Optimization of Static Operating Rule Curves for Gated Spillways of Dams Under Flood Conditions

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ABSTRACT

Optimal operation of dam reservoirs plays a vital role in mitigating flood-induced damages. This study introduces a novel approach to develop static operating rules for gated spillways, aiming to derive a set of robust operational policies that perform consistently across a wide range of flood scenarios without requiring complex real-time optimization. To this end, an integrated framework was developed by coupling a Genetic Algorithm (GA) with the Storm Water Management Model (SWMM), a dynamic hydraulic simulation model developed by the U.S. Environmental Protection Agency (EPA). The objective function was defined as minimizing the sum of peak outflows, and a comprehensive set of operational and safety constraints was incorporated to ensure the realism of the solutions. The results demonstrated that the derived optimal rules could reduce the peak outflow by 8% to 57% compared to the baseline scenario (fully open gates during floods), with an average reduction of 21.6% across the analyzed flood events. Performance analysis revealed that this success stems from an intelligent strategy based on the optimal utilization of the reservoir's storage capacity and controlled flow releases. By providing a set of fixed, operational, and efficient rules, this research offers a reliable tool to directly enhance the safety of downstream communities at no extra cost. Furthermore, its methodological framework is generalizable for developing similar operating policies in large, multi-reservoir systems.

KEYWORDS
Flood Control, Reservoir Operation, Genetic Algorithm, Static Operating Rules, Gated Spillways, SWMM, Hydraulic Modeling.

1. Introduction

The effective management of water resources and the control of floods are of escalating global importance, especially given the increased occurrence of extreme climatic events. Dams, as one of the most significant components of water infrastructure, fulfill a crucial function in water storage, power generation, and particularly in diminishing the damage caused by floods. However, optimizing the operation of dam reservoirs under flood conditions is a complex and multifaceted challenge. It requires accounting for diverse, and at times contradictory, objectives, hydraulic and operational limitations, and the intrinsic uncertainties associated with forecasting inflows. The body of research in this domain has undergone a notable transformation from classical models to integrated, intelligent frameworks. Initial studies, such as the work by Unver and Mays [1], were centered on nonlinear programming.

With subsequent growth in computational power, Genetic Algorithms (GA) and their derivatives emerged as principal instruments in this field. For example, Lei et al. [2] established the superiority of the multi-objective NSGA-II algorithm over single-objective GA in deriving operational rules. This trajectory continued with the development of other evolutionary algorithms like DREAM for tackling complex problems [3] and models based on game theory (MOGM) to manage conflicts among stakeholders [4]. Recent research efforts have increasingly focused on hybrid optimization algorithms. These approaches aim to combine the strengths of different metaheuristic methods while mitigating their individual limitations. For example, a novel hybrid algorithm known as F-HGAPSO integrates Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to address the issue of premature convergence and enhance peak flood reduction performance [5]. Another pivotal theme in this area is addressing uncertainty, especially concerning inflow prediction. Scholars have utilized a variety of methods for risk and uncertainty analysis, such as Copula-based Monte Carlo simulations [6], dynamic Bayesian networks [7], and vulnerability index analysis [8]. More recently, advancements in artificial intelligence have steered the focus toward employing deep learning models for uncertainty management. As an illustration, Xu et al. [9] put forward an optimization model for dam gate operations that handles prediction uncertainty via deep learning ensemble models; their results indicated a substantial reduction in peak flow and reservoir water level. Robust multi-objective optimization (RMOO) models have also been formulated for decision-making in uncertain scenarios, which mitigate system risk through optimized pre-discharges [10]. Beyond the algorithms themselves, there is a heightening focus on creating comprehensive and operational management frameworks. Research by scholars like Cheng and Chau [11] underscored the necessity of integrated management systems, while other studies have focused on optimizing complex systems that include cascaded reservoirs and flood detention areas [12-14]. Modern approaches, such as optimizing water pre-release with the aid of large-scale data, seek to generate greater vacant capacity in reservoirs ahead of severe flood events [15]. Moreover, extensive review studies conducted by Tariq et al. [16], Jain et al. [17], and Mehta et al. [18] have emphasized the significance of a risk-based approach, finding a balance between conflicting goals, and the imperative for real-time operations. In addition, research is trending towards dynamic decision-making for establishing the optimal reservoir water level in response to variable seasonal conditions, in order to simultaneously optimize resource utilization and flood preparedness [19]. Beyond operational optimization frameworks, accurate hydraulic characterization of gated structures remains a critical component of reliable flood routing and rule derivation. Several recent experimental and data-driven studies have focused on improving the prediction of discharge coefficients for various gate configurations. Laboratory investigations have demonstrated the influence of geometric features such as sills on radial gate discharge coefficients [20], while advanced machine learning approaches—including Gaussian Process Regression [21], genetic programming–based expert systems [22], multiple non-linear regression models [23], and hybrid artificial intelligence techniques such as SVM, ANN, RF, and related methods [24]—have shown strong predictive capability for sluice and oblique gate hydraulics. Furthermore, experimental validation combined with data-driven modeling has enhanced the reliability of discharge estimation for inclined slide gates under different hydraulic conditions [25]. These developments highlight the growing integration of experimental hydraulics and intelligent modeling approaches, which provide a stronger foundation for defining

operational rules in gated dam systems. Despite these wide-ranging advancements, a significant research gap remains: many advanced models necessitate real-time optimization and sophisticated forecasting systems, the implementation of which is arduous or unfeasible for many operational dams. In contrast, there is a compelling need to develop fixed, pre-defined, yet intelligent operating rules capable of delivering stable and dependable performance across a broad spectrum of flood scenarios, without requiring computationally intensive processes during a crisis. Gated dams present unique operational challenges compared to ungated (overflow) dams. Unlike ungated systems, where discharge is primarily governed by the reservoir water level and spillway geometry, gated dams require active and timely gate manipulation to regulate outflow. This introduces additional complexity, including the need for coordinated gate operations, rapid decision-making under uncertain inflow conditions, and the risk of operational or mechanical failure. In flood situations, improper gate management may lead either to excessive downstream discharge or to dangerous water level rise within the reservoir. Therefore, developing robust and predefined operating rules for gated systems is particularly important to enhance safety and reduce reliance on real-time subjective decisions. This research aims to bridge this gap by concentrating on gated dams. The principal objective of this study is the development and assessment of a suite of optimal and practical operating rules for the gated structures of a dam, utilizing a genetic algorithm and precise SWMM hydraulic modeling. The innovation of this research is centered on presenting a method to attain operating rules that exhibit robust performance under varied flood scenarios. This objective is realized through the formulation of an optimization problem with a "minimize the sum of peak outflows" objective function, as well as through the precise application and calibration of a comprehensive set of operational and physical constraints. This methodology results in the generation of logical and defensible rules, which can serve as a practical tool for dam managers and operators to enhance decision-making and augment safety under flood conditions.

2. Materials and Methods

2.1. Study Area

For this research, the Dez Dam and its reservoir were selected as the case study. Dez Dam is a double-arch concrete dam constructed on the Dez River, one of the most voluminous and sediment-laden rivers in western Iran. It is located 23 km northeast of Andimeshk in the Zagros Mountains (Figure 1). The construction of the dam was completed in 1962 (1341 in the Iranian calendar). The geographical location of the dam and its catchment basin is shown in Figure 1. With a height of 203 meters, it was considered one of the tallest dams in the world at the time of its construction. The primary objectives for its construction were to supply irrigation water for 125,000 hectares of downstream land, generate hydroelectric power, and control the region's seasonal floods.

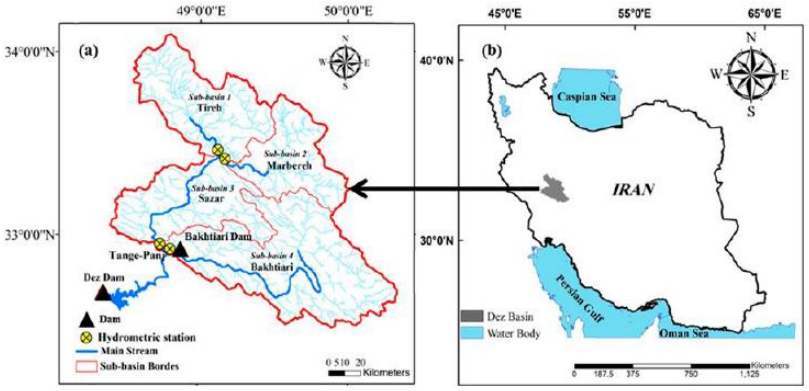


Figure 1: Location map of the Dez Dam and reservoir.

The dam has multiple outlet structures. To meet downstream irrigation demands, three conical valves were installed at an elevation of 222.7 meters, each capable of releasing 60 m³/s. However, these valves have been buried under heavy sedimentation since approximately 2001 (the year 1380) and have effectively lost their functionality. Two spillway tunnels, with diameters of 14 and 12.6 meters, are located at an elevation of 290 meters to discharge large floods, each capable of releasing a flow of 3000 m³/s. The dam's powerhouse, with eight 65 MW units, has a maximum energy production capacity of 520 MW, with its water supplied through two intakes at an elevation of 270 meters. Figure 2 shows a purely schematic (symbolic) arrangement of Dez Dam outlets and operational status (this figure does not reflect actual scale or exact component locations). Figure 3 shows the monthly inflow and outflow volumes for the Dez Dam reservoir between 1997 and 2015 (Persian years 1376 to 1394).

To evaluate and optimize the dam's performance under critical conditions, a set of significant historical flood events entering the reservoir was selected as the model's input scenarios. Figure 4 displays the hydrographs of these notable flood events. As can be seen, these events cover a wide spectrum of hydrological characteristics, from floods with a peak discharge of less than 1,000 m³/s to very large floods with peaks approaching 7,000 m³/s. This diversity in volume, shape, and timing of the flood peak clearly demonstrates the necessity of developing robust operating rules that can perform effectively against a wide range of threats.

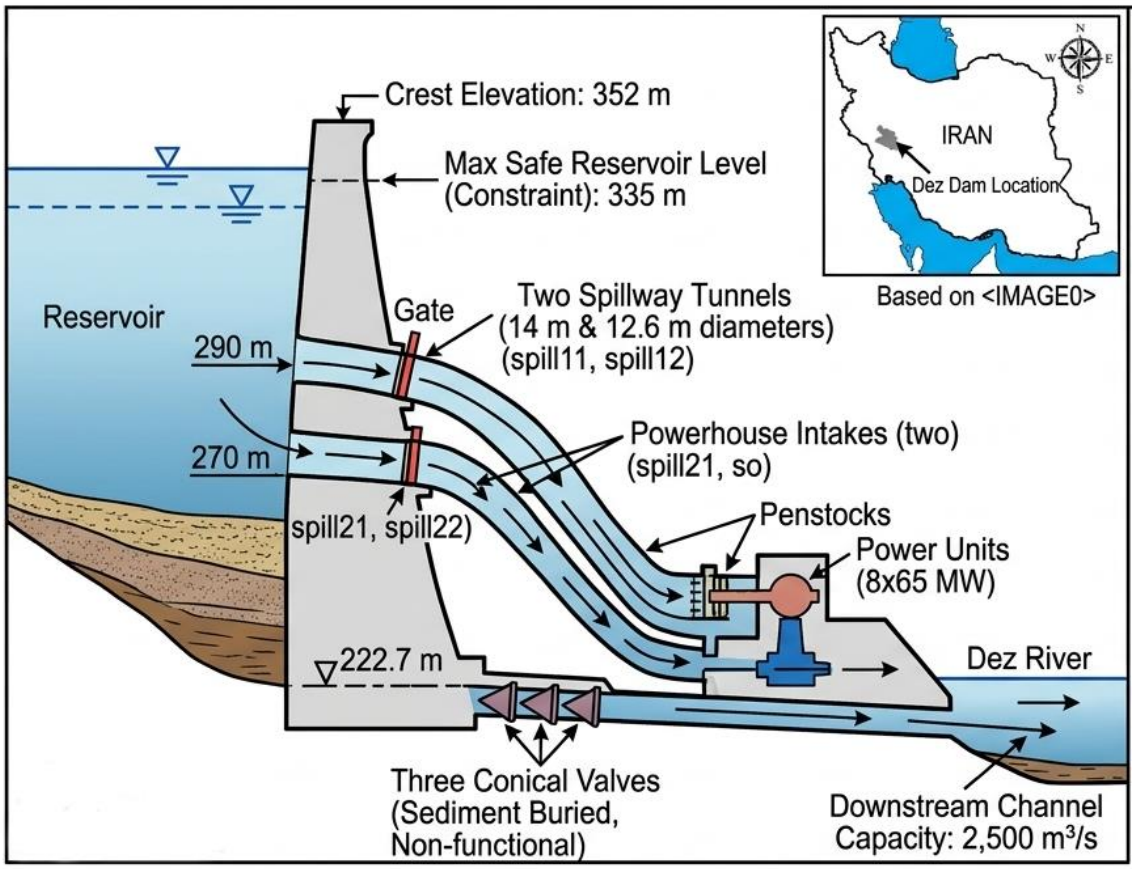


Figure 2: Schematic (symbolic) representation of Dez Dam outlet arrangement and operational status (Not to scale; does not represent actual dam geometry or exact component locations)

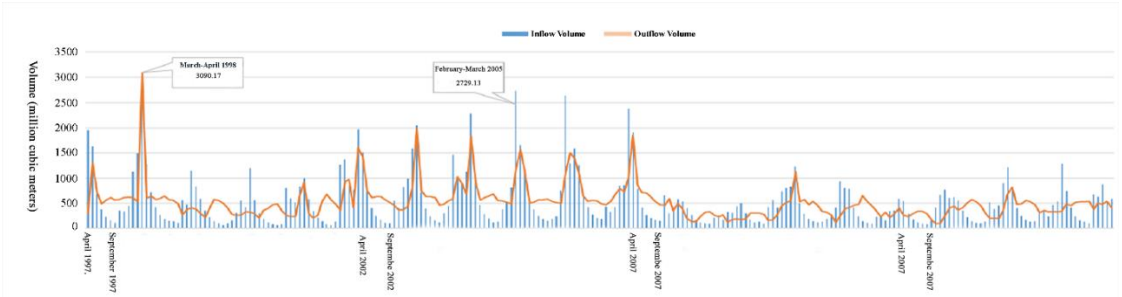


Figure 3: Monthly inflow and outflow volume (million cubic meters, MCM) for the Dez Dam reservoir between 1997 and 2015

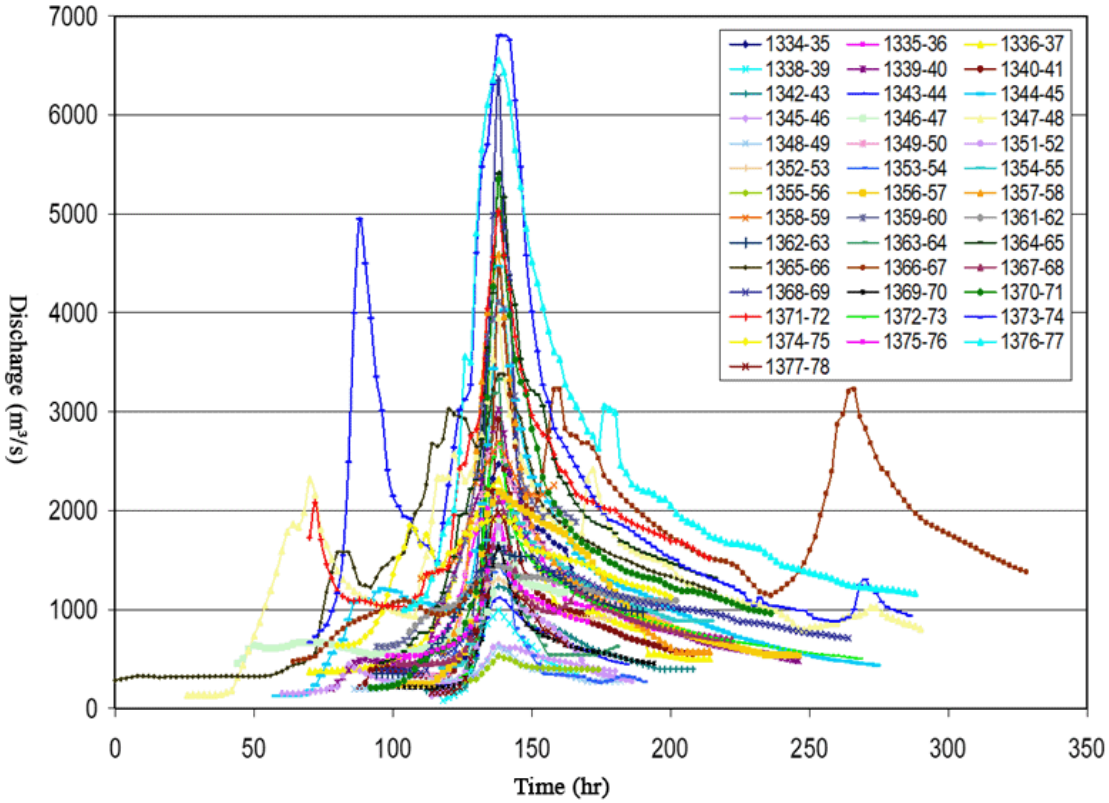


Figure 4: Hydrographs of some of the most significant inflow events to the Dez Dam (Persian years).

2.2. Reservoir Routing Model

To accurately simulate the hydraulic behavior of the dam reservoir and perform flood routing within the system, the Storm Water Management Model (SWMM), developed by the United States Environmental Protection Agency (EPA), was used. SWMM is a dynamic rainfall–runoff and hydraulic simulation model capable of performing continuous or event-based simulations of unsteady flow in complex water systems. It solves the full one-dimensional Saint-Venant equations, allowing detailed representation of storage units, hydraulic structures, conduits, and control elements. Due to its robust numerical engine and flexibility in modeling hydraulic structures such as gates, spillways, and outlets, SWMM provides a reliable platform for simulating reservoir routing and operational scenarios under flood conditions. Due to its advanced capabilities in dynamic and unsteady flow simulation in complex systems, this model is considered a powerful and reliable tool for analyzing hydro-hydraulic systems such as dams, canals, and rivers. The base model of the Dez reservoir, which includes the

geometric and hydraulic characteristics of the reservoir, spillways, and other related structures, was implemented in an input file. To evaluate the performance of the operating rules under various conditions, a set of real and historical flood hydrographs was used. These hydrographs, representing diverse flood scenarios with different return periods and volumes, were extracted from the historical series of inflow data and applied as input to the model. A key aspect of this study's methodology is the dynamic coupling between the optimization model (written in Python) and the SWMM simulation engine. This connection was established using the pyswmm library. Unlike traditional methods where control rules are statically defined in the [CONTROLS] section of the SWMM input file, this section was bypassed in our research. Instead, to evaluate each set of operating rules (each "individual" in the genetic algorithm), the SWMM simulation loop was controlled step-by-step by a Python script. At each time step, the script reads the instantaneous water level in the reservoir from the SWMM model, calculates the optimal gate opening percentage for each of the four outlets based on the operating rules being tested, and then applies these new settings back to the SWMM model. This dynamic process enabled a precise and realistic real-time evaluation of each set of operating rules, providing key variables such as outflow discharge and reservoir water level to the optimization algorithm for calculating the objective function and penalties. The complete dynamic coupling process between the Python optimization model and the SWMM engine is presented as a flowchart in Figure 5.

2.3. Optimization Framework

To find the optimal operating rules for the outlet gates of Dez Dam, an optimization framework based on a Genetic Algorithm (GA) was developed. As a powerful metaheuristic search method, the Genetic Algorithm is capable of solving complex, nonlinear problems with large search spaces, which is why it was selected for this research. The entire optimization process was implemented in the Python programming language, utilizing the robust and efficient DEAP (Distributed Evolutionary Algorithms in Python) library.

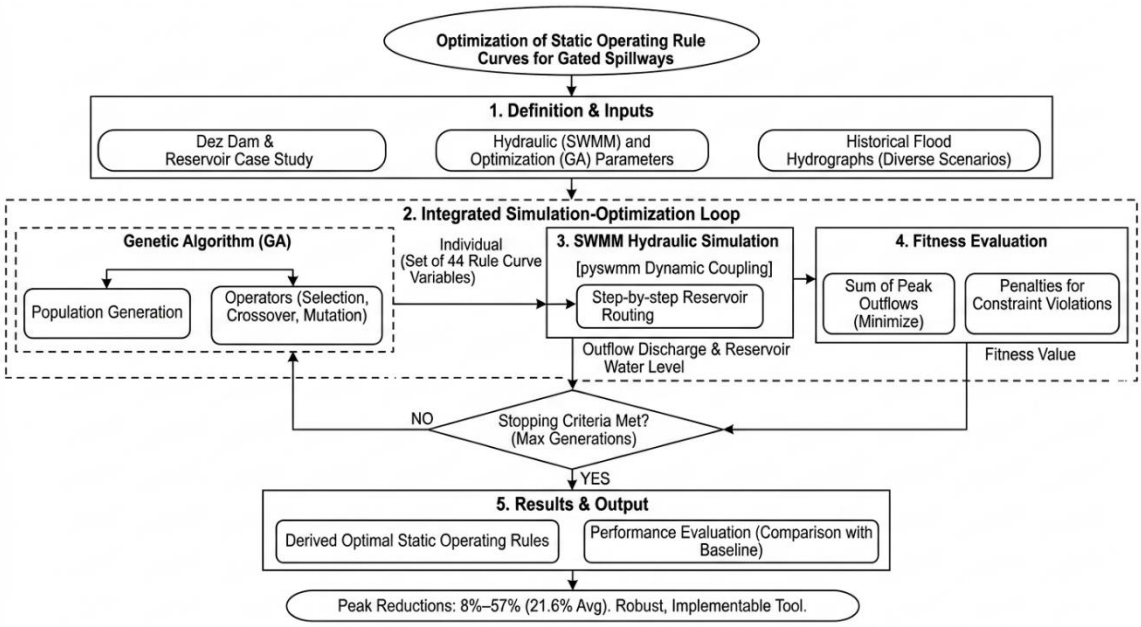


Figure 5: Flowchart of the dynamic coupling between the Python-based optimization model (GA) and the SWMM simulation engine via pyswmm

2.3.1. Decision Variables

The decision variables in this optimization problem consist of a set of 44 variables that define the piecewise constant rule curves for the dam's two spillways and two power tunnels (spill11, spill12, spill21, spill22). Each of these 44 variables represents the gate opening percentage (a continuous value from 0 to 100) for a specific gate within a defined range of reservoir water depth. To enhance the model's precision and flexibility, the depth intervals were defined in 5-meter increments; the rules for the upper-level gates (spill11, spill12) start at a depth of 70 meters, while the rules for the upper lower-level gates (spill21, spill22) begin at 90 meters. The 5-meter depth increment was selected as a compromise between operational resolution and computational tractability. Preliminary sensitivity analyses were conducted using smaller depth intervals (e.g., 2–3 meters); however, these significantly increased the number of decision variables and computational burden without yielding meaningful improvements in peak reduction performance. Therefore, the 5-meter discretization was considered sufficiently detailed to capture operational behavior while maintaining algorithm efficiency. Each chromosome in the genetic algorithm is a 44-element vector representing a complete set of these operating rules.

2.3.2. Objective Function

The main goal of this research is to develop rules that can effectively and sustainably control the peak outflow across a wide range of flood scenarios. Accordingly, the objective function that the GA aims to minimize was defined as the "sum of peak outflows across all simulated flood events". This choice, as opposed to minimizing only a single maximum peak, steers the algorithm toward finding more robust solutions that exhibit acceptable performance against both small and large floods. The final fitness value of each individual in the population is calculated from the sum of this primary objective function and the sum of weighted penalties incurred from violating operational constraints. To provide a clearer mathematical representation, the overall fitness function is defined as:

$$F = \sum_{i=1}^{N} Q_{peak.i} + \sum_{j=1}^{M} W_j, P_j \quad (1)$$

where:

- $Q_{peak,i}$ represents the peak outflow corresponding to flood event i,
- N is the total number of simulated flood events,
- P_j denotes the penalty term associated with constraint j,
- w_j is the weighting coefficient assigned to constraint j,
- M is the total number of defined operational and safety constraints.

