


Article

Decision Optimization for Water and Electricity Shared Resources Based on Fusion Swarm Intelligence

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Abstract: As one of the most important water conservancy projects, reservoirs use water resources to achieve essential functions, such as irrigation, flood control, and power generation, by intercepting rivers. As climate extremes and global warming increase, the world's water reserves are being tested, and reservoir operators are being challenged. This paper investigates the optimal allocation of shared resources for hydropower to achieve rational decisions for reservoir operations. Firstly, a power resource model is constructed based on the real hydroelectric generator theory. Furthermore, based on the established power resource model combined with the influence of weather type and multi-region heterogeneous demand, this paper constructs a multi-objective hydropower shared resource allocation optimization model, with the lowest hydropower resource supply cost and the shortest time hydropower resource supply time as the optimization objectives. Secondly, for the problem that the traditional population intelligence algorithm easily falls into the local optimum when solving complex problems, the improvement of the MOPSO algorithm is completed by introducing the Levy flight strategy and differential evolution. Finally, simulation experiments were carried out, and cutting-edge algorithms, such as the GA algorithm and WOA algorithm, were selected for simulation comparison to verify the effectiveness of the constructed model and algorithm. The simulation results show that the research in this paper can contribute to effective decision-making for reservoir operators and promote intelligent reservoir operation.

Keywords: resource decision optimization; hydropower plant operation; multi-objective optimization; MOPSO algorithm

MSC: 90-XX

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1. Introduction

In recent years, the international pressure of supply and demand of coal, oil, and natural gas has increased and prices have continued to rise, and many countries in Europe and the United States and many countries such as China, India, and Brazil have experienced energy and power shortages of varying degrees [1], while hydropower generation, as a clean energy source, has an important position in solving the problem of power energy shortage [2]. Reservoir hydropower management is the application of reservoir capacity to meet the water needs of cities, while relying on water levels to generate electricity in a planned manner, according to the tasks undertaken by the reservoir and the prescribed scheduling principles, while ensuring the safety of the dam. The optimization model of reservoir management is a constrained nonlinear programming problem, and numerous solution methods have been explored at home and abroad, including traditional algorithms, such as linear programming, nonlinear programming [3], stepwise optimization algorithms [4], dynamic programming [5], and their improvement algorithms, as well as intelligent evolutionary algorithms, such as genetic algorithms [6], particle swarm algorithms [7], and

ant colony algorithms [8]. With the rapid development of population intelligence, all the above problems have been solved; Dehghani, M et al. completed the prediction of reservoir power generation based on the gray wolf algorithm combined with an adaptive neural network [9]; Hu, H et al. solved the problem of multi-stage scheduling of hydropower by decomposing the quantum behavior of the particle swarm optimization algorithm [10]. The Particle Swarm Optimization algorithm is known for its easy implementation [11–15] and the improved LDMOPSO algorithm has superior performance, which makes it stand out among intelligent algorithms. In the field of reservoir, water level modeling, articles [16,17] introduce a water level modeling method for sustainable reservoirs and the water level in the TGR region; the effects of hydropower turbines on reservoir benefits are discussed linearly and nonlinearly in articles [18,19], respectively; articles [20,21] discuss the modeling of water supply and demand and cleverly apply intelligent technological products. This paper proposes an improved chaotic evolutionary multi-objective particle swarm algorithm, combined with reservoir decision optimization, to achieve multi-objective planning with the lowest reservoir management cost and the highest social benefit and compares the proposed algorithm with the frontier algorithm, and the results show that the algorithm has faster convergence and higher optimization-seeking accuracy. It can provide technical support for giving full play to the comprehensive benefits of reservoirs and improving the intelligent management capability of hydropower plants.

2. Materials and Methods

2.1. Background

The water supply from dams and reservoirs is decreasing in many regions due to extreme weather conditions, and water levels in many lakes around the world are at historic lows due to water shortages. Extreme heat and drought conditions are putting significant pressure on natural resource management, and it is now urgent to address the issue of hydropower resource management promptly.

2.2. Overview of Hydropower Management Strategies for Reservoir Systems

The reservoir system that contains hydroelectric turbines undertakes two main system functions; on the one hand, the hydroelectric turbines rely on water level generation to provide the share of hydroelectric power generation in the power supply demand, and on the other hand, to meet the water demand of the cities. Based on satisfying the above two demands, minimizing the management cost of the reservoir system, and maximizing the benefits of the reservoir system, this paper firstly establishes a water level replenishment model of the reservoir system based on the dynamic changes in the water level of the reservoir system, and then this paper establishes a multi-objective optimization model in terms of the maintenance, and benefits of the reservoir management system, firstly based on the established water level replenishment model of the reservoir system. Based on the water level replenishment model of the reservoir system, the reservoir system management model with the objective function of minimizing the management cost is established by considering the maintenance cost of water resources, the equipment cost of electricity generation, and the maintenance cost of electricity storage; furthermore, based on the queuing theory model and the proposed social satisfaction index, the annual net income of the reservoir system, the annual income of hydroelectric power generation of the reservoir system, the annual income of water resources of the reservoir system, the annual freight of water resources of the reservoir system, the annual freight of imported external water resources, and the annual freight of water resources of the reservoir system are considered. The annual freight of water resources, the annual cost of introducing the consumption of external water resources and the aspect of management cost are also considered, and a reservoir system efficiency model with maximized comprehensive benefits as the objective function was established.

2.3. Model Assumptions

1. The surface area of the reservoir is smooth and equal to the bottom area of the reservoir, the projection of the water surface on the bottom of the reservoir coincides exactly with the bottom, and the side walls of the reservoir are smooth surfaces that are perpendicular to the bottom of the reservoir.
2. The actual daily water level of the reservoir is taken as the height of the water level after the change from the previous day, and the influence of the water level on the relevant variables due to the process of daily change is ignored in the model establishment.
3. The natural loss of water storage in the reservoir is only evaporation loss, ignoring the loss of water storage caused by other factors and the effect of temperature change on the coefficient of the Antony equation.
4. The installation location of the reservoir's power generation water turbines is located below the permitted water level height, each reservoir utilizes the same energy conversion capacity of the water turbines and the same height from the bottom of the reservoir, the water turbines can store the excess energy, and the number of water turbines in each reservoir is the same, ignoring the loss of power supply.
5. The initial water level height of the day is used as the calculated value of each parameter index, ignoring the dynamic change in water level during the day on water level management and hydroelectric power generation.
6. The transportation cost of water resources diverted by the reservoir system to the same waterworks each time is independent of the amount diverted, ignoring the losses in the process of transporting water resources from the reservoir system to the water company.

2.4. Symbol Description

Table 1 shows the description of the main mathematical symbols.

Table 1. Description of the main mathematical symbols.

Set Cardinality	Symbol Description
res	Set the cardinality of the number of reservoirs
ci	Set cardinality of the number of cities requiring water supply
day	Set cardinality of the number of days in the year
num	Set cardinality of the total number of water turbines
Parameter	Symbol Description
i	The i -th reservoir ($0 \leq i \leq res$)
j	Day j of the year
S_i	The water surface area of the i -th reservoir
h_{ins}	Height of the water turbine from the bottom of the lake
$V_{i,j}$	The volume of day j of the i th reservoir
$h_{i,j}$	The available water level height on day j of the i th reservoir
$Th_{i,j}$	The actual water level on day j of the i th reservoir
lh	Minimum allowable water level height
Vo_i	The initial volume of the i -th reservoir
$\Delta V_{i,j}$	The amount of water level change on day j of the i th reservoir
$Su_{i,j}$	External water supply on day j of the i -th reservoir
$Pr_{i,j}$	Precipitation replenishment on day j of the i -th reservoir
$Ev_{i,j}$	Evaporation loss on day j of the i -th reservoir
$E_{i,j}$	Hydroelectric power generation on day j of the i -th reservoir
$Em_{i,j}$	Electrical energy storage on day j of the i -th reservoir
Eq_j	Total demand for electricity generated by hydroelectricity in each city on day j
$Qa_{i,j}$	The amount of water released on day j of the i -th reservoir
hst	Maximum permissible water level height
Decision variable	Symbol Description
h_{ins}	Installation height of hydropower turbine from the bottom of the reservoir
μ	Average daily number of external water diversions from a single reservoir
PQ	Water replenishment consumption of water plants

