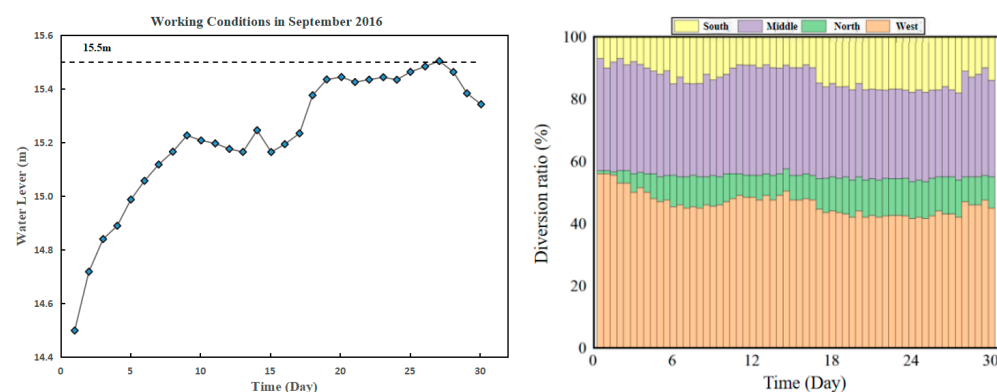


Figure 6. Water-level regulation and diversion ratio control of MPC during the impoundment stage (September 2016).

3.2. Performance Under Steady Water-Level Scenario

Figure 7 illustrates the regulation performance under small inflow fluctuations ($\pm 1000 \text{ m}^3/\text{s}$, representing about 90% of the operation period). The Waizhou water level was maintained very close to the target, with a maximum deviation of only 0.09 m. The controller prioritised smooth gate operations and accurate diversion ratios; a slight water-level deviation on 14 February was deliberately allowed to minimise flow fluctuations, showing the trade-off capability of MPC. Table 7 presents the results.

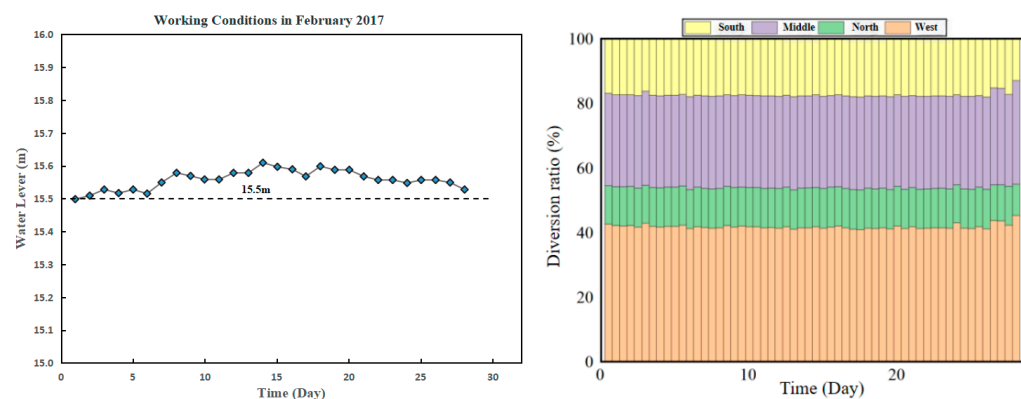


Figure 7. Water-level regulation and diversion ratio control of MPC during the stable stage (February 2017).

Table 7. Performance under the steady water-level scenario (February 2017).

Metric	Natural Condition	MPC Regulation	Improvement/Compliance
Mean water level (m)	12.95	15.52	/
Maximum daily drawdown (m/d)	0.34	0.09	≤ 0.5 (compliant)
Max diversion ratio deviation (%)	41.5	3.8	$\leq 5\%$ (compliant)
Average control increment (m^3/s per 12 h)	/	9.7	/
Gate movements (count)	/	6	/

3.3. Performance Under Flood Discharge Scenario

Figure 8 shows the response during a sudden flood wave in the dry season. The MPC controller gradually opened the gates to release water while strictly respecting the daily drawdown limit (maximum observed 0.49 m/d). The diversion ratio deviation remained below 5% (maximum 4.9%), and the total outflow was allocated according to the branch discharge capacities. On 22 March, when the Waizhou flow peaked at $2050 \text{ m}^3/\text{s}$, the South

and North branches reached their maximum flow capacities, demonstrating that the MPC controller properly enforces hydraulic constraints. Table 8 summarises the performance.

