An improved particle swarm optimization algorithm for the three gorges project operation optimization

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Abstract. The paper presents an algorithm combining simplex downhill search particle swarm optimization (SDPSO) for solving reservoir operation optimization (ROO) problems, with a new search strategy: reflecting the worst particle through the particle swarm centroid to generate a new particle and guiding the evolution direction of each particle. The ROO problem is a complicated dynamically constrained nonlinear, non-convex optimization problem that is important for reservoir operation system, consisting of continuous control variables. The proposed algorithm is examined on Three Gorges Project (TGP) that provided a better operational effect result with greater effectiveness and obtains more power generation with lower insurance rate reservoir sum runoff.

1. Introduction

1.1. Background
Compared with other power resources, hydropower enjoys exceptional advantages and merits that bring electricity energy without producing any pollution. Reservoir operation optimization (ROO) yields maximum comprehensive benefits which is the subject of heightened concern due to its advantage of increasing the benefits of reservoirs without increasing investment as the non-structural measure. The optimization technology had played a more and more important role in looking for solutions to the program of ROO. Generally, the main objective of ROO was to maximize the reservoirs power generation efficiency except for satisfied various complicated reservoirs operation constraints [1], such as flood control constraints, which requires that the reservoirs water level must fix flood limiting water level. Application of system analysis theory to ROO has been an important research tendency for purpose of making use of reservoir storage capacity and maximizing benefits. Research on ROO has been strongly affected by operational theory and computer technology. For example, more and more new technology was applied to medicine, which brought all human beings huge benefits [2]. And then, in order to solve ROO problems, we introduced the new computational technology and technique to reservoirs operation [3].

1.2. Literature review and research question
During recent decades, many conventional optimization algorithms have been used to solve the ROO problems, including linear programming [4], nonlinear programming [5], quadratic programming [6], lagrangian relaxation [7, 8], dynamic programming [9], the progressive optimality algorithm [10]. Since
1990s, Intelligent algorithms, such as artificial neural nets [11], fuzzy rule method [12], artificial bee colony algorithm [13], genetic algorithm [14, 15], differential evolution algorithm [16] and particle swarm optimization [17-19], have been used to solve ROO problem, which has been proved effective. Janson and Middendorf [20] proposed a hierarchical PSO which establishes a hierarchy among particles based on a tree-like structure, which makes constant progress by test different dynamic functions. Li and Yang [21] combined standard PSO with a random number strategy that got a better solution to the problems. Wang et al. [22] proposed an improved PSO based on memory-based. Blackwell and Branke [23] used the atomic metaphor to improve algorithm. Parrott and Li [24] proposed a Speciation-based PSO, which distributes the many swarm particles over a high number of species. Yang and Li [25] created an adaptive number of sub-groups by means of the hierarchical clustering method. Nickabadi et al. [26] proposed an improved PSO based on competitive clustering. Hashemiand Meybodi [27] combined the algorithm of PSO with the algorithm of Cellular Automata (CA), and proposed a new algorithm which could be called cellular PSO.

However, the ROO was considered as a high dimensional and non-linearity optimal problem, which including many constraints and becomes more complicated, and the ROO model should be continuous and differentiable. The conventional optimization algorithms could not meet the demand of ROO problem accurate solutions, especially for large-scale reservoir systems. Modern heuristic algorithms had lots of advantages, such as easy implementation and good properties, which were applied to ROO problems more and more widely. For example, particle swarm optimization (PSO) [28, 29] has demonstrated good performance in optimization of ROO problem [30-32]. The individual with the best fitness could be considered as the global optimum solution to the optimization problem, there are competitive performance and some undesirable dynamic characteristics in progress of searching for the best solution. However, there are challenging tasks for PSO, such as premature convergence and falling into the local optimum. Focus on the drawbacks of PSO, many academics try to improve PSO from the following aspects, random number generation techniques [33], mutation, time varying acceleration coefficients and inertia weight variation.

