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Multi-Reservoir Flood Control Operation Using Improved Bald Eagle Search Algorithm with ε Constraint Method

Wenchuan Wang [1,*], Weican Tian [1], Kwokwing Chau [2], Hongfei Zang [1], Mingwei Ma [1], Zhongkai Feng [3] and Dongmei Xu [1]

[1] Henan Key Laboratory of Water Resources Conservation and Intensive Utilization in the Yellow River Basin, College of Water Resources, North China University of Water Resources and Electric Power, Zhengzhou 450046, China
[2] Department of Civil and Environmental Engineering, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China
[3] College of Hydrology and Water Resources, Hohai University, Nanjing 210024, China
* Correspondence: wangwenchuan@ncwu.edu.cn or wangwen1621@163.com

Abstract: The reservoir flood control operation problem has the characteristics of multiconstraint, high-dimension, nonlinearity, and being difficult to solve. In order to better solve this problem, this paper proposes an improved bald eagle search algorithm (CABES) coupled with ε-constraint method (ε-CABES). In order to test the performance of the CABES algorithm, a typical test function is used to simulate and verify CABES. The results are compared with the bald eagle algorithm and particle swarm optimization algorithm to verify its superiority. In order to further test the rationality and effectiveness of the CABES method, two single reservoirs and a multi-reservoir system are selected for flood control operation, and the ε constraint method and the penalty function method (CF-CABES) are compared, respectively. Results show that peak clipping rates of ε-CABES and CF-CABES are both 60.28% for Shafan Reservoir and 52.03% for Dahuofang Reservoir, respectively. When solving the multi-reservoir joint flood control operation system, only ε-CABES flood control operation is successful, and the peak clipping rate is 51.76%. Therefore, in the single-reservoir flood control operation, the penalty function method and the ε constraint method have similar effects. However, in multi-reservoir operation, the ε constraint method is better than the penalty function method. In summary, the ε-CABES algorithm is more reliable and effective, which provides a new method for solving the joint flood control scheduling problem of large reservoirs.

Keywords: flood control operation; bald eagle search algorithm; multi-reservoir; ε constraint method; penalty function method

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1. Introduction

According to the global climate risk index 2021, approximately 11,000 extreme meteorological disasters have occurred in the past 20 years, resulting in approximately 475,000 deaths and economic losses of nearly USD 2.56 trillion. Global warming caused by greenhouse gas emissions has significantly affected the regional hydroatmospheric cycle process, resulting in frequent occurrence of disaster problems such as extreme drought, rainstorm, flood, high temperatures, and heat waves, which have seriously restricted the balanced development of regional economy, society, and ecological environment [1–4]. Floods are the most common and harmful among all kinds of natural disasters. They have a high frequency of occurrence, a wide range of coverage, and a strong ability to damage the environment, causing heavy losses to countries and citizens [5].

Reservoirs are the most common water conservancy projects used for runoff regulation and flood control, so they are an important research object for flood control. Reservoir operation refers to the operation of upstream water according to different inflow conditions, using reservoir storage function, combined with the existing storage capacity, which is an important nonengineering measure. In reservoir operation, different constraints are set up to optimize the problem, such as water balance, discharge constraints, water level constraints, etc. This is a high-dimensional, nonlinear, multistage, multiconstraint process [6,7]. Therefore, determining how to use modern methods to realize flood control of a reservoir is an important and practical problem.

At present, mathematical programming methods and emerging intelligent heuristic optimization algorithms are most often used to solve the reservoir (group) optimal operation problem. The advantages of mathematical programming, dynamic programming [8], linear programming [9], nonlinear programming [10], and other methods are well established; however, they also have some problems. During reservoir operation, due to the diversity of research contents and complex data, it is difficult to give consideration to efficiency and accuracy, and it is easy to produce the "dimensionality problem" [11–13]. In order to better solve this problem, researchers continue to explore optimization algorithms and make great breakthroughs. The emergence of modern intelligent heuristic optimization algorithms is the result of continuous exploration, such as particle swarm optimization (PSO) [14], genetic algorithm (GA) [15], water cycle algorithm (GCA) [16], and improved firefly algorithm (YYFA) [17]. These modern heuristic algorithms have strong robustness, and overcome the shortcomings of low efficiency of traditional algorithms to a certain extent. However, due to the diversity and complexity of reservoir flood control operation by itself, as well as the actual flood control operation process, there will be a variety of uncertainties. In the process of solving the optimal solution, a simple optimization algorithm has difficulty meeting various constraints at the same time, so it also needs to adopt relevant constraint processing techniques.

In recent years, due to the simple and efficient execution process of the penalty function, researchers have widely used constrained evolutionary algorithms to solve the reservoir constraint problem [18–23]. However, due to the difficulty in selecting the penalty factor, the performance of the algorithm strongly depends on the selection of the parameter, which makes it difficult to obtain high-quality solutions. The processing technique based on ε constraint was proposed by Takahama and Sakai [24]. The core idea is that individuals whose degree of default is less than ε are regarded as feasible solutions through the setting value of ε, and it makes full use of the information of the infeasible solution with better objective function value in the infeasible region. Compared with the penalty function method, it has better convergence [17,25–27].

The bald eagle search algorithm (BES) is a new swarm intelligence algorithm proposed in recent years [28]. The algorithm has simple initial conditions and strong global search ability, and can effectively solve various complex numerical optimization problems. In the past, this algorithm has been applied to a variety of practical problems for optimization [29–33]. Nevertheless, BES may fall into local optimal solution and fail in the computation of reservoir flood control operation. Therefore, this paper proposes an improved bald eagle search algorithm (CABES) to solve the reservoir flood control operation problem. By introducing Cauchy mutation, integrating adaptive weight factor and Levy flight strategy, the optimal solution position is perturbed and mutated to improve the anti-local extreme value ability, improve the search accuracy of the algorithm, mine the global optimal solution, and combine the constraint processing technology to obtain the optimal flood control operation scheme.

The rest of this paper is as follows: Section 2 introduces the CABES algorithm and constraint processing technology. Section 3 presents the flood control operation model. The specific reservoir information and operation scheme analysis are discussed in Section 4. Section 5 provides the final conclusion.

2. CABES Algorithm and Constraint Processing Technology

2.1. BES Algorithm

Alsattar, Zaidan and Zaidan [28] first proposed the BES algorithm, which is a new global search optimization technology. The algorithm simulates the behavior of eagles in the process of hunting to prove that the cooperative sequence of each stage of hunting is reasonable. Accordingly, the algorithm can be divided into three parts, namely, selection stage, search stage, and swoop stage.

(1) Selection stage

During the selection stage, eagles determine the search space based on the number of prey in the area to prepare for the next search and predation. The new position of the bald eagle is set as $L_{i,new}$, and its position update equation is as follows:

$$L_{\mathrm{i},new} = L_{best} + p * q(L_{mean} - L_i) \tag{1}$$

where p is a parameter that controls the position change, and is a random number within (1.5, 2); q is a random number between 0 and 1; L_{best} is the best position selected from the current population position; L_{mean} is the position of the average distribution of vultures computed according to the distribution of all eagles after the search; and L_i is the current position of the *ith* vulture.

(2) Search stage

In the selected search space, the bald eagle moves in different directions in a spiral space to pursue the prey, quickly search for the best position to capture the prey, and prepare for the next dive. The location is updated as follows:

$$\theta(i) = a * pi * q \tag{2}$$

$$d(i) = \theta(i) + R * q \tag{3}$$

$$d_x(i) = d(i) * \sin(\theta(i)), d_y(i) = d(i) * \cos(\theta(i)) \tag{4}$$

$$x(i) = d_x(i)/\max(|d_x|), y(i) = d_y(i)/\max(|d_y|) \tag{5}$$

$$L_{i,new} = L_i + x(i) * (L_i - L_{mean}) + y(i) * (L_i - L_{i+1}) \tag{6}$$

where a and R are random numbers that control the spiral trajectory, with value ranges of [5, 10] and [0.5, 2], respectively; *pi* is 3.14; and *x(i)*, *y(i)* represent the position of the eagle in coordinates. For other parameters, please refer to the selection stage.

(3) Swoop stage

At this stage, the eagle flies from the best position in the search space to the target prey, and all points move towards the best position. The position update equation at this stage is as follows:

$$\theta(i) = a * pi * q, d(i) = \theta(i) \tag{7}$$

$$d_x(i) = d(i) * \sinh(\theta(i)), d_y(i) = d(i) * \cosh(\theta(i)) \tag{8}$$

$$x_1(i) = d_x(i)/max(|dx|), y_1(i) = d_y(i)/\max(|dy|) \tag{9}$$

$$L_{i,new} = q * L_{best} + x_1(i) * (L_i - c_1 * L_{mean}) + y_1(i) * (L_i - c_2 * L_{best}) \tag{10}$$

where c_1 and c_2 are two random numbers with value ranges of [1, 2], which increase the movement intensity of the bald eagle to the best and center points.

2.2. CABES Algorithm

Although the initial conditions of the BES algorithm are simple, the convergence speed is fast. However, the search step size of the algorithm in the selection stage is a fixed value, and it is easy to fall into a local optimum and difficult to jump out during the optimization process of complex functions. In addition, the search stage only updates the location information of the current population, ignoring the location information generated by other iterations of the algorithm, so that the algorithm lacks information in the process of searching and updating the location, resulting in inaccurate location updates. Therefore, the following two strategies are proposed to improve these two aspects. On the basis of the BES algorithm, Cauchy mutation strategy and hybrid dynamic selection strategy combining adaptive weight and Levy flight are added to improve the CABES algorithm.

2.2.1. Cauchy Mutation Strategy

In recent years, the Cauchy mutation strategy has been applied to improve the performance of optimization algorithms due to its excellent perturbation ability. Wang et al. [34] used Cauchy mutation to strengthen the performance of the firefly algorithm (FA). Zhao et al. [35] introduced Cauchy mutation to the grasshopper algorithm to enhance the global search ability of the algorithm. The adaptive Cauchy mutation symbiotic search algorithm was proposed by Miao et al. [36] to improve the optimization performance of the original algorithm. Zhao et al. [37] used Cauchy mutation to improve the exploration ability of the moth–flame optimization algorithm, which is conducive to jumping out of the local optimum. Therefore, this paper introduces the Cauchy mutation strategy in the algorithm selection stage, and uses its good perturbation ability to facilitate the mutated individuals to jump out of the local extreme value.

The standard one-dimensional Cauchy distribution density function is as follows [38]:

$$f(x) = \frac{1}{\pi}\frac{1}{x^2+1}\ ,\ -\infty < \mathrm{x} < \infty \tag{11}$$

The improved Equation (1) is as follows:

$$L'_{\mathrm{i},new} = L_{best} + C(\lambda) * (L_{mean} - L_i) \tag{12}$$

where is the Cauchy factor, which obeys the density function distribution.