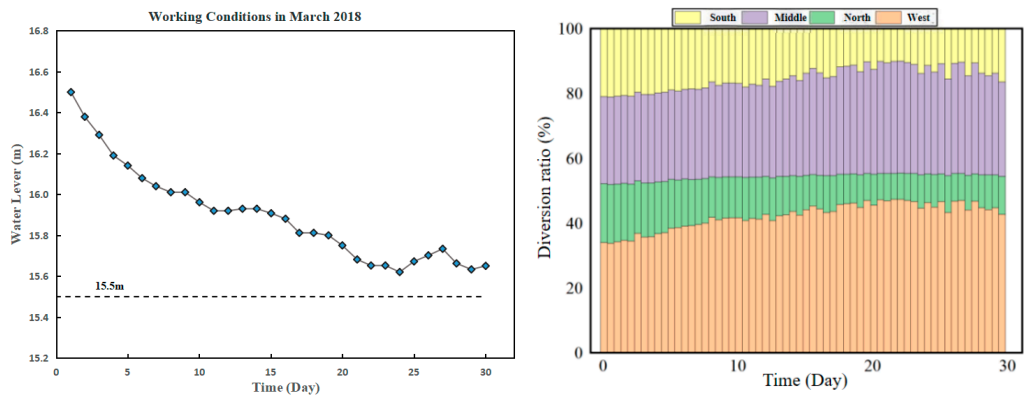


Figure 8. Water-level regulation and diversion ratio control of MPC during the flood discharge scenario (March 2018).

Table 8. Performance under the flood discharge scenario (March 2018).

Metric	Natural Condition	MPC Regulation	Improvement/Compliance
Mean water level (m)	13.68	15.45	/
Maximum daily drawdown (m/d)	1.58	0.49	≤0.5 (compliant)
Max diversion ratio deviation (%)	35.2	4.9	≤5% (compliant)
Average control increment (m ³ /s per 12 h)	/	51.2	/
Gate movements (count)	/	22	/

Across all three scenarios, the MPC framework consistently satisfied the following operational constraints: daily water-level variation ≤ 0.5 m/d, diversion ratio deviation $\leq 5\%$, and moderate control activity (6–22 gate movements over 30 days). The results confirm that the offline-optimised control sequences effectively mitigate the spatiotemporal hydrodynamic imbalance in the Lower Ganjiang River.

4. Discussion

4.1. Advantages of the Proposed MPC Framework

The proposed MPC framework integrates an improved integral time-delay model with rolling-horizon optimisation that explicitly considers flow propagation delays, branch discharge limits, and water-level variation constraints. Compared with the current threshold-based hysteretic operation (Section 2.1.2), the MPC controller proactively adjusts branch discharges to maintain the target water level while optimising diversion ratios. The validation results (Section 3) demonstrate that the framework achieves:

- (1) Water-level stabilisation within 15.5 ± 0.2 m under all three scenarios;
- (2) Compliance with the daily drawdown limit (≤ 0.5 m/d) and diversion ratio deviation ($\leq 5\%$);
- (3) A 21.3% reduction in water-level fluctuation (peak-to-peak) during the storage scenario compared to the natural state.

These results confirm that the MPC framework can effectively mitigate the spatiotemporal hydrodynamic imbalance in the Lower Ganjiang River.

4.2. Comparison with Alternative Control Strategies

To contextualise the performance of the proposed MPC framework, we qualitatively compare it with the following three alternative approaches commonly used in river regulation:

- (1) Current hysteretic rule-based control (Section 2.1.2): reacts only when the Waizhou water level crosses 15.5 m. It suffers from time lags, overshoot, and oscillations. No multi-objective coordination is included, and gate movements are frequent and not optimised.
- (2) PID control: A proportional–integral–derivative controller could continuously adjust gate openings to reduce water-level error. However, the long and variable time delay (≈ 2 h) causes integral windup and oscillations. Moreover, a single PID loop cannot simultaneously enforce diversion ratio constraints or branch discharge limits.
- (3) Static optimisation (e.g., solving optimal diversion ratios offline and applying them as fixed rules): this approach can balance flow distribution under average conditions, but it cannot adapt to inflow variations or respect daily water-level change limits. The MPC framework, by contrast, recomputes the control sequence every 12 h based on updated inflow forecasts, providing adaptability.