1.3. Research purpose

In order to overcome the PSO defects, which could not jump out of the local optima and pass through the critical point, our research focus on the PSO mutation. The Simplex downhill search (SDS), which was first proposed by Nelder and Mead [34, 35] in 1965, which was included in the SCE-UA method (abbreviation for shuffled complex evolution method developed), proposed by Duan et al in 1992 [36]. In the research, inspired by the SDS scheme, we proposed a new particle swarm algorithm called simplex downhill search PSO (SDSPSO). For conquering the premature convergence, we introduced SDS operator into PSO with a new search strategy: reflecting the worst particle through the particle swarm centroid to generate a new particle and guiding the evolution direction of each particle. First, a cluster of particles, considered as a simplex in the SCE-UA method. In the course of the SCE-UA method evolution, a simplex could search the best solutions to the problem based on the optimization strategy, which was introduced to our improved PSO algorithm, which might be called the evolution strategy in PSO. Then, diversity and competition of particles were balanced in SDSPSO. Second, since the SDSPSO was an improved method of PSO, other strategies in PSO could also be added to it (e.g., adaptive strategy and mutation strategy).

This research in the paper presented in two-fold. Firstly, an improved variant of PSO named as simplex downhill search particle swarm optimization (SDSPSO) has been proposed and secondly it has been applied for solving reservoir operation optimization (ROO) problems. Optimal decisions were presented using SDSPSO for the Three Gorges Project (TGP) in the abundant water period and low water period. The rest of the paper is organized as follows. In Section 2, mathematical problem of the ROO work is presented. In Section 3, original PSO is described, the proposed SDSPSO is discussed. In Section 4, we presented and discussed simulation results. Finally, conclusions of the present paper are drawn in Section 5.

2. Problem formulation
2.1. Objective function
The ROO problem could be formulated as a constrained optimization problem. In this research, the aim of ROO is maximizing comprehensive benefits as much as possible by reservoirs optimization operations for during the operation periods based on flood control safety. It is related to a given reservoirs operation over \( T \) intervals as follows:

\[
F = \max \sum_{i=1}^{T} N^i \cdot M^i
\]

(1)

In the formula, \( F \) represents the hydropower generation, kWh, \( M_i \) represents the period of the \( t \)-th operation interval, s; and \( N_t \) represents the output in the \( t \)-th operation interval, kW. The reservoir output \( N_t \) and the corresponding other variables could be calculated as following formula:

\[
N^i = A \cdot O^i \cdot H^i
\]

(2)

\[
O^t = I^t - \left( V^i(Z) - V^{i+1}(Z) \right) / M^i
\]

(3)

\[
H^t = Z^t - TZ^t(O)
\]

(4)

Where \( A \) is the comprehensive output coefficient; \( O \), is the rate of discharge in the t-operation interval, m\(^3\)/s; \( H \) is the water head for power generation in the \( t \)-th operation period of time, m; \( V \) and \( V^{i+1} \) (m\(^3\)) is the storage volume in the \( t \)-th and \( t+1 \)-th operation interval, which is a dependent variable of \( Z \) (m); \( Z_t \) is the storage level in the \( t \)-th operation interval; It is the the reservoir inflow in the \( t \)-th operation interval, m\(^3\)/s; \( TZ \), \((m)\) is the tail-waterlevel, which is a dependent variable of \( O \). Therefore, reservoir water storage level \( Z \) and discharge \( O \) could be selected as decision variables. In our research, reservoir water storage levels \( Z \) could be considered as the decision variables.

