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Adaptive Genetic Algorithm for Daily Optimal Operation of Cascade Reservoirs and its Improvement Strategy

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Abstract For the specialty of cascade reservoirs optimization and the premature convergence of GA, several improvement strategies are presented in this paper. Firstly, solution space generation method is found application to generate feasible initial population. Secondly, chaos optimization is adopted to optimize initial population. Thirdly, new selective operators, trigonometric selective operators, are proposed to overcome the fitness requirement of non-negative and to maintain the diversity of population. Fourthly, adaptive probabilities of crossing and mutation are adopted in order to improve the convergence speed of GA. Besides, elitist strategy is used to ensure that the best individual can be remained in each generation. Furthermore, the performance of these proposed improvement strategies was checked against the historical improvement strategies by simulating optimal operation of Three Gorges cascade reservoirs premised on historical hourly inflows, and the comparison yields indications of superior performance. In these proposed improvement strategies, trigonometric selective operators are feasible and effective for optimizing operation of cascade reservoirs. These new selective operators could help GA to find a more excellent solution in the same algebra, and the performance of convergence speed is advanced. Adaptive probabilities of crossing and mutation have better performance than other improvement strategies, such as annealing chaotic mutation and simulated annealing of large probability of mutation, because this method realizes the twin goals of maintaining diversity in the population and advancing the convergence speed of GA.

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1 Introduction

Water resources system optimization is an important task in water resources management, various researches involving physical model and mathematical model have been developed by pundits. Loucks et al. (1981) proposed stochastic programming to address uncertainties in water resources management. Barros et al. (2003) prevented nonlinear programming (NLP) to optimize large-scale hydropower system operations. He et al. (2010) developed downscaling method to slove disaggregation model of daily rainfall and concluded that the approach could be used to downscale daily rainfall series to hourly. Jing and Chen (2011) combined semi-distributed land use-based runoff process and WATFLOOD model to understand the interactions between climate and hydrological processes in subarctic wetlands. Suo et al. (2011) proposed an inventory-theory-based interval-parameter two-stage stochastic programming (IB-ITSP) model through integrating inventory theory into an interval-parameter two-stage stochastic optimization framework. This method addresses system uncertainties with complex presentation and reflects transferring batch and period in decision making problems. As one of the water resources system optimization, the revenue of reservoir can be improved by carrying out optimal operation without additional investment. Therefore optimal operation of reservoir has always been a key issue, and various optimization techniques that have been suggested and developed include gradient-based search, linear programming (LP), NLP, dynamic programming (DP), etc. (Yeh 1985; Simonovic 1992; ReVelle 1997; Pursimo et al. 1998; Chau and Albermani 2003; Labadie 2004). The traditional approaches have gained much popularity and certain success. However, DP faces the “curse of dimensionality” and these optimization techniques can only be applied for small and simplified problems, such as optimal operation of a single reservoir(Yang and Chen 1989; Chang et al. 1990). Recently, many modern intelligent heuristic approaches such as Genetic Algorithm (GA), Simulated Annealing (SA), Artificial Neural Network (ANN), Chaotic Optimization Algorithm and combinations of these above methods have been developed for optimizing multi-reservoir system operation (Naccarino et al. 1988; Yan et al. 1993; Arce et al. 2002). Among them GA is an adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetic. Its basic concept is to simulate process in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest (Holland 1975). As such it represents an intelligent exploitation of a random search within a defined search space to solve complexities problems. Oliveira and Loucks (1997) employed GA to derive multi-reservoir operation operating policies and concluded that the approach can be applied to example reservoir systems used for water supply and hydropower. Chang and Chen (1998) used two types of GA, real-coded and binary-coded, to optimize a flood control reservoir, and demonstrated that real-code one had produced superior results compared to the other method. Louati et al. (2011) applied a GA for optimization of a complex reservoir system with multiple objectives.

However, with the increase of the larger problem scale of water resources system optimization, especially for the problem with many nonlinear constraints such as cascade reservoirs regulation, GA is most frequently faced with the problems of premature convergence and local optimal deficiency. In order to overcome these shortcomings, numerous researchers have developed various improvement strategies. Goldberg et al. (1989a) defined a messy genetic algorithm (MGA), which could solve more difficult problems than had been possible to date with other GAs by processing variable-length strings. Srinivas and Patnaik (1994) proposed an adaptive genetic algorithm (AGAa) with adaptive probabilities of crossover and mutation. This efficient approach realized the twin goals of improving convergence speed and maintaining diversity in the population of GA. Furthermore, various improved GAs has been applied in water resources system optimization. Chang et al. (2005) developed GA with real-value coding and this improved GA had better performance of convergence speed is proved. Cheng et al. (2008) presented a hybrid method that combined a genetic algorithm with chaos optimization algorithm. In this new method chaos was adopted to optimize the initialization in order to improve species quality, and standard mutation operator was replaced by annealing chaotic mutation operation to avoid the search being trapped in local optimum. Chen et al. (2010) applied an adaptive genetic algorithm (AGAb) with a double dynamic mutation operator to implement eco-friendly operation of cascade reservoirs in the Southwest of China. And it was shown that the new mutation operator advances search accuracy. As can be seen from the literatures, these improved GA have shown excellent performance. However, the improvement of GA about solving prematurity in the selection process has not involved in till now. GAs are affected by the selection process, premature convergence of GA would be avoided well through improving selection method. Meanwhile, several different improvements have been applied in crossing mutation operation. It is significant task to find an advanced one to optimize cascade reservoirs operation.

