Multi-Objective Optimization of Water-Sedimentation-Power in Reservoir Based on Pareto-Optimal Solution*

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Abstract: A multi-objective optimal operation model of water-sedimentation-power in reservoir is established with power-generation, sedimentation and water storage taken into account. Moreover, the inertia weight self-adjusting mechanism and Pareto-optimal archive are introduced into the particle swarm optimization and an improved multi-objective particle swarm optimization (IMOPSO) is proposed. The IMOPSO is employed to solve the optimal model and obtain the Pareto-optimal front. The multi-objective optimal operation of Wanjiazhai Reservoir during the spring breakup was investigated with three typical flood hydrographs. The results show that the former method is able to obtain the Pareto-optimal front with a uniform distribution property. Different regions (A, B, C) of the Pareto-optimal front correspond to the optimized schemes in terms of the objectives of sediment deposition, sediment deposition and power generation, and power generation, respectively. The level hydrographs and outflow hydrographs show the operation of the reservoir in details. Compared with the non-dominated sorting genetic algorithm-II (NSGA-II), IMOPSO has close global optimization capability and is suitable for multi-objective optimization problems.

Keywords: multi-objective optimization of water-sedimentation-power; optimal operation of reservoir; Pareto-optimal solution; particle swarm optimization

Reservoir sedimentation in heavily silt-laden rivers has a strong impact on the benefits of reservoirs. It is crucial to carry out multi-objective optimization of water-sedimentation-power according to different inflow water and sediment conditions of the reservoirs to balance sedimentation and power generation benefit. The biggest difference between multi- and single-objective optimal operation of reservoirs is that there exists an optimal solution set (Pareto-optimal set). The goal of multi-objective optimal operation of reservoirs is to obtain an optimal approximation of the Pareto-optimal set. Most research converts the multiple objectives into a single overall objective using method based on constraint [1, 2] and weighting method [3]. The former method is unable to attend to every objective at one time; the latter requires the weights of multiple objectives, but the weights are prone to subjective factors. Genetic algorithm has been widely used for multi-objective optimization, such as MOGA [4], NSGA [5] and NPGA [6]. Particle swarm optimization (PSO) algorithm is a population-based global stochastic optimization technique [7] and particularly suitable for multi-objective optimization problems.

In this paper, a multi-objective optimal operation model of water-sedimentation-power in reservoir is established with power-generation, sedimentation and water storage taken into account. Moreover, an improved multi-objective particle swarm optimization (IMOPSO) is proposed by introducing the inertia weight self-adjusting mechanism and Pareto-optimal archive into PSO based on the concept of Pareto optimality. IMOPSO is employed to solve the multi-objective optimal model and obtain the Pareto-optimal front. A case study shows that the former method is able to obtain the Pareto-optimal front with a uniform distribution property and the Pareto-optimal front can reflect the results of each optimized plan directly.

1 Model description

Reservoir sedimentation contradicts with power generation in reservoir operation. A drawdown of water
level and an increase in outflow discharge are required to reduce siltation and improve the sedimentation effectiveness, which will affect power generation adversely; high water level and reduction of surplus water are beneficial to power generation, but those will cause more siltation. A multi-objective optimal operation model of water-sedimentation-power in reservoir is established to coordinate reservoir deposition and power generation in reservoir operation and improve the comprehensive benefits of reservoirs.

Multi-objective function:

\[
\text{opt } E = \left\{ \sum_{t=1}^{T} P_t, \sum_{t=1}^{T} W_t \right\}
\]

where \( E \) is the comprehensive benefits; \( P_t \) is the electric energy generated in time interval \( t \); \( W_t \) is the amount of sediment deposited or scoured in \( t \); \( T \) is the total number of time intervals.

Constraint conditions:

1. Water balance constraint

\[
V_{t+1} = V_t + (Q_t - Q_{out}^t)m
\]

where \( V_{t+1} \) is the water storage at the end of \( t \); \( V_t \) is the water storage at the beginning of \( t \); \( Q_t \) is the inflow discharge in \( t \); \( Q_{out}^t \) is the outflow discharge in \( t \); \( m \) is the transfer coefficient between discharge and water storage.

