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Application of Strongly Constrained Space Particle Swarm Optimization to Optimal Operation of a Reservoir System

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Abstract: In view of the low efficiency of the particle swarm algorithm under multiple constraints of reservoir optimal operation, this paper introduces a particle swarm algorithm based on strongly constrained space. In the process of particle optimization, the algorithm eliminates the infeasible region that violates the water balance in order to reduce the influence of the unfeasible region on the particle evolution. In order to verify the effectiveness of the algorithm, it is applied to the calculation of reservoir optimal operation. Finally, this method is compared with the calculation results of the dynamic programming (DP) and particle swarm optimization (PSO) algorithm. The results show that: (1) the average computational time of strongly constrained particle swarm optimization (SCPSO) can be thought of as the same as the PSO algorithm and lesser than the DP algorithm under similar optimal value; and (2) the SCPSO algorithm has good performance in terms of finding near-optimal solutions, computational efficiency, and stability of optimization results. SCPSO not only improves the efficiency of particle evolution, but also avoids excessive improvement and affects the computational efficiency of the algorithm, which provides a convenient way for particle swarm optimization in reservoir optimal operation.

Keywords: PSO; SCPSO; water balance equation; reservoir optimal operation

1. Introduction

Water is a limited non-renewable energy source and a major constraint on social development. With the rapid development of society, human demand for water resources is increasingly vigorous, and so it is important to improve the efficient utilization of water resources [1–6]. The construction of water storage and hydropower projects provide the possibility for the optimal allocation of water resources and the integrated optimal scheduling of reservoirs is an important way to improve the efficiency of water resource utilization. Now, there are about 100,000 reservoirs in China, so it is urgent to seek optimal operation strategies for reservoirs through the solution of an optimal operation model of a multi-reservoir power system. However, the problem of reservoir optimal operation is a comprehensive optimization problem including hydrology, water energy, water environment, and ecology. Usually, multi-objective optimization is a nonlinear decision-making process, which needs to be analyzed by a certain calculation method [7,8].

Over the past few decades, researchers have developed various optimization methods, such as early linear programming, nonlinear programming, and multiple evolutionary algorithms, which enrich the calculation system of optimization methods and make the algorithms mature gradually, but each method has its limitations. For example, the dynamic programming algorithm (DP algorithm) is the most widely used traditional mathematic programming approach in determining the optimal strategy of a reservoir, which is based on the principle of optimality [9–11]. The DP algorithm can be considered to be the closest to the true value of the calculation methods and can easily deal with the nonlinear and non-convex optimization problems, but when applied to the cascade reservoir group, the problem of "dimension disaster" appears [12,13]. The progressive optimal algorithm (POA) is developed on the basis of the DP algorithm, and can deal with the problem of low dimensions, but the optimization results depend on the determination of the initial trajectory [14,15]. Similarly, when the genetic algorithm (GA), the artificial bee colony algorithm (ABC), the artificial fish-swarm algorithm (AFSA), or the glowworm swarm optimization (GSO) are applied to reservoir optimization problems, there are inherent defects, such as the inability to converge [16–19], premature convergence, convergence to local optimal solutions, and instability of results. The main reason is that the evolutionary algorithm adopts random search mode and the reservoir multi-objective optimization decision has less feasible space, which makes the search ability of the evolutionary algorithm in dealing with the optimal operation of reservoirs is limited, and it is difficult to achieve satisfactory results [20–23].