In order to overcome these flaws, the new selective operators, trigonometric selective operators, are proposed in the paper. These proposed selective operators achieve keeping diversity of population by overcoming fitness requirement of non-negative to solve prematurity in the selection process of GA. Moreover a hybrid architecture jointed five improvement strategies is presented. Firstly, solution space generation method is applied to generate feasible initial population. Secondly, chaos optimization is used to optimize initial population. Thirdly, trigonometric selective operators are applied to overcome fitness requirement of non-negative. Fourthly, adaptive probabilities of crossing and mutation are adopted in order to improve convergence speed of GA. The probabilities of crossing and mutation vary depending on fitness value of the solutions. Finally, elitist strategy is used to ensure that the best individual can not be destroyed in each generation. The main characteristic of this hybrid architecture is to fully apply these five improvement strategies respective advantages. This research takes Three Gorges cascade reservoirs as case study, and checks the performance of those improvement strategies against the historical improvement strategies.

2 Mathematical Model for Cascade Reservoirs Daily Scheduling

Cascade reservoirs consist of several reservoirs located in serial at the same river basin. Thus cascade reservoirs have hydraulically coupling features. Even though a reservoir system is designed for multiple purposes, these multiple objectives can be combined into a single objective function by weighting factor approach. Therefore this paper focuses on optimal operation of Three Gorges cascade reservoirs, and the single objective is to maximize generation output over 24 h periods according to historical hourly inflows of Three Gorges reservoir.

In mathematical model for cascade reservoirs daily scheduling, the objective function is got by the addition of each objective function of single reservoir, which forms the cascade reservoirs. It can be repressed as

$$\max\left\{\sum_{i=1}^{m}\sum_{t=1}^{T}N_{i,t}\left(Q_{L_{i,t}},H_{i,t}\right)\right\}\quad \forall t=1,2,\ldots,12\&\forall i=1,2,\ldots,m \tag{1}$$

Subject to the following constraints:

- Water balance equation

$$V_{i,t+1}=V_{i,t}+\left(I_{i,t}-Q_{L_{i,t}}-Q_{S_{i,t}}\right)\Delta t \tag{2}$$

- Reservoir water level limits

$$Z_{\min_{i,t}}\le Z_{i,t}\le Z_{\max_{i,t}} \tag{3}$$

$$Z_{i,0}=Z_i^{'},Z_{i,T}=Z_i^{''} \tag{4}$$

- Reservoir discharge limits

$$Q_{\min_{i,t}}\le Q_{i,t}\le Q_{\max_{i,t}} \tag{5}$$

- Hydropower station power generation limits

$$N_{\min_{i,t}}\le N_{i,t}\le N_{\max_{i,t}} \tag{6}$$

- Hydraulically coupling constraints

$$I_{i,t}=a\times Q_{i-1,t}+b \tag{7}$$

where

i	the sequence number of reservoirs. Reservoirs are sequentially numbered from upstream to downstream by their position in cascade reservoirs.
m	the number of cascade reservoirs.
T	the schedule period, T=24 h.
$H_{i,t}$	the generating head of i^{th} reservoir in period t, m. It presents water level difference between upstream and downstream. In which, the upstream water level is mean water level, and the downstream water level is obtained by $Q_{i,t}$ and downstream water level-discharge curve.
$V_{i,t}$	volume of reservoir storages of i^{th} reservoir at the beginning of period t, m^3.
$V_{i,t+1}$	volume of reservoir storages of i^{th} reservoir at the end of period t, m^3.
$I_{i,t}$, $Q_{L_{i,t}}$, $Q_{S_{i,t}}$	inflow, power discharge and surplus discharge of i^{th} reservoir in period t, m^3/s.
$Z_{\min_{i,t}}$, $Z_{i,t}$, $Z_{\max_{i,t}}$	minimum water level, operating water level and maximum water level of i^{th} reservoir in period t, m.
$Z_{i,0}$, $Z_{i,T}$	the initial and final water level of i^{th} reservoir, m.
$Z_i^{'}$, $Z_i^{''}$	the given initial and given final water level of i^{th} reservoir to control the water consumption in the whole schedule period, m.
$Q_{\min_{i,t}}$, $Q_{i,t}$, $Q_{\max_{i,t}}$	minimum discharge volume, discharge volume and maximum discharge volume of i^{th} reservoir in period t, m^3/s. And $Q_{i,t}=Q_{L_{i,t}}+Q_{S_{i,t}}$.

$N_{\min_{i,t}}, N_{i,t}, N_{\max_{i,t}}$	firm power, operating power and installed capacity of i^{th} hydropower station, 10^4 kW.
$Q_{i-1,t}$	outflow of (i-1)th reservoir (namely, upstream reservoir in the case of i^{th} reservoir), m^3/s.
a, b	the coefficients to be obtained via measured data.

In period t, there is a hydraulically coupling constraint in cascade reservoirs optimal operation. In traditional research (Mei and Zhu 2002; Tang et al. 2008) the lags between two dams, time taken by the flow to reach the downstream reservoir, is considered by

$$I_{i,t} = q_{i,t} + Q_{i-1,t-\tau_i} \tag{8}$$

Where, $q_{i,t}$ denotes local flow inflow of i^{th} reservoir in period t; $Q_{i-1,t-\tau_i}$ is discharge volume of (i-1)th reservoir in period t-τ_i, in which τ_i measured the time taken by the flow from (i-1)th reservoir (namely, upstream reservoir) to i^{th} reservoir (namely, downstream reservoir).

However, τ_i is not a constant, and its change value closely relates to $Q_{i-1,t}$ and river conditions. Moreover, the variation can not be calculated by specific mathematical equations. Thus, correