Automated real-time reservoir operation based on runoff forecast and mathematical optimization: current state-of-the-art with a case study in India

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Abstract. Automated real-time reservoir operation has emerged as a critical solution for optimizing water resource management in an era of increasing climate variability and extreme weather events. While manual dam operations often rely on rule-based approaches and operator intuition, they are prone to errors, particularly during emergencies. Advances in short-term runoff forecasting and mathematical optimization offer transformative potential to address these challenges by enabling data-driven decision-making. This paper explores the integration of runoff forecasts with the WEB.BM reservoir optimization model to achieve efficient and reliable dam operations, with a case study focusing on the Damodar River Basin in India. The case study presents preparation for the integration of a runoff forecasting model developed by AECOM with a reservoir optimization framework tailored for the Damodar Valley Corporation (DVC) reservoir system. The study utilizes historical flood events and a 6-hour timestep to test the combined framework. The optimized model, configured for the basin’s unique hydrology, subdivides the catchment into key sub-regions to align with the forecasting model and incorporates hydrological channel routing to simulate flow dynamics accurately. Testing scenarios include three historical floods (2000, 2006, and 2009) with forecast horizons of 1, 2, and 3 days, assessing the model’s ability to maintain downstream flow within the safe channel capacity of 2850 m³/s at Jamalpur. The findings demonstrate significant improvements over historical operations, with peak flow reductions of up to 50 percent achieved through optimized pre-flood and automated drawdowns conducted within 1, 2 or 3 days before the incoming flood, thus mimicking responses to the information from the runoff forecasting system. The model effectively balances reservoir releases, downstream channel flows, and tributary inflows, mitigating flood risks even under conservative assumptions of starting storage levels. For the 2009 flood, the model reduced peak flows at Jamalpur from 7649 m³/s to 5500 m³/s, 3517 m³/s and 2850 m³/s for the respective 1, 2 and 3-day available runoff forecasts. The other two historical floods in 2000 and 2006 required only 1 and 2 days of respective flood forecasts to keep downstream flows within the threshold boundaries, thus eliminating flood damage. This showcases the model’s ability to dynamically adapt reservoir operations to evolving inflow conditions, significantly outperforming traditional rule-based systems. The uniqueness of this approach lies in its integration of real-time data acquisition systems (RTDAS), runoff forecasting, and optimization within a single operational framework. This eliminates reliance on static rule curves, offering a scalable and adaptable solution for multi-reservoir systems worldwide. With ongoing advancements in remote sensing and forecasting technologies, the framework presented here serves as a template for modernizing dam operations and enhancing flood resilience globally. This research underscores the potential for transformative improvements in water resource management through predictive and automated solutions.

Keywords: Dynamic Channel Routing, Model Predictive Control, Real-Time Data Acquisition Systems, Real-Time Reservoir Optimization

1 Introduction and literature review

Efficient and reliable reservoir operation is critical for water resource management, balancing flood control, irrigation, hydropower generation, and municipal water supply. As climate-driven extreme weather events grow in intensity and frequency, traditional manual and rule-based reservoir operations reveal their limitations. These methods often rely on static operating rules and operators' intuition, which can lead to suboptimal decisions, especially during emergencies. The integration of real-time runoff forecasting and mathematical optimization offers a transformative opportunity to address these challenges by enabling dynamic, data-driven decision-making. With more than 6,000 large dams, India faces acute challenges in managing floods and droughts. The Damodar River Basin, located in eastern India and known for its flood-prone nature, served as a case study highlighting the complexities and potential of modern reservoir optimization techniques. With multi-reservoir systems designed for flood mitigation, hydropower, and irrigation, optimizing the basin's operations has significant implications for disaster risk reduction and sustainable water management.

Various models have been developed for reservoir optimization, ranging from traditional rule-curve-based approaches to advanced mathematical programming methods. Rule-curve models, though widely used, are static and often fail under dynamic inflow conditions. Various optimization strategies have been used in the past. Among else, these include Linear programming (LP), Dynamic programming (DP) and numerous heuristic solvers that employ various evolutionary strategies that mimic the evolution and behaviour of biological systems. A comprehensive coverage of the state-of-the-art optimization solution strategies is provided by Rardin [1]. Although there have been numerous attempts to apply various solution strategies in reservoir optimization, there is no universally accepted tool among practitioners that can handle all existing complexities of modern water resources systems. As documented by Ilich and Todorović in their recent literature review paper [2], only a small fraction of 2.5% of all publications have been applied to the real world in some way by the relevant reservoir management agencies. Reliable runoff forecasts are quickly improving, using the satellite-based data obtained through remote sensing and sophisticated algorithms that utilize various forms of machine learning and artificial intelligence [3]. The solution concept presented here is known as the Model Predictive Control (MPC) [4], and it relies on the combined use of runoff forecasts and mathematical optimization. The process eliminates the need to use the "upper rule curves" on reservoirs, thus offering a compromise solution between hydropower producers and dam operators, since it does not require lowering the FRL over the entire wet season, but only during the flood events. The emergence of this solution approach was foreseen long before the development of the internet and the currently available computer power by Yazicigil et al. [5], which later gained further momentum with the improvements in remote sensing and runoff forecasting technology, as boldly forecasted by Howard in his paper titled "Death to Rule Curves" [6]. Other early attempts include Wasimi et al. [7] who examined the short-term operation of multi-reservoir systems during floods to regulate reservoirs and minimize flood damage, while Karamouz et al. [8] developed a Bayesian stochastic dynamic programming model, incorporating forecast uncertainties and updating probabilities using Bayesian decision theory, which provided a robust framework for managing reservoirs under uncertain conditions.

Other researchers have explored optimization techniques such as genetic algorithms, which Merabtene et al. [9] utilized for drought risk management in water resource systems. Hsu et al. [10] developed a real-time flood control operation model specifically designed for typhoon-induced floods, while Chang [11] implemented a penalty-type genetic algorithm for rational reservoir flood operation. Wei et al. [12] focused on real-time operations for flood control using the tree-based release rules. Xu et al. [13] expanded on these advancements by proposing an integrated flood risk identification model for multi-reservoir systems, emphasizing forecast uncertainties.

Most of the above publications focus on the importance of runoff forecasting skills, while the inclusion of complex flood routing constraints into mathematical optimization gets very limited attention. Yet, this aspect of optimal flood operation is just as important as is the accuracy of the forecast, since the optimization program must include the differential equations of flow as constraints to optimization in order to properly account for flood propagation mechanisms. There is only a handful of tools that focus on modelling capabilities to generate globally optimal solutions such as the WEB.BM model used in this study [14], and their real-world applications are covered in a tiny fraction of the available literature [14, 2]. The principal reason is that most publications ignore the routing transformation as constraints embedded in dynamic optimization networks, especially when minimizing flood damage is not the only objective. This study aims to address the proper inclusion of difficult channel routing constraints within the multi-reservoir framework that could also be used within the multi-purpose operational framework [15].

This study uniquely integrates short-term runoff forecasting with real-time reservoir optimization, providing a seamless framework tested using historical flood events in the Damodar Basin. By incorporating dynamic channel routing transformations at 6-hour intervals into the optimization process, the study enhances operational accuracy and offers a scalable solution for multi-reservoir systems worldwide. The results demonstrate the effectiveness of pre-flood drawdowns enabled by optimization, significantly reducing peak flows and downstream flood risks. With advancements in remote sensing and real-time data acquisition systems, this approach modernizes reservoir operations to meet contemporary challenges. By combining predictive models with optimization, this research not only enhances flood resilience but also contributes to global efforts for sustainable water resource management.

2 Study objectives and methodology

The principal objective of this study is to verify the WEB.BM model capability to manage floods subject to the available short-term forecasts with 1, 2 or 3 days lead time by using the Damodar River Basin in India as a case study. The approach begins with data preparation, where historical inflow and outflow records for key reservoirs, including Tilaiya, Konar, Maithon, and Panchet, are collected. The eventual use of the model in real-time will be based on the short-term runoff forecasts with 1, 2, and 3-day horizons generated using the runoff forecasting model based on weather forecasts and rainfall-runoff relationships established through calibrated hydrological simulations. The runoff forecasting model is still under development [16]. The integrated model will be tested using real-time forecasts over the next three monsoon periods. In the absence of real-time data, a hindcast approach is used in this study where historical daily data are interpolated into 6-hourly intervals assumed to be available much like the 6-hourly runoff forecasts will be available after the forthcoming integration.

2.1 Hydrological channel routing

Most hydrology textbooks explain hydrological channel routing as a transformation of inflow into a river channel into outflow by using the Muskingum linear model [17], while ignoring the fact that this model can only be calibrated for a single hydrological event of a specific and known magnitude by defining the routing coefficients that correspond to the average travel time a flow along a given river reach during the specific flood. The problem is that the magnitude of future floods is not known, thus requiring a non-linear routing scheme where the routing coefficients are determined as a function of travel time, which is a function of the channel flow. An elegant solution to dynamic flood routing with coefficients that vary as a function of the channel flow has been around for over 50 years as defined by Williams [18], although often overlooked by the mainstream textbooks on hydrology. The first significant application of the Williams routing equation was originally developed by the US Corps of Engineers, the **S**tream **S**ynthesis **A**nd **R**eservoir **R**outing (SSARR) [19]. A major advantage of this model is that it does not need any channel geometry as input data, nor does it require Manning’s coefficients. Once the travel time vs flow relationship is available, the calibration consists of deciding how many sequential phases a given river reach should be divided into, which is conducted using repeated simulation trials until the observed downstream hydrograph closely matches the simulated channel outflow. As with the other river routing methods, the governing equation is related to channel storage change over a time step, which is a function of average inflow and outflow:

$$\frac{I_{t-1}+I_t}{2} - \frac{O_{t-1}+O_t}{2} = \frac{\Delta S}{t} \tag{2}$$

By subtracting both sides of the above equation with Ot-1, multiplying by t/(Ot-Ot-1) and by letting ΔS/(Ot-Ot-1) = TS, the above equation becomes:

$$O_t = \frac{\left[\frac{I_{t-1}+I_t}{2} - O_{t-1}\right]\cdot t}{TS+\frac{t}{2}} + O_{t-1} \tag{3}$$

where the term TS represents the average travel time along a river reach for given flow conditions, evaluated either by reading from the TS vs Q table or by using a functional form of the travel time vs flow curve as:

$$TS = \frac{Kts}{\left(\frac{O_{t-1}+O_t}{2}\right)^n} \tag{4}$$

The routing coefficients Kts and n must previously be determined by finding the best-fit curve for a given set of the available (TS, Q) coordinates. In physical terms, *Kts* represents the length of the river reach, while the exponent *n* is related to the slope of the reach. Alternatively, TS can be determined for any given flow rate by linear interpolation from a table of (TS, Q) points obtained from observations. In the above definition of TS, the base of the denominator:

$$\frac{O_{t-1}+O_t}{2} \tag{5}$$

which is powered by exponent *n* that represents the estimate of the average outflow from a given reach during the time step *t*. For sufficiently small time steps, the variations of flow are also small, so it is common to assume $O_{t-1} = O_t$. The model typically conducts two to three iterations by updating O_t and recalculating the travel Ts time by using the updated coefficients before it converges to the final solution. Expression (5) can also be converted to the following form:

$$O_t = \frac{t}{2T_S+t} I_{t-1} + \frac{t}{2T_S+t} I_t + \frac{T_S-t/2}{T_S+t/2} O_{t-1} \tag{6}$$

The above form is identical to the well-known Muskingum linear routing form:

$$O_t = C_1 I_{t-1} + C_2 I_t + C_3 O_{t-1} \tag{7}$$

It can be noted that the SSARR routing coefficients listed in equation (6) sum up to 1 (i.e. C1+C2+C3 = 1), which is also the condition for the Muskingum routing coefficients. In other words, the SSARR routing method uses an identical formula as does the Muskingum routing procedure, except that the values of the routing coefficients *Ci* are determined in a different way, which has some obvious advantages:

- The only required information for the values of routing coefficients is the time of travel vs flow relationship for a given river reach and the length of the calculation time step. No other data related to the channel geometry, gradient or roughness are required.
- The values of routing coefficients undergo dynamic adjustments as the modelling moves through different flow regimes between dry seasons and wet seasons, in a much more elegant and precise way than in the case of using the classical Muskingum method, which is used with fixed coefficients developed for a specific hydrological event.

Implementations of the SSARR method may rely on different estimates of the average channel flow during a given time step. Input data requirements include the time of travel versus the flow table for a river reach, where the time of travel is given in hours while flows are given in m^3/s. To ensure the numerical stability of this approach, the calculation time step is selected such that the travel time along the reach is at least more than twice the length of the calculation time step, i.e. Ts ≥ t/2. If this condition is not satisfied, the routing coefficients that multiply I_t and I_{t-1} become greater than 0.5, and the mass conservation rule which requires that the sum of all three coefficients be equal to 1 is no longer maintained. Similar conditions exist in the classical Muskingum method. Since the routed flows are not precisely known in advance, the SSARR routing method is iterative, requiring recalculation of the routing coefficients as a function of Q_t at the end of each iteration until the convergence criteria are satisfied. The WEB.BM model executes several repeated runs for each simulated time step by using the steady-state solution as the initial starting solution, which is then corrected for the effects of routing from one iteration to another until the convergence criteria are fulfilled. This approach is particularly useful when solving several time steps simultaneously since it moves the reservoir releases earlier in time in each iteration such that the effects of routing can be combined with the operational objectives.

2.2 Mathematical definition of the problem

If the optimization problem is defined using maximization of benefits in LP formulation, the pricing vector P_i associated with flood damage would have a negative sign for any flow that exceeds the full bank channel capacity, indicating that benefits would be maximized if the reservoirs could be operated such that the overbank spills are minimized or completely avoided if possible. The objective function would be applicable for all time steps that are solved simultaneously, and for all river reaches that may be associated with the flood damage, which explains the double summation over both time (t) and space (i):

$$Objective\ Function = Max \sum_{t=1}^{m} \sum_{i=1}^{l} Q_{i,t} P_i \tag{8}$$

Subject to:

$$\sum_{i=1}^{m} A_i Q_i = b_n \qquad \forall\, i, n \in N \tag{9}$$

$$\begin{aligned} &0 \leq Q_{i,t} \leq U_{i,t} \\ &0 \leq Q_{i,t} \leq f\left(Q_{k,t}\right) \qquad \forall\, i, t \end{aligned} \tag{10}$$

Equation (9) represents the mass balance at network node n, with A_i representing the incidence matrix coefficient that is typically equal to either -1, 0 or 1, with -1 and 1 denoting the incoming and outgoing flows for network arcs that are associated with a given node n, while b_n represents local inflow into node n, which is set to zero for nodes that have no tributary inflows. Index i represents each link (also known as “arc”) in the network. Expression (9) is applied to all nodes in the network. Furthermore, when solving multiple time step optimization, the mass balance equation (9) is applied to each node n in the network and to each time step t over the selected solution horizon. Expression (10) represents the upper bound on flows, which can be either set to constants $U_{i,t}$ representing for example the maximum storage or canal capacity that should not be exceeded, or it can be defined as a function of flow in some other network component k, such as the channel flow relationship defined by the channel routing equation.

2.3 Understanding the Weight Factors

The purpose of the weight factors is to define the importance of allocating water to each model component, where some components may be broken down into several operating zones to enable the use of LP. The conceptual use of weight factors is explained in Figure 1 which shows two reservoirs, three diversion canals and several river reaches.

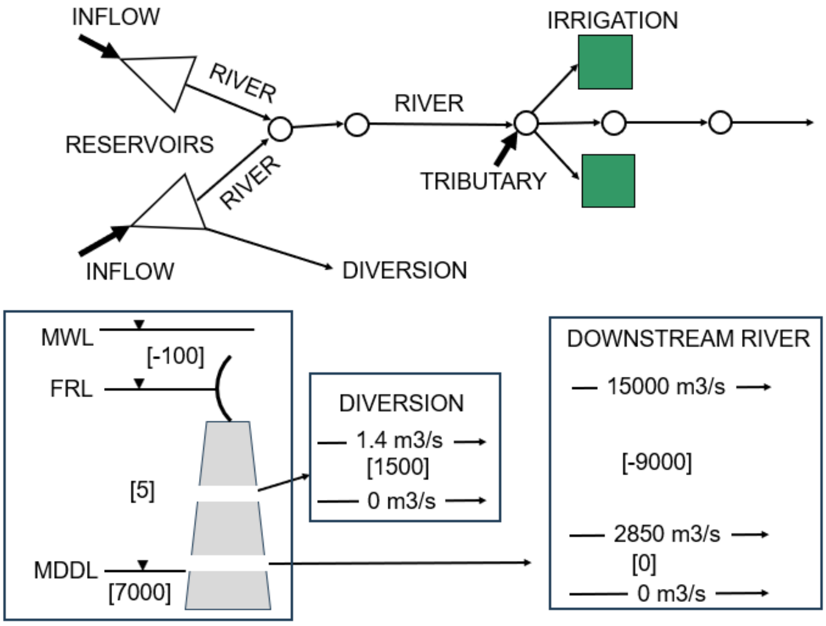

Figure 1. Schematic representation of weight factors

There are typically at least three operating zones associated with reservoirs, representing the dead storage zone, conservation zone, and flood storage zone, with their respective weight factors of 7000, 5 and -100 shown in Figure 1. The mechanism of setting up and using these weight factor values is explained further below. There is only one operational zone for a diversion canal that takes water out of storage, with its corresponding weight factor of 1500.

The most downstream river reach for which flood protection needs to be implemented through optimal reservoir operation has two zones in the above example. The zone with flow values up to 2850 m^3/s has a weight factor of zero, while the flow zone that accepts any flows above 2850 m^3/s has a weight factor set to -9000. Since the model uses maximization of the objective function, the high negative value signifies a highly undesirable condition of allocating flows to this zone. Several important rules should be noted:

- Each zone has a positive upper bound which is greater than the lower bound
- Weight factors are assigned to each zone arbitrarily by the user
- There is more than one set of weight factors that will give identical flow allocation

The weight factors represent the importance of maintaining desired flow levels. For example, the storage level should never drop below the Maximum Draw Down Level (MDDL), also known as the top of the dead storage zone, hence the high priority of 7000 applied for each unit of storage below MDDL. One can think of the weight factor as the value of water in monetary units per m^3 of storage in a particular zone, or better yet per m^3/s of flow, since storage is internally converted to the units of flow by dividing the target storage with the length of the simulated time step. For storage between MDDL and the Full Reservoir Level (FRL), the weight factor is only 5. Since the objective is to maximize the product of flow allocated to each zone with its related weight factor, the model would allocate water from storage to the diversion canal where the weight factor is 1500, much larger than the priority of storing water in the reservoir. Hence, the final allocation in each time interval will take water from storage, where its value is only 5, to the diversion canal, where its value is 1500. Diversion canals can be used to supply municipalities or irrigation. The upper bound of the diversion canal may represent canal capacity, or it may represent water demand as is the case above, where the diversion limit set to 1.4 m^3/s may correspond to the municipal demand in one particular time step. It is easy to see that any solution that keeps the storage at FRL, meets the diversion requirement from the reservoir and keeps the downstream flow below 2850 m^3/s is optimal, since it maximizes the value of the objective function.

If the reservoir starts at FRL and the reservoir inflow is greater than 2850 plus the diversion target, the downstream channel will begin to spill, which marks the beginning of flooding. The cost of flooding is very high (-9000 per m^3/s, where the negative sign indicates a monetary loss per unit of flow above the threshold). Consequently, the model would not flood the river valley right away, but would rather begin to fill the flood storage zone at the reservoir, which has a weight factor of -100. This also represents a loss (reduction) to the value of the objective function which is to be maximized by -100 per unit of flow, but this loss is not as large as the loss of -9000 per unit of flow associated with spills at the downstream channel. In other words, the model will first put extra inflow into the flood storage zone above FRL before allowing downstream channel spills. When solved simultaneously for several 6-hourly periods, the model begins to release flows from storage (without violating the downstream limit of 2850 m^3/s) before the peak inflow arrives, thus increasing the flood storage zone dynamically on the basis of inflow forecast, starting storage levels and all other runoff forecast on the tributaries upstream of the critical river reach which is designated for flood protection.

3 Case study -- development and results of modelling scenarios

Figure 2 shows the current layout of the system, which ends before the bifurcation near Jamalpur. It is felt that keeping the flows within full bank capacity at Jamalpur would be the best way for reservoirs to minimize the negative effects of downstream flooding. The following labels are used in the schematic in Figure 2:

- Blue lines represent natural water courses (river reaches and tributaries)
- Blue coloured areas represent the surface water of the reservoirs created by dams
- Red lines with arrowheads represent diversion canals
- Green areas in square format represent irrigation blocks

It should be noted that all reservoirs have flood storage zones, since their initial design included flood management as one of the operational objectives. The remaining objectives are water supply to municipalities, industry and irrigation, along with the generation of power at Maithon, Panchet and Tilaiya dams with installed capacities of 60, 80 and 4 MW, respectively. The intent of this modelling exercise was to investigate possible responses of the model to the known inflows assuming 1, 2 or 3-day inflow forecasts. Three distinct historical floods from the historical years 2000, 2006 and 2009 were selected for this purpose. Floods in 2000 and 2006 were recorded in the second half of September, while the 2009 flood was recorded in

August. Designation STO-1, STO-2 or STO-3 implies a solution based on the assumed runoff forecasting horizon of one, two or three days ahead. The goal of the model is to find the best way to operate the four reservoirs to maintain the downstream flow at Jamalpur at or below 2850 m^3/s, which is its current full-bank capacity. The model minimizes the deviations from this flood threshold when they are inevitable. All model runs were executed assuming the starting storage is at the Full Reservoir Level (FRL). The distance between Tilaiya and Maithon reservoirs along the river thalweg is subdivided into four sub-catchments, each one represented by two sequential river reaches and a tributary at the end of the reach. The two river reaches are used to implement hydrological river routing depicted for some of them in Figure 2.

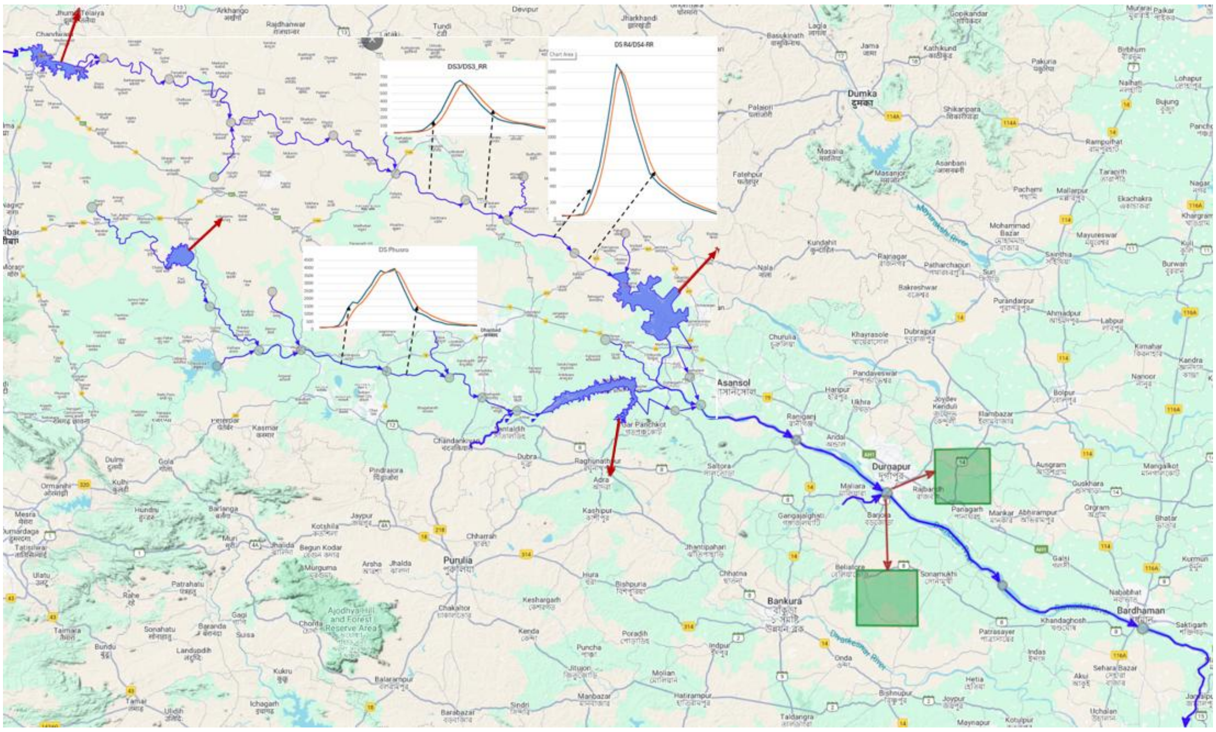

Figure 2. Damodar River Basin modelling schematic

Reservoir operation is aimed at minimizing flows above 2850 m^3/s at the Jamalpur located at the downstream end of the system. Finding the right reservoir releases is complicated by the transformation of flow caused by river routing processes on river reaches both upstream and downstream of the reservoirs, by the influx of flow from the tributaries and by reduction at diversion canals. There is often a substantial local inflow downstream of the reservoirs which must be taken into account when setting the reservoir releases, along with all other constraints related to river routing throughout the river basin. The starting reservoir levels were set to correspond to the full supply levels, which is the most conservative assumption. From the three historical floods analyzed, the worst flood was in 2009, resulting in a mean daily maximum of 7649 m^3/s. Assuming only 1-day runoff forecast, the model managed to lower the flood peak to 5500 m^3/s at Durgapur and 5000 m^3/s at Jamalpur.

There is still some violation of the flow target of 2850 m^3/s at Jamalpur with a 2-day forecast scenario for 2009 flood that reached 3517 m^3/s as seen in Figure 4, but once the 3-day forecast is introduced the flood damage completely disappears, as shown in Figure 5.