The particle swarm optimization (PSO) algorithm is one of the most widely used algorithms among artificial intelligence techniques and has received extensive attention and recognition after having been applied to the reservoir optimization problem for the first time since 2002 [24–27]. Also, PSO has been successfully applied to lots of optimization problems in water resources management, but it is still difficult to get rid of the inherent problems of evolutionary algorithms. Based on this, many scholars focus on the improvement of the search ability of the algorithm itself, such as the model parameters, the evolution pattern, and the mixing of various algorithms, among which the most successful is the introduction of local patterns in the original particle swarm algorithm. At the same time, an inertia weight factor was introduced to update the location and speed in the research of original PSO, and proposed the adaptive particle swarm optimization algorithm, which greatly improved the performance of the PSO algorithm [28–30]. It is also a common method to solve reservoir optimization problems by using various algorithms, such as GA-PSO, PSO-EDA (estimation of distribution algorithm), and PSO-BP (back-propagation) [31–34]. These studies play an important role in perfecting particle swarm optimization. However, such improved algorithms, especially the introduction of the hybrid algorithms, make the algorithm more and more complex and reduce the computational efficiency. On the other hand, based on the multi-objective optimization problem of reservoirs, it is proposed to find the non-inferior solution set as the initial result [35–37]. For example, researchers put forward a multi-version constrained particle swarm optimization algorithm using the continuity equation to define a set of new boundary decision variables for the optimal operation of cascade reservoirs [38,39]. Others try to improve the feasible domain of the genetic algorithm to optimize the water and sand transfer problem [40,41]. These studies improve the efficiency of the algorithm by reducing the search space to a certain extent. However, some think that this method is too ambitious for a feasible constraint space and may cause invalid solutions. This paper presents a PSO algorithm that is dedicated to avoiding the use of unnecessary improvements and to solving optimization problems [42].

In order to balance the calculation efficiency and the stability result of the algorithm, this paper suggests using the water balance equation as a constraint to find a new spatial search "corridor" within the traditional search interval. Particles are optimized in this corridor and all particles meet the water balance constraints in order to increase the number of effective particles (SCPSO; strongly constrained particle swarm optimization). Compared with DP and traditional PSO, the results showed that SCPSO is more efficient and satisfactory in seeking an optimal strategy.

2. Materials and Methods

2.1. Reservoir Optimization Problem

2.1.1. Function

In order to test the performance of the proposed model, this paper is taking the maximum output model of the generator in a hydropower project as an example.

Objective function:

$$N = \max\left\{\sum_{t=1}^{n} K_t q_t H_t\right\}. \tag{1}$$

Among them: N is the power schedule, K_t is comprehensive output coefficient of reservoir, q_t represents the electricity generation flow of the reservoir in period t, the unit is m^3/s; H_t is the water head in period t, n is the number of flood periods.

2.1.2. Constraints

Water balance equation:

$$V_{t+1} = V_t + I_t - q_t \tag{2}$$

where V_t are the initial and terminal storage volumes in period t, I_t, q_t means the inflow and outflow of the reservoir in period t.

Storage volume limits:

$$V_{min,t} \leq V_t \leq V_{max,t} \tag{3}$$

where $V_{min,t}, V_{max,t}$ are the upper and lower limits of storage volume at the end of period t.

Outflow limits:

$$q_{min,t} \leq q_t \leq q_{max,t} \tag{4}$$

where $q_{min,t}, q_{max,t}$ are the lower and upper water discharge rate limits in period t.

Power Output limits:

$$N_{min,t} \leq N_t \leq N_{max,t} \tag{5}$$

where $N_{min,t}, N_{max,t}$ are the limits of power output in period t.

2.2. SCPSO Algorithm

The PSO algorithm has strong spatial search ability. In addition to the common parameters such as population size, maximum speed, maximum number of iterations, inertia weight factor, and acceleration constant, the algorithm also has an implicit important parameter: feasible area. The feasible area of bird population foraging is space in nature, which is a parameter that must be realized. However, the feasible domain is not so easy to implement in the reservoir optimization problem. The penalty function method is the most commonly used solution when the damage constraint appears, and can be constrained in the feasible area, but the punishment is difficult to grasp in the structure of the function. For the optimal scheduling problem of reservoirs, the essence of which is the space–time process of water allocation, everything is inseparable from the basic principle of water balance. Based on the above problems, this paper proposes a strongly-constrained particle swarm optimization algorithm that brings water balance constraint into the search for feasible regions. The algorithm emphasizes the importance of the water balance constraint, and the rest of the constraints use the constant penalty function method to avoid the problem of feasible regions.

2.2.1. Constraint Processing

In the process of reservoir optimization, the processing method of inequality constraints is usually similarly to the penalty function method, that is, the data that violates the constraint is forced to be constrained so as to not violate the state. In the reservoir, inequality constraints include outflow constraints and reservoir capacity constraints. When initializing particles, the inequality constraints may not be satisfied, so that the particles meet the constraints:

$$q_t = \begin{cases} q_{max,t}, & q_t > q_{max,t} \\ q_{min,t}, & q_t < q_{min,t} \end{cases}. \tag{6}$$

Similarly, when the storage capacity constraints do not meet the conditions, they can also be handled in the same way.

2.2.2. Available Options

The flow rate that can be released for a reservoir depends on the water balance formula and the inequality constraints such as the discharge constraints at the period t. From this we can substitute Equation (3) into Equation (1):

$$v_{t-1} + I_t - q_{max,t} \le v_t \le v_{t-1} + I_t - q_{min,t}. \tag{7}$$

Equation (7) is the feasible interval calculated by the reservoir capacity according to the water balance at the period t. However, the storage capacity of the moment v_t needs to satisfy the constraint of Equation (2), therefore, by substituting Equation (3) into Equation (7), we can see that:

$$max\{v_{t-1} + I_t - q_{max,t}, v_{min,t}\} \le v_t \le min\{v_{t-1} + I_t - q_{min,t}, v_{max,t}\}. \tag{8}$$

Equation (8) is the initial formula for calculating the boundary of the feasible domain. Within this feasible region (the part enclosed by a dotted line in Figure 1), except for the last one, the PSO algorithm can select any value to satisfy the water constraint and the outflow constraint. For the above constraint space calculation, due to the use of a one-way constraint solution, there will be a large number of infeasible solutions at the last moment.

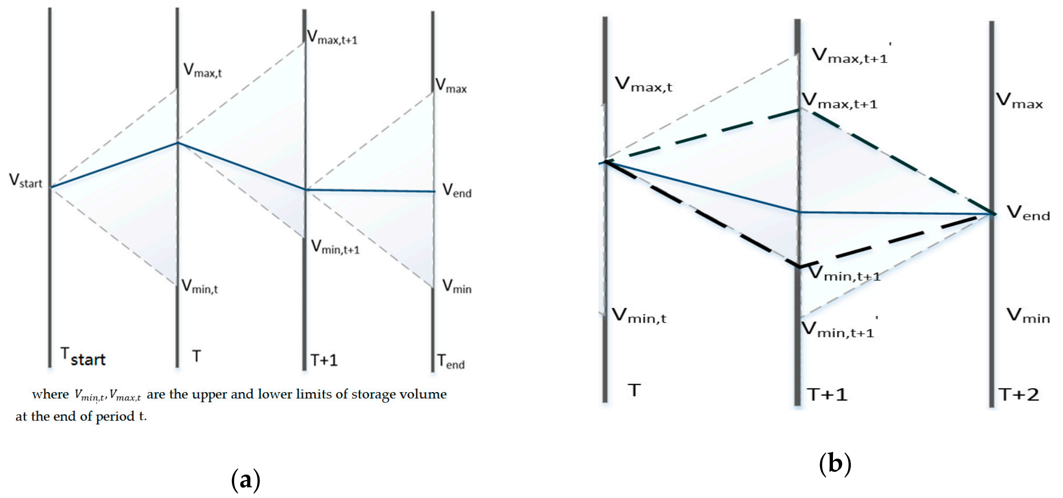


Figure 1. (**a**) Feasible spatial and feasible regions of each stage; (**b**) strong constraints feasible space schematic.

For the particle swarm optimization algorithm with strongly constrained space, the feasible space is further constrained to the above situation, as shown in Figure 1b—the black dotted line range. For a fixed reservoir and specific incoming water, the inflow of each time period and the capacity of the reservoir to start and end are known. Then, based on Equation (2), further constraints can be made.

$$v_t = v_{t+1} - I_{t+1} + q_{t+1} \tag{9}$$

Substituting Equation (4) into Equation (9):

$$v_{t+1} - I_{t+1} + q_{min,t+1} \le v_t \le v_{t+1} - I_{t+1} + q_{max,t+1}. \tag{10}$$

Substituting Equation (3) into Equation (10):

$$max\{v_{t+1} - I_{t+1} + q_{min,t+1}, v_{min,t}\} \le v_t \le min\{v_{t+1} - I_{t+1} + q_{max,t+1}, v_{max,t}\}. \tag{11}$$

In view of this, we can get another feasible interval of v_t at the time t, and combine this interval with the interval of Equation (11) to get the final optimization space:

$$\begin{aligned} &max\{v_{t+1} - I_{t+1} + q_{min,t+1}, v_{t-1} + I_t - q_{max,t}, v_{min,t}\} \le v_t \\ &\le min\{v_{t+1} - I_{t+1} + q_{max,t+1}, v_{t-1} + I_t - q_{min,t}, v_{max,t}\} \end{aligned} \tag{12}$$

Equation (12) can be used as the final feasible domain boundary calculation formula.