2.2.2. Fusion of Adaptive Weights and Levy Flight Strategy

The adaptive weight factor is a very important parameter. When the weight factor is large, the algorithm uses relatively more time for global search. When the weight factor is small, the algorithm uses relatively more time for local search and can finely find the best solution. Therefore, many scholars used adaptive weight factors to improve the optimization effect of the algorithm [14,39–41].

The adaptive weight factor is as follows:

$$\omega = \sin\left(\frac{\pi * t}{2Maxt} + \pi\right) + 1 \tag{13}$$

where t is the current iteration number and $Maxt$ is the maximum iteration number.

After introducing the weight factor into the search phase, the position update Equation (6) is changed to the following form:

$$L'_{i,new} = \omega * L_{i,new} \tag{14}$$

Levy flight strategy can enhance the global search ability of the algorithm, which is characterized by random flight with alternate search range. In recent years, researchers have used Levy flight to solve search and optimization problems, proving that it can effectively improve the search ability and solution accuracy of optimization algorithms in the solution space [42–45]. Levy flight is a non-Gaussian random process, and its step size follows Levy distribution.

$$levy(s) \sim \left|s\right|^{-1-\beta}, 0 < \beta \le 2 \tag{15}$$

where s is the step size, which can be obtained from the following equation:

$$s = \frac{\mu}{|v|^{\frac{1}{\beta}}}, \mu\ and\ v \sim N(0,\sigma^2) \tag{16}$$

After introducing the Levy flight factor into the search phase, the position update Equation (6) is changed into the following form:

$$L'_{i,new} = levy * L_{i,new} \tag{17}$$

In order to further improve the optimization performance of the algorithm, a dynamic selection strategy is adopted to update the target position. The adaptive weight strategy and Levy flight strategy are alternately executed under a certain probability to dynamically update the target position. The adaptive weight strategy is used to expand the search field of the algorithm. In Levy flight strategy, Levy flight is used to perturb and mutate at the optimal solution position to obtain a new solution, which improves the defect that the algorithm falls into local area. As for which strategy to adopt to update the target location, it is determined by the selection probability P [46], and its calculation formula is as follows:

$$P = -\exp\left(1 - \frac{t}{Maxt}\right)^{20} + \Omega \tag{18}$$

where Ω is the adjustment parameter, and the value is 0.05. The specific selection method is as follows:

If rand < P, select adaptive weight strategy to update the position, otherwise select Levy flight strategy to update the target position.

Figure 1 shows the flowchart of the CABES algorithm. In Figure 1, N is the population number, $Maxt$ is the maximum number of iterations, t is the current number of iterations, $rand$ is a randomly generated number, and P is the selection probability of Equation (18).

2.3. Experiment Design and Test Function

In order to comprehensively test the optimization ability of the improved algorithm CABES, six complex test functions were selected for function extremum optimization testing to verify the optimization performance and convergence ability of the algorithm. Functions are derived from CEC2017 benchmark test function set, including multimodal functions (F3, F6, F8) and composition (F21, F23, F24) type functions [47]. Please refer to Table 1 for details. The multimodal function is used to test the exploration ability and the ability to jump out of the local optimum of the algorithm, and the composite function is used to test the comprehensive ability of the algorithm. The simulation test compares the CABES algorithm with BES and PSO.

2.3.1. Algorithm Performance Analysis

In order to ensure the fairness and objectivity of the experiment, the benchmarking algorithms use the same software and hardware platform to run independently for 30 times under the same conditions. The optimal value, average value, and standard deviation are recorded, and the results are shown in Table 2. The running environment is Windows 10 and the programming language is MATLAB R2018a. The population size is N = 50, the dimension is 50, and the maximum evolution algebra is $Maxt$ = 1000. In terms of algorithm parameter settings, the parameters of BES and CABES algorithm are both a = 10, R = 1.5. In PSO algorithm, the learning factors $c1$ and $c2$ are both 0.5, and w = 0.8. The values of these parameters are the same as those of the original literature and source code of the respective algorithms.

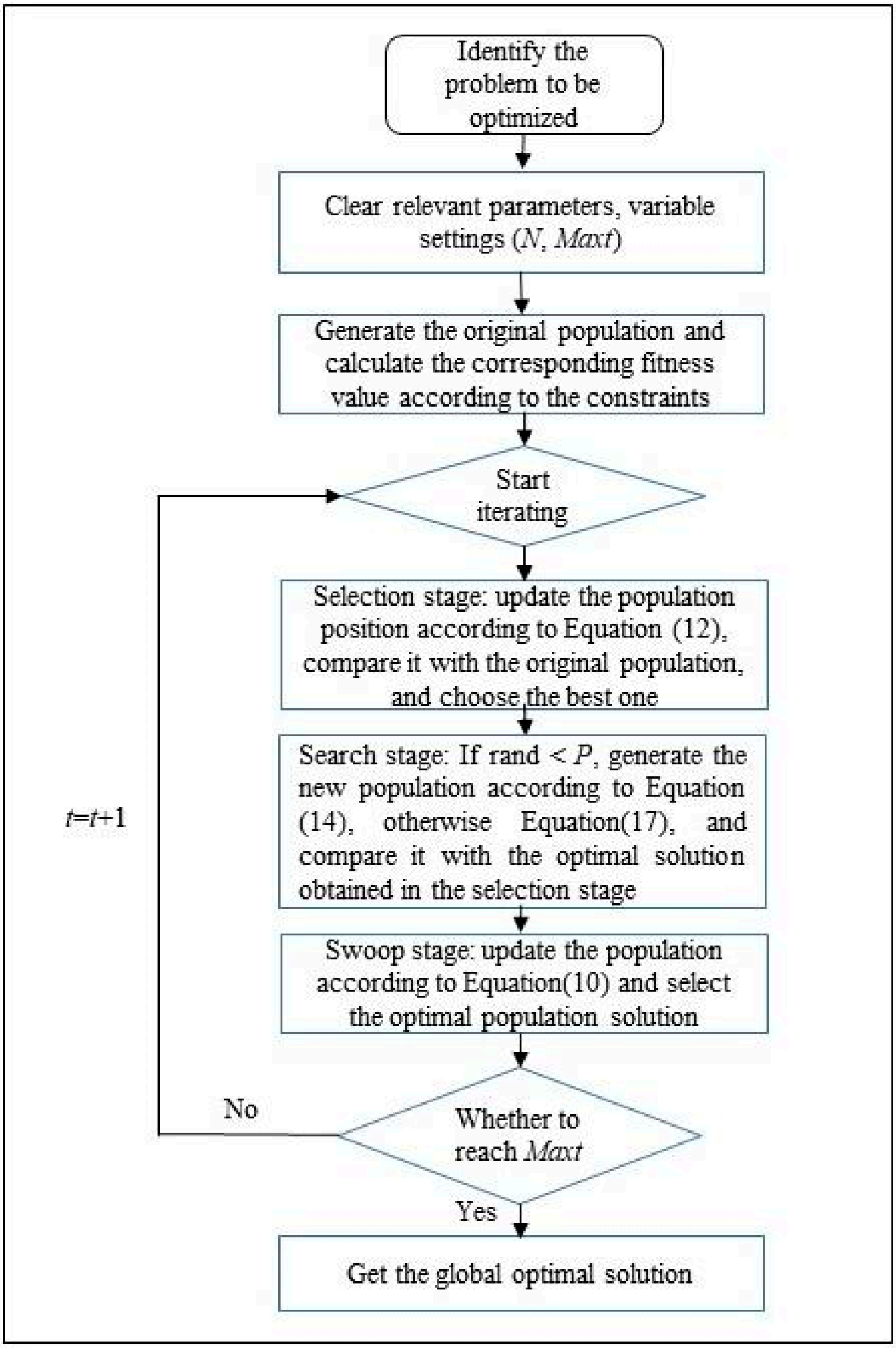


Figure 1. Flow chart of CABES algorithm.

Table 1. CEC2017 test functions.

Function	Type	Optimal Value
F3	Multimodal Functions	300
F6		600
F8		800
F21	Composition Functions	2100
F23		2300
F24		2400

Table 2. Optimization results of CEC2017 test functions.

Function	Algorithm	Best	Mean	Standard Deviation
F3	BES	1923.52	8122.14	4478.09
	CABES	300.97	407.68	114.32
	PSO	107,727.00	208,286.00	50,031.60
F6	BES	633.39	645.92	8.27
	CABES	600.00	600.26	0.49
	PSO	641.00	656.00	9.30
F8	BES	995.01	1078.79	45.07
	CABES	937.30	1021.51	53.32
	PSO	1011.17	1151.26	51.50
F21	BES	2451.43	2520.37	35.48
	CABES	2402.34	2465.49	31.28
	PSO	2556.89	2675.77	54.98
F23	BES	2926.15	3041.84	68.74
	CABES	2844.83	2913.47	37.91
	PSO	3087.86	3297.07	116.25
F24	BES	3101.64	3235.85	100.43
	CABES	3011.04	3085.16	45.82
	PSO	3293.15	3478.19	124.40

The mean value shows that the algorithm has better average performance of single precision in repeated experiments. The standard deviation value verifies the good algorithm robustness of the algorithm. The best value indicates that the improved algorithm can fully explore and exploit the solution space of the problem and find the global optimal solution with high accuracy. It can be seen from Table 2 that for functions F3, F6, F21, F23, and F24, the best values, mean values, and variances on these five functions achieved the best results under the condition of 50 dimensions.

The above solution results and analysis show that, compared with BES and PSO, the CABES algorithm has better overall solution performance. The problems that the BES algorithm often encounters, namely, easily falling into local extremum and experiencing unstable optimization performance when solving global optimization of complex functions, are well solved by the CABES algorithm, with stronger stability and robustness.

2.3.2. Wilcoxon Sign Rank Sum Test

In order to verify the significant difference between the improved CABES algorithm and other benchmarking algorithms in the experimental results, and further evaluate the optimization performance of the algorithm, a nonparametric statistical test method, namely, Wilcoxon rank sum test, is used for statistical analysis. Table 3 shows the statistical test results of CABES and other benchmarking algorithms for solving six representative functions at D = 50 for the CEC2017 test function set suite. Among them, symbols '+', '−', and '=' are used to indicate that the optimization results of CABES are superior, inferior, and equivalent to other comparison algorithms, respectively. Results with $p < 0.05$ can be considered a strong test of the significance of rejecting the null hypothesis.

Table 3. *p*-value for Wilcoxon's rank-sum test on each algorithm.

