

Article

Monthly Hydropower Scheduling of Cascaded Reservoirs Using a Genetic Algorithm with a Simulation Procedure

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Abstract: This study integrates genetic algorithms with simulation programs, applying the genetic algorithm's (GA) fitness calculation within the simulation to reduce complexity and significantly improve the efficiency of the optimization process. Additionally, the simulation introduces the concept of "Field Leveling" (FL), utilizing a push–pull strategy to explore more space for absorbing and utilizing unnecessary spillage for energy generation, thereby maximizing electricity production and ensuring optimal reservoir scheduling. Two methods are provided, namely the field-leveling genetic algorithms GAFL1 and GAFL2. GAFL1 involves only pushing and does not include a push–pull process; thus, it cannot optimize spillage. On the other hand, GAFL2 implements a complete push–pull strategy, continuously exploring additional space to absorb and utilize unnecessary spillage. Both GAFL1 and GAFL2 achieved reasonable results; specifically, compared to SQP, GAFL1 improved firm yield by 8.3%, spillage increased by 2.2 times, and total energy decreased by 1.2%. GAFL2, building on the basis of GAFL1, effectively reduces spillage under all hydrological conditions without affecting the highest priority of stable output. However, the impact of reducing spillage on energy generation is not consistent; in wet and dry years, reducing spillage increases energy generation. However, in normal years, a reduction in spillage corresponds with decreased energy generation.

Keywords: monthly hydropower scheduling; cascaded reservoirs; genetic algorithm; simulation procedure; field-leveling procedure



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1. Introduction

The continuous growth in global energy demand and the pressures of environmental conservation compel us to explore sustainable energy solutions. In this context, hydropower systems are considered important contributors to advancing sustainable energy development, despite the necessity to minimize their impact on ecosystems during implementation [1]. Specifically, the functions of reservoirs extend beyond power generation to include the regulation and management of water resources, which are crucial for sustaining human development. However, the effective management of water resources faces increasing challenges, such as water scarcity and environmental degradation, necessitating urgent improvements [2,3]. In basin development, the strategic construction of cascaded reservoirs and hydroelectric stations maximizes the utilization of water resources and hydraulic potential, becoming a vital strategy for comprehensive river resource development [4]. The optimized operation of these facilities, especially hydraulic scheduling, not only enhances the efficiency of reservoirs but also promotes the simultaneous conservation of water resources and energy while effectively reducing operational costs and environmental impacts.

Therefore, developing optimal operational strategies to address water scarcity and meet the demands for responsible resource management in water resource engineering is critical to achieving sustainable economic, social, and environmental goals [5].

Scheduling cascaded hydroelectric stations in a complex interconnected reservoir system is a daunting challenge due to intricate nonlinear relationships, numerous constraints, input uncertainties, and dynamic correlations among key variables such as reservoir storage and head. This issue has garnered widespread attention in both academic and engineering circles. Two main categories of optimization methods are employed to tackle this challenge. Mathematical programming methods—such as linear programming (LP) proposed by Yoo et al. [6], dynamic programming (DP) by Bellman [7], and mixed integer programming (MIP) [8]—excel in solving nonlinear and non-convex problems, making them well suited for long-term hydro-scheduling. On the other hand, intelligent algorithms, including particle swarm optimization (PSO) generated from the foraging behavior of birds [9] and genetic algorithms (GAs) simulating the survival of the fittest principle in nature [10,11], offer practical solutions by effectively handling nonlinear constraints and data mining algorithms [12]. However, complex scenarios, especially in multidimensional, nonlinear, and large-scale reservoir optimization, may pose challenges for traditional optimization algorithms, leading to issues like local optima and feasibility problems within the solution space [13]. The significant challenge often encountered with intelligent algorithms lies in their ability to efficiently generate a diverse set of solutions evenly distributed across the entire feasible region, which is crucial for optimizing complex problems. This challenge becomes particularly pronounced when dealing with intricate constraints. A comprehensive review by Nicklow et al. [14] highlights the importance of intelligent algorithms in water resource planning and management but underscores their limitations in handling constraints effectively. To tackle this issue, intelligent algorithms employed in optimal reservoir operation frequently resort to penalty functions to convert constrained problems into unconstrained ones [15,16]. Therefore, the integration of intelligent algorithms with mathematical programming methods has become a growing trend in solving complex hydro-scheduling problems. Saadat et al. [17] introduced an enhanced stochastic dynamic programming method, RISDP, which overcomes infeasible conditions and dimensionality issues, improving reservoir operation efficiency and boosting performance by 15% in real-case studies. Rani et al. [18] introduced the DP-PSO algorithm, combining dynamic programming with particle swarm optimization. Li et al. [19] presented IGA-SA, a hybrid approach of genetic algorithms and simulated annealing. Through parallel computing, efficiency in solving is enhanced, making them highly suitable for large-scale parallel processing.

The genetic algorithm (GA), proposed by American scholar John Holland in the 1970s, is an optimization algorithm based on natural selection and genetic principles used to solve search and optimization problems. However, solving the optimization scheduling of cascaded reservoirs with complex constraints and multiple objectives is a formidable challenge for the GA [10,11]. In practice, Zhang et al. [20] addressed issues such as a reduced convergence capability and low search efficiency observed in traditional algorithms during the evolutionary process by proposing an improved genetic algorithm combined with parallel computing technology, effectively enhancing model convergence. Wang et al. [21] introduced a parallel genetic simulated annealing (GSA) algorithm, effectively combining genetic algorithm and simulated annealing to avoid premature convergence. Reddy et al. [22] successfully proposed a multi-objective genetic algorithm (MOGA), applied to the Badra reservoir system. Li et al. [23] improved the simulated annealing genetic algorithm by introducing niche technology to avoid local optima. Li et al. [24] introduced IGA-SA, a hybrid approach of genetic algorithm and simulated annealing, superior to traditional genetic algorithms. Arunkumar et al. [11] combined the chaos technique with a genetic algorithm to achieve better results. Fayaed et al. [25] proposed an integrated random dynamic genetic algorithm utilizing artificial neural networks. Kan Yang et al. [26] proposed effective optimization strategies for cascaded reservoir systems. Liu, S et al. [27]

addressed the HUC problem by combining DP with the GA, minimizing the overflow volume and unit operation time in inefficient areas. Xu, B. et al. [28] proposed an improved genetic algorithm utilizing random operators for optimization within the feasible range of variables by gradually converting reservoir constraints into singular variable constraints and considering crossover points or mutation points in adjacent periods.