2.5. Water Level Replenishment Model for Reservoir Systems

Based on the daily variation in the dam water level and Table 1, the water level replenishment model for hydropower dams was established by considering precipitation replenishment, water evaporation, and external water demand for reservoir water consumption as follows: Equation (1) represents the calculation of the volume of the j th day of the i th reservoir; Equation (2) is the calculation of the available water level height of the reservoir, where the minimum allowable water level height $lh_{i,j}$ denotes the minimum height allowed for the reservoir water level; Equation (3) is the change in the actual water level height of the reservoir; Equation (4) represents the calculation of the change in water level of the j th day of the i th reservoir; Equation (5) represents the equation for calculating the evaporation loss of the reservoir, where $pm_{i,j}$ denotes the daily average saturated vapor pressure of water in the reservoir on day j of reservoir i , $p_{i,j}$ denotes the actual daily average hydraulic pressure of water on the surface of the reservoir on day j of reservoir i , $vm_{i,j}$ denotes the daily average wind speed on day j of reservoir i ; Equation (6) is the Antoni equation for calculating the daily average saturated vapor pressure of water in the reservoir on day j of reservoir i , $T_{i,j}$ is the temperature on day j of reservoir i ; Equation (7) is the external constraint of water supply, when the available water level height of the reservoir is greater than or equal to 0, with no outside water supply; when the available water level height of the reservoir is lower than 0, that is, the actual water level height of the reservoir is lower than the minimum allowable water level height, there is a need to use the outside water supply, and the added water supply should restore the water level to the minimum allowable water level height; Equation (8) represents the actual water level height of the reservoir limit, that is, the actual water level of the reservoir height should be maintained below the maximum allowable water level height.

$$V_{i,j} = S_i h_{i,j} \quad (1)$$

$$h_{i,j} = Th_{i,j} - lh \quad (2)$$

$$Th_{i,j} = \frac{Vo_i + \sum_{n=1}^j \Delta V_{i,n}}{S_i} \quad (3)$$

$$\Delta V_{i,j} = Su_{i,j} + Pr_{i,j} - Ev_{i,j} - Qa_{i,j} \quad (4)$$

$$Ev_{i,j} = 5.2(pm_{i,j} - p_{i,j})(1 + 0.135vm_{i,j})S_i \quad (5)$$

$$\lg pm_{i,j} = 10.07 - \frac{1657.46}{T_{i,j} + 227.02} \quad (6)$$

$$\text{s.t.g } Su_{i,j} = \begin{cases} 0 & \text{if } h_{i,j} \geq 0 \\ S_i |h_{i,j}| & \text{if } h_{i,j} < 0 \end{cases} \quad (7)$$

$$Th_{i,j} = \begin{cases} Th_{i,j} & Th_{i,j} < hst \\ hst & Th_{i,j} \geq hst \end{cases} \quad (8)$$

2.6. Reservoir System Management Model

Based on the previously mentioned working assumptions about the hydroelectric turbine and the developed complementary model of the reservoir, a height planning model for the installation of the hydroelectric turbines that minimizes the maintenance costs was developed. Equation (9) is the hydroelectric turbine energy conversion model, where $Pe_{i,j}$ denotes the output power of a single hydroelectric turbine at day j of the i th reservoir, $Pe_{i,j+1}$ denotes the output power of a single hydroelectric turbine at day $(j + 1)$ of the i th reservoir, t denotes the daily working time of the hydroelectric turbine, β denotes the electrical energy conversion efficiency of the hydroelectric turbine; Equation (10) denotes the electrical energy storage of hydroelectric power; Equation (11) denotes the relationship between the output power of hydropower turbine and the height drop of water level, α is the relationship

coefficient; Equation (12) is the calculation of the total demand of electric energy generated by hydropower in each city, where $Et_{n,j}$ denotes the total demand of electric energy in each city, ϕ is the proportion of hydropower generation to the total demand of electric energy; Equation (13) is the objective function of minimizing the management cost, where c_0 is the daily maintenance cost of maintaining the unit volume of water resources, c_1 is the maintenance cost of the equipment required to generate a unit of electric energy from hydroelectric power, and c'_1 is the daily storage management cost required to store and manage a unit of electric energy; Equation (14) is the constraint of electric energy storage, i.e., the daily storage of electric energy should be greater than 10% of the daily demand for hydroelectric power; in this model, h_{ins} is the decision variable.

$$E_{i,j} = \beta \frac{num}{res} \left(\frac{Pe_{i,j} + Pe_{i,j+1}}{2} \right) t \quad (9)$$

$$Em_{i,j} = \sum_{n=1}^j (E_{i,n} - Eq_n) \quad (10)$$

$$Pe_{i,j} = \alpha \frac{num}{res} (Th_{i,j} - h_{ins}) \quad (11)$$

$$Eq_j = \sum_{n=1}^{ci} Et_{n,j} \phi \quad (12)$$

$$\min Z_t = c_0 \sum_{j=1}^{day} \sum_{i=1}^{res} S_i Th_{i,j} + c_1 \sum_{j=1}^{day} \sum_{i=1}^{res} E_{i,j} + c'_1 \sum_{j=1}^{day} \sum_{i=1}^{res} Em_{i,j} \quad (13)$$

$$\text{s.t.g} \sum_{i=1}^{res} E_{i,j} - Eq_j \geq 0.1 Eq_j \quad (14)$$

2.7. Water Demand Service Model Based on Queuing Theory

In the actual working situation of water supply, the water resources of reservoirs are supplied to the tap water plants in each city through pipeline transportation. Assuming that the reservoir system will set a supplementary consumption PQ for each tap water plant, that is, after each consumption of PQ water resources by the tap water plant, the reservoir will draw out PQ water resources to the tap water plant to replenish the demand of the tap water plant, and the tap water introduction demand satisfies Poisson distribution, based on the M/M/S model of queuing theory, the following formula can be obtained.

$$\lambda = \frac{\sum_{n=1}^{300} Qa_{m,n}}{300ciPQ} \quad (15)$$

$$\rho = \frac{\lambda}{res\mu} \quad (16)$$

$$L_t = L_q + res\rho \quad (17)$$

$$L_q = \frac{(res\rho)^2 \rho}{res!(1-\rho)^2} \left[\sum_{k=0}^{res-1} \frac{1}{k!} \left(\frac{\lambda}{\mu} \right) + \frac{1}{res!} \frac{1}{1-\rho} \left(\frac{\lambda}{\mu} \right)^{res} \right]^{-1} \quad (18)$$

$$L_t = \frac{(res\rho)^2 \rho}{res!(1-\rho)^2} \left[\sum_{k=0}^{res-1} \frac{1}{k!} \left(\frac{\lambda}{\mu} \right) + \frac{1}{res!} \frac{1}{1-\rho} \left(\frac{\lambda}{\mu} \right)^{res} \right]^{-1} + res\rho \quad (19)$$

$$W_s = \frac{1}{\mu - \lambda} \quad (20)$$

$$\text{s.t.g} \mu_{\min} \leq \mu \leq \mu_{\max} \quad (21)$$

$$PQ_{\min} \leq PQ \leq PQ_{\max} \quad (22)$$

In Equations (15)–(20), λ is the average daily number of introduced demands at the waterworks, μ is the average daily number of external water diversions from a single reservoir, ρ is the service intensity of the reservoir system, L_q , L_t , and W_s are the total number of demands to be introduced at the waterworks, the total number of demands being introduced and to be introduced at the waterworks, and the waiting time in the demand queue for the average daily introduced demands at one waterworks, respectively; Equations (21) and (22) are the constraints of the queueing theory model, where Equation (21) is the limit of the average daily number of external water drawdowns from a single reservoir, and Equation (22) is the limit of the supplementary consumption that the waterworks will set.

Based on the queueing theory model established, it is known that the smaller the service intensity ρ of the reservoir system, the shorter the average daily introduction demand of one tap water plant waiting time W_s in the demand queue, and the larger the supplementary consumption PQ , the higher the planning efficiency of the reservoir system, and the higher the corresponding social satisfaction, so the social satisfaction index is proposed as follows:

$$\delta = \frac{PQ}{\rho W_s} \quad (23)$$

2.8. Model for Maximizing the Benefits of Reservoir Systems

In the actual working environment, the costs consumed by the reservoir system are the delivery cost of water resources, the subscription cost of external water supply, the maintenance cost of the reservoir system, and the benefits are the income from the supplied hydropower resources and the income from water resources. Combined with the social satisfaction indicators proposed in the previous section, a model for maximizing the benefits of reservoir water resources is established as follows:

$$Z_t = Z_e + Z_c - Z_d - Z_s \quad (24)$$

$$Z_e = c_2 \sum_{i=1}^{day} Eq_i \quad (25)$$

$$Z_c = c_3 \sum_{n=1}^{300} \sum_{i=1}^{ci} L_t \omega_i Qa \quad (26)$$

$$\bar{d} = \frac{\sum_{m=1}^{ci} \sum_{n=1}^{res} d_{m,n}}{cires} \quad (27)$$

$$Z_d = c_4 day L_t \bar{d} \quad (28)$$

$$Su_t = \sum_{i=1}^{res} \sum_{j=1}^{300} Su_{i,j} \quad (29)$$

$$Z_s = c_5 Su_t \quad (30)$$

$$Z_2 = \delta Z_t \quad (31)$$

Equation (24) is the calculation of the annual net income of the reservoir system, where Z_t , Z_e , Z_c , Z_d , Z_s are the annual net income of the reservoir system, the annual income of hydroelectric power generation of the reservoir system, the annual income of water resources of the reservoir system, the annual freight of water resources of the reservoir system, and the annual cost of introducing the consumption of external water resources, respectively; Equation (25) is the calculation of the annual income of hydroelectric power generation of the reservoir system, where c_2 is the selling price per unit of electricity of hydroelectric power generation; Equation (26) is the annual revenue of water resources

of the reservoir system, where c_3 and ω_i are the unit price of water resources and the loss rate, respectively; Equation (27) is the average distance of water resources drawn from the reservoir to the water company each time; Equation (28) is the annual freight of water resources of the reservoir system, where c_4 is the cost of transporting water resources per unit distance; Equation (29) is the calculation of the supply of external water resources, where Su_i is the annual supply of external water resources; Equation (30) is the calculation of the annual cost of introducing the consumption of external water resources, where c_5 is the unit selling price of external water resources; Equation (31) is the calculation of the benefit considering social satisfaction, where Z_2 is the benefit of the reservoir system; in the model, μ and PQ are the decision variables.

Equation (32) is the total formulation of the comprehensive social and economic benefits of the reservoir obtained by substituting each variable according to Equation (24).

$$\max Z_2 = \sum_k^{ci} \sum_j^{300} \frac{PQ}{\rho W_s} \left(c_2 \sum_{i=1}^{day} Eq_i + c_3 \sum_{m=1}^{ci} \sum_{n=1}^{300} Qa_{m,n} - c_4 day L_t \frac{\sum_{m=1}^{ci} \sum_{n=1}^{res} d_{m,n}}{cires} - c_5 \sum_{i=1}^{res} \sum_{j=1}^{300} Su_{i,j} \right) \quad (32)$$

2.9. Standard MOPSO Algorithm

In the particle swarm algorithm, each particle is an alternative solution and changes its position in the d-dimensional solution space, according to the global optimum and individual optimum values to continuously approach the optimal solution. The velocity and position updating strategies are shown in Equations (33) and (34).

$$v_i(k+1) = wv_i(k) + c_1 r_1 (x_{pbest}(k) - x_i(k)) + c_2 r_2 (x_{gbest}(k) - x_i(k)) \quad (33)$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (34)$$

where i is the particle number; k is the current iteration number; $x_{pbest}(k)$ is the best position of particle i up to the k th generation; $x_{gbest}(k)$ is the best position of all particles up to the k th generation, and our individual and global learning factors, which are generally between 0 and 2; r_1 and r_2 are the random constants in $[0, 1]$; w is the inertia weight, which, in order to regulate the exploration and mining ability of the algorithm, often uses a linearly decreasing value w according to the number of iterations k . The formula is as follows:

$$w(k) = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times k \quad (35)$$

where w_{\max} and w_{\min} are the upper and lower limits of inertia weights; k_{\max} is the maximum number of iterations.

2.10. Improved MOPSO Algorithm Based on Levy Flight Strategy and Differential Evolution

The Levy flight strategy is a kind of random wandering that favors a larger search step, and its basic characteristic is the combination of a short-distance flight and random long-distance flight, and its "heavy-tailed" distribution normal distribution structure can build a stable optimization system. The "heavy-tailed" distributed normal distribution structure is able to stabilize the optimization system, and its pose method is as follows:

$$x_{i,iter} = \begin{cases} x_{i,iter} + rand_i \times fl_{i,iter} \times (m_{j,iter} - x_{i,iter}), & rand_j \geq AP_{j,iter} \\ x_{i,iter} \times (1 + levy(\lambda)), & otherwise \end{cases} \quad (36)$$

where $levy(\lambda)$ denotes a flight movement that obeys the Levy distribution and which satisfies the following equations:

$$levy(\lambda) \sim 0.01 * \frac{u}{|v|^{-\beta}} \quad (37)$$

$$u \sim N(0, \sigma_u^2), v \sim N(0, \sigma_v^2) \quad (38)$$

$$\sigma_u = \left[\frac{\Gamma(1 + \beta) \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \beta * 2^{\frac{\beta-1}{2}}} \right]^{\frac{1}{\beta}}, \sigma_v = 1 \quad (39)$$

The differential evolution strategy is introduced to enhance the global search capability by crossover, variation, and selection operations in the differential evolution (DE) algorithm to improve its convergence speed and search accuracy.

(1) Variation

Two search agents in the population are randomly selected to carry out the transfer of information between search agents, as shown by the following equation:

$$v_{i,iter+1} = x_{r1,iter} + F * (x_{r2,iter} - x_{r3,iter}) \quad (40)$$

where $v_{i,iter+1}$ is the mutated population, $F \in [0, 2]$ is the mutation operator; $x_{r2,iter}$ and $x_{r3,iter}$ are randomly selected search agents that differ from each other.

(2) Crossover

The partial replacement of the two parent structures based on the crossover probability is performed by the following equation.

$$u_{ij,iter+1} = \begin{cases} v_{ij,iter}, rand \leq CR \\ x_{ij,iter}, rand > CR \end{cases} \quad (41)$$

where $CR \in [0, 1]$ is the crossover operator, $rand$ is the random number generated between $[0, 1]$, and $u_{ij,t+1}$ is the new population generated by the crossover.

(3) Select

The search agent needs to be judged by the fitness function value after the mutation and crossover operations to carry out the retention of the original population or the new population generated by the crossover. The selection equation is as follows:

$$x_{i,iter+1} = \begin{cases} u_{i,iter+1}, fitness(u_{i,iter+1}) < fitness(x_{r1,iter+1}) \\ x_{r1,iter+1}, otherwise \end{cases} \quad (42)$$

The specific steps of the hybrid differential particle swarm algorithm (LDMOPSO) based on the Levy flight strategy are as follows:

- (1) Initialize the particle swarm populations $x_{i,iter}$, $v_{i,iter+1}$, $u_{ij,iter+1}$, $m_{i,iter}$, set the initial parameters, and define the decision variables.
- (2) Randomly select a particle individually and calculate the initial fitness function value.
- (3) If $rand \geq AP_{i,iter}$, then execute Equation (34); if $rand < AP_{i,iter}$, then execute Equation (36).
- (4) Calculate and record the new position fitness value and update the particle's new memory position $m_{i,iter+1}$.
- (5) Perform variation, crossover, and selection operations on the current search agent according to Equations (40)–(42), and record the target fitness function value $fitness$.
- (6) Record the total reservoir benefit I according to Equation (32).
- (7) Output the optimal solution if the maximum number of iterations is reached, and continue to execute steps 2~6 if it is not reached, until the iteration reaches the maximum.

In summary, the flow chart of the improved LDMOPSO algorithm is shown in Figure 1.

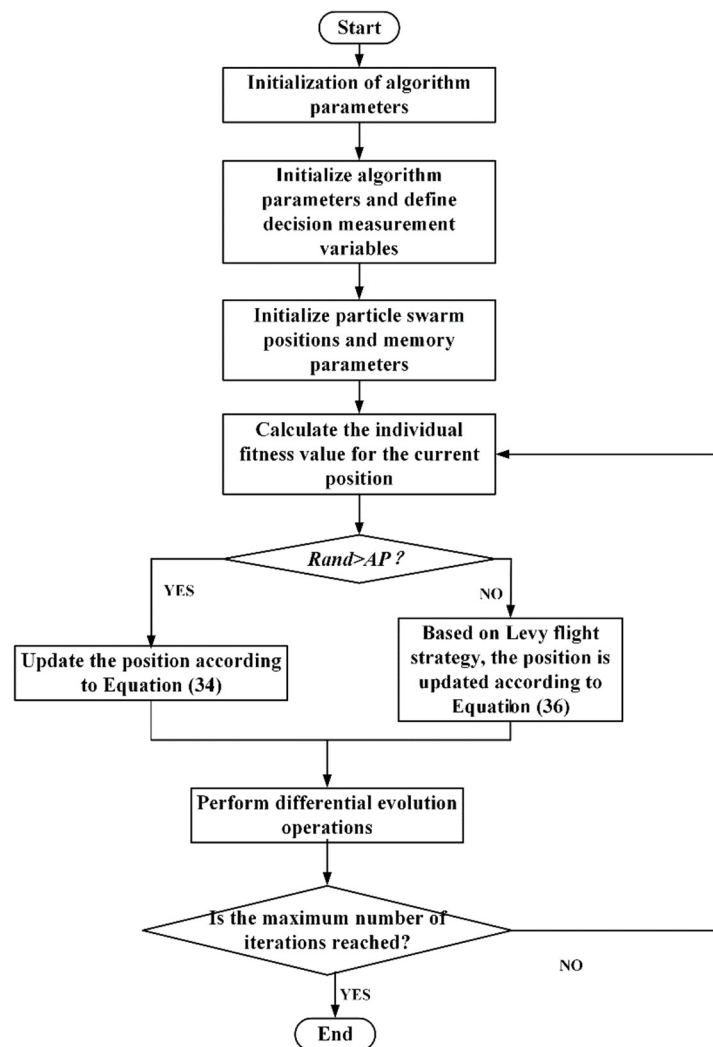


Figure 1. Implementation of the LDMOPSO algorithm.