Compared with Equation (8), all the particles used in the SCPSO algorithm satisfy the water balance constraint and the outflow constraint in all time periods, so as to ensure the algorithm's optimization within a feasible area.

The flow chart of the application of the strongly constrained particle swarm algorithm in the reservoir is as follows (Figure 2):

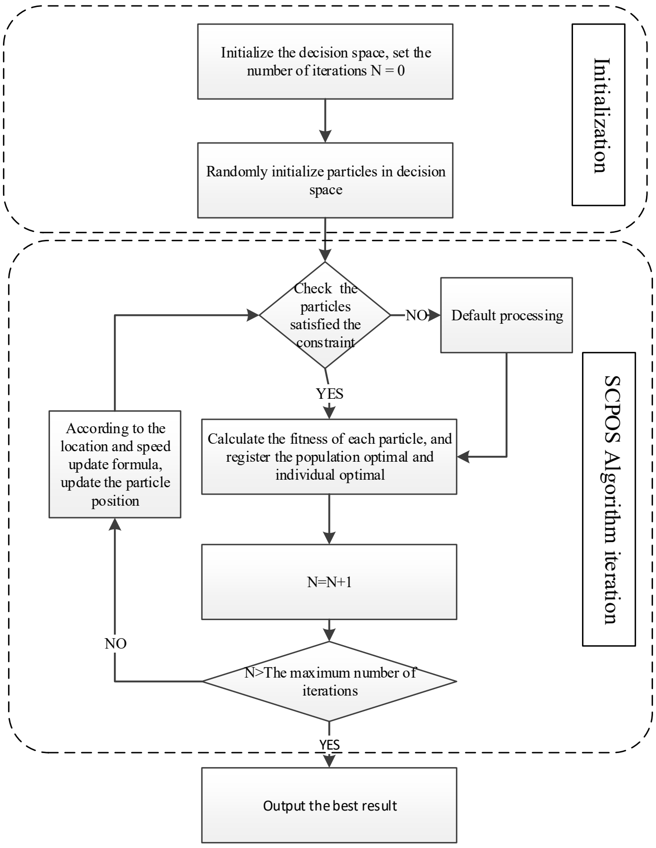


Figure 2. Calculation process of the strongly constrained particle swarm optimization (SCPSO) algorithm.

2.3. Case Study

In order to prove the adaptability of the proposed SCPSO algorithm, this paper takes the Hongjiadu Reservoir in the Wujiang River basin as an example, analyzes the performance of the strongly constrained particle swarm optimization algorithm (SCPSO) by comparing it with the standard PSO algorithm and the DP algorithm.

The Wujiang cascade hydropower station contains five hydropower stations, namely Hongjiadu, Dongfeng, Suofengyin, Wujiangdu, and Goupitan (Figure 3). Among them, Hongjiadu as a lead reservoir has strong regulation performance and can be used as a typical object for verification and analysis. The key parameters of Wujiang Cascade power station are shown in Table 1.

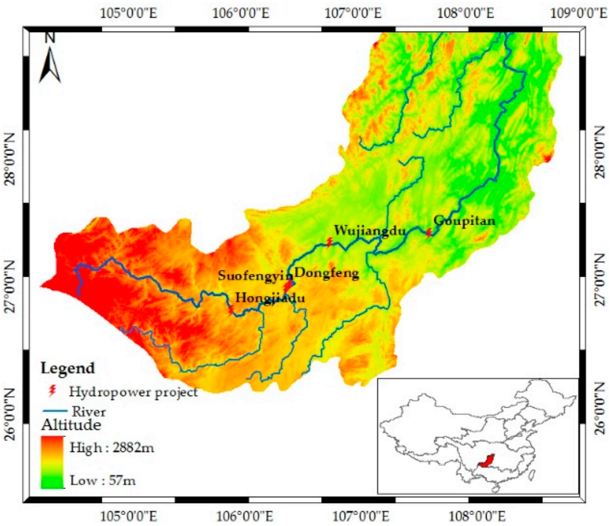


Figure 3. Location of Hongjiadu reservoir in the Wujiang River basin in China.