2. Reservoir storage capacity constraint

\[
V_{t, \text{min}} \leq V_t \leq V_{t, \text{max}}
\]

where \( V_{t, \text{min}} \) is the guaranteed water storage in \( t \); \( V_{t, \text{max}} \) is the maximum allowable water storage in \( t \).

3. Characteristic constraint of hydropower units

\[
P_t = f_s \left(Q_t, H_t\right)
\]

where \( f_s \) is the characteristic function of the units; \( Q_t \) is the power discharge of unit \( s \) in \( t \); \( H_t \) is the hydraulic head of the hydropower plant in \( t \).

4. Reservoir capacity curve constraint

\[
L_{in}^s = f_i \left(V_t\right)
\]

where \( L_{in}^s \) is the water level in \( t \); \( f_i \) is the relation function between water level and storage capacity.

5. Constraint of relation between tail-water level and outflow

\[
L_{down}^s = f_2 \left(Q_{out}^t\right)
\]

where \( L_{down}^s \) is the tail-water level in \( t \); \( f_2 \) is the relation function between tail-water level and outflow discharge.

6. Hydropower plant output constraint

\[
N_{\text{min}} \leq P_t \leq N_{\text{max}}
\]

where \( N_{\text{min}} \) is the minimum allowable output; \( N_{\text{max}} \) is the maximum allowable output.

7. Maximum outflow constraint

\[
Q_{out}^t \leq Q_{\text{max}}^t
\]

where \( Q_{\text{max}}^t \) is the maximum allowable outflow discharge in \( t \).

8. Constraint of characteristics of reservoir sedimentation

\[
W_t = \sum \left(L_{in}^s, Q_t, Q_{out}^t, S_t^m, \beta_t^m, \beta_{bed}^m\right)
\]

where \( S_t^m \) is the sediment concentration of the inflow in \( t \); \( \beta_t^m \) is the size distribution of the suspended load of the inflow in \( t \); \( \beta_{bed}^m \) is the initial size distribution of the bed material.

9. Non-negative constraint

All the variables are non-negative (\( \geq 0 \)).

2 Algorithm description

The particle swarm optimization algorithm is a novel population-based evolutionary optimization technique \([7]\). PSO is motivated from the simulation of social behavior. Unlike other evolutionary computational algorithms using evolutionary operators to manipulate the individuals, each individual is treated as a volume-less particle (a point) and flies in the search space with a velocity. The velocity is dynamically adjusted according to its own flying experience and the group’s flying experience so that the individuals of the population can be expected to move towards better solution areas. PSO has been proven to be a general, robust and powerful search mechanism. In this paper, an improved version of PSO is proposed in which the inertia weight self-adjusting mechanism and Pareto-optimal archive based on the concept of Pareto optimality are introduced into PSO to handle multi-objective optimization.

2.1 Basic concepts of Pareto-optimality \([8]\)

For a multi-objective minimization problem:

\[
\min f(u) = \left\{ f_1(u), f_2(u), \cdots, f_s(u) \right\}
\]

s.t. \( g_i(u) \leq 0 \)

where \( f() \) is the objective function; \( u \) is the vector of decision variables. Based on the assumption that set \( U \) is the feasible region of \( u \) limited by the constraints, the concepts of Pareto-optimality are as follows.

**Definition 1** (Pareto Dominance): Given \( u_1, u_2 \in U \) and their corresponding objective vectors \( f(u_1) \) and \( f(u_2) \), if \( \forall i \in \{ 1, \cdots, n \}, f_i(u_1) \leq f_i(u_2) \) and \( \exists j \in \{ 1, \cdots, n \}, f_j(u_1) < f_j(u_2) \), \( u_1 \) is said to dominate \( u_2 \), denoted \( u_1 \succ u_2 \).