This study addresses the common challenges encountered when using intelligent algorithms to manage complex system scheduling, particularly in generating diverse and uniformly distributed feasible solutions for reservoir management. Our main objective is to optimize reservoir energy management and scheduling by integrating genetic algorithms (GA) with simulation programs, thereby improving overall efficiency and output. This paper introduces an improved method for genetic algorithms, where the fitness function calculations are performed directly within the simulation program, significantly reducing the computational load on the genetic algorithm. This integration minimizes the risks of local optima and dimensionality disasters while significantly enhancing the efficiency of the optimization process. This study incorporates the concept of field leveling (FL) [29] into the simulation program, which mimics the practice of soil leveling using a push–pull strategy to explore additional spaces for absorbing and utilizing excess spillage for power generation. We offer two strategies: GAFL1 and GAFL2. GAFL1 involves only forward pushing and does not engage in a push–pull process; thus, it does not optimize spillage. In contrast, GAFL2 implements a complete push–pull strategy, continuously exploring additional spaces to absorb and utilize unnecessary spillage for optimized energy use. This research optimizes reservoir scheduling through innovative strategies, achieving a maximized power output and enhanced operational efficiency. The practical application of these strategies can significantly benefit the system, including increased energy generation and enhanced adaptability to various hydrological conditions, providing a new optimization tool for reservoir management.

2. Problem Formulation

Monthly hydropower scheduling is formulated to maximize the firm power output and energy production sequentially during a planning horizon, expressed as

$$\max W_1 \cdot F + W_2 \sum_{i=1}^N \sum_{t=0}^{T-1} P_{it} \quad (1)$$

where W_1 and W_2 are weights represented as $W_1 \gg W_2$, prioritizing firm power output (F) over energy production; i and t are subscripts for the reservoir and time-step, respectively; P_{it} is the power output in MW in time-step t .

Constraints include the following:

- (1) Water balance is

$$V_{i,t+1} = V_{it} + \left(\sum_{j \in \Omega(i)} Q_{jt} + I_{it} - Q_{it} \right) \cdot \frac{\Delta t \cdot 24 \times 3600}{100,000,000} \quad (2)$$

with

$$\begin{cases} V_{i,0} = V_i^{\text{ini}} \\ V_{i,T} = V_i^{\text{end}} \end{cases} \quad (3)$$

where V_{it} is the storage in hm^3 at the beginning of time-step t of reservoir i ; Q_{it} is the release in m^3/s in time-step t from reservoir i ; I_{it} is the local inflow in m^3/s in time-step t into reservoir i ; $\Omega(i)$ is the set of reservoirs immediately upstream of reservoir i ; Δt is the number of days in time-step t ; V_i^{ini} and V_i^{end} are initial and target storages in hm^3 at the beginning and end of the planning horizon, respectively. In this study, both are substituted with the normal water level.

- (2) Upper and lower bounds on storage or release are expressed as

$$\begin{cases} V_i^{\text{dead}} \leq V_{it} \leq V_{it}^{\text{max}} \\ Q_i^{\text{min}} \leq Q_{it} \leq Q_i^{\text{max}} \end{cases} \quad (4)$$

where V_i^{dead} is dead storage in hm^3 of reservoir i , representing the lower storage volume. V_{it}^{max} is upper bound on the storage at the beginning of t of reservoir i , equal to the flood control limited storage during flooding seasons and the normal storage during dry seasons; Q_i^{min} and Q_i^{max} are lower and upper bounds on the release from reservoir i in time-step t .

- (3) Firm hydropower output is expressed as

$$\sum_{i=1}^N P_{it} \geq F \quad (5)$$

where N = number of hydroplants/reservoirs.

- (4) The capacity of hydropower output due to the release available is

$$P_{it} \leq A_i \cdot Q_{it} \cdot h_{it} \quad (6)$$

and water heads are expressed as

$$P_{it} \leq G_i^{\text{max}}(h_{it}) = \min \left[\left(c_i^{(0)} h_{it} + d_i^{(0)} \right), \left(c_i^{(1)} h_{it} + d_i^{(1)} \right) \right] \quad (7)$$

which, as illustrated in Figure 1, is equivalent to

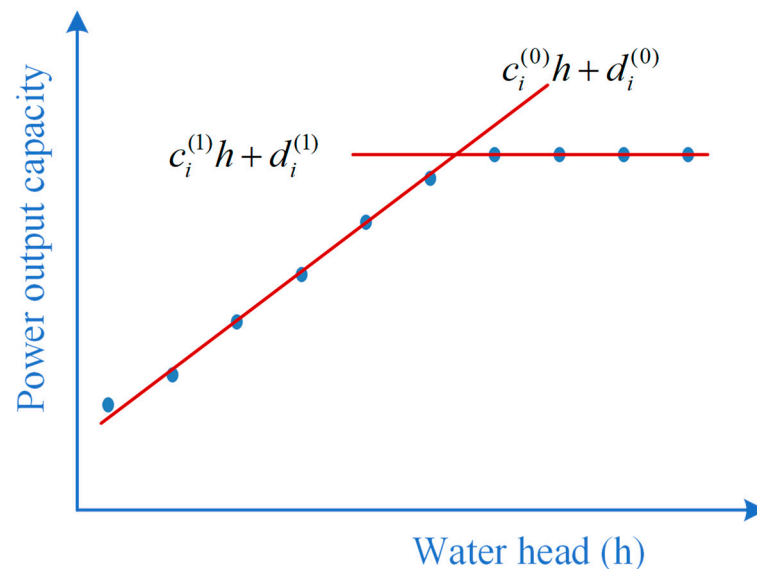


Figure 1. Capacity of hydropower output due to water head.

$$\begin{cases} P_{it} \leq c_i^{(0)} h_{it} + d_i^{(0)} \\ P_{it} \leq c_i^{(1)} h_{it} + d_i^{(1)} \end{cases} \quad (8)$$

with

$$h_{it} = Z_i^u(\bar{V}_{it}) - Z_i^d(Q_{it}) = \left[\alpha_i \cdot \left(\bar{V}_{it} - \hat{V}_i^{(0)} \right)^{\beta_i} + \hat{Z}_i^u \right] - \left[\chi_i \cdot \left(Q_{it} - \hat{Q}_i^{(0)} \right)^{\delta_i} + \hat{Z}_i^d \right] \quad (9)$$

$$\bar{V}_{it} = \frac{V_{it} + V_{i,t+1}}{2} \quad (10)$$

where A_i is the power generating efficiency in $\text{MW}\cdot\text{s}/\text{m}^4$; h_{it} is the water head in time-step t of hydroplant i ; $G_i^{\max}(\cdot)$ is the capacity of hydropower output of i , a function of water head; $c_i^{(0)}, c_i^{(1)}, d_i^{(0)}$ and $d_i^{(1)}$ are coefficients to be estimated to fit the power output capacity with piecewise linearization; $Z_i^u(\cdot)$ and $Z_i^d(\cdot)$ are forebay and tailwater elevations, dependent of the water storage and release, respectively, of reservoir i ; $\alpha_i, \beta_i, \hat{V}_i^{(0)}$ and $\hat{Z}_i^u$ are coefficients/parameters to be estimated for the relationship curve between storage and forebay water level.

3. Solution Techniques

Instead of solving the original problem directly, this work applies a genetic algorithm (GA) to

$$\min_{S_{it}} f = \text{Simu}(S_1, S_2, \dots, S_N | \text{type} = 1) \quad (11)$$

which also determines the solution

$$[V, Q, P] = \text{Simu}(S_1, S_2, \dots, S_N | \text{type} = 2) \quad (12)$$

where S_{it} represents the decision variables, interpreted as the storage targeted in hm^3 at the beginning of time-step t for reservoir i ; $\text{Simu}(\dots)$ is a simulation procedure that returns the fitness of an individual solution represented by a decision matrix

$$S = [S_1, S_2, \dots, S_N] \quad (13)$$

when $\text{type} = 1$ or the hydro-scheduling solution, then

$$\begin{cases} V = [V_1, V_2, \dots, V_N] \\ Q = [Q_1, Q_2, \dots, Q_N] \\ P = [P_1, P_2, \dots, P_N] \end{cases} \quad (14)$$

when $\text{type} = 2$, then

$$\begin{cases} S_i = [S_{i0}, S_{i1}, \dots, S_{iT-1}, S_{iT}] \\ V_i = [V_{i0}, V_{i1}, \dots, V_{iT-1}, V_{iT}] \\ Q_i = [Q_{i0}, Q_{i1}, \dots, Q_{iT-1}] \\ P_i = [P_{i0}, P_{i1}, \dots, P_{iT-1}] \end{cases} \quad (15)$$

where the initial storage is always

$$S_{i0} = V_{i0} = V_i^{\text{ini}} \quad (16)$$

All the constraints will be satisfied after the simulation, and the fitness of an individual child/solution in the GA will be determined as

$$\text{Simu}(S | \text{type} = 1) = W_1 \cdot F + W_2 \cdot \sum_{i=1}^N \sum_{t=0}^{T-1} P_{it} \quad (17)$$

With

$$F = \min_{0 \leq t \leq T-1} \sum_{i=1}^N P_{it} \quad (18)$$

An individual solution in the GA is represented by the decision matrix S , which, serving as the target storages at each time-step t , may not be the same as the storages at the scheduling solution determined after the simulation. However, it is essential that the S , when generated randomly in the GA and happening to be optimum, should be equal to the storage V at the scheduling solution to theoretically ensure the capability of the GA to find the optimum solution to the problem.

3.1. Methodology

3.1.1. Genetic Algorithm

The genetic algorithm (GA) is an optimization technique inspired by the principles of biological evolution. It is a powerful tool for addressing complex problems by iteratively exploring and enhancing potential solutions. Emulating the essence of Darwin's theory of evolution, the GA progressively refines solutions through a process that mirrors natural selection, genetic crossover, and mutation. This approach allows the GA to navigate solution spaces efficiently, identifying optimal outcomes in a manner akin to the evolutionary mechanisms observed in nature.

As illustrated in Figure 2, an improved description of the genetic algorithm encompasses the following pivotal stages:

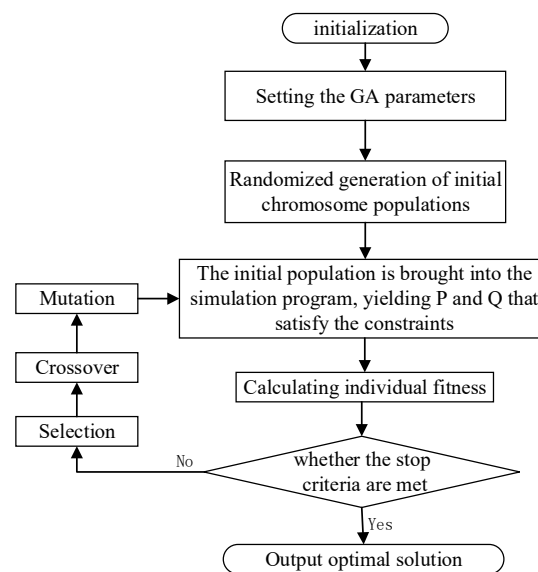


Figure 2. Flow chart of the genetic algorithm.

- (1) Randomization generates an initial population of individuals randomly representing potential solutions to the problem under consideration.
- (2) Evaluation to assess an individual's fitness in the population, involving the execution of a simulation program to gauge its suitability or quality.
- (3) Termination criterion to make a crucial decision to determine whether the algorithm should proceed with its iterative process, relying on whether the predefined number of iterations or other criteria have been satisfied.
- (4) Selection to choose parent solutions from the present population at probabilities determined by the fitness values, serving as a fundamental aspect of the genetic algorithm's underlying principles.
- (5) Crossover between parent individuals by exchanging genetic information to generate child solutions as a fundamental genetic mechanism to create novel potential solutions.
- (6) Mutation to introduce diversity and explore a more comprehensive solution space, enhancing the algorithm's capacity to break free from local optima and uncover improved solutions.
- (7) Iteration to steadily approach improved solutions until the predefined termination criteria are satisfied, guaranteeing that the algorithm iteratively hones its solutions across multiple generations.

3.1.2. Simulation at a Time-Step

The simulation will travel from the upstream to downstream reservoirs one by one, moving forward in time from the initial storage at the beginning of the scheduling horizon

or backward from the target storage at the end of the scheduling horizon, either guided with or without minimizing spillages during the simulation procedure.

Figure 3 illustrates how the simulation works at a time-step when moving forward to determine the storage ($V_{i,t+1}$) at the end of this time-step (t), given the storage (V_{it}) at the beginning of this time-step and the target storage ($S_{i,t+1}$) at the end of this time-step. The simulation looks as follows.

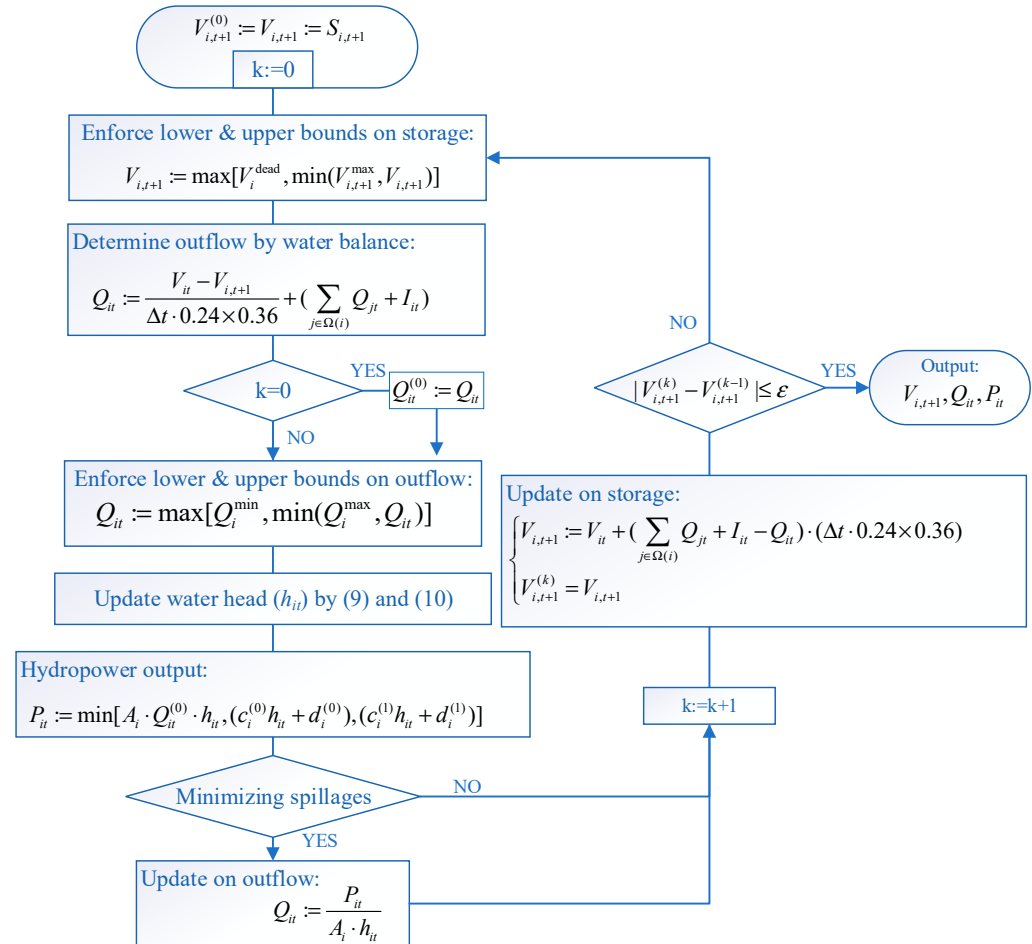


Figure 3. Forward simulation in a time-step.

- (1) The lower and upper bounds on storage and outflow (4) are enforced with

$$V_{i,t+1} := \max[V_i^{\text{dead}}, \min(V_{i,t+1}^{\text{max}}, V_{i,t+1})] \quad (19)$$

$$Q_{it} := \max[Q_i^{\text{min}}, \min(Q_i^{\text{max}}, Q_{it})] \quad (20)$$

- (2) The water is balanced when updating the storage and release with the following:

$$Q_{it} := \frac{V_{it} - V_{i,t+1}}{\Delta t \cdot 0.24 \times 0.36} + \left(\sum_{j \in \Omega(i)} Q_{jt} + I_{it} \right) \quad (21)$$

$$V_{i,t+1} := V_{it} + \left(\sum_{j \in \Omega(i)} Q_{jt} + I_{it} - Q_{it} \right) \cdot (\Delta t \cdot 0.24 \times 0.36) \quad (22)$$

The hydropower output is determined by considering its capacity and available release, as follows:

$$P_{it} := \min \left[A_i \cdot Q_{it}^{(0)} \cdot h_{it}, \left(c_i^{(0)} h_{it} + d_i^{(0)} \right), \left(c_i^{(1)} h_{it} + d_i^{(1)} \right) \right] \quad (23)$$

where $Q_{it}^{(0)}$ is the available release originally determined by the target storage ($S_{i,t+1}$) and should also be targeted when updating the water head to accurately estimate the hydropower output capacity.

- (3) The iteration of updating water heads, indexed with k , continues until convergence, as follows:

$$\left| V_{i,t+1}^{(k)} - V_{i,t+1}^{(k-1)} \right| \leq \varepsilon \quad (24)$$

where ε is a small converging accuracy value.

- (4) The release will be updated with

$$Q_{it} = \frac{P_{it}}{A_i \cdot h_{it}} \quad (25)$$

to reduce spillages if the simulation is guided by minimizing spillages.

This one-step simulation forward in time, shown in Figure 3, is readily adaptable to the one-step backward simulation, only by changing all the subscripts “ $t + 1$ ” to “ t ” and keeping all the others unchanged, except for the storage update, which should be replaced with

$$V_{it} := V_{i,t+1} - \left(\sum_{j \in \Omega(i)} Q_{jt} + I_{it} - Q_{it} \right) \cdot (\Delta t \cdot 0.24 \times 0.36) \quad (26)$$

The one-step backward simulation determines the storage (V_{it}) at the beginning of this time-step (t), given the storage ($V_{i,t+1}$) at the end of this time-step and the target storage (S_{it}) at the beginning of this time-step.

3.1.3. Simulation Procedure during a Scheduling Horizon

The simulation procedure will take different strategies dependent on whether or not guided with minimizing spillages, which in many cases will help yield a satisfactory solution very fast but may not be able to theoretically ensure the optimum be derived since the optimum, when randomly generated, is very likely to be modified when updating the outflow with Equation (25) to reduce spillages. The simulation procedures are summarized as follows:

- (1) Simulation procedure without minimizing spillages:

For hydropower reservoirs taking turns one by one from the upstream to downstream, let

$$\begin{cases} V_{i0} = V_i^{\text{ini}} \\ S_{iT} = V_i^{\text{end}} \end{cases} \quad (27)$$

Then, do the one-step forward simulation for $t = 0, 1, \dots, T - 1$. This procedure ensures that a solution randomly generated in the GA, if it is also a feasible solution to the problem, will be the same as the storages at the scheduling solution since the simulation procedure can achieve the target storages without violating any constraints.

- (2) Simulation procedure with minimizing spillages:

Here, the FL algorithm is used to minimize spillages. The FL algorithm simulates the process of land leveling and iteratively adjusts the storage capacity through the “one-step forward,” “one-step backward,” and “one-more-step forward” steps to optimize the storage capacity for the following calculation. The following are the specific steps used, and each step is performed sequentially for upstream to downstream reservoirs:

- (a) Set boundary condition with Equation (27), then move forward to absorb spillages but keep the storage at the end of the scheduling horizon to be decided later by performing a one-step forward simulation for $t = 0, 1, \dots, T - 2$.
- (b) Take Equation (3), then move backward to absorb spillages but keep the storage at the beginning of the scheduling horizon unchanged by performing a one-step backward simulation for $t = T - 1, T - 2, \dots, 1$.
- (c) Carry out step (a) but for $t = 0, 1, \dots, T - 1$ to allow the storage to be changeable at the end of the scheduling horizon.

Depending on whether spillages are minimized or not, this study will investigate two strategies, GAFL1 and GAFL2, representing genetic algorithms without and with minimizing spillages in the field-leveling procedure, respectively.

4. Case Studies

4.1. Engineering Background

The Jinsha River, situated in the upper reaches of the Yangtze River in China, boasts abundant hydropower potential owing to its substantial elevation drop and ample water resources. The river hosts several large-scale hydropower facilities, including the Wudongde plant, with an installed capacity of 10.2 gigawatts (GW), and the Xiangjiaba plant in Yunnan Province, which generates an impressive annual output of 30 billion kilowatt-hours (kWh). The Jinsha River's cascaded reservoir system comprises four critical reservoirs arranged from upstream to downstream: Baihetan, Wudongde, Xiluodu, and Xiangjiaba. Table 1 provides an overview of some fundamental characteristics of these four reservoirs.

Table 1. Basic characteristics of cascaded hydropower reservoirs.

Name	Annual Inflow (m ³ /s)	Installed Capacity (MW)	Storage Capacity (108 m ³)	Minimum Storage (108 m ³)	Minimum Release (m ³ /s)	Maximum Release (m ³ /s)	Operability
Wudongde	3442	10,200	74.08	33.04	900	37,000	Seasonal
Baihetan	3647	16,000	206	85.69	600	37,000	Annual
Xiluodu	4640	12,600	126.7	51.12	800	37,000	Annual
Xiangjiaba	4255	6400	51.63	40.74	1200	37,000	Seasonal

4.2. Results of Curve Fitting

Table 2 provides the coefficients defining the two linear equations to establish the connection between the maximum hydropower output and water head, as a segmented linearization adopted.

Table 2. Capacity of hydropower output of each hydropower plant.

Name	$c_i^{(0)}$	$d_i^{(0)}$	$c_i^{(1)}$	$d_i^{(1)}$
Wudongde	147.3	−10,723	0	10,200
Baihetan	179.1	−19,518	0	16,000
Xiluodu	83.523	−3746.1	0	12,600
Xiangjiaba	99.715	4498.5	0	6400

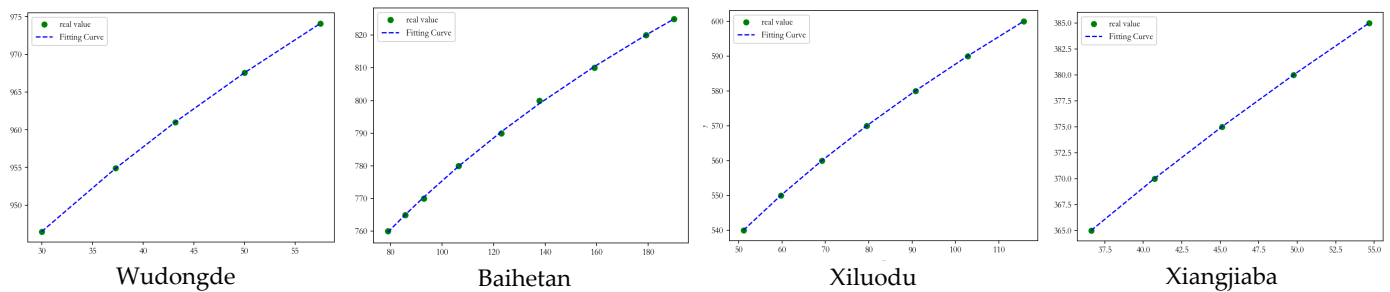
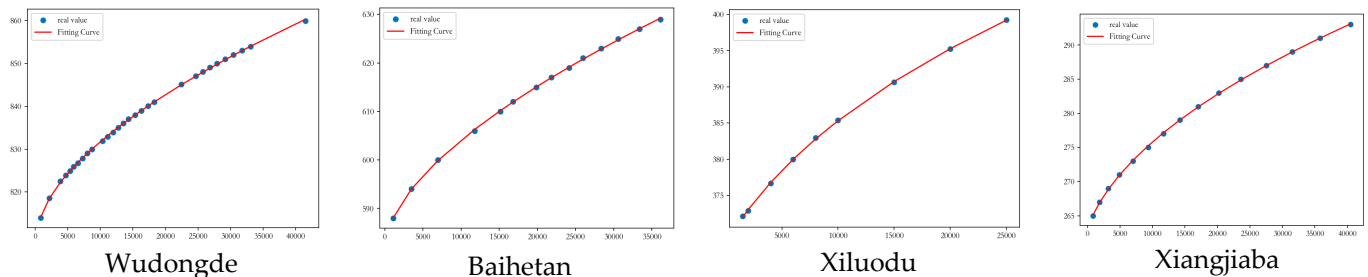
Tables 3 and 4 presents the parameters estimated using the nonlinear least squares method in PyCharm, which are used to define two exponential functions representing the relationship curves of the forebay water level vs. reservoir storage and the tailwater level vs. release. The nonlinear least squares method is a powerful optimization technique that fits nonlinear models to data by minimizing the sum of squared residuals. The coefficient of determination (R^2) measures the fitting accuracy, which has an outstanding value of 99% for all four reservoirs. Figures 4 and 5 illustrate the relationship curves for forebay water levels and reservoir storage volumes, as well as tailwater levels and discharge volumes, respectively, providing a visual representation of the fitting outcomes.

Table 3. Parameters estimated for the forebay relationship curve.

Name	α_i	$\hat{V}_i^{(0)}$	β_i	$\hat{Z}_i^u$	R ²
Wudongde	2.279478	25.60485	0.789139	939.11483	0.99995
Baihetan	23,475.46	54.03911	0.004469	23,234.35	0.99919
Xiluodu	16.7551	10.60725	0.486809	438.43423	1
Xiangjiaba	65.0419	7.620728	0.287402	171.70311	0.99993

Table 4. Parameters estimated for the tailwater relationship curve.

Name	χ_i	$\hat{Q}_i^{(0)}$	δ_i	$\hat{Z}_i^d$	R ²
Wudongde	0.126124	456.664	0.565465	808.6672	0.99961
Baihetan	0.087444	432.3818	0.598788	582.3239	0.99978
Xiluodu	0.093096	5025.77	0.583048	365.2306	0.99977
Xiangjiaba	0.078117	1051.57	0.566308	261.4179	0.9998

**Figure 4.** Forebay relationship fitting curves.**Figure 5.** Tailwater relationship fitting curves.

4.3. Data Sources

The runoff series generally follows a Pearson's Type III probability distribution; statistical parameters are determined using frequency analysis to establish criteria for categorizing runoff into wet, normal, and dry years. For instance, the hydrological years 2000 (wet year), 1978 (normal year), and 1976 (dry year) are selected as examples, with corresponding probability percentages of 7.5%, 50.9%, and 86.0%, respectively. To illustrate hydrological trends, Figure 6 depicts the inflow volume into the headwater power station for these representative years, along with the inflow volume data from 1983 used for a comparison with SQP [30].

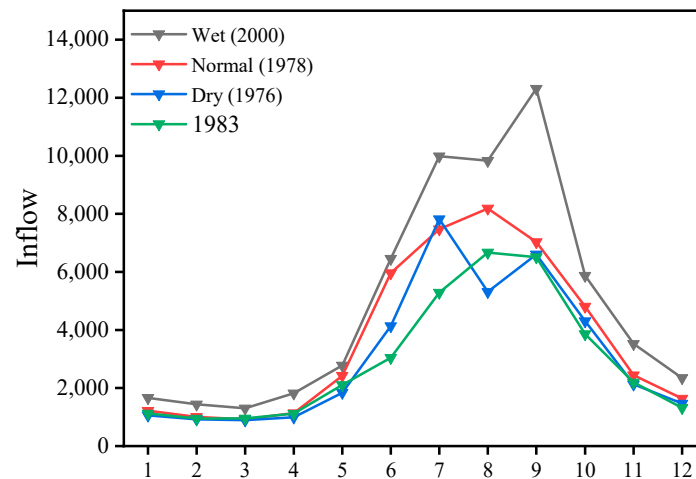


Figure 6. Inflow trend at Wudongde during a hydrologic year.

4.4. Results Analysis

4.4.1. Comparison GAFL1 vs. SQP

This study explores various methods employing traditional genetic algorithms, which, however, prove to be insufficient for a comparison with the current GAFL1 due to challenges in effectively handling the complexity of constraints. Thus, a comparison has been made between the outcomes obtained from the present method and those derived from a validated Sequential Quadratic Programming (SQP) approach [30]. The SQP approach formulates quadratic programming by linearizing the hydropower output, capacity, and constraints for cascaded reservoirs through a first-order Taylor expansion.

To ensure a scientifically rigorous and impartial comparison, both algorithms are configured with the same objective function, two weight factors (in a 1000:1 ratio), and water head, outflow, and generating discharge constraints. To attain essential parity and maintain fairness and accuracy in the comparison, the original water head formula (Equation (9)) is converted into Formula (28), ensuring that both models adhere to identical constraints.

$$h_{it} = Z_i^u(\bar{V}_{it}) - Z_i^d(Q_{it}) \\ = \left[\alpha_i \cdot \left(\bar{V}_{it} - \hat{V}_i^{(0)} \right) + \hat{Z}_i^u \right] - \left[\beta_i \cdot \left(Q_{it} - \hat{Q}_i^{(0)} \right) + \hat{Z}_i^d \right] \quad (28)$$

Table 5 presents the firm yield, total energy, and spillage results obtained with the GAFL1 (genetic algorithm with minimizing spillages in field-leveling procedure) and SQP (Sequential Quadratic Programming) methodologies. Despite the GAFL1 causing a spillage that is more than double and subsequently reducing total energy by approximately 1.2%, it outperforms SQP with a notable 8.3% improvement in firm yield at the highest priority level.

Table 5. Comparison of results between GAFL1 and SQP (1983).

Model	Firm Yield (MW)	Total Energy (10 ⁶ kWh)	Spillage (hm ³)
GAFL1	9769.25	152,951.62	3550.03
SQP	9020.0	154,778.4	1607.7
Improvement	8.3%	−1.2%	2.2 times

Table 6 elucidates the scheduling outcomes for total energy and spillage in various reservoirs using the GAFL1 and SQP methods. A discernible observation reveals that the increase in spillage from the GAFL1 approach is primarily concentrated in the Baihetan and Xiluodu Reservoirs. This augmentation leads to a less favorable total energy outcome

when compared to SQP for these two reservoirs. Notably, the Xiangjiaba Reservoir under the GAFL1 methodology registers a spillage result of zero, a remarkable deviation from SQP, entailing a substantial reduction of 1884.4 hm³ in spillage and, consequently, a conspicuously prominent enhancement in total energy.

Table 6. Comparison of the result of each hydropower plant.

NAME	Reservoir Type	GAFL1		SQP	
		Total Energy (10 ⁶ kWh)	Spillage (hm ³)	Total Energy (10 ⁶ kWh)	Spillage (hm ³)
Wudongde	Seasonal	27,962.7	0.0	30,458.0	0.0
Baihetan	Annual	45,131.2	2426.3	47,798.3	0.0
Xiluodu	Annual	47,101.6	1123.8	48,784.8	323.4
Xiangjiaba	Seasonal	32,756.1	0.0	27,737.3	1284.4

4.4.2. Comparison between GAFL1 and GAFL2

The field-leveling procedure [29] utilizes an iterative push and pull strategy to assist the simulation in reducing spillages, thereby creating the potential to generate more hydropower energy. Figure 7 illustrates the convergence processes of the objective function values in GAFL1 and GAFL2, with both showing a monotonically increasing trend, ensuring convergence toward the limit. The most notable improvements for both methods were observed in the second iteration, and convergence was achieved in the 15th and 10th iterations, respectively.