Each penalty term is activated only when a constraint violation occurs and is proportional to the magnitude of violation. Larger violations result in proportionally larger penalty values, thereby steering the optimization process toward feasible and operationally defensible solutions.

2.3.3. Constraints and Penalty Functions

One of the key innovations of this study is the definition and precise calibration of a comprehensive set of operational and safety constraints to ensure that the optimized rules are not only mathematically optimal but also logical and defensible from an engineering and operational standpoint. The violation of any of these constraints adds a penalty to the individual's fitness value, proportional to the severity of the violation. These constraints, defined based on standard principles of dam engineering and water resources management, include the following:

a) **Dam Safety Constraint:** To prevent any risk to the dam's stability, the water level

must not exceed the maximum safe reservoir level (typically the dam crest or the top of the flood control pool). This constraint is the most critical in dam operation, and its observance takes precedence over all other objectives [26]. In this study's dam, the maximum safe level was set at 335 meters, and any solution causing the water level to surpass this limit was effectively eliminated from the optimization process by receiving a very large penalty (1e12).

b) **Operational Guide Curve:** To balance water storage for uses like agriculture and energy production with creating empty storage for flood control, an operational guide curve or target level is used. Optimal operation aims to keep the reservoir water level as close as possible to this curve [27]. In this research, the target level was defined as 308 meters, and deviations from this level were controlled with two separate penalty factors (for higher and lower levels).

c) **Ramping Rate Constraint:** To prevent sudden and drastic changes in the released flow, which can cause erosion of the riverbed and banks, endanger human life, and harm the downstream ecosystem, the rate of change of the outflow is limited [28]. In this study, the maximum allowable rate of change for the total outflow was set to 3,000 m^3/s per hour.

d) **Downstream Channel Capacity:** The outflow from the dam must always be less than the maximum safe capacity of the downstream channel to prevent flooding and damage to residential and agricultural areas. This constraint is a primary objective in reservoir operation for flood control [29]. Accordingly, the maximum safe discharge capacity of the downstream channel was assumed to be 2,500 m^3/s.

e) **Operational Stability Constraints:** To extend the service life of the equipment and prevent rapid, high-wear maneuvers, two additional constraints were defined:

i) **Limiting the rate of change of the reservoir water level:** Rapid changes in the reservoir level can jeopardize the stability of the reservoir's bank slopes. Therefore, limiting the drawdown rate is a critical consideration for safe operation [30]. In this research, this rate was limited to 1 meter per hour.

ii) **Limiting gate adjustment changes:** Frequent and rapid gate maneuvers lead to increased wear and tear on mechanical and hydraulic equipment. Limiting the amount of gate setting changes in short time steps is a standard operational practice to increase the lifespan and reliability of the structures. In this study, the maximum allowable change in any gate's setting in a single simulation time step was set to 50%.

2.3.4. Genetic Algorithm Parameters

The main parameters of the Genetic Algorithm, which control its performance, were configured as follows after preliminary investigations and based on experience from similar studies, considering the 44 decision variables in the problem:

- Population Size: 140
- Max Generations: 1000
- Crossover Probability: 0.8
- Mutation Probability: 0.2
- Genetic Operators: Tournament selection, Simulated Binary Crossover (SBX), and Polynomial Bounded mutation were used. The eta (η) parameter, which controls the distribution of offspring from these operators, was set to 20.0.

3. Results

This section presents the results from the optimization process and the performance evaluation of the optimal operating rules. First, the performance and convergence of the optimization algorithm are described. Then, the derived optimal rules are presented. Finally, the hydraulic performance of these rules in controlling various floods is evaluated and compared with the baseline scenario.

3.1. Performance and Convergence of the Optimization Algorithm

The optimization process was executed using the genetic algorithm for 1000 generations with a population of 140 individuals. Throughout the algorithm's execution, the fitness value of the best individual in each generation was continuously monitored. Observations showed that in the initial generations, the fitness value decreased sharply due to the high diversity of the population, indicating the algorithm's rapid movement toward desirable regions of the search space. As the generations progressed, this rate of improvement gradually slowed, and in the final generations, the best fitness value converged to a nearly stable and constant level. This convergence behavior indicates that the algorithm successfully reached an optimal or near-optimal solution and that further generations would not yield significant improvements, thereby confirming the validity and efficiency of the optimization process. The complete optimization process (1000 generations with a population size of 140) required approximately several days of computational time on a standard desktop computer (Intel i7 processor, 16 GB RAM). This computational demand is associated with the repeated dynamic coupling between the Genetic Algorithm and the SWMM hydraulic simulation for multiple flood scenarios. It should be emphasized that this optimization is performed offline for rule derivation purposes only. Once the optimal static operating rules are obtained, their implementation does not require any further computational effort, making the approach practically feasible for real-world dam operation.

3.2. Optimal Operating Rules

The final output of the optimization process is a set of 44 decision variables that constitute the optimal operating rules for the Dez Dam spillways. These rules specify the optimal opening percentage for each of the four dam gates at different reservoir water levels. The complete details of these derived rules are presented in Table 1. This table effectively represents the optimal guide curve that forms the basis for the dam's operation under flood conditions. This curve reveals an intelligent, nonlinear strategy discovered by the algorithm. A key feature is the reduction in gate opening at intermediate water levels (approximately 280 to 295 meters). This action allows the reservoir to absorb and attenuate the flood wave by utilizing its storage capacity. Subsequently, at higher levels, the gate is opened rapidly to release the flow in a controlled manner, thereby ensuring the dam's safety. This dynamic behavior is significantly more efficient than a simple, linear rule.

3.3. Hydraulic Performance Evaluation of the Optimal Rules

To evaluate the operational efficiency of the derived optimal rules, they were applied to several different flood scenarios within the SWMM hydraulic model. The performance of these rules was compared with two other hydrographs: the reservoir inflow hydrograph and the outflow hydrograph from the baseline scenario (all gates fully open). The results of this comparison for nine extreme flood events are displayed in Figure 6. Also, for easier interpretation, these optimal rules are also presented graphically in Figure 7, which shows the opening percentage of each gate as a function of reservoir water level.