Table 1. Key parameters of hydropower projects in Wujiang.

Types	Hongjiadu	Unit
Normal water level	1140	m
Limit of water level	1140	m
Lowest water level	1076	m
Highest water level	1142.34	m
Output coefficient	8.5	
Generator assembly capacity	600	MW
Generator minimum output	171.5	MW
Minimum discharge	50	m^3/s
Initial water level	1139	m
Terminal water level	1139	m
Downstream initial water level	975	m
Safety relief	500	m^3/s
Storage capacity	44.97	$10^8 m^3$
Minimum storage capacity	11.36	$10^8 m^3$
Adjust ability	Yearly	

For the maximum output model, the main purpose is to maximize the efficiency of water resource utilization, while meeting other conditions. We compared the performance of the SCPSO, PSO, and DP algorithms from three aspects in this paper: calculation results, calculation efficiency, and calculation stability, and discussed the advantages of the SCPSO algorithm in terms of the rationality of the results, the number of particles in particle swarm optimization, the influence of iteration times on the results, and the speed of particle optimization.

The parameter setting of the particle swarm algorithm has a certain impact on the results, and the parameters need to be tested when dealing with specific issues. This parameter is set as follows, as shown in Table 2. All experiments are programmed by Visual Studio.Net 2010 under the Win7 operating system on a system equipped with an Intel core i-5 3450 CPU and 12G of RAM.

Table 2. Key parameters of algorithms. DP: dynamic programming; PSO: particle swarm optimization.

Types	PSO	SCPSO	DP
Acceleration constant (C1)	2.05	2.05	-
Acceleration constant (C2)	2.05	2.05	-
Inertia weight (W_{max})	0.9	0.9	-
Inertia weight (W_{min})	0.1	0.1	-
Constriction factor X	0.72	0.72	-
Maximum particle velocity (Vmax)	3	3	-
Minimum particle velocity (Vmin)	−3	−3	-
Grid precision	3000	3000	500
Particle number	500	500	-
Number of iterations	300	300	-

3. Results

3.1. Benefit Value

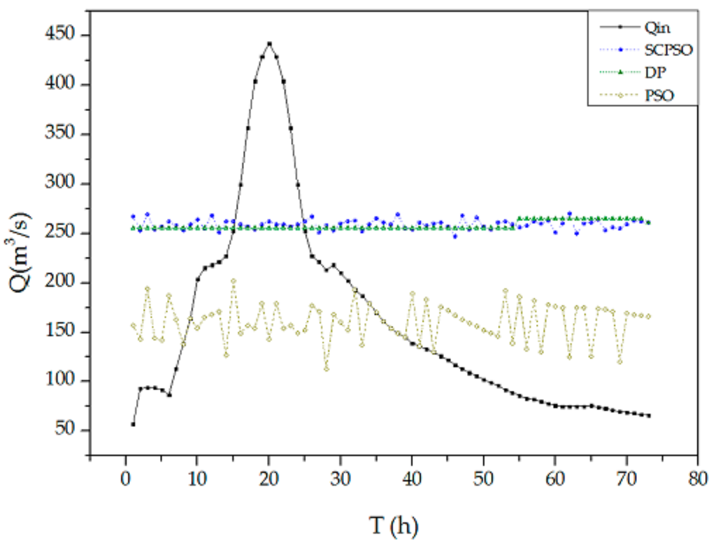
Based on the maximum output model, we compared the results of SCPSO, PSO, and DP algorithms, as shown in Table 3.

Table 3. The benefit value of different algorithms in kW.

	DP	PSO	SCPSO
Benefit Value	26,095,710	21,264,810	26,106,335

Among the three algorithms, the SCPSO algorithm performs best; the flood optimization result is basically the same as the dynamic programming algorithm; the worst result is the standard PSO algorithm, as shown in Table 3. It should be noted that the DP algorithm is slightly inferior to the SCPSO algorithm because its grid precision is coarser than the particle swarm optimization algorithm. In summary, from the calculation results, the SCPSO algorithm can get good results.

Figure 4 shows the decision-making processes of the SCPSO, PSO, and DP algorithm. The outflow of the DP algorithm is linear, and the results of the SCPSO and PSO algorithm fluctuate in different sizes. Moreover, the fluctuation of the SCPSO algorithm is smaller, and is similar to that of the DP algorithm, and the results of the PSO algorithm fluctuate greatly.