The proposed MPC framework therefore offers distinct advantages as follows: predictive feedforward compensation for delays, explicit handling of multiple constraints, and rolling-horizon adaptation to changing inflows.

4.3. Practical Limitations and Their Implications

The current implementation has several limitations that must be acknowledged explicitly.

Incomplete state update. A core component of true MPC is the state-update step, where the model's predicted state is corrected using real-time measurements (e.g., water-level feedback) before the next optimisation. In our offline validation, the controller did not receive live sensor data; instead, it ran in an open-loop manner using historical inflow sequences. Consequently, this study provides a framework for real-time regulation with offline validation, rather than a deployed real-time system. Future work must integrate the controller with an online data stream (e.g., from the Jiangxi Provincial Hydrological Monitoring Centre) to close the feedback loop.

Assumptions on gate dynamics. The model simplifies gate control to direct discharge manipulation because the actual discharge coefficients of the Nanchang Water Control Project are not yet available (the project is under construction). Once the project is completed and field data become available, the model should be re-calibrated to include realistic gate-discharge relationships. This will improve the accuracy of the control sequences.

4.4. Future Work

Instead of speculative proposals such as digital twins or graph neural networks, we outline a concise, actionable plan as follows: integrate the MPC framework with real-time water level and discharge telemetry from the existing hydrological monitoring network, implement the state-update mechanism, and test the controller in a hardware-in-the-loop or small-scale field pilot; quantify the impact of inflow forecast errors (0–30%), model parameter uncertainties, and measurement noise on water-level tracking and constraint satisfaction; perform a quantitative benchmark against a well-tuned PID controller with Smith predictor and against static rule-based operation using the same validation scenarios; and explore faster solvers (e.g., OSQP or ACADOS) to reduce the computation time below 1 s, enabling shorter control cycles if required. These steps will transform the current offline framework into a practical real-time control system.

5. Conclusions

This paper proposes a hydrodynamic regulation framework that couples an improved integral time-delay model with model predictive control (MPC). A nonlinear state-space equation is constructed with multi-objective constraints (water-level tracking error, discharge deviation, and control increment). The rolling-horizon optimisation is solved using the CasADi-IPOPT toolchain. The framework is validated offline at the Nanchang Water Control Project in the Lower Ganjiang River. The main conclusions are as follows:

- (1) Control sequence reconstruction experiments based on historical flood processes show that when MPC offline optimisation results are input into the MIKE21 hydrodynamic model, the simulated water level and the optimised sequence exhibit highly consistent fluctuation trends, confirming that the ID model accurately characterises the dynamic response of complex river network systems.
- (2) Under three typical scenarios (water storage, steady water level, and flood discharge), the MPC controller stabilises the Waizhou water level within 15.5 ± 0.2 m while satisfying daily water-level variation ≤ 0.5 m/d (safety constraint) and diversion ratio deviation $\leq 5\%$ (optimisation target). These results demonstrate the effectiveness of the offline-optimised sequences.
- (3) Through receding horizon optimisation and feedforward prediction based on inflow forecasts, the system adaptively adjusts branch diversion ratios, achieving a spatiotemporally balanced hydrodynamic distribution across the four branches of the Lower Ganjiang River under natural inflow heterogeneity (range 428–3427 m³/s).
- (4) Compared qualitatively with the current hysteretic control strategy, the MPC framework proactively compensates for time-delay effects, eliminating water-level overshoot and oscillation (e.g., proactive buffer adjustment in the storage scenario). It ensures ecological diversion ratios while reducing gate operation frequency, providing a promising framework for advanced regulation of complex river networks.

Author Contributions: Conceptualization, L.T.; methodology, Z.H.; software, X.Z.; validation, Z.H.; formal analysis, S.Z.; investigation, X.Z.; data curation, S.Z.; writing—original draft preparation, S.Z.; writing—review and editing, Z.H.; visualisation, X.Z.; supervision, L.T.; project administration, L.T.; funding acquisition, Z.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Key Research and Development Programme of China (No. 2022YFC32060301), Science and Technology Project of Jiangxi Provincial Department of Water Resources (No. 202426ZDKT24).

Data Availability Statement: All data of the model used in this research can be requested from the corresponding author through the indicated e-mail.

Conflicts of Interest: The authors declare no conflicts of interest.

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