In the process of solving the ROO problem, there are relaxable or soft constraints, as well as rigid or hard constraints. There are all kinds of constrained conditions in ROO problem, which involves complicated procedures and combinations. Therefore, ROO problem might be considered as a complex combinatorial optimization problem with difficulties in solution finding. In order to solve an ROO problem, we must focus all attention on the main issues, such as flood prevention and power generation. The ROO is a multiple objects problem, which could be considered as single object based on an external penalty, and convert into an unconstrained one. For reservoir operation, the most important is the safety of flood control. Generally, during the flood season, the reservoir operation water level usually maintains at flood control level (reservoir inflow is equal to reservoir discharge) which must follow flood control operation rule. Hence, we want to maximum power generation from the hydropower station by reservoir operation during the non-flood season in the study. In order to derive feasible optimal operating rules within all constraints, we designed the fitness function with penalty terms, and objective function is associated with infeasible solutions with penalty values:

\[
f(Z) = F(Z) + P \cdot \min \left\{N - N_{\text{inf}}, 0\right\}
\]

(5)

Where \( f(Z) \) represents the fitness, \( F(Z) \) represents the total power generation efficiency over entire operation period, \( P \) represents a penalty term coefficient, and \( N_{\text{inf}} \) represents the minimum output of power plant.

2.2. Constraints
There are many equality and inequality constraints in ROO problem.

a) The water quantity balance equation is

\[
V^{i+1} = V^i + \left( I^t - O^t \right) \cdot M^i, \quad t = 1, 2, \ldots, T
\]

(6)

In the equation, we consider that the water volume is balance, due to without giving any consideration of evaporation and leakage that accounting for little. The other constraints could be written as

\[
(V, Z, O, N)^i \leq (V, Z, O, N)^i \leq (V, Z, O, N)^u, \quad t = 1, 2, \ldots, T
\]

(7)

Where \( l \) and \( u \) represent the lower and upper ROO limits in the \( t \)-th operation period, respectively. Where \( V, Z, O, N \) represent reservoirs storage, reservoirs level, discharge flow and output, respectively.
3. Methodology

3.1. The standard particle swarm optimization
In 1995, Kennedy and Eberhart first put forward the particle swarm optimization (PSO), which is a method for solving all kinds of optimization problems, such as non-continuous, non-differential and multi-peak function optimization problem [37, 38]. In PSO algorithms, each solution is represented by a particle, each particle search for a position that optimize objective function (fitness) with changing direction and velocity according to both own experience and the experience of the whole swarm. Each particle improves its search direction and speed to the optimum particle in the process of iteration.

There are two important elements in each individual of the PSO algorithm, which are the flying direction (speed) and position during each generation. We denote $X$ as a plan in a $d$-dimensional optimization problem, $X_i^k=(x_{i,1}^k, x_{i,2}^k, ..., x_{i,d}^k)$ as the location of the $i$-th solution at $K$-th generations, and $V_i^k=(v_{i,1}^k, v_{i,2}^k, ..., v_{i,d}^k)$ as the corresponding individuals position shift velocity. The velocity and position of the $i$-th solution at the next generation $k+1$ is updated based on the Eq. (8) and Eq. (9). A particle flies toward good plans based on the PSO algorithm search strategies by the population in the search space.

\[
v_{i,d}^{k+1} = w \cdot v_{i,d}^k + c_1 \cdot \text{rand}_1 \cdot (p_{i,d}^k - x_{i,d}^k) + c_2 \cdot \text{rand}_2 \cdot (g_{d}^k - x_{i,d}^k) \tag{8}
\]

\[
x_{i,d}^{k+1} = x_{i,d}^k + v_{i,d}^{k+1} \cdot \Delta t \tag{9}
\]

Where $p_{i,d}$ represents the $i$-th particle having the best fitness as far as $k$-th iteration; $g_d$ represents the particle having the best position among the whole population as far as $k$-th iteration; $w$ is the inertia weight factor; $c_1, c_2$ is acceleration constants, respectively.

3.2. Simplex downhill search particle swarm optimization
In order to improve the search strategies of PSO and jump out of the ROO problem local optima, we presented an improved PSO algorithm in cooperation with the simplex downhill search strategy. The simplex downhill search (SDS) method was first proposed by Nelder and Mead [33] in 1965, which could be considered that a simplex has random searching ability of adaptive evolutionary. To design an efficient SDS structure. First, a simplex was proposed and considered as “one individual” that contains a cluster of individuals in swarm. Second, the SDS method should inheritance good strategy of the PSO algorithm. By setting a cluster of particles as “one individual” (one simplex), the simplex downhill search method combined with the improved algorithm not only enabled most particles to search the feasible region more carefully but also permitted part of particles to jump out of the local region base on simplex downhill search strategy. Thereby, the improved PSO algorithm has an important feature, meeting the demand of exploration and exploitation searches.

In PSO, the direction of an individual’s and population’s evolution was followed by $p_{best}$ and $g_{best}$, respectively. The local and globa optima existed in the feasible region where more particles moved based on convergence property, as defined by $p_{best}$ and $g_{best}$. For improving the search strategies of PSO, we identified a simplex that contains a cluster of particles as the one individual, and $p_{best}$ was also the best solution of the simplex. In SDS method, each particle of a simplex was a potential ‘parent’ for the PSO next generation reproducing offsprings, and allowed the algorithm to guide the all particles search toward the better direction in the feasible search space. Every particle was given at least one chance to participate in the reproduction process before being displaced. Thus, the algorithm does not miss any information contained in all the population. The SDS method was illustrated graphically in Figure 1, where the dots (○) indicated the locations of the points in a simplex before beginning evolution. The symbol □ represents the locations of the new points generated by the iterative process. The ‘reflection’ step, which reflecting the worst individual which has worst fitness through the centroid of simplex consisted of other points which got rid of the worst point. Because the worst point has lowest fitness, which was replaced the new point by ‘reflection’ step. The new point improved the population diversity with this evolution step.
Under the proposed SDPSO algorithm was presented briefly as follows:

(I) Initialize $q$ simplexes, corresponding $q$ particles, the number of points in each simplex, $n$, the population size $pop = q \times n$, generate the population and evaluate the fitness. Then, one simplex is correspond to a $p_{best}$ value, $p_{best} = \max(f(X_i), \ldots, f(X_j), \ldots, f(X_q))$, $i=1,2,\ldots,q$, and update and modification based on Eq. (5) and Eq. (6).

(II) In each simplex, we identified the worst point of the simplex and computed the centroid of simplex consisted of the other points which got rid of the worst point as following:

$$m_{best} = \frac{\sum_{j=1}^{n-1} X_j}{n-1} \quad (10)$$

And then, we obtained a new point by a reflection step, $X_{i_{new}} = m_{best} - X_{i_{worst}}$. The new point would replace the worst point in the simplex when the fitness of the new point was better than that of the worst point.

(III) The proposed algorithm was stop based on we set rules, such as the iteration number or the calculation accuracy requirement of solution. Otherwise, continue calculation process until the terminate rules was reached. The proposed SDPSO flow chart was showed in Figure 2 and the Pseudo was showed in Figure 3.

4. Case studies

4.1. Simplex downhill search particle swarm optimization

The proposed algorithm is tested from in terms of efficiency and precision by a set of six constrained test functions, which are given in Table 1, including the test functions form, the bounds of solutions and the optima value. To test the performance of the SDPSO, test functions were used for comparison with original PSO (OPSO), Shi and Eberhart [39] proposed WPSO which was considered as a method of a $w$ linearly decreasing by the evolution step as:

$$w = w_{\text{max}} - \left( w_{\text{max}} - w_{\text{min}} \right) \cdot \frac{k}{g} \quad (11)$$

Where $k$ represents the current number of iteration progress, and $g$ is the maximum number of evaluations.
Start

Initialization

Objective function Evaluation

Find the current best solution $p_{best}$, of $i$th simplex and the worst point $X_{worst}^{i}$ of the $i$th Simplex.

Computed the centroid $m_{best}$ of the $i$th simplex without including the worst point.

Update particles of simplex by eq.(8) and (9)

Update $X_{worst}^{i}$ of the $i$th Simplex by reflection step

Update $P_{best}$ and $G_{best}$

Termination condition is reached or not?

NO

YES

Output the best solution

Pseudo code of SDSPSO

Initialize the population: $k = 0$, random initialize $X_{j}(k)$, evaluate $f(X'_{j}(k))$

For $k=1$ to maximum iteration

For $i = 1$ to $q$

   For $j = 1$ to $n$

      If $f(X'_{j}(k)) > f(p_{best})$

         $p_{best} = X'_{j}(k)$

      End if

   End for $j$

   End for $i$

End for $k$

End

$mbest_{i} = \sum_{j=1}^{n} X_{j}^{i}/n-1$ (Removed the worst point in simplexes)

$X_{worst}^{i} = X_{worst}^{i-1} \pm \left( m_{best} - X_{worst}^{i-1} \right)$

If $|X_{worst}^{i}| > X_{max}$

   Randomly generate $X_{worst}^{i}$ within the search space

End if

For $j = 1$ to $n-1$ (removed the worst point in simplexes)

   $v_{j}^{new} = w \cdot v_{j}^{old} + c_{1} \cdot rand \cdot (p_{j}^{best} - x_{j}^{i})$

   $x_{j}^{i} = x_{j}^{i} + v_{j}^{new} \cdot \Delta t$

End for $j$

End for $i$

End

Figure 2. The flow chart of proposed SDSPSO.

Figure 3. The Pseudo of proposed SDSPSO.

Table 1. Test functions used for validation.

| Name                | $D$ | Formula                                                                 | Bounds          | Theoretical optima/f($x^*$) |
|---------------------|-----|-------------------------------------------------------------------------|-----------------|-----------------------------|
| Schwefel Function   | 30  | $f_{1}(x) = 418.9825 \times \text{dim} + \sum_{i=1}^{\text{dim}} -x_{i} \sin \sqrt{|x_{i}|}$ | [-500, 500]     | [1, 1, ..., 1]/0           |
| Rastrigin Function  | 30  | $f_{2}(x) = \sum_{i=1}^{\text{dim}} \left[ 10 + x_{i}^2 - 10 \cos(2\pi x_{i}) \right]$ | [-500, 500]     | [0, 0, ..., 0]/0           |
| Ackley Function     | 30  | $f_{3}(x) = 20 + \exp(1) - 20 \exp \left[ -\frac{0.2}{\text{dim} \sum_{i=1}^{\text{dim}} x_{i}^2} \right]$ | [15, 30]        | [0, 0, ..., 0]/0           |
| Sphere Function     | 30  | $f_{4}(x) = \sum_{i=1}^{\text{dim}} x_{i}^2$                             | [-5.12, 5.12]   | [0, 0, ..., 0]/0           |
| Schwefel Function   | 30  | $f_{5}(x) = \sum_{i=1}^{\text{dim}} x_{i}^2 + \sum_{i=1}^{\text{dim}} 0.5 i x_{i} + \left( \sum_{i=1}^{\text{dim}} 0.5 i x_{i}^2 \right)^4$ | [-10, 10]       | [0, 0, ..., 0]/0           |
Rastrigin Function

\[
f_6(x) = \sum_{i=1}^{\text{dim}} \left[ 100(x_i^2 - x_i) + (x_i - 1)^2 \right]
\]

[-30, 30] [1,1,…,1]/0

After repeated experiments we made 30 independent runs for each optimization method. The original PSO (OPSO), Shi and Eberhart proposed a \( w \) linearly decreasing with the evolution steps PSO (WPSO), and SDSPSO have been written in FOTRAN code and tested in our computers. After many experiments, we tested enough parameters values, the value parameters related to three optimization methods were presented in Table 2. Some other methods such as DE, CMAES, have also been simulated in FORTRAN for solving the same problem and compared with the result obtained with the proposed algorithm.

Table 2. Parameters setting of different methods.

| Parameters             | OPSO | WPSO | SDSPSO |
|------------------------|------|------|--------|
| Inertia weight         | 0.729| Eq. (11) | Eq. (11) |
| \( W_{\text{max}} \)  | -    | 0.9  | 0.9    |
| \( W_{\text{min}} \)  | -    | 0.4  | 0.4    |
| Acceleration coefficient | 2.0  | 2.0  | 2.0    |
| Population size        | 100  | 100  | 100    |
| Generations            | 10000| 10000| 10000  |
| Experiments number     | 30   | 30   | 30     |
| Number of simplexes    | -    | -    | 10     |

Simulation results presented in Table 3 and Figure 4 with different POP size. Obviously, we could not obtain the global optima value for all of the optimizations, it showed that SDSPSO had the better performance in searching the solution and fitness.

Table 3. Test functions performance of different methods.

| Parameters | CMAES | DE     | OPSO   | WPSO   | SDSPSO  |
|------------|-------|--------|--------|--------|---------|
| \( f_1(x) \) | -6393 | -9853  | -9332  | -8991  | -5448   |
| \( f_2(x) \) | -22.42| -14560 | -37.8  | -24.87 | -21.88  |
| \( f_3(x) \) | -0.029| -169.92| -7.15E-2| -0.8769| -8.03E-2|
| \( f_4(x) \) | -3.62E-29| -1.36| -7.26E-36| 0      | 0      |
| \( f_5(x) \) | -1.11E-28| -1.0E+10| -6.42E-12| -2.89E-31| -1.4E-45|
| \( f_6(x) \) | -12.9 | -1.73E+8| -64.73 | -146.41| -5.73   |

Comparing the results of Table 3 and Figure 4, it is possible to indicate that SDSPSO had the better performance in all test functions. It applied the SDSPSO to solve Schwefel’s function, which got many local optima solutions, and effected the global optimum solution.

Compared with other algorithms, the proposed SDSPSO was proved that the outstanding results could be obtained from applications of the proposed SDSPSO to ROO problems in reservoir operation systems.
Figure 4. Convergence trajectory of different method for Test Schwefel, Rastrigin, Ackley, Sphere, Zakharov and Rosenbrock Functions.

4.2. SDSPSO for ROO problem

4.2.1 The ROO problem solving by the proposed algorithm. The Three Gorges Project (TGP) is located in the Yangtze River in China. The TGP has a height of 175 m and a length of 2335 m, and many discharge facilities, including the spillway dam, bottom intake gate and table hole gates. Table 4 showed characteristic parameter of the TGP.
Table 4. The salient features of the TGP.

| items                        | value | units          |
|------------------------------|-------|----------------|
| Total capacity               | 39.3  | billion m³     |
| Machine units                | 32    | sets           |
| Firm output                  | 4990  | MW             |
| Installed capacity           | 2.25×10⁴ | MW           |
| Flood control storage level  | 145   | m              |
| Maximum storage level        | 175   | m              |

The main object of the TGP operation is flood control and power generation. In order to secure the safety, the reservoir storage level maintains 145 m (flood control reservoir storage level) during the flood season (from June to September), the TGP storage level is generally lower than the reservoir flood control storage level. The storage level of the TGP might kept at 175 m at end of October. Therefore, we could make the optimal operation during the operation period between November and the end of April of the following year, and then obtain the benefits by regulating the operation of the TGP.

The Yichang station represents TGP inflow, and the station runoff varies: the sum of runoff is over 79% including all flood season between May and October. Water resource utilization might become important during non-flood period of a low-flow year because less runoff by ROO.

4.2.2 The ROO problem solving by the proposed algorithm. The storage level of TGP is maintain or lower than the reservoir flood control level during flood season between June and September, which is discharge equal to reservoir inflow, and there is no optimal space for the TGP operation. There are 28 time-intervals (considering as one operation interval is a period of ten days) during operation period between September to June of the following year.

The ROO of TGP was used for comparison with OPSO, WPSO, and SDSPSO algorithms under 30%, 50%, 75% and 90% of the insurance rate reservoir sum runoff. In the study, a period of ten days inflow data to TGP in 33 years were available. Since this paper was an algorithm research, 33 years of data is sufficient. These algorithms, all the parameter settings were the same as Table 2 expect to generations and population size, was applied to solve ROO optimize problems of TGP. The details of the proposed SDSPSO for solving the TGP optimal operation problems were introduced as following:

(1) Structure of individuals. The PSO population includes pop particles and each individual is a series of decision variables. For the ROO problem of the TGP operation, reservoir water storage levels were set as the decision variables. Therefore, for each particle P, which include T intervals, an array of control decision variables was described as P=(Z₁, Z₂, ..., Zₜ), which could be considered as a simplex.

(2) Initialization. The individuals are initialized according to the random number, which given by

Zₜ= Zₜ,min + (Zₜ,max−Zₜ,min)•Rnd().

(3) Update and modification. We have proposed the new strategy to improve the updating rule of the velocity and global search ability by SDPSO, which was applied to ROO problem, and the process of update and modification described in section 3.2.

(4) Stopping criteria. When the iteration number or the calculation accuracy requirement of solution was reached, the evolution progress was stopped. Otherwise, evolution progress continues.

We imported all required data to the ROO problem model for simulation, and the data includes historic inflows, reservoir and power stations properties was shown in Table 4, and a total of 33 years of historic inflow data was available for ROO problem, which was shown in Table 5. The storage-capacity-area (V-Z-S) was shown in Figure 5, and tail water level-discharge (TZ-O) curves of TGP was also shown in Figure 5, which we could compute the i-th TZ according to i-th reservoir discharge in Eq. (4), and then obtain the i-th Hₜ.
Table 5. The insurance rate reservoir inflow of the TGP.

| Insurance Rate | 30%  | 50%  | 75%  | 90%  |
|----------------|------|------|------|------|
| 1887           | 1995 | 1971 | 1951 | 1977 |
| 1902           | 1909 | 1968 | 1986 | 1977 |
| 1893           | 1984 | 1944 | 1951 | 1977 |
| 1948           | 1941 | 1973 | 1927 | 1977 |
| 1994           | 1954 | 1914 | 1940 | 1977 |
| 1904           | 1960 | 1924 | 1901 | 1977 |
| 1933           | 1949 | 1891 | 1962 | 1977 |
|                | 1966 | 1930 | 1972 | 1977 |
|                |      |      |      | 1939 |
|                |      |      |      | 1981 |

Figure 5. The storage-capacity and storage-area, Tail water level-discharge curves of TGP.

We set up population size 100, 200 and 300, and the number of generation was 1000, the other parameters was same as shown in Table 2. The corresponding each year and mean power generation (mpg) were shown in Table 6. It showed that the proposed SDSPSO got the best mean power generation of different popsizes than the other methods for the TGP reservoir operation. It could obtain more power generation with lower insurance rate reservoir sum runoff, which meant that there was more stream in low insurance rate. Compare OPSO methods, the proposed algorithm presented a more significant advantage under 50% and 75% insurance rate reservoir sum runoff, this is because there were medium and small flood but large flood, which we could make full use of water resource and not bring flood risk based on more excellent algorithms. It also shown that more power generation was obtained with more popsize under 50% and 75% insurance rate reservoir sum runoff.

The efficiency and convergence of SDSPSO and other methods were also compared in the paper. Take 1933, 1966, 1939, 1962 from different the insurance rate of TGP reservoir sum runoff as examples, from Figure 6, it was clearly showed that the proposed SDSPSO has got better results than that of other methods. It demonstrated that the results obtained by SDSPSO were the best one. Compare other two methods, the proposed SDSPSO algorithm presented a more significant advantage with increasing insurance rate reservoir sum runoff, this is because that could highlight the algorithm superiority under little rate reservoir sum runoff. In other words, there was plenty of room for optimization with less reservoir sum runoff.
Table 6. The insurance rate reservoir inflow of the TGP. Performance of different methods in the TGP operation (10^6 million kWh).