Algorithm	CABES vs. BES	CABES vs. PSO
Function	*p*-value win	*p*-value win
F3	0.00 (+)	0.00 (+)
F6	0.00 (+)	0.00 (+)
F8	0.00 (+)	0.00 (+)
F21	0.00 (+)	0.00 (+)
F23	0.00 (+)	0.00 (+)
F24	0.00 (+)	0.00 (+)
(+/−/=)	6/0/0	6/0/0

From the statistical test results of Table 3, which shows the improved CABES algorithm compared with BES and PSO algorithms, the test *p*-values on all six functions are less than 0.05 and the symbol is '+', rejecting the null hypothesis. It can be seen that there are significant differences between the computation results of CABES and the other five benchmarking algorithms, and CABES is significantly better.

2.4. Constraint Processing Technology

It is unsustainable to rely solely on evolutionary algorithms to solve complex constrained optimization problems. In the optimization process, the essence of evolutionary algorithms is to generate offspring, and the essence of constraint processing technology is to select high-quality individuals from candidate individuals to enter the next generation, and then make the population converge to the optimal solution. The core of the constrained optimization evolutionary algorithm is determining how to effectively balance the objective function of the population and the degree of constraint violation. In order to achieve this goal, this paper couples the CABES algorithm with two constraint processing techniques, the ε constraint method and penalty function method, to improve the ε-CABES algorithm and CF-CABES algorithm, respectively.

2.4.1. ε. Constraint Method

The essence of the constraint handling method is to replace the ordinary comparison method with the level comparison method to evaluate the advantages and disadvantages of individuals, and convert an algorithm conventionally used to solve unconstrained optimization problems into an algorithm for solving constrained optimization problems [24]. Therefore, the performance of such algorithms is mainly determined by the performance of evolutionary algorithms. In general, a constrained optimization problem of minimizing a target value in the D-dimensional space can be described as follows:

$$\begin{array}{ll} \text{minimize} & z(x), x = (x_1, x_2, \ldots, x_D) \\ \text{subject to} & \begin{array}{c} g_i(x) \leq 0, i = 1, \ldots, m \\ lb_k \leq x_k \leq ub_k, k = 1, \ldots, D \end{array} \end{array} \tag{19}$$

where *z(x)* is the objective function; x is the decision vector; *g(x)* is the inequality constraint; lb_k and ub_k are the upper and lower limits of the *i-th* decision component, respectively. Therefore, a solution that meets all constraints is a feasible solution, and a solution that does not meet any constraint is an infeasible solution. The constraint violation G of the infeasible solution can be defined as

$$G(X) = \sum_{i=1}^{m} \max\{0, g_i(x)\} \tag{20}$$

The advantages and disadvantages of two solutions X_1, X_2 are compared by Equation (21).

$$(X_2, F_2, G_2)\text{is better than}(X_1, F_1, G_1) \Leftrightarrow \begin{cases} F_2 < F_1,\ if\ G_1 = 0 \cap G_2 = 0; \\ F_2 < F_1, if\ G_2 = 0 \cap \varepsilon(i) \geq G_1 > 0; \\ F_2 < F_1,\ if\ G_1 = 0 \cap \varepsilon(i) \geq G_2 > 0; \\ G_2 < G_1,\ if\ G_1 > 0 \cap G_2 > 0; \\ G_2 = 0 \cap G_1 > \varepsilon(i). \end{cases} \tag{21}$$

where *ε(i)* is obtained from Equation (22).

$$\varepsilon(i) = \begin{Bmatrix} \varepsilon(i-1)/1.035, & \varepsilon > 10^{-6} \\ 0, & \varepsilon \leq 10^{-6} \end{Bmatrix} \tag{22}$$

2.4.2. Penalty Function Method

The main idea of the penalty function method is to construct penalty terms based on the degree of violation of individual constraints. By adding penalty terms to the objective function, the penalty fitness function is constructed, and the constrained optimization problem is transformed into an unconstrained optimization problem [48,49]. The general penalty fitness function can be defined as follows:

$$F_l = f_l + c\sum_{k=1}^{R} r_k G_k \tag{23}$$

where F_l and f_l are the transformed objective function and original objective function of the l-th individual, respectively; R is the number of constraints; c is the penalty factor; and r_k is the number of constraint violation levels set for each constraint.

3. Flood Control Operation Model

3.1. Objective Function

The objectives of reservoir flood control optimal operation are to ensure the safety of the reservoir itself, meet the requirements of reservoir flood control optimization, and protect the safety of downstream flood control objects. The first two flood control objectives require that the upstream water level of the reservoir should not be too high, so as to achieve the safety of the reservoir and reduce the upstream inundation loss. Ensuring the safety of downstream flood control objects requires that the discharge of the reservoir should not be too large, and the flood should be blocked with more storage. The objects of upstream and downstream flood control have a certain conflict. This paper aims to reduce the peak discharge on the basis of giving full play to the regulation and storage capacity of the reservoir, so as to ensure the safety of downstream protection objects.

In this paper, the maximum peak clipping criterion is taken as the objective to solve the dispatching problem. The maximum peak clipping is the minimum sum of squares of the reservoir discharge process, so the objective function constructed here is as follows [50]:

$$f(q) = \min\sum_{t=1}^{T} [q_{it} + R_{i+1}(t)]^2 \tag{24}$$

where $q_i(t)$ is the reservoir discharge at time t; $R_{i+1}(t)$ is the inflow between the reservoir and the downstream protection zone at time t. If there is no interval water, it is 0.

3.2. Constraint Conditions

(1) Constraint equation of reservoir water balance:

$$V_{t+1} - V_t = (I_t - q_t) \triangle t \tag{25}$$

(2) Upper and lower limits of water level constraints:

$$H_{\min} \leq H_t \leq H_{\max} \tag{26}$$

(3) Discharge capacity constraints:

$$q_t \leq q(Z_t) \tag{27}$$

(4) Restriction of water level at the end of the period:

$$H_t = H_{end} \tag{28}$$

(5) Non-negative constraint: all the above variables are non-negative values.

V_t and V_{t+1} are the reservoir capacity at t and t + 1, respectively, and the unit is m^3; I_t is the inflow of the reservoir at time t; q_t is the average discharge of the reservoir during t period, which is m^3/s; H_t is the corresponding water level at time t; H_{min} and H_{max} are the lower and upper limits of water level at time t, expressed in m; $q(Z_t)$ is the discharge capacity corresponding to the corresponding water level at time t; H_{end} corresponds to the water level at the end of the whole dispatching period, and the corresponding unit is m.

4. Case Studies

In order to verify the rationality and superiority of the CABES algorithm, as well as the difference between the two constraint processing technologies, this paper selects two single reservoirs and a multi-reservoir system for flood control operation. Among them, Shafan Reservoir and Dahuofang Reservoir in China are selected for the single reservoirs, and three reservoirs in the Luan River Basin are selected for the multi-reservoir system.

In the process of flood control and dispatch, the flood process of Shafan Reservoir has the characteristics of relatively few flood sequences and short duration. However, the flood process of Dahuofang Reservoir has many sequences and a long period of time. Therefore, in theory, a flood control operation model with a stronger performance and higher computing power is required to complete the operation. Compared with the single-reservoir operation, the multi-reservoir system has different regulation performance, different hydrological characteristics, and different profit goals. It is not only possible but also necessary to carry out the joint dispatch of the multi-reservoir system. By implementing the joint dispatch of the multi-reservoir system, the advantages of each reservoir project will be better exhibited, and the goals of flood control and profit will be achieved.

In order to enhance the depth of the analysis of the results, this section also uses the original BES algorithm and the classic PSO algorithm to perform flood control operation for the abovementioned reservoirs (groups) by combining two constraint processing techniques, and compares the results with those of the ε-CABES algorithm. Parameters of each algorithm are selected from those of the optimal solution obtained in each original document [17,50,51].

Because the Shafan Reservoir, Dahuofang Reservoir, and Luanhe Reservoir group have different constraints and difficulties in solving, in order to ensure that the operation scheme meets the constraints and reaches the optimal solution, some parameters are different according to different reservoir characteristics. The parameter settings are shown in Table 4.

Table 4. Parameter settings of different algorithms.

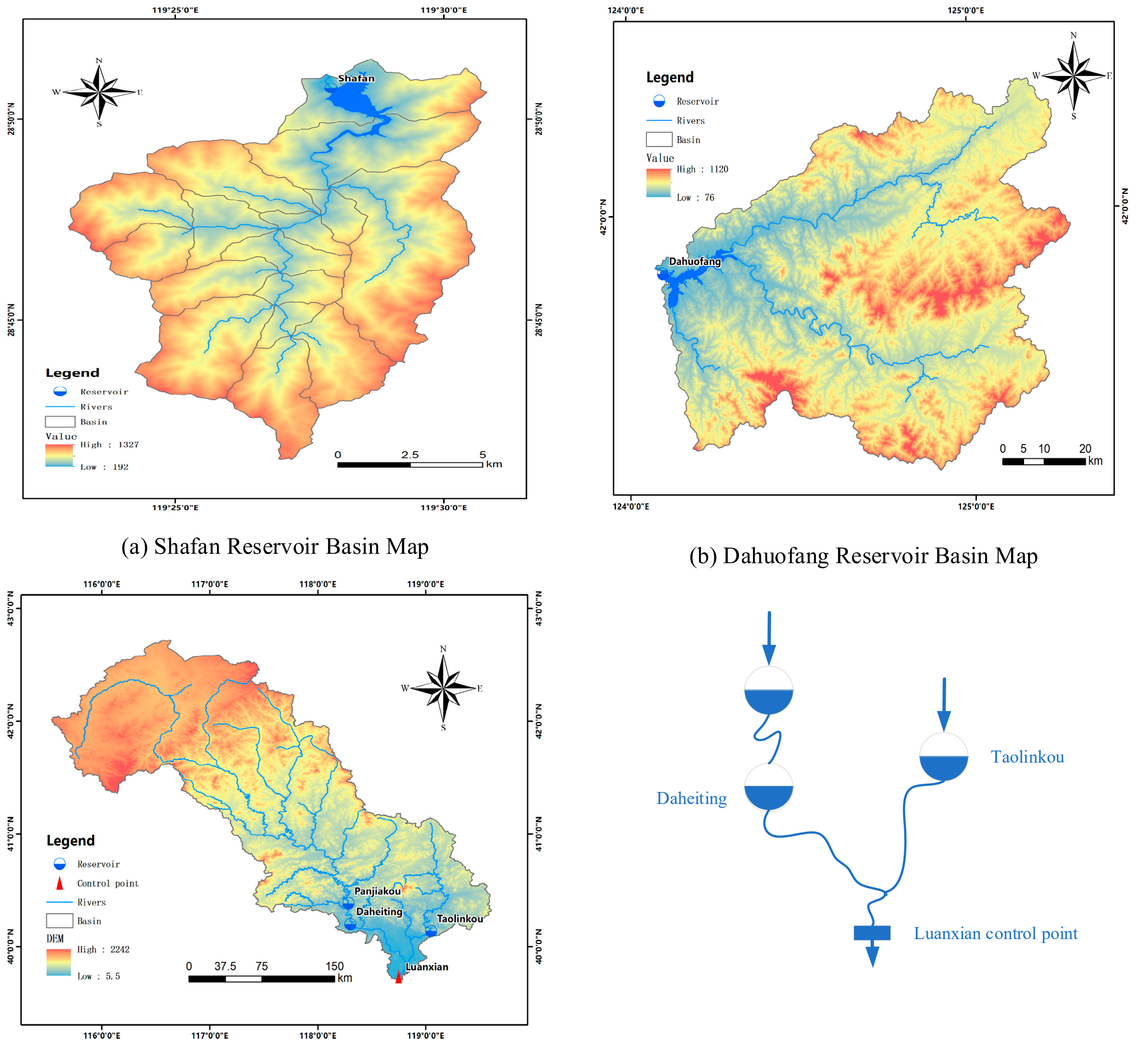
Algorithm		**ε-CABES**	**ε-BES**	**ε-PSO**	**CF-CABES**	**CF-BES**	**CF-PSO**
Parameters	ε	10,000	10,000	10,000			
	c (penalty factor)				10^6	10^6	10^6
	N (Shafan)	50	50	50	50	50	50
	Maxt (Shafan)	500	500	500	500	500	500
	N (Dahuofang)	150	150	150	150	150	150
	Maxt (Dahuofang)	1000	1000	1000	1000	1000	1000
	N (Luan River)	200	200	200	200	200	200
	Maxt (Luan River)	100,000	100,000	100,000	100,000	100,000	100,000
	w			0.8			0.8
	c_1			0.5			0.5
	c_2			0.5			0.5