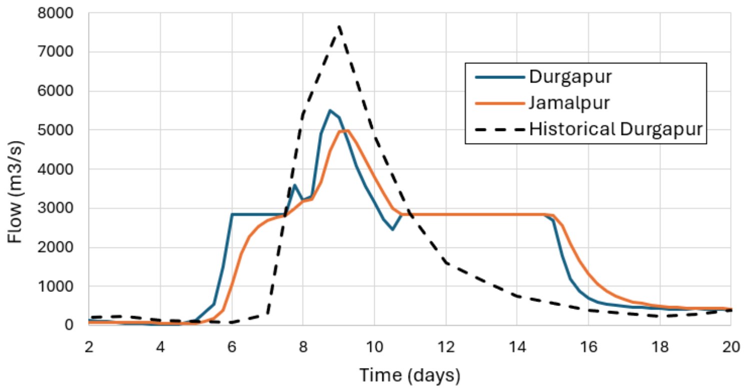

Figure 3. Historical and simulated 2009 flood at Durgapur Barrage, 1-day forecast

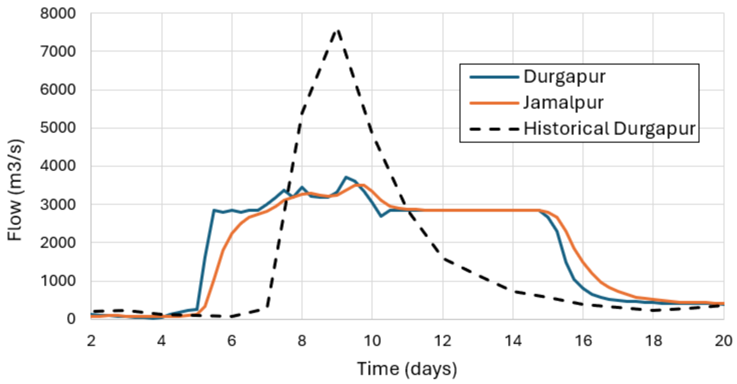

Figure 4. Historical and simulated 2009 flood at Durgapur Barrage, 2-day forecast

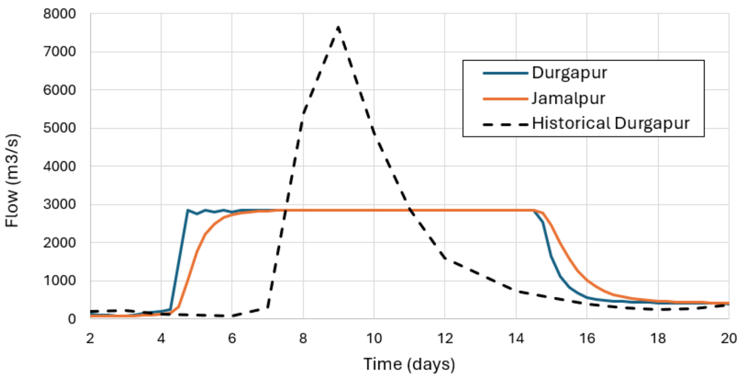

Figure 5. Historical and simulated 2009 flood at Durgapur Barrage, 3-day forecast

The above improvements are possible by initiating pre-flood drawdown by the model which results from the use of optimization within the multiple time step solution framework. The longer the forecast, the larger the pre-flood drawdown. Figure 6 shows the Maithon reservoir levels for all three scenarios (1, 2 and 3-day forecasts). A similar trend can be observed with the Panchet Reservoir levels in the three scenarios for the 2009 flood, as shown in Figure 7. Figures 8 and 9 show the 2006 flood at Durgapur and Jamalpur for 1 and 2-day forecasts. In this case, the 2-day forecast only marginally exceeds the flood threshold, while the 2000 flood could have been handled with a single-day forecast, as shown in Figure 10. Given that the tributary inflows and diversions are subject to fluctuations, the reservoir releases also show fluctuations. This results in the plots of the time series of reservoir elevations that do not look smooth, as seen in Figures 6 and 7. However, this is an expected result from combining all available variables and routing transformations that must be included in the model.