3. Results

In this paper, the algorithm programming tool is MATLAB R2021a, the operating system is Windows 10, the computer memory is 16G, and the CPU is Intel i5-1135G7.

3.1. Parameter Selection and Adaptation Convergence

The algorithm performance is highest when $N = 50$, $AP = 0.1$, and $fl = 2$ are taken. Therefore, the parameters of the LDMOPSO algorithm are as follows: the maximum number of iterations is $iter_{max} = 100$, the population size is $N = 50$, the perceptual probability is $AP = 0.1$, the flight distance is $fl = 2$, the initial variation operator is $F_0 = 0.4$, and the crossover operator is $CR = 0.1$. A total of 50 simulation experiments were conducted and the improved algorithms were compared with the more popular algorithms in a side-by-side manner. The average objective function curves of each of the four algorithms over 50 runs are shown in Figure 2.

3.2. Water Level Model Simulation

Based on different combinations of water level M of reservoir A and water level P of reservoir B, which can meet the demand for electricity and water in each state, we use the water level height of 50 m as a measurement scale to calculate the results and obtain the results of water withdrawal from the two reservoirs, as shown in the Figure 3.

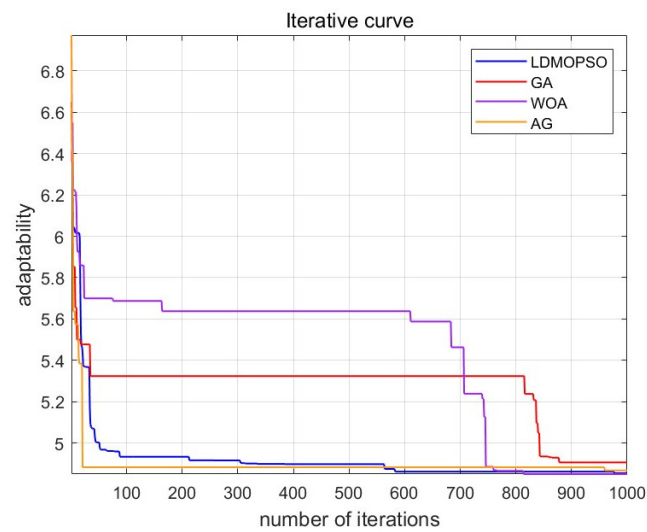


Figure 2. The average objective function convergence curves of each of the 4 algorithms over 50 runs.

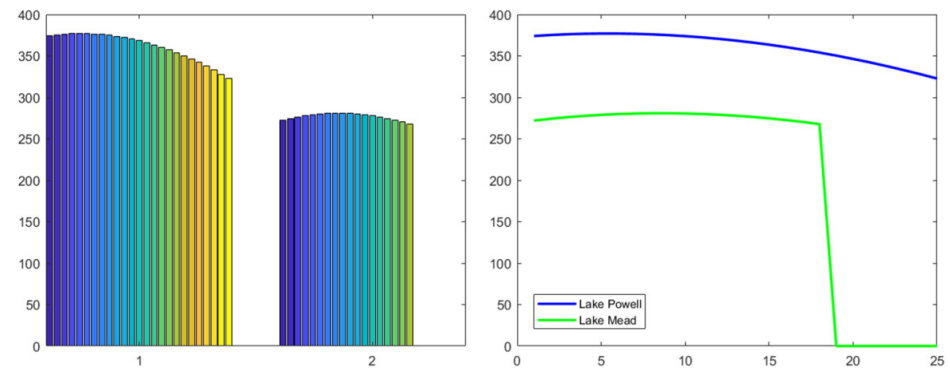


Figure 3. Water level change curves of two reservoirs.

3.3. Optimization Results and Comparison

The iterative optimization of the objective function is shown in Figure 4 and the running time and optimization results of the four algorithms derived from the data in Table 2 are shown in Table 3.