Q means the flow rate, and Qin means the inflow of Hongjiadu resevoir

Figure 4. Decision-making processes of different algorithms.

3.2. Efficiency of SCPSO

In this study, we compared the computation time of each algorithm ten times, as shown in Table 4. Among them, the precision of the DP algorithm grid is 500 and the precision of the particle swarm is 3000. Obviously, the DP algorithm takes the longest time, followed by the SCPSO algorithm, and the fastest is the PSO algorithm.

Table 4. Runtime of different algorithms in s.

Times	1	2	3	4	5	6	7	8	9	10	Average
DP	76	75	75	74	76	75	75	76	76	75	75.3
PSO	18	17	17	18	17	17	18	17	18	18	17.5
SCPSO	26	23	28	25	32	24	25	26	24	25	25.8

In the PSO algorithm, because the program has set the early termination mechanism, the PSO algorithm ends the iteration before 120 iterations, and SCPSO exits the iterative solution after 250 iterations, so the PSO algorithm takes less time. The authors tried to keep the accuracy of the grid division of the dynamic programming algorithm consistent with the two PSO algorithms, but the calculation time is too long at almost five minutes. As a result, the computational efficiency of the particle swarm algorithm of an information sharing mechanism is far higher than that of the dynamic programming algorithm. The SCPSO algorithm is forced to increase the water balance constraint, making the calculation time slightly slower than the standard PSO algorithm.

3.2.1. Effective Particles

In this case, the PSO algorithm generates effective particles after 150 iterations, and after 300 iterations, the effective particles are maintained at the level of 40%, which is very disadvantageous to the optimization decision-making, as shown in Figure 5a.

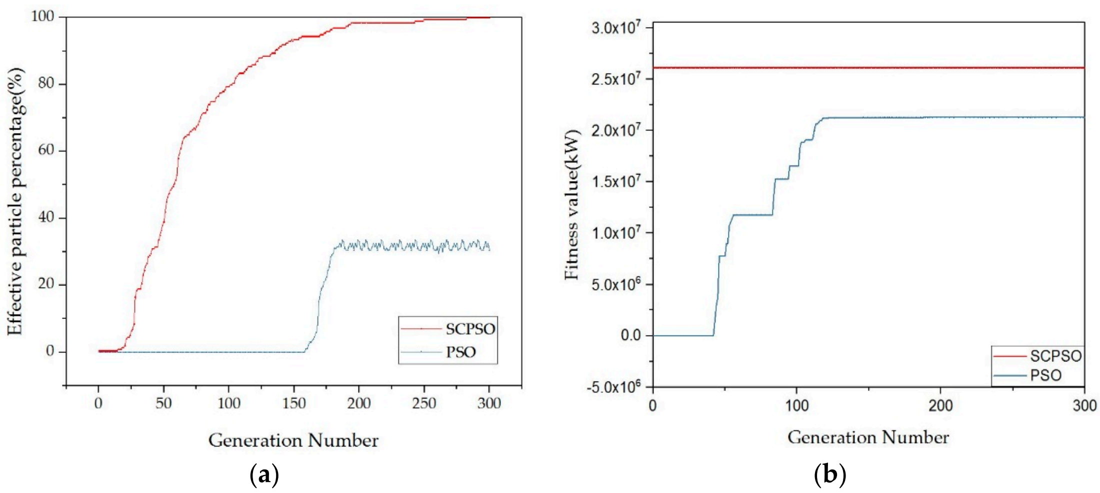


Figure 5. (**a**) Effective particles of SCPSO and PSO algorithms; (**b**) Comparison of benefit value between SCPSO and PSO algorithms.

However, because the constraint space of the particles is sited in advance, effective particles are generated in the beginning of iterations in the SCPSO algorithm. The particle efficiency increases significantly during iteration, and most particles can be converted into effective particles after several iterations.

3.2.2. Effective Particle Number

The state of particles affects the effect of particle convergence. Therefore, we give a different number of particles to analyze the effect of particle number on the optimization of the algorithm.