4.1. Basic Information of Reservoirs

Shafan Reservoir is located in Jinhua City, Zhejiang Province. The reservoir controls a watershed area of 131 km^2. The design flood control standard is once in 50 years, and the check flood standard is once in 1000 years. The basin map of Shafan Reservoir is shown in Figure 2a. When the starting water level is the normal storage level of 270 m, the maximum allowable water level for flood control is the design flood level of 272.91 m, and the safe discharge of the downstream channel of the reservoir is 400 m^3/s. There are only five time periods, and the flood control dispatch work is carried out based on the criterion of maximum peak shaving.

Another reservoir is Dahuofang Reservoir, located in Liaoning Province, which is a comprehensive water conservancy project in the Hun River Basin [52]. The reservoir controls a drainage area of 5437 km^2, and its main function is flood control and urban water supply. Figure 2b shows the reservoir basin map. The design flood standard of the reservoir is once in a thousand years, and the design check flood standard is once in a thousand years. According to the latest approved flood control standard of Dahuofang Reservoir, the design flood level of the reservoir is 136.63 m, and the check flood level is 139.32 m. The normal high-water level and flood-limit water level of the reservoir are 131.5 m and 126.4–127.8 m, respectively. Taking the flood of Dahuofang Reservoir on 28 July 1991 as an example, there are 46 flood periods. The reservoir operation is based on the principle of maximum peak shaving. In the computation, it is necessary to ensure the safe operation demand of the reservoir, reduce the discharge volume as much as possible, and homogenize the flood discharge process of the reservoir.

The multi-reservoir system is located in the Luan River Diversion Project located in Qianxi County, Hebei Province, China. It is mainly composed of Panjiakou Reservoir, Daheiting Reservoir, and Taolinkou Reservoir. The Panjiakou Reservoir is located in the middle reaches of the Luan River, the Daheiting Reservoir is located on the main stream of the Luan River 30 km downstream of the main dam of the Panjiakou Water Control Project, and the Taolinkou Reservoir is located on the Qinglong River, a tributary of the Luan River. The map of the Luanhe River Basin is shown in Figure 2c. The three reservoirs form a mixed-type multi-reservoir system, and the basic characteristics of each reservoir are shown in Table 5. During the flood control of the multi-reservoir system, there is a flood process between the three reservoirs and the control point in Luan County, and it is necessary to carry out flood computation to obtain the outflow process of the total watershed. The locations between different reservoirs and flood control points are shown in Figure 2d. The specific flood evolution steps and relevant information of the watershed can be found in Chen et al. (2021).



(a) Shafan Reservoir Basin Map (b) Dahuofang Reservoir Basin Map (c) Luanhe River Basin Map (d) Location distribution of reservoirs in Luanhe River

Figure 2. Reservoir basin maps of the study areas.

Table 5. Basic characteristics of reservoirs in Luanhe River.

Characteristic Parameters	Panjiakou	Daheiting	Taolinkou
Checking flood level (m)	227.00	133.70	144.32
Design flood level (m)	224.50	133.00	143.40
Total storage capacity (10^8 m^3)	29.30	4.73	8.59
Benefit storage capacity (10^8 m^3)	19.50	2.07	7.09
Dead water level (m)	180.00	122.00	104.00
Normal water level (m)	222.00	133.00	143.00
Flood limit water level (m)	216.00	133.00	143.00

4.2. Flood Control Operation Process Based on CABES Algorithm

The steps of using the ε-CABES algorithm to solve reservoir flood control operation are summarized as follows:

Step 1. (Initializatidn): Population size N, total iterations $Maxt$, constraint violation ε, or penalty factor c are determined. According to the water level at the end of different periods of the reservoir, the number of N groups of particles at the end of the period is randomly generated as the initial population of each generation. According to the constraint conditions, the corresponding fitness value is computed.

Step 2. (Selection stage): The selection operation is performed according to Equation (12). Through the new position solution generated by the Cauchy mutation, the relevant constraints are used to solve the objective function value, and then combined with Equation (17) to select the pros and cons of the solution.

Step 3. (Search stage): A new position solution is generated according to Equation (14) or Equation (17). The objective function value is also computed according to the constraints, and the optimal solution is selected in combination with Equation (21).

Step 4. (Swoop stage): The position solution generated by Equation (10) is compared with the previous solution through the search and selection stages by Equation (21).

Step 5. If the current number of iterations reaches the maximum number of iterations, the iteration ends and the optimal result is obtained. Otherwise, continue to Steps 2–4 and continue to iterate.

Similarly, the steps of CABES flood control operation using penalty function method are roughly the same as those of ε-CABES flood control operation. The difference is that Equation (23) is used when using constraints to solve the objective function value. Moreover, in the three stages of steps 2–4, the comparison of Equation (21) is no longer used; instead, the comparison of the size of the fitness value is simply used to evaluate the pros and cons of the solution.

4.3. Results and Discussion

In this section, the flood control operation of two single reservoirs and a three-reservoir mixed multi-reservoir system is computed. CABES, BES, and PSO are used, and two constraint processing techniques are combined. In order to avoid random differences, the three algorithms run independently 10 times. The parameters used in the algorithm are shown in Table 4. The flood control operation results of each method, the objective function values generated in the operation process, and the comparison of iteration duration are recorded. In order to verify the stability of the algorithm, five eigenvalues such as 'minimum value 'and' standard deviation' are used for analysis. Tables 6–8 are the operation results of the Shafan Reservoir, Dahuofang Reservoir, and Luanhe multi-reservoir system. Only the data of successful dispatching are recorded in each table. Figures 3 and 4, respectively, show the operation process and convergence curve of Shafan Reservoir and Dahuofang Reservoir. The left side is the operation process, and the right side shows the convergence curve of each algorithm in the iteration process. Figure 5 shows the operation process and convergence curve of ε-CABES in the Luanhe multi-reservoir system. Figures 6–10 show the flow charts of CF-CABES, ε-BES, CF-BES, ε-PSO, and CF-PSO operation failures. Here, the Panjiakou Reservoir is used as an example that does not meet the constraints.

Table 6. Comparison of operation results of different algorithms for Shafan Reservoir.

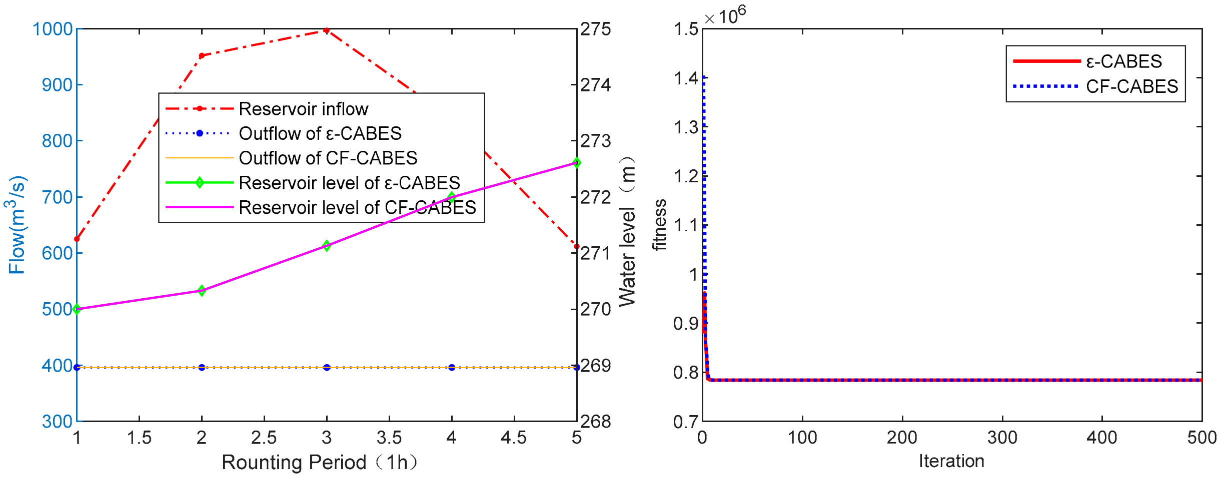
Algorithm	ε-CABES	ε-BES	ε-PSO	CF-CABES	CF-BES	CF-PSO
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
Minimum	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
Mean	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
Median	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
Maximum	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00	784,080.00
Standard deviation	0.00	0.00	0.00	0.00	0.00	0.00
Iteration duration (s)	3.74	2.99	1.49	2.96	2.25	1.29
Peak clipping rate (%)	60.28	60.28	60.28	60.28	60.28	60.28

Table 7. Comparison of operation results of different algorithms for Dahuofang Reservoir.

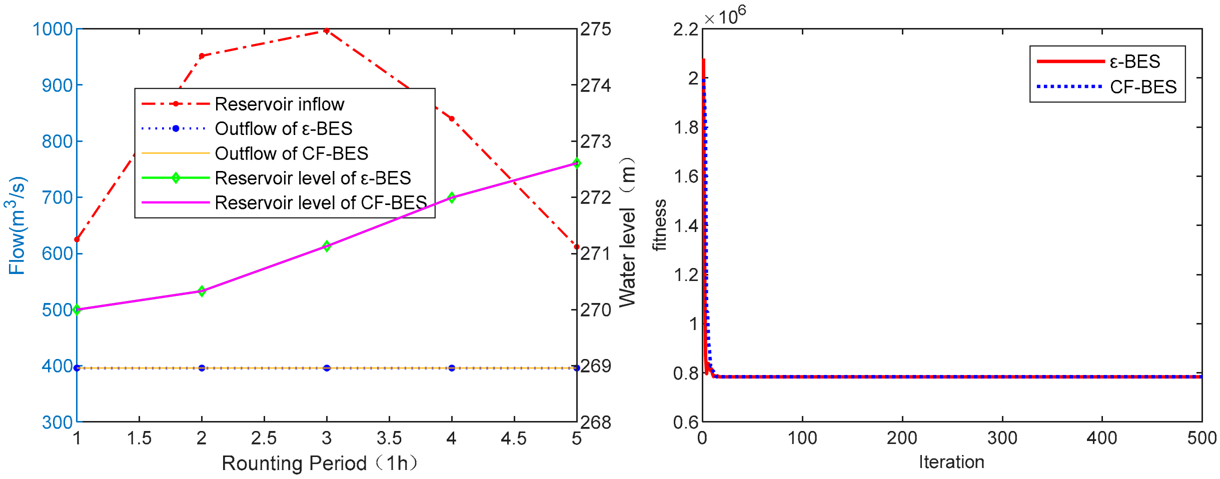
Algorithm	ε-CABES	ε-BES	CF-CABES	CF-BES
	30,737,530.83	30,737,888.76	30,737,530.88	30,737,817.37
	30,737,532.02	30,737,871.90	30,737,532.03	30,737,731.38
	30,737,531.31	30,737,852.62	30,737,530.82	30,737,731.27
	30,737,532.18	30,737,577.04	30,737,530.95	30,737,782.44
	30,737,531.09	30,738,027.34	30,737,537.61	30,774,732.07
	30,737,530.96	30,737,649.03	30,737,530.90	30,737,576.15
	30,737,530.85	30,738,846.39	30,737,531.89	30,737,736.26
	30,737,533.62	30,738,133.48	30,737,531.25	30,737,633.93
	30,737,530.95	30,737,944.77	30,737,530.82	30,737,844.28
	30,737,531.10	30,737,641.22	30,737,531.16	30,737,681.17
Minimum	30,737,530.83	30,737,577.04	30,737,530.82	30,737,576.15
Mean	30,737,531.49	30,737,943.25	30,737,531.83	30,741,426.63
Median	30,737,531.09	30,737,880.33	30,737,531.06	30,737,733.82
Maximum	30,737,533.62	30,738,846.39	30,737,537.61	30,774,732.07
Standard deviation	0.89	363.18	2.08	11,702.62
Iteration duration (s)	34.18	26.51	31.43	20.44
Peak clipping rate (%)	52.03	51.91	52.03	51.91

Table 8. Operation results of reservoirs in Luanhe River Basin using different methods.

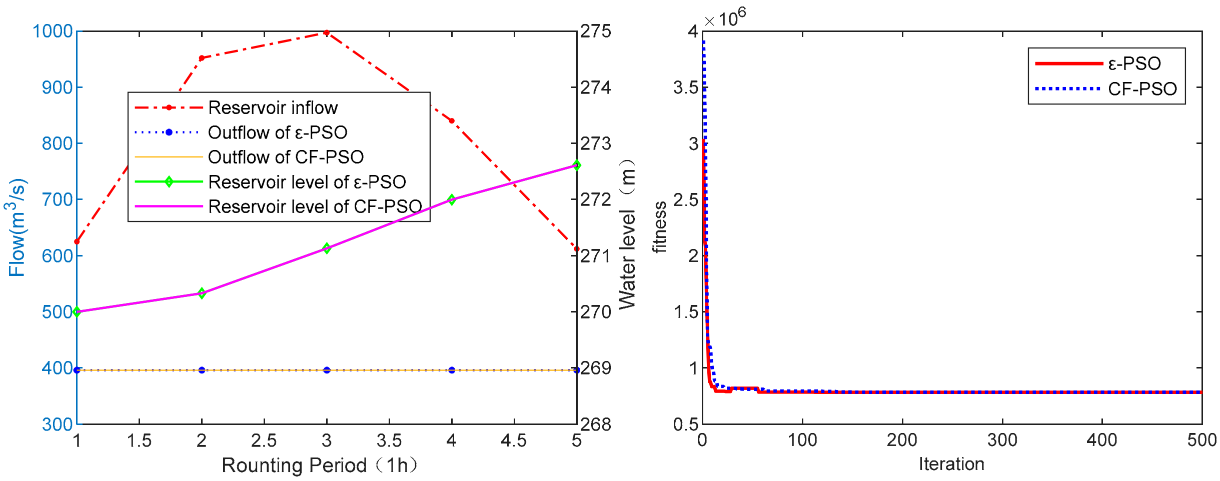
Algorithm	ε-CABES
	1,176,703,090.13
	1,177,927,824.01
	1,176,640,533.05
	1,175,832,077.13
	1,177,365,505.25
	1,177,167,086.15
	1,177,890,549.69
	1,176,890,264.34
	1,177,026,241.21
	1,182,787,126.17
Minimum	1,175,832,077.13
Mean	1,177,623,029.71
Median	1,177,096,663.68
Maximum	1,182,787,126.17
Standard deviation	1,175,832,077.13
Iteration duration (s)	4849.48
Peak clipping rate (%)	51.76



(a) Flood control results and convergence process of CABES



(b) Flood control results and convergence process of BES



(c) Flood control results and convergence process of PSO

Figure 3. Comparison of operation processes of different algorithms in Shafan Reservoir.

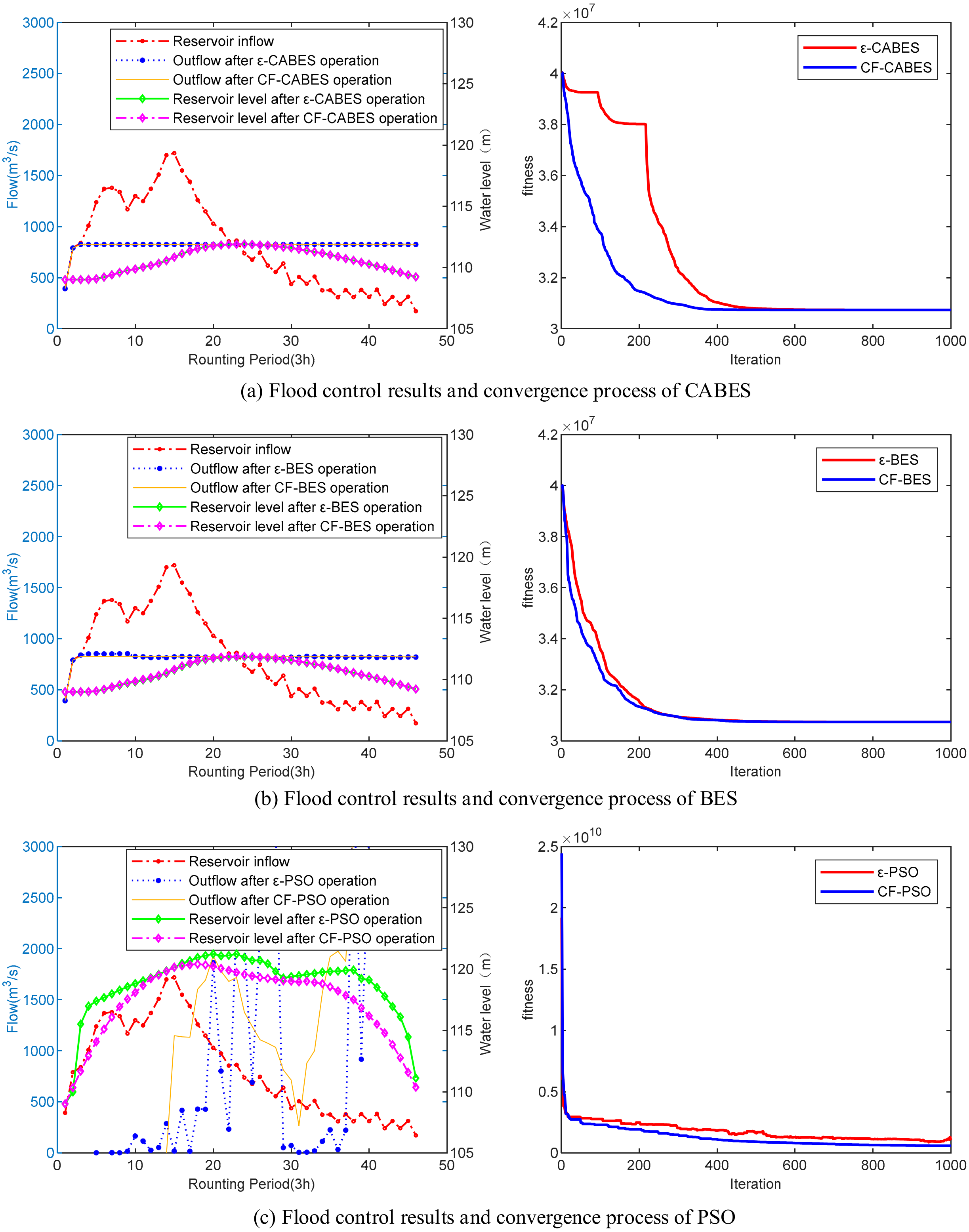


Figure 4. Comparison of operation processes of Dahuofang Reservoir with different algorithms.

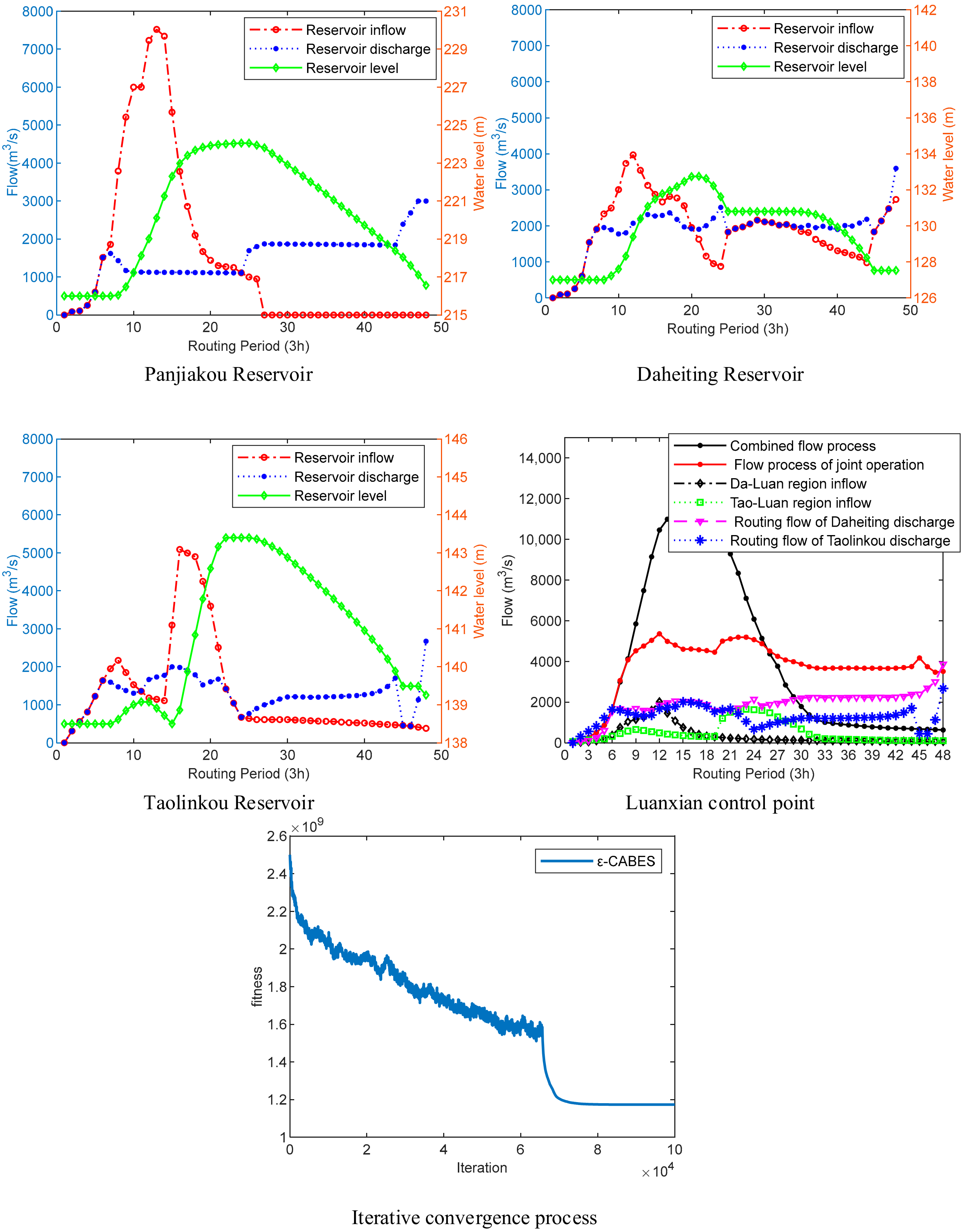


Figure 5. Operation process using ε-CABES for reservoirs in Luanhe River Basin.

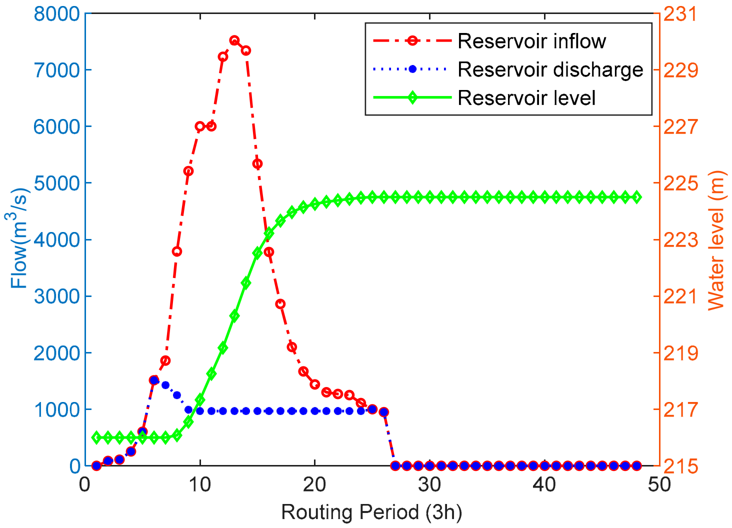


Figure 6. Operation process using CF-CABES for reservoirs in Luanhe River Basin.

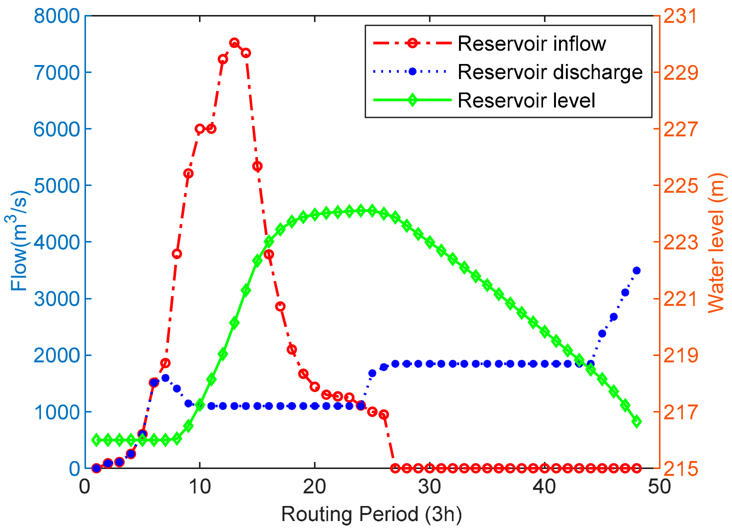


Figure 7. Operation process using ε-BES for reservoirs in Luanhe River Basin.

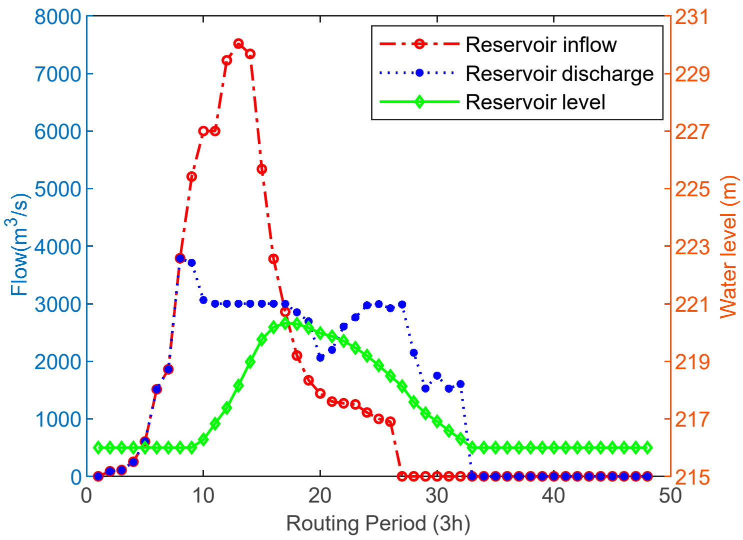


Figure 8. Operation process using CF-BES for reservoirs in Luanhe River Basin.

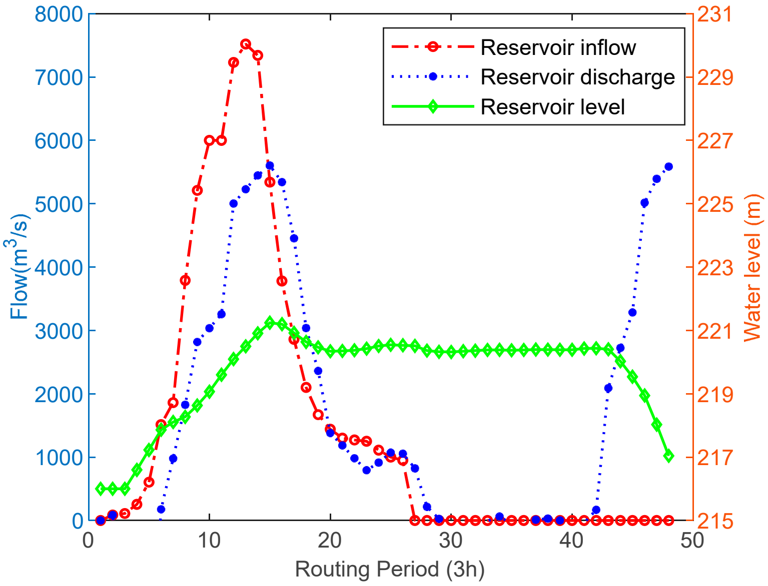


Figure 9. Operation process of Panjiakou Reservoir using ε-PSO.

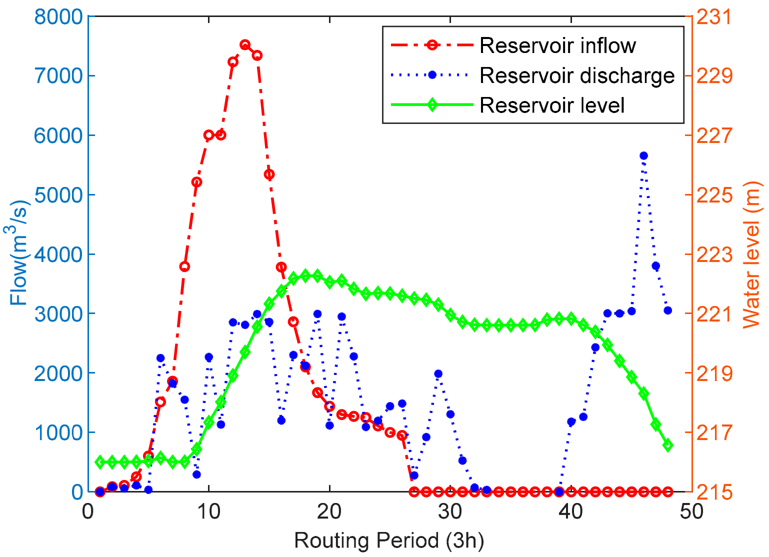


Figure 10. Operation process of Panjiakou Reservoir using CF-PSO.

It can be seen from Table 6 that the final peak shaving rate obtained by using the six methods of ε-CABES, ε-BES, ε-PSO, CF-CABES, CF-BES, and CF-PSO to solve the flood control operation strategy in Shafan Reservoir is the same. Stable results can be obtained for each computation. In Figure 3, the operation results of the three algorithms are the same. This is because Shafan Reservoir has fewer variables and simple constraints, and the flood period is short, which belongs to a relatively simple reservoir scheduling problem. Therefore, the requirement for the solution level of the algorithm is not high. It can be seen from Figure 3 that even if different constraint processing techniques are combined, the convergence process curves of each algorithm are very close, and the later stage reaches the same level of stability and obtains the same optimal solution.

It can be seen from Table 7 that under the same constraint processing technology, when solving the flood control scheme of Dahuofang Reservoir, the peak clipping rate of CABES is 0.23% higher than that of BES. As shown in Figure 4, for CABES, BES, and PSO combined with different constraint processing techniques, the final results are not the same. CABES and BES find a suitable scheduling scheme, while PSO does not meet the constraints, so it does not schedule successfully. This is because, compared with Shafan

Reservoir, Dahuofang Reservoir has more complex variables and constraints, and higher requirements for the algorithm. Moreover, the standard deviation of the CABES algorithm is far less than that of the BES algorithm when it is used to find a dispatching scheme for many times, which shows that the CABES algorithm has a better stability when it is used to solve slightly complex reservoirs. In the case of the same algorithm, the ε constraint processing method and penalty function method have the same effect. Similarly, in terms of standard deviation, the reservoir operation scheme obtained by using the ε constraint processing method is more stable than the penalty function method. However, neither ε-PSO nor CF-PSO found a suitable operation scheme.

From Table 8, it can be found that only the ε-CABES method finds a suitable operation scheme when solving the flood control operation scheme for the mixed multi-reservoir system. Figure 5 shows the flood control operation process of the three reservoirs and the flood routing process of the Luanxian control point. The Luanxian control point includes the confluence process after the optimal joint operation, the original confluence process, the flood regulation flow of each reservoir, and the water from the two subareas of the Luanxian control point. The bottom of the figure records the iterative process curve of the algorithm. The curve of the algorithm is stable in the later operation, indicating that the result is stable and convergent, and it is considered that the optimal value is reached. Therefore, ε-CABES achieves the goal of joint flood control operation.

From Figures 6–10, it can be found that the flood level does not return to the initial level at the last moment of operation, when CF-CABES solves Panjiakou Reservoir under the same optimization algorithm, and there is a danger for the next flood control. Under the same constrained processing technique, when ε-BES is compared to ε-CABES, the discharge flow exceeds the lower discharge flow constraint and therefore does not meet the constraint. CF-BES, CF-PSO, and ε-PSO do not find a suitable operation solution because they all exceed the lower discharge flow constraint.

This shows that for the reservoir operation problem with few constraints and simple variables (Shafan Reservoir), the traditional optimization algorithms such as PSO and BES can be solved perfectly. However, when facing the Dahuofang Reservoir with increasing constraints and more complex dimensions, the PSO algorithm has difficulty in finding a suitable operation solution, and the BES algorithm is quite effective. Yet, when facing the Luanhe multi-reservoir system with multiple reservoirs, only ε-CABES finds a suitable operation solution.

4.4. Conclusions of the Case Study Results

Through the three examples of two single reservoirs and a reservoir cluster of three reservoirs, the following findings are made.

(1) The length of flood period of a reservoir (group) has different requirements for the performance of algorithm and constraint processing technology. For reservoirs with few time periods, this is a simple operation problem, which requires low computational power of algorithms. Therefore, different algorithms combined with different constraint processing techniques can achieve appropriate flood control operation effects. With the increase of the number of time periods, better algorithms are needed to find the optimal strategy. The combination of conventional algorithms and constraint processing technology is difficult to sustain.

(2) Through the flood control operation results of the Dahuofang Reservoir and Luan River Basin multi-reservoir system with more time periods, it can be observed that, under the same constraint processing technology, the CABES optimization algorithm proposed in this paper can achieve better results than those of the BES optimization algorithm before improvement, while the classical PSO algorithm does not find a suitable operation scheme in both instances. This demonstrates that as the complexity of the solution problem increases, the CABES algorithm obtained by improving the Cauchy mutation strategy and fusing the adaptive weighting factor with the Levy

flight strategy is somewhat advanced and practical, improving the ability of the original algorithm to solve complex problems.

(3) When the same algorithm uses two constraint processing techniques, the results of the operation scheme obtained by the two constraint processing methods are consistent when solving the operation scheme of Shafan Reservoir and Dahuofang Reservoir. However, in the dispatching of a mixed multi-reservoir system, the dispatching results are quite different. Therefore, it can be considered that the ε constraint treatment technology and the penalty function method have the same effect on the optimization treatment technology of a single reservoir, but the optimization effect of the ε constraint treatment technology is better than that of the penalty function method on more complex constraint problems.

5. Conclusions

Reservoir (group) flood control operation is a complex high-dimensional problem with many constraints. To solve this problem, this paper proposes a new constrained optimization algorithm, namely, ε-CABES algorithm. The algorithm combines the advantages of the BES algorithm and the ε constraint processing technology. In order to verify the rationality and effectiveness of the method, an example computation is carried out through the flood control operation of two single reservoirs and the joint flood control operation of a multi-reservoir system, and another processing technology is used. The penalty function method and the optimization algorithms BES and PSO are compared and analyzed. The main conclusions are as follows:

(1) The CABES algorithm is used to solve the three instances, and the comparative analysis with the operation results of the BES and PSO algorithms shows that the CABES algorithm has better global search ability and better solution accuracy. Cauchy mutation and fusion of adaptive weight factor and Levy flight strategy can improve the performance of the algorithm in solving reservoir optimal operation.

(2) The effect of the ε constraint processing technique is equivalent to that of the penalty function method in the relatively simple single-reservoir operation problem, and in the more complex multi-reservoir operation problem, the solution effect is ahead of the penalty function method. In general, the ε constraint processing technology has better convergence and achieves better optimization results.

(3) For the dispatching problem of Shafan Reservoir with short time period, the dispatching schemes required by different algorithms are basically the same; for Dahuofang Reservoir with long time period, the dispatching schemes of each algorithm are different. It shows that the length of the number of periods in the reservoir operation will affect the stability and difference of the operation results of each algorithm.

(4) The ε-CABES algorithm can better solve the strong constraints, multistage, and nonlinear combination problems in the optimal operation of reservoir flood control, and provides an effective method for the optimal operation of reservoir flood control.

To sum up, this paper discusses the proposed algorithm and constraint processing technology by taking reservoir (group) flood control operation as an example. In solving the reservoir problem with short flood period and simple process, the coupling of conventional classical algorithms PSO, BES, and penalty function method can be solved. However, as the scale of the reservoir increases and the time period becomes longer, it becomes a more complex constraint problem. The methods mentioned above are not enough to find a suitable flood control operation strategy, and algorithms and constraints with better performance and higher solution accuracy are required, that is, the ε-CABES method proposed in this paper. However, it should be noted that as the complexity of the problem increases, the time consumed by the ε-CABES method is more than that of the penalty function constrained evolution method. Therefore, the next stage of work is to find more suitable optimization algorithms and processing technologies, and improve the complexity of the model as much as possible while improving the model's optimization capabilities.

Author Contributions: W.W.: conceptualization, methodology, writing—original draft. W.T.: program implementation, data curation, writing—original draft preparation. K.C.: writing—editing and original draft. H.Z.: writing—original draft, investigation. M.M.: writing—original draft. Z.F.: investigation. D.X.: formal analysis. All authors have read and agreed to the published version of the manuscript.

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References

1. Blöschl, G.; Hall, J.; Viglione, A.; Perdigão, R.A.P.; Parajka, J.; Merz, B.; Lun, D.; Arheimer, B.; Aronica, G.T.; Bilibashi, A.; et al. Changing climate both increases and decreases European river floods. *Nature* **2019**, *573*, 108–111. [CrossRef] [PubMed]
2. Iyakaremye, V.; Zeng, G.; Yang, X.; Zhang, G.; Ullah, I.; Gahigi, A.; Vuguziga, F.; Asfaw, T.G.; Ayugi, B. Increased high-temperature extremes and associated population exposure in Africa by the mid-21st century. *Sci. Total Environ.* **2021**, *790*, 148162. [CrossRef] [PubMed]
3. Sein, Z.M.M.; Zhi, X.; Ullah, I.; Azam, K.; Ngoma, H.; Saleem, F.; Xing, Y.; Iyakaremye, V.; Syed, S.; Hina, S.; et al. Recent variability of sub-seasonal monsoon precipitation and its potential drivers in Myanmar using in-situ observation during 1981–2020. *Int. J. Climatol.* **2022**, *42*, 3341–3359. [CrossRef]
4. Xing, Y.; Shao, D.; Liang, Q.; Chen, H.; Ma, X.; Ullah, I. Investigation of the drainage loss effects with a street view based drainage calculation method in hydrodynamic modelling of pluvial floods in urbanized area. *J. Hydrol.* **2022**, *605*, 127365. [CrossRef]
5. Kundzewicz, Z.W.; Su, B.; Wang, Y.; Xia, J.; Huang, J.; Jiang, T. Flood risk and its reduction in China. *Adv. Water Resour.* **2019**, *130*, 37–45. [CrossRef]
6. Rahimi, H.; Ardakani, M.K.; Ahmadian, M.; Tang, X. Multi-Reservoir Utilization Planning to Optimize Hydropower Energy and Flood Control Simultaneously. *Environ. Process.* **2020**, *7*, 41–52. [CrossRef]
7. Zhu, F.; Zhong, P.-a.; Sun, Y.; Xu, B. Selection of criteria for multi-criteria decision making of reservoir flood control operation. *J. Hydroinform.* **2017**, *19*, 558–571. [CrossRef]
8. Yakowitz, S. Dynamic programming applications in water resources. *Water Resour. Res.* **1982**, *18*, 673–696. [CrossRef]
9. Barros Mario, T.L.; Tsai Frank, T.C.; Yang, S.-l.; Lopes Joao, E.G.; Yeh William, W.G. Optimization of Large-Scale Hydropower System Operations. *J. Water Resour. Plan. Manag.* **2003**, *129*, 178–188. [CrossRef]
10. Unver, O.I.; Mays, L.W. Model for real-time optimal flood control operation of a reservoir system. *Water Resour. Manag.* **1990**, *4*, 21–46. [CrossRef]
11. Bai, T.; Wu, L.; Chang, J.-x.; Huang, Q. Multi-Objective Optimal Operation Model of Cascade Reservoirs and Its Application on Water and Sediment Regulation. *Water Resour. Manag.* **2015**, *29*, 2751–2770. [CrossRef]
12. Zhang, W.; Liu, P.; Chen, X.; Wang, L.; Ai, X.; Feng, M.; Liu, D.; Liu, Y. Optimal Operation of Multi-reservoir Systems Considering Time-lags of Flood Routing. *Water Resour. Manag.* **2016**, *30*, 523–540. [CrossRef]
13. Li, J.; Zhong, P.A.; Yang, M.; Zhu, F.; Chen, J.; Xu, B.; Liu, W. Dynamic and Intelligent Modeling Methods for Joint Operation of a Flood Control System. *J. Water Resour. Plan. Manag.* **2019**, *145*, 04019044. [CrossRef]
14. Chen, H.-t.; Wang, W.-c.; Chen, X.-n.; Qiu, L. Multi-objective reservoir operation using particle swarm optimization with adaptive random inertia weights. *Water Sci. Eng.* **2020**, *13*, 136–144. [CrossRef]
15. SeethaRam, K.V. Three Level Rule Curve for Optimum Operation of a Multipurpose Reservoir using Genetic Algorithms. *Water Resour. Manag.* **2021**, *35*, 353–368. [CrossRef]
16. Xu, Y.; Mei, Y. A modified water cycle algorithm for long-term multi-reservoir optimization. *Appl. Soft Comput.* **2018**, *71*, 317–332. [CrossRef]
17. Chen, H.-t.; Wang, W.-c.; Chau, K.-w.; Xu, L.; He, J. Flood Control Operation of Reservoir Group Using Yin-Yang Firefly Algorithm. *Water Resour. Manag.* **2021**, *35*, 5325–5345. [CrossRef]
18. Chang, L.-C. Guiding rational reservoir flood operation using penalty-type genetic algorithm. *J. Hydrol.* **2008**, *354*, 65–74. [CrossRef]
19. He, Y.; Xu, Q.; Yang, S.; Liao, L. Reservoir flood control operation based on chaotic particle swarm optimization algorithm. *Appl. Math. Model.* **2014**, *38*, 4480–4492. [CrossRef]
20. Kumar Jha, D.; Yorino, N.; Zoka, Y.; Sasaki, Y.; Hayashi, Y.; Iwata, K.; Oe, R. Incorporating Penalty Function to Reduce Spill in Stochastic Dynamic Programming Based Reservoir Operation of Hydropower Plants. *IEEJ Trans. Electr. Electron. Eng.* **2010**, *5*, 531–538. [CrossRef]
21. Moeini, R.; Soltani-nezhad, M.; Daei, M. Constrained gravitational search algorithm for large scale reservoir operation optimization problem. *Eng. Appl. Artif. Intell.* **2017**, *62*, 222–233. [CrossRef]