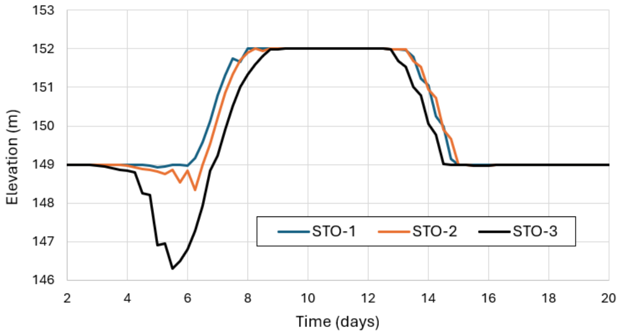

Figure 6. Maithon storage, 2009 flood, 1,2 and 3-day forecasts

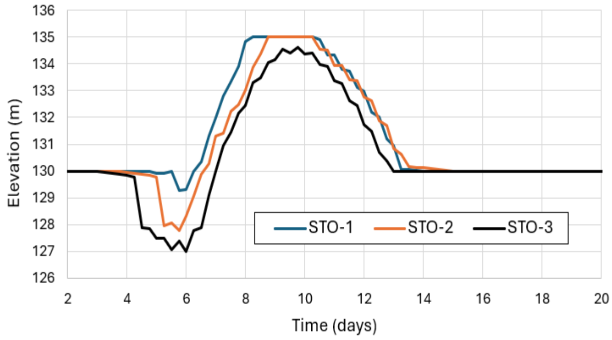

Figure 7. Panchet storage, 2009 flood, 1,2 and 3-day forecasts

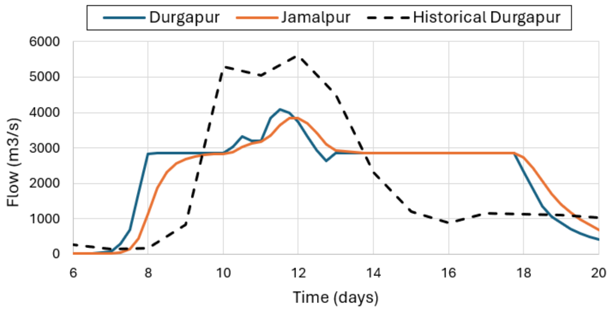

Figure 8. 2006 flood at Durgapur Barrage, 1-day forecast

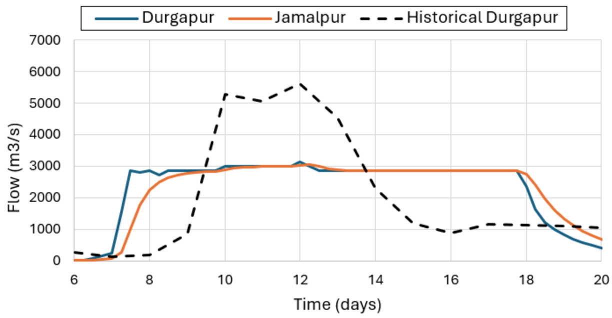

Figure 9. 2006 flood at Durgapur Barrage, 2-day forecast

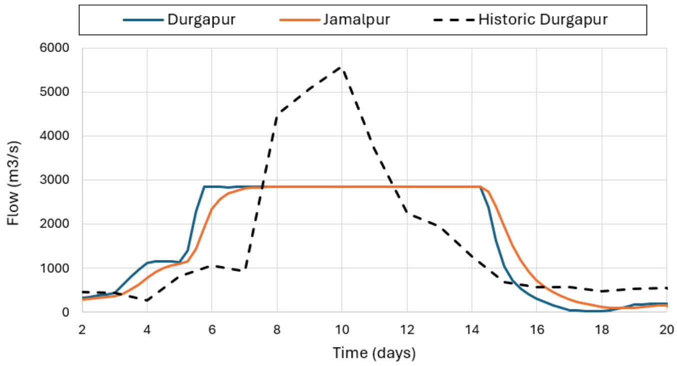

Figure 10. 2000 flood at Durgapur Barrage, 1-day forecast

4 Conclusions and Recommendations

The numerical tests presented above are based on hindcast historical inflows available for 1, 2 or 3 days ahead. The model shows significant improvements compared to historical operations as a function of the length of the forecasting horizon. The ability to simultaneously balance multiple reservoirs based on their unique inflow hydrographs and common downstream objectives to minimize flood damage can be significant in large river basins with multiple reservoirs, showing a reduction of around 50 percent compared to the historically recorded peak flows at Durgapur Barrage. The use of forecasting models should be verified in real-time by taking advantage of the RTDAS connected to the existing SCADA systems. The work presented here shows that one of the two key components of automated reservoir operation is readily available and available for testing using historical data. Future tests should involve the use of real-time data along with testing its integration with the runoff forecasting models.

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