The population size of the PSO algorithm has an obvious influence on the optimal value, and the impact is divided into three stages in this case. When the size of the population is less than 50, PSO algorithm cannot get optimal value; while the size of the particle number is between 50 and 300, it can approach the optimal value quickly; when the size of the population exceeds 350, the effect of population size on the optimal value is almost negligible. Therefore, in practical use, the time factor may be considered comprehensively, and the population size may be appropriately selected.

The population size of the SCPSO algorithm does not affect the optimal value significantly, but it has a significant effect on the time consumption. The smaller the number of particles, the shorter the time it takes, and with the increase in the number of particle groups, the increase of the objective function value is not obvious, as shown in Table 5.

Table 5. Results of SCPSO and PSO algorithms for the number of different particles.

Particle Number	SCPSO		PSO	
	Output (kW)	Time (s)	Output (kW)	Time (s)
50	26,106,192	5	0	3
100	26,106,255	12	500,000	13
150	26,106,294	18	2,000,000	16
200	26,106,324	22	3,400,000	18
250	26,106,344	26	15,264,810	24
300	26,106,363	29	20,264,810	28
350	26,106,380	32	21,264,810	34
400	26,106,343	38	21,264,810	36
450	26,106,423	49	21,264,810	43
500	26,106,632	76	21,264,810	73

3.3. *Stability of SCPSO*

Due to their computational efficiency, evolutionary algorithms are widely used in the optimization of various fields, however, the stability of the algorithm has been a controversial issue. In actual use, it often needs to be calculated several times to find its maximum value or average to be used, which has brought inconvenience to the actual work.

Table 6 shows the results of the fitness value, calculated ten times from SCPSO, and the results of multiple calculations are almost the same. Thus, we consider that the SCPSO algorithm is very stable and can meet the requirement of algorithm stability in practical applications.

Process of Benefit Value

Figure 5b is the process of benefit value during the iteration number. Because the original particles do not restrict the water balance, the PSO algorithm has a large number of particles at the beginning of the iterations and the benefit value is 0. After more than 40 iterations, the state that violated the constraint was shaken off and its benefit value quickly converged to the optimal value. After 100 iterations, the benefit value keeps the local optimal solution unchanged.

In comparison, the SCPSO algorithm can get a good result at the beginning of the iteration, and converge to the optimal value quickly with the increase of iteration times. After about 10 iterations, the fitness value has approached the optimal value, and the results of the SCPSO algorithm slowly approach the optimal value range until the optimal value remains unchanged after 200 iterations.

Table 6. Multiple benefit value of the SCPSO algorithm in kW.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Average**
SCPSO	26,106,760	26,106,755	26,106,794	26,106,724	26,106,784	26,106,713	26,106,730	26,106,743	26,106,723	26,106,762	26,106,749

4. Discussion

In this study, we constructed a particle swarm optimization algorithm with strongly constrained space based on the water balance equation and applied it in the Wujiang River basin. Our results presented here demonstrate that the SCPSO algorithm has performed well in results, convergence, and convergence speed of the computational results compared with the PSO algorithm. Moreover, the computation time is slightly increased under the simple improvement by water balance.

This finding is significant for the application of the SCPSO algorithm in reservoirs because it offers the possibility of using fewer changes to achieve greater improvement. To our knowledge, the PSO algorithm has been applied to reservoir optimization for the first time since 2002, and a larger number of improvements in the PSO algorithm to adapt the optimal operation of reservoirs have emerged. Some researchers improve the efficiency of particle search ability by setting the initial feasible region and optimizing it near the feasible region [43,44]. Although this method improves the efficiency of particles, the selection of the initial feasible region has a greater impact on the results. At the same time, the calculation of the initial feasible region also increases the calculation time; it is also a common method to solve reservoir optimization problems by using various algorithms and construct a new hybrid optimization algorithm to improve the search efficiency of the PSO algorithm [45,46]. This kind of method increases the complexity of the algorithm and limited its popularity and application in China [47]. In the present study, we increased the percentage of effective particles to increase their adaptability to reservoir optimization problems under the unchanging structure of the PSO algorithm and discussed the superiority of the SCPSO algorithm from the convergence speed, the total number of particles, and effective particles. This particular setup makes a direct comparison of the PSO algorithm more meaningful.