22. Ngoc, T.A.; Hiramatsu, K.; Harada, M. Optimizing the rule curves of multi-use reservoir operation using a genetic algorithm with a penalty strategy. *Paddy Water Environ.* **2014**, *12*, 125–137. [CrossRef]
23. Wang, W.; Jia, B.; Simonovic, S.P.; Wu, S.; Fan, Z.; Ren, L. Comparison of Representative Heuristic Algorithms for Multi-Objective Reservoir Optimal Operation. *Water Resour. Manag.* **2021**, *35*, 2741–2762. [CrossRef]
24. Takahama, T.; Sakai, S. Constrained Optimization by ε Constrained Differential Evolution with Dynamic ε-Level Control. In *Advances in Differential Evolution, Chakraborty, U.K., Ed.*; Springer: Berlin/Heidelberg, Germany, 2008; pp. 139–154. [CrossRef]
25. Chen, C.; Yuan, Y.; Yuan, X. An Improved NSGA-III Algorithm for Reservoir Flood Control Operation. *Water Resour. Manag.* **2017**, *31*, 4469–4483. [CrossRef]
26. Stanovov, V.; Akhmedova, S.; Semenkin, E. Combined fitness–violation epsilon constraint handling for differential evolution. *Soft Comput.* **2020**, *24*, 7063–7079. [CrossRef]
27. Zhou, J.; Zou, J.; Zheng, J.; Yang, S.; Gong, D.; Pei, T. An infeasible solutions diversity maintenance epsilon constraint handling method for evolutionary constrained multiobjective optimization. *Soft Comput.* **2021**, *25*, 8051–8062. [CrossRef]
28. Alsattar, H.A.; Zaidan, A.A.; Zaidan, B.B. Novel meta-heuristic bald eagle search optimisation algorithm. *Artif. Intell. Rev.* **2020**, *53*, 2237–2264. [CrossRef]
29. Alsaidan, I.; Shaheen, M.A.M.; Hasanien, H.M.; Alaraj, M.; Alnafisah, A.S. A PEMFC model optimization using the enhanced bald eagle algorithm. *Ain Shams Eng. J.* **2022**, *13*, 101749. [CrossRef]
30. Angayarkanni, S.A.; Sivakumar, R.; Ramana Rao, Y.V. RETRACTED ARTICLE: Hybrid Grey Wolf: Bald Eagle search optimized support vector regression for traffic flow forecasting. *J. Ambient Intell. Humaniz. Comput.* **2021**, *12*, 1293–1304. [CrossRef]
31. Eid, A.; Kamel, S.; Zawbaa, H.M.; Dardeer, M. Improvement of active distribution systems with high penetration capacities of shunt reactive compensators and distributed generators using Bald Eagle Search. *Ain Shams Eng. J.* **2022**, *13*, 101792. [CrossRef]
32. Ferahtia, S.; Rezk, H.; Abdelkareem, M.A.; Olabi, A.G. Optimal techno-economic energy management strategy for building's microgrids based bald eagle search optimization algorithm. *Appl. Energy* **2022**, *306*, 118069. [CrossRef]
33. Sayed, G.I.; Soliman, M.M.; Hassanien, A.E. A novel melanoma prediction model for imbalanced data using optimized SqueezeNet by bald eagle search optimization. *Comput. Biol. Med.* **2021**, *136*, 104712. [CrossRef]
34. Wang, W.-c.; Xu, L.; Chau, K.-w.; Xu, D.-m. Yin-Yang firefly algorithm based on dimensionally Cauchy mutation. *Expert Syst. Appl.* **2020**, *150*, 113216. [CrossRef]
35. Zhao, S.; Wang, P.; Heidari, A.A.; Zhao, X.; Ma, C.; Chen, H. An enhanced Cauchy mutation grasshopper optimization with trigonometric substitution: Engineering design and feature selection. *Eng. Comput.* **2021**, *38*, 4583–4616. [CrossRef]
36. Miao, F.; Yao, L.; Zhao, X. Symbiotic organisms search algorithm using random walk and adaptive Cauchy mutation on the feature selection of sleep staging. *Expert Syst. Appl.* **2021**, *176*, 114887. [CrossRef]
37. Zhao, X.; Fang, Y.; Liu, L.; Xu, M.; Li, Q. A covariance-based Moth–flame optimization algorithm with Cauchy mutation for solving numerical optimization problems. *Appl. Soft Comput.* **2022**, *119*, 108538. [CrossRef]
38. Wu, Q. Hybrid forecasting model based on support vector machine and particle swarm optimization with adaptive and Cauchy mutation. *Expert Syst. Appl.* **2011**, *38*, 9070–9075. [CrossRef]
39. Nickabadi, A.; Ebadzadeh, M.M.; Safabakhsh, R. A novel particle swarm optimization algorithm with adaptive inertia weight. *Appl. Soft Comput.* **2011**, *11*, 3658–3670. [CrossRef]
40. Rauf, H.T.; Malik, S.; Shoaib, U.; Irfan, M.N.; Lali, M.I. Adaptive inertia weight Bat algorithm with Sugeno-Function fuzzy search. *Appl. Soft Comput.* **2020**, *90*, 106159. [CrossRef]
41. Shukla, A.K.; Singh, P.; Vardhan, M. An adaptive inertia weight teaching-learning-based optimization algorithm and its applications. *Appl. Math. Model.* **2020**, *77*, 309–326. [CrossRef]
42. Sun, Y.; Wang, X.; Chen, Y.; Liu, Z. A modified whale optimization algorithm for large-scale global optimization problems. *Expert Syst. Appl.* **2018**, *114*, 563–577. [CrossRef]
43. Khalilpourazari, S.; Khalilpourazary, S. An efficient hybrid algorithm based on Water Cycle and Moth-Flame Optimization algorithms for solving numerical and constrained engineering optimization problems. *Soft Comput.* **2019**, *23*, 1699–1722. [CrossRef]
44. Wang, W.-C.; Xu, L.; Chau, K.-W.; Liu, C.-J.; Ma, Q.; Xu, D.-M. Cε-LDE: A lightweight variant of differential evolution algorithm with combined ε constrained method and Lévy flight for constrained optimization problems. *Expert Syst. Appl.* **2023**, *211*, 118644. [CrossRef]
45. Seyyedabbasi, A. WOASCALF: A new hybrid whale optimization algorithm based on sine cosine algorithm and levy flight to solve global optimization problems. *Adv. Eng. Softw.* **2022**, *173*, 103272. [CrossRef]
46. He, Q.; Lin, J.; Xu, H. Hybrid Cauchy mutation and uniform distribution of grasshopper optimization algorithm. *Control Decis.* **2021**, *36*, 1558–1568. [CrossRef]
47. Wu, G.; Mallipeddi, R.; Suganthan, P. *Problem Definitions and Evaluation Criteria for the CEC 2017 Competition and Special Session on Constrained Single Objective Real-Parameter Optimization; Technical Report*; National University of Defense Technology, Changsha, Hunan, PR China and Kyungpook National University, Daegu, South Korea and Nanyang Technological University: Singapore, 2016.
48. Zheng, Y.; Meng, Z.; Shen, R. An M-Objective Penalty Function Algorithm Under Big Penalty Parameters. *J. Syst. Sci. Complex.* **2016**, *29*, 455–471. [CrossRef]

49. Tessema, B.; Yen, G.G. An Adaptive Penalty Formulation for Constrained Evolutionary Optimization. *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.* **2009**, *39*, 565–578. [CrossRef]
50. Diao, Y.; Ma, H.; Wang, H.; Wang, J.; Li, S.; Li, X.; Pan, J.; Qiu, Q. Optimal Flood-Control Operation of Cascade Reservoirs Using an Improved Particle Swarm Optimization Algorithm. *Water* **2022**, *14*, 1239. [CrossRef]
51. Ferahtia, S.; Rezk, H.; Djerioui, A.; Houari, A.; Motahhir, S.; Zeghlache, S. Modified bald eagle search algorithm for lithium-ion battery model parameters extraction. *ISA Trans.* **2022**, *in press*. [CrossRef]
52. Ma, L.; Zhang, T.; Li, Q.; Wang, T. Spatial distribution, risk assessment, and source identification of the potentially toxic elements in the water-level fluctuation zone of the Dahuofang Reservoir, Northeast China. *Environ. Monit. Assess.* **2021**, *193*, 454. [CrossRef]