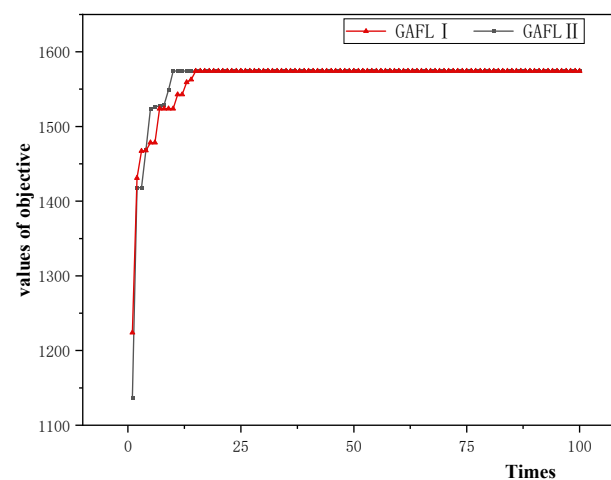


Figure 7. Iteration process of the GAFL2 optimization.

Table 7 outlines the CPU times for both methods and the genetic algorithm's parameters. It is noteworthy that the CPU time for GAFL2 exceeds that of GAFL1, primarily due to a significant enhancement in the push–pull process within GAFL2. The parameters for these methods are based on prior research and have undergone subsequent refinement [31]. The stopping criterion for the algorithm is termination upon the completion of the designated number of iterations.

Table 7. GAFL function setting attributes.

Performances	Population Size	Iteration Number	CPU Time	Crossover Fraction	Migration Fraction
GAFL1	500	100	218.077 s	0.89	0.89
GAFL2	500	100	639.010 s	0.89	0.89

Table 8 compares the performance of GAFL1 and GAFL2 in terms of firm yield, total energy, and spillage for four reservoirs on the upper Jinsha River, considering three typical hydrologic scenarios: a wet year, a normal year, and a dry year. The results indicate that in all hydrological conditions, the FL technique successfully minimizes spillage without compromising the priority of firm yield (Increases or decreases are marked with $\uparrow$ and $\downarrow$ in the table). Based on these findings, it is evident that reducing spillage enhances energy in both dry and wet years. However, the impact of this reduction is not consistent; during normal years, while spillage decreases, the total energy also increases. This suggests a variable influence of spillage control on energy, depending on the hydrological conditions of the year.

Table 8. Comparison without vs. with minimizing spillages.

Performances	Wet (2000)		Normal (1978)		Dry (1976)	
	GAFL1	GAFL2	GAFL1	GAFL2	GAFL1	GAFL2
Firm yield (MW)	15,743.8	15,743.8	11,596.1	11,596.1	10,388.6	10,388.6
Total energy (10 ⁶ kWh)	306,753.7	307,081 $\uparrow$	188,385.1	186,975.2 $\downarrow$	163,464.2	163,464.6 $\uparrow$
Spillage (hm ³)	29,674.5	29,298.2 $\downarrow$	7743.7	6899.5 $\downarrow$	1417.4	1414.5 $\downarrow$

To elucidate the anomaly observed in normal years, as shown in Table 8, Figure 8 compares the scheduling processes of the GAFL1 and GAFL2 algorithms across three typical hydrological years, examining monthly energy (P), water head (h), and spillage (spl) in cascade reservoirs. It is observed that during both wet and dry years, the differences in h under the two methods are minimal, thus allowing for an increase in energy generation concurrent with reduced spillage. However, in normal years, despite a reduction in spillage, there is a significant decrease in head, which does not substantially aid in increasing energy generation. This leads to the phenomenon reported in Table 7, where a decrease in spillage during normal years does not increase energy generation, but rather causes a decrease. This discrepancy highlights the complex interdependencies between head, spillage, and energy generation under varying hydrological conditions.

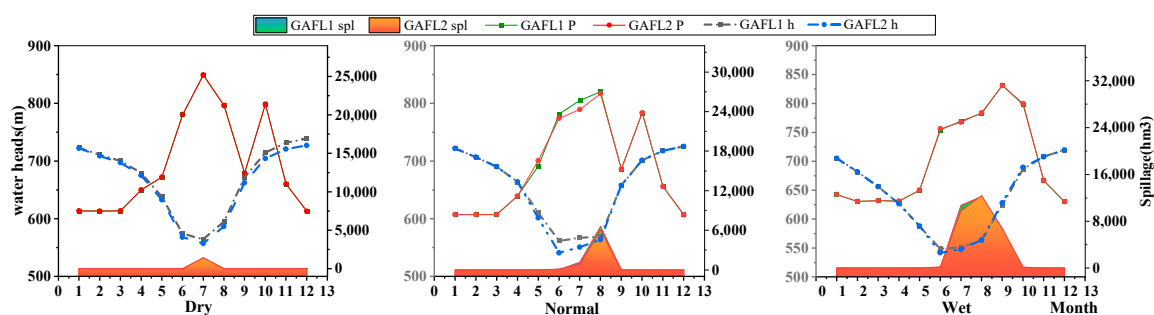


Figure 8. Comparing spillage and water heads between GAFL1 and GAFL2.

Figure 9 shows the monthly scheduling processes of (a) GAFL1 and (b) GAFL2, detailing the operation of the four reservoirs along the Jinsha River during a normal year. In this context, Z_{min} represents the minimum water level for the year, typically set as the dead water level, while Z_{max} corresponds to the upper water level limit, enforced as the normal water level during the dry season and the flood control level during the flood season. By comparing the reservoir outflow (area charts of spillage and generation discharge) with the inflow (red line), the storage and release dynamics at different times can be analyzed. When the inflow exceeds the outflow, the reservoir stores water, causing the water level to

rise; conversely, the reservoir releases water, causing the water level to drop. Both GAFL1 and GAFL2 methods yield reasonable results, storing water during the dry season and releasing it during the flood season, thereby minimizing spillage, maximizing hydropower generation, and ensuring optimal utilization of water resources.