| rate | year | \( \text{popsize}=100 \) | \( \text{popsize}=200 \) | \( \text{popsize}=300 \) |
|------|------|------------------|------------------|------------------|
|      |      | MPSO | WPSO | MPSO | WPSO | MPSO | WPSO | MPSO | WPSO | MPSO | WPSO | MPSO | WPSO | MPSO | WPSO |
| 1987 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 | 614.40 | 614.00 |
| 1990 | 671.65 | 671.60 | 671.65 | 671.60 | 671.65 | 671.60 | 671.65 | 671.60 | 671.65 | 671.60 | 671.65 | 671.60 | 671.65 | 671.60 | 671.60 | 671.60 |
| 1993 | 636.68 | 636.60 | 636.68 | 636.60 | 636.68 | 636.60 | 636.68 | 636.60 | 636.68 | 636.60 | 636.68 | 636.60 | 636.68 | 636.60 | 636.60 | 636.60 |
| 1994 | 656.71 | 656.65 | 656.61 | 656.59 | 656.61 | 656.59 | 656.61 | 656.59 | 656.61 | 656.59 | 656.61 | 656.59 | 656.61 | 656.59 | 656.61 | 656.59 |
| 1996 | 673.80 | 673.74 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 |
| 1999 | 567.85 | 567.79 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 |
| 2002 | 607.47 | 607.41 | 607.35 | 607.29 | 607.35 | 607.29 | 607.35 | 607.29 | 607.35 | 607.29 | 607.35 | 607.29 | 607.35 | 607.29 | 607.35 | 607.29 |
| 2005 | 547.49 | 547.43 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 |
| 2008 | 684.04 | 684.03 | 683.97 | 683.91 | 683.97 | 683.91 | 683.97 | 683.91 | 683.97 | 683.91 | 683.97 | 683.91 | 683.97 | 683.91 | 683.97 | 683.91 |
| 2011 | 673.80 | 673.74 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 | 673.68 | 673.62 |
| 2014 | 567.85 | 567.79 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 | 567.73 | 567.67 |
| 2017 | 547.49 | 547.43 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 | 547.37 | 547.31 |
| 2020 | 544.63 | 544.57 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 |
| 2023 | 544.63 | 544.57 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 |
| 2026 | 544.63 | 544.57 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 | 544.51 | 544.46 |

The diagrams show the fitness evolution over generations for different methods: OPPO, WPSO, and SDPSO. The graphs demonstrate the improvement in fitness with increasing generations for each method.
Figure 6. Convergence trajectory of different method in years of 1933, 1966, 1939, 1962 \((\text{popsize}=100)\).

Figure 7. The intervals of reservoir storage level of different method for TGP in years of 1933, 1966, 1939, 1962 \((\text{popsize}=300)\).

In Figure 7, the TGP storage levels variations of different years were shown respectively, it was seen that OPSO and WPSO has lower storage level than SDSPSO which might fall into local optima for ROO problem. In Figure 8, the TGP discharge variations of different years were shown respectively. Because TGP an ambitious project, although there was little difference of storage level and discharge among
three methods from Figure 8, it might bring great power generation benefit by the proposed algorithm as shown Table 6.

![Figure 8](image_url)

**Figure 8.** The intervals of reservoir discharge of different method for TGP in years of 1933, 1966, 1939, 1962 (popsize=300).

An obvious practical application of TGP operation based on the proposed algorithm, decision makers could regulate and optimize the reservoirs discharge and reservoirs water level based on the inflow of reservoirs, which bring the benefit and the function of the reservoir.

5. Conclusions and future research

In the research, we proposed a new particle swarm optimization (SDSPSO) to solve the TGP operation optimization problem which was in cooperation with the simplex downhill search strategy, which was implemented by a new search strategy: reflecting the worst point in a particle (simplex) through the centroid of the other points. The SDSPSO using parallel computing approach was applied to the Three Gorges Project (TGP) in the abundant water period and low water period. All of the results show that the proposed SDSPSO could get the best result in some aspects, such as power generation and convergence performance among all algorithms. The proposed algorithm presented a more significant advantage under 50% and 75% insurance rate reservoir sum runoff.

Although our proposed method could not completely prevent premature convergence for PSO applied to ROO problem, we might provide some research for the other searchers to improve the PSO algorithm.
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