Table 1. Derived optimal operating rules for the Dez Dam gates.

Row	Gate Name	Water Level (m)	Opening Percentage (%)
1	spill11	275	40.37
2	spill11	280	69.3
3	spill11	285	47.28
4	spill11	290	6.8
5	spill11	295	2.65
6	spill11	300	0.1
7	spill11	305	36.74
8	spill11	310	94.94
9	spill11	315	94.58
10	spill11	320	21.53
11	spill11	325	86.07
12	spill11	330	92.23
13	spill11	335	58.39
14	spill12	275	23.75
15	spill12	280	87.45
16	spill12	285	16.24
17	spill12	290	24.56
18	spill12	295	0.03
19	spill12	300	0.03
20	spill12	305	57.16
21	spill12	310	16.02
22	spill12	315	92.73
23	spill12	320	4.26
24	spill12	325	21.07
25	spill12	330	46.16
26	spill12	335	14.33
27	spill21	295	17.2
28	spill21	300	3.05
29	spill21	305	16.41
30	spill21	310	33.26
31	spill21	315	75.65
32	spill21	320	60.05
33	spill21	325	5.67
34	spill21	330	98.41
35	spill21	335	42.07
36	spill22	295	2.6
37	spill22	300	28.6
38	spill22	305	49.73
39	spill22	310	68.08
40	spill22	315	46.66
41	spill22	320	82.13
42	spill22	325	3.41
43	spill22	330	2.04
44	spill22	335	48.34

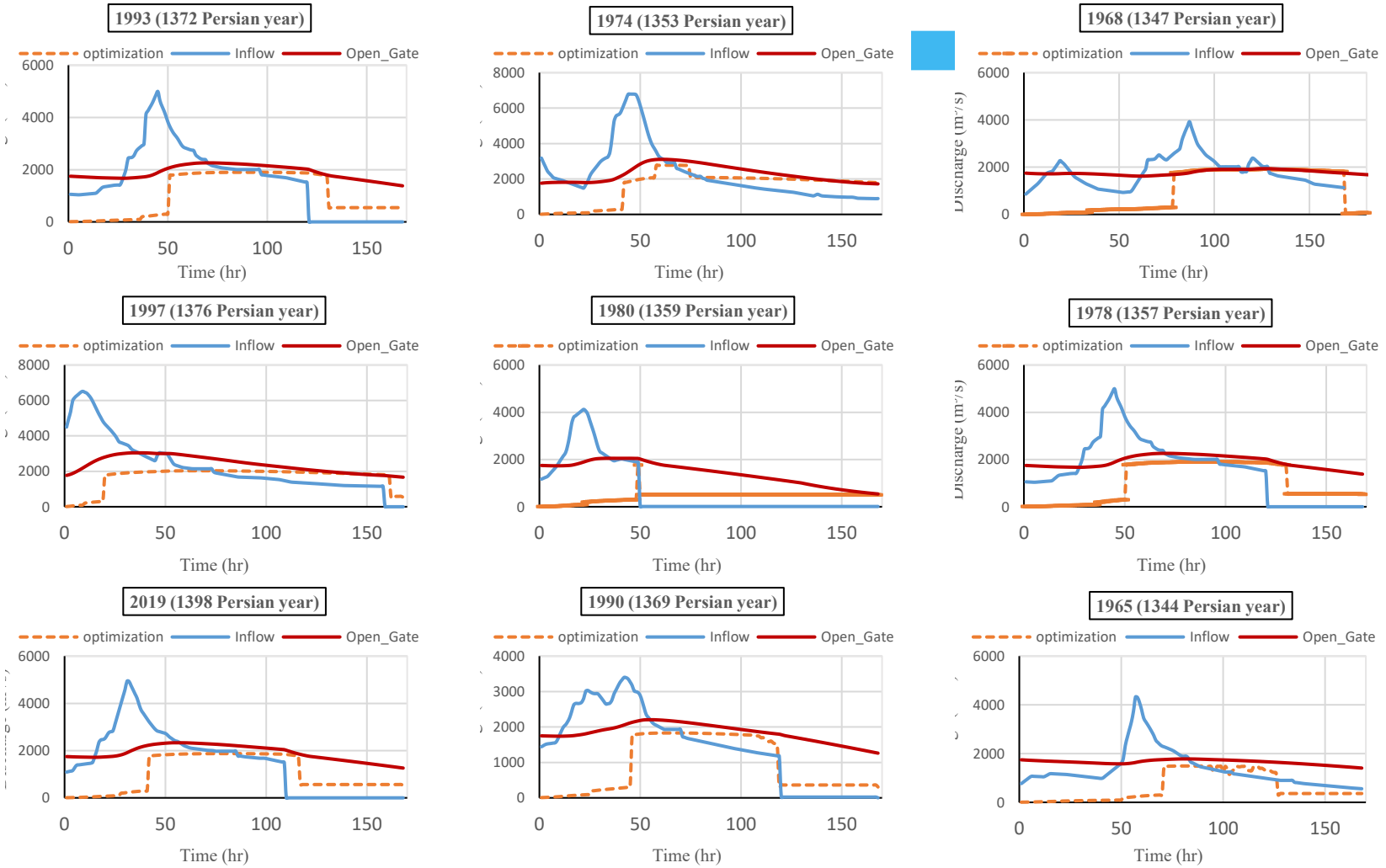


Figure 6: Comparison of inflow, optimal outflow, and baseline outflow (fully open gates) hydrographs for 9 different flood events.