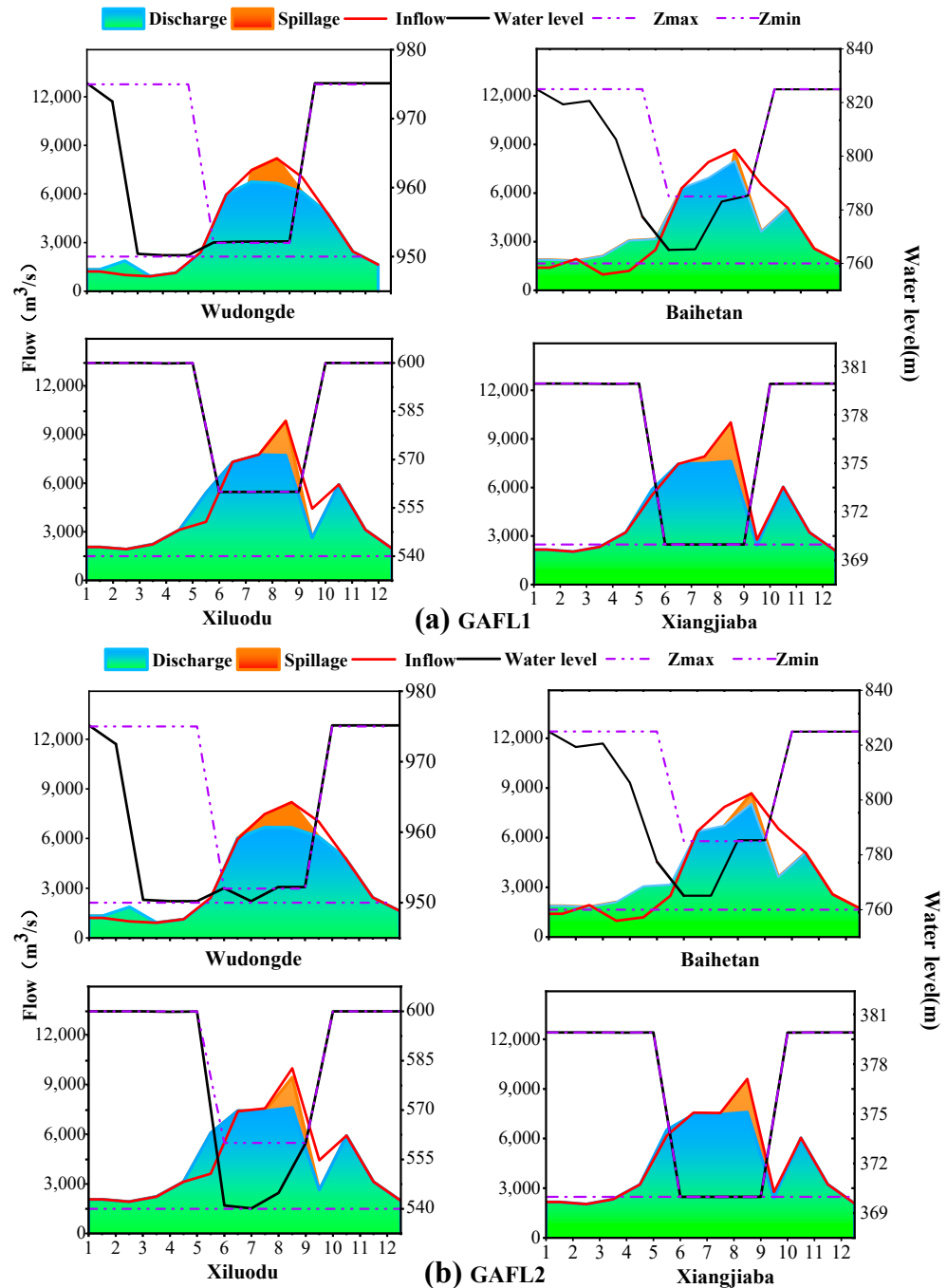


Figure 9. The scheduling process for the four reservoirs derived using the two methods.

5. Conclusions

This study integrates genetic algorithms (GAs) with a simulation program, specifically transferring the computation of the fitness function to the simulation in order to address issues of “dimensionality disaster” and local optima commonly encountered in the scheduling of cascade reservoirs. The objective is to maximize energy generation and ensure optimal output. Additionally, this study incorporates the concept of FL into the simulation program. This approach utilizes a push–pull strategy to explore additional spaces

for harnessing and utilizing unnecessary spillage for energy generation, thus achieving optimal reservoir scheduling. It achieves this using two specific strategies: GAFL I, which includes only a forward push step in the simulation, and GAFL2, which features a sequence of forward push, backward pull, and another forward push to enhance the utilization of resources. Thus, this reveals the following:

- (1) This study verifies the feasibility and scientific basis of GAFL by comparing the data from the results of GAFL1 and Sequential Quadratic Programming (SQP). The results show that although GAFL1's spillage increased by 2.2 times compared to SQP and total energy slightly decreased, GAFL1 significantly improved firm yield by 8.3% at the highest priority level. This highlights GAFL1's advantage in prioritizing firm yield despite increased spillage, demonstrating its potential for optimizing reservoir operation under specific operating priorities.
- (2) Because the solution of the fitness function part is implemented within the simulation program, the workload of the genetic algorithm is reduced, thereby significantly improving the efficiency of the optimization process. Both GAFL1 and GAFL2 exhibit good convergence effects, achieving convergence of the objective function values in the 15th and 10th iterations, respectively. This indicates that both versions of the algorithm can quickly reach optimal or near-optimal solutions within a limited number of iterations, making them highly effective in addressing complex optimization problems in reservoir scheduling.
- (3) The comparative results between GAFL1 and GAFL2 show that GAFL2's strategy comprising a push forward, a pull back, and a push forward again can minimize spillage to the greatest extent. This proves that it is effective in reducing spillage under all hydrological conditions without impacting the highest priority stable output.
- (4) The results indicate that across all hydrological years, FL can maximize the reduction in spillage without affecting the highest priority stable output. Based on this, it is observed that in both drought and wet years, reducing spillage increases energy generation. However, the impact of this reduction is variable; in normal years, although spillage decreases, total energy generation also reduces.

In summary, although the comparison between GAFL1 and SQP shows an increase in spillage with a significant improvement in firm yield, it highlights the potential of GAFL1 in prioritizing outputs; GAFL2, on the other hand, demonstrates the efficiency of the optimization algorithm in quickly achieving optimal solutions. Both strategies effectively address complex reservoir scheduling optimization issues. However, despite this, this study has limitations due to its reliance on specific simulation environments and parameter settings, which may affect the generalizability of the results and their applicability to other types of reservoir systems. Furthermore, although the research indicates that spillage can be effectively reduced under various hydrological conditions, the relationship between the increase in total energy and the reduction in spillage is not evident in normal hydrological conditions, suggesting that further research and strategy optimizations are needed for adaptations to take place regarding various hydrological changes.

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