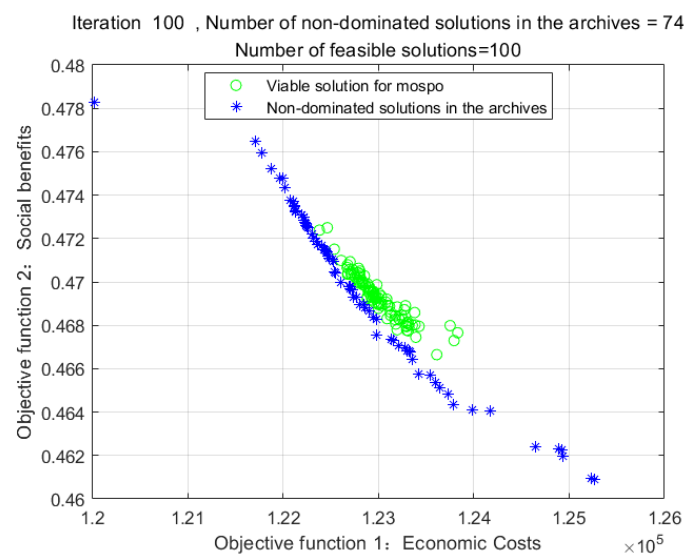


Figure 4. Iterative optimization of objective functions.

Table 2. Comparison of water level combination data when meeting water and electricity demand.

M	P	Reservoir A				Reservoir B				C (City)	
		Pumping Capacity	Time *	Date *	Day *	Pumping Capacity	Time *	Date *	Day *	Obtain Water Volume	
150	200	53.1446	30	15	4.3	37.2515	24	22	1.1	47.1594	
	250	45.6665	24	23	0.4	43.0118	22	15	2.9	45.4416	
	300	31.1520	26	22	1.5	50.6133	18	16	0.7	38.5286	
200	200	12.3629	18	14	2.4	36.0509	25	19	2.2	5.1771	
	250	13.1961	18	13	1.1	43.0118	22	14	3.4	12.9712	
	300	11.9846	18	15	0.7	52.4506	18	14	2.5	21.1984	
250	200	16.7230	25	18	1.4	36.3123	25	21	1.9	9.7986	
	250	16.5363	18	14	1.7	43.3025	22	17	1.4	16.6021	
	300	17.1903	22	17	2.3	51.4292	18	16	0.9	28.3828	
300	200	21.9575	17	13	1.4	36.5512	25	23	0.3	15.2720	
	250	21.8460	21	21	0	43.5932	22	22	0	22.3025	
	300	21.6229	18	21	0	52.5714	18	18	0	31.1376	

* Data from the Internet.

Table 3. Comparison of the operation process of the four algorithms.

<i>Optimal Solution</i>	<i>Optimization Final Value (USD)</i>	<i>Running Time (s)</i>
LDMOPSO	2434.58	17.92
GA	2330.62	23.63
WOA	2403.66	19.45
AG	2380.74	22.14

4. Discussion

By comparing with the other three algorithms, the LDMOPSO algorithm has a strong advantage in search capability and running time, especially since the worst solution in 50 runs is significantly higher than the other algorithms, and it is not easy to fall into the local optimal solution. Based on a real environment of a reservoir for water level model simulation, the optimization of social benefits by the LDMOPSO algorithm compared with the other five algorithms resulted in an average increase in reservoir benefits by 2434.58. Therefore, the LDMOPSO algorithm can find a better strategy for solving the hydropower pipe resource optimization problem, which greatly reduces resource consumption and improves the comprehensive benefits.

5. Conclusions

This paper develops a multi-objective mathematical model with the minimum resource management cost and the highest social benefit. Based on the multi-objective particle swarm algorithm (MOPSO), the Levy flight strategy and differential evolution strategy are introduced to improve the global search capability of the particle swarm algorithm to solve this model. Through simulation experiments, the established model and algorithm are compared with the GA algorithm, WOA algorithm, and AG algorithm after 50 calculations, respectively, and the analysis of experimental results shows that the established algorithm has a faster convergence speed compared with other algorithms, and has stronger global search ability, which does not easily fall into the local optimum, and can effectively improve the efficiency of the reservoir system. It provides a reference for the decision optimization of the reservoir system for hydropower management, but there are still problems of high computational complexity and low generality, and future research should focus on considering the decision optimization under a variety of complex situations to improve the generality of the algorithm.

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