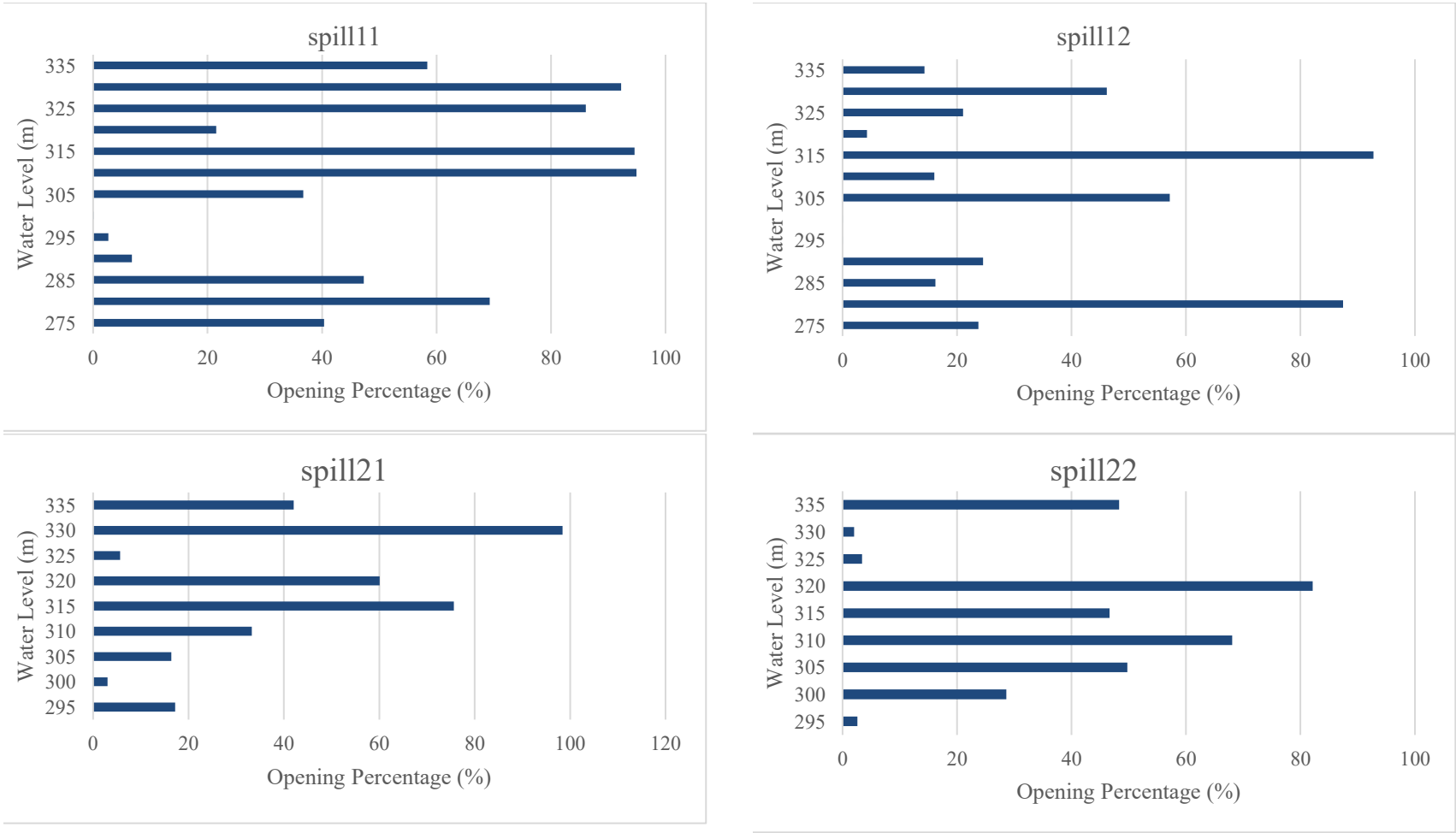


Figure 7: Optimal gate opening percentage curves for spill11, spill12, spill21, and spill22 as a function of reservoir water level.

The diagrams in Figure 6 clearly illustrate that the optimal operating rules have effectively attenuated the incoming flood peaks. Across all investigated scenarios, the peak outflow under the optimal rules (the 'Optimization' plot) is substantially lower than the peak outflow from the baseline scenario (the 'Open_gate' plot). This finding indicates that the optimization approach yields a far more efficient strategy compared to a simplistic, static alternative.

In analyzing the results, it's important to note the differentiated behavior of the optimal strategy when faced with floods of varying magnitudes. The primary objective of this study is the control of large, destructive floods that have the potential to cause downstream damage. According to the operational constraints defined in the model, the safe discharge capacity of the downstream channel is assumed to be 2500 m^3/s. Floods with a peak inflow below this threshold are not considered a significant threat and can pass through the system without causing damage or requiring complex optimization maneuvers. Consequently, the optimization process and performance analysis are appropriately focused on major flood scenarios where reducing the peak outflow is of high operational importance and directly contributes to enhancing the safety of the downstream community. For this reason, a detailed analysis of minor flood events, for which optimization yields no significant risk reduction, is omitted from this section. Among the analyzed events, Event 47 exhibited the highest peak reduction (57.1%). A closer examination of its hydrograph reveals that this flood was characterized by a relatively sharp and concentrated peak combined with moderate total volume. This configuration allowed the reservoir to effectively absorb a substantial portion of the inflow before reaching critical water levels. Consequently, the optimized rules were able to delay and attenuate the peak discharge significantly. In contrast, floods with longer duration and larger volumes reduce the available storage flexibility, thereby limiting the achievable peak attenuation.

3.4. Summary of Results and Overall Comparison

For a detailed quantitative analysis and a comprehensive comparison of the optimal rules' performance across all scenarios, the key results related to peak flood reduction are summarized in Table 2. This table presents the peak inflow and outflow values for the two operating scenarios (baseline and optimal), along with the percentage of performance improvement achieved through optimization for each of the nine events studied.

Table 2: Summary of results and performance comparison of the optimal rules in reducing peak flood.