4.1. Rationality of the Results

The DP algorithm is considered to obtain the globally optimal solution, and the benefit value calculated by SCPSO is near to the DP algorithm, which indicated that the SCPSO algorithm also has the same ability as the DP algorithm. However, the result of the PSO algorithm only accounts for 80% of the DP algorithm and it can be considered that the PSO algorithm failed to obtain the global optimal solution, but only obtained the local optimal solution in this study.

The outflow process of the DP algorithm is the same as that of the SCPSO algorithm, which keeps the flow as a constant variable, meaning that they are trying to keep the generator sets with the same output interval basically during the calculation period. This is consistent with the theory which has already been proved [48], which indicated that the SCPSO algorithm can obtain the global optimal solution.

However, there is some fluctuation in the outflow in Figure 4, and the reason may be the setting of the minimum discharge flow and the fluctuation caused by the water grid level.

4.2. Effectiveness of the SCPSO Algorithm

The main idea of PSO is the information sharing mechanism among particles, including the influence of global and local optimal particles, therefore, effective particles meeting all constraints are significant for optimization [49]. Based on the number of effective particles in the optimization process of SCPSO and PSO algorithms, we discussed the advantages of the SCPSO algorithm in this study.

4.2.1. Effective Particles

In fact, the fundamental premise of reservoir optimal operation is to improve benefits by changing the spatial and temporal distribution of water volume, and its basic premise is the water balance equation [50]. In this study, we constructed a non-inferior solution space to improve the efficiency of particle optimization based on the water balance equation, and the results showed that SCPSO has more than 50% of effective particles at the beginning of iterations, and the number of final effective particles is more than twice that of PSO, which greatly improves the efficiency of optimization.

Moreover, there is a need for at least 300 particles to calculate the results in the PSO algorithm, however, the results of 50 particles are similar to those of 500 particles in the SCPSO algorithm. The results demonstrate that the benefit value of the SCPSO algorithm is not affected by the number of particles, which is of great significance in reducing the calculation time because it offers the possibility of using fewer particles to achieve good values in less time.

4.2.2. Convergence Speed

A good smart algorithm not only needs to be able to converge to the global optimal solution, but also have a good convergence speed [51].

In this study, we accounted the processing of benefit value of the SCPSO algorithm and the PSO algorithm under 300 iterations to test the convergence speed. The results indicated the SCPSO algorithm can get a better result than that of the PSO algorithm during the iterations. Moreover, the results calculated by the SCPSO algorithm was near the global optimal solution value in the first iteration, while the PSO algorithm does not get any effective particles in under 50 iterations or has an inability to converge. This is the direct expression of using the water balance equation to construct an initial feasible region, which means the convergence speed of the SCPSO algorithm is faster and the result is better than that of the PSO algorithm. It also shows that the number of effective particles has an important influence on the optimization of the PSO algorithm.

4.3. Study Limitations

In theory, the result of the DP algorithm should not be lower than that of the SCPSO algorithm, and the reason is that the computing grid of the DP algorithm is too coarse. We have tried to set the grid of the DP algorithm in accordance with the particle swarm optimization algorithm, but its computing time is too long, so we did not emphasize this point.

Also, this paper only uses a single objective function to verify the superiority of the SCPSO algorithm, but it has not been applied to multi-objective decision-making or cascade reservoir groups. Therefore, we will do further research and analysis in this respect in the future.

5. Conclusions

Particle swarm optimization (PSO) has good application prospects in dealing with multi-objective optimization problems. Its application in reservoir optimization problems enables the reservoir multi-objective decision-making to have a broader prospect, but due to the random nature of the initial particles, a large number of particles are in an infeasible area, resulting in difficulties in solving. In order to overcome this problem, a large number of complex improvement methods are applied to PSO. Based on this, this paper attempts to solve the above problems by using the water balance equation as a constraint and constructing a strongly constrained space particle swarm optimization algorithm. The SCPSO algorithm is applied to verify the efficiency of the Hongjiadu hydropower project. The results lead to the following conclusions.

- The SCPSO algorithm has good computational performance, and the results are obviously better than the standard PSO algorithm, which is basically consistent with the result of the DP algorithm.
- The SCPSO algorithm is also highly efficient, and its calculation time is basically the same as that of the standard PSO.
- The SCPSO algorithm has good computational stability; the results of multiple calculations are almost the same.

The optimization idea of the SCPSO algorithm is not only applicable to the PSO algorithm but also can be applied in other aspects of reservoir water balance planning and water resource management.

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