Event ID (Year)	Peak Inflow (m^3/s)	Peak Outflow - Baseline (m^3/s)	Peak Outflow - Optimal (m^3/s)	Peak Reduction (%) (relative to baseline)
72	4,991.50	2,227	1,893	15
53	6,749	3,105	2,769	10.8
47	4,500	2,800	1,200	57.1
76	6,464	3,190	2,019.50	36.7
59	4,054	2,051	1,887	8
57	4,992	2,243	1,875.60	16.4
98	4,926	2,326	1,873	19.5
69	3,332	2,126	1,817	14.5
91	4,302	1,781	1,493	16.2
Average	-	-	-	21.6

A review of the quantitative results presented in Table 2 numerically confirms the significant success of the optimization approach. As can be observed, the optimized operating rules performed better than the baseline scenario in all tested scenarios, without exception. The degree of improvement in peak flood reduction varied between 8.0% and 57.1%, depending on the characteristics of the input hydrograph. It should be noted that these nine events were selected as representative samples from a wide range of floods studied. The analysis of other flood events also showed similar results within the same performance range; to avoid verbosity and repetition, their detailed presentation has been omitted here. Considering all scenarios, the optimal rules were able to reduce the peak outflow by an average of approximately 21.6% compared to the baseline scenario. This consistent success in peak reduction across all test scenarios demonstrates the robustness and high efficiency of the solution presented in this research, indicating that these rules can be a reliable tool for significantly increasing the safety of downstream areas.

4. Discussion

The results presented in this research clearly demonstrate that using an optimization framework based on a genetic algorithm, coupled with a hydraulic routing model, can significantly improve the operational performance of the Dez Dam under flood conditions. The consistent success of the optimized rules in reducing peak outflow across all nine diverse flood scenarios highlights the high efficiency and robustness of the adopted approach. This remarkable success is the result of an intelligent operating strategy discovered by the algorithm. Instead of a passive and simplistic reaction, such as fully opening the gates or operating them based on experience, the optimal rules more effectively mitigate the flood peak by utilizing the reservoir's storage volume at the beginning of the flood and then releasing the flow in a controlled and steady manner. This dynamic strategy, a key achievement of this study, shows that with proper temporal and volumetric management, the existing capacity of a dam can be utilized far more efficiently.

When positioning the present results within the broader literature, it is important to consider both performance magnitude and methodological objectives. Previous studies using multi-objective NSGA-II frameworks (e.g., Ref. [2]) or hybrid algorithms such as F-HGAPSO (Ref. [5]) have reported notable improvements in flood control performance under various system configurations. Although direct quantitative comparison is constrained by differences in case studies and modeling assumptions, the peak reduction range achieved in this study (8%–57%, average 21.6%) is consistent with the order of magnitude reported in advanced evolutionary optimization studies. A key distinction, however, lies in the objective of the proposed framework: rather than relying on computationally intensive real-time optimization, this study derives static yet robust operating rules that can be implemented without online computation during flood events.

Of course, achieving this level of optimality was not without its challenges and trade-offs. The process of fine-tuning the six soft operational constraints was itself a significant challenge, requiring a deep understanding of the system's behavior and numerous trial-and-error tests. To reach its primary goal of "minimizing the sum of peaks," the genetic algorithm sometimes had to accept small penalties for violating other constraints. These trade-offs show that in real-world operations, there is no "absolute ideal" solution; rather, the best solution is the point that strikes an optimal balance between conflicting objectives and limitations. The significance of the present work lies in the fact that by defining and applying a comprehensive set of constraints, it guided this balance toward solutions that are not only mathematically optimal but also defensible and logical from an engineering and operational perspective.

Despite these significant achievements, acknowledging the study's limitations is essential for outlining future research directions. One challenge was the single-objective focus of this research on flood control. The Dez Dam is a multipurpose structure with other objectives, such as power generation and water supply, which may conflict with the goal of flood control. The solutions presented here are not necessarily optimal for these other objectives, although an effort was made to meet them by applying operational constraints. These limitations themselves create valuable opportunities for future research. The next step could be to move toward a multi-objective optimization model that simultaneously considers flood control, power generation, and environmental needs, not just for a single dam but for a series of cascaded, parallel, or combined dams. This could provide more comprehensive solutions that are closer to the real needs of operators. Finally, integrating this optimization model with real-time forecasting systems could lead to the creation of a dynamic decision support system, which would be a major step toward modernizing and increasing the management efficiency of the country's large dams.

Overall, by providing a transparent methodology and efficient, stable rules, this research has established a solid and practical foundation for future studies and for the tangible improvement of dam flood management. Despite the demonstrated robustness of the derived rules across multiple historical flood scenarios, sensitivity to inflow uncertainty remains an important consideration. The current framework relies on deterministic historical hydrographs, and therefore its performance depends on the representativeness of these selected events. In real-world applications, forecast errors, nonstationary climate patterns, and extreme outlier events may affect operational outcomes. Future research could extend the proposed methodology by incorporating stochastic Genetic Algorithm variants, ensemble-based inflow generation, or robust optimization techniques that explicitly consider uncertainty bounds. Such extensions would allow the derivation of operating rules that remain effective under probabilistic inflow scenarios and evolving hydrological conditions.

A practical concern that may arise from the optimal rule curves shown in Figure 7 is the presence of rapid variations in opening percentages at certain water level intervals. While these theoretical jumps may appear impractical at first glance, it is important to emphasize that modern dam gate systems are fully automated. Hydraulic or electric actuators, controlled by PLCs, can precisely achieve any required opening percentage without manual intervention. The control system can also interpolate between the discrete 5-meter intervals to ensure smooth transitions. Therefore, the derived rules are entirely feasible with currently available automation technologies, and no operational impracticality exists.

5. Conclusion

This study presented an integrated simulation–optimization framework for deriving static operating rules for gated spillways with a primary focus on flood mitigation. By coupling a Genetic Algorithm (GA) with a detailed hydraulic routing model and incorporating a comprehensive set of operational and safety constraints, the framework produced operational rules capable of consistently reducing peak outflows across diverse flood scenarios.

The results demonstrated that the derived rules achieved peak reductions ranging from 8% to 57%, with an average reduction of 21.6% relative to the baseline scenario. These findings confirm that structured offline optimization can significantly enhance flood control performance while maintaining operational feasibility. Importantly, the developed rules are directly implementable without requiring real-time computational resources, making them suitable for practical dam management contexts.

While the present study focused on a single case study, the methodological framework is transferable to other gated dams with similar hydraulic characteristics. As a practical next step, pilot implementation of the proposed operating rules at other major Iranian dams is recommended to evaluate real-world performance, institutional adaptability, and long-term safety improvements. Such applications would provide valuable empirical evidence for broader adoption and could contribute meaningfully to strengthening national flood risk management strategies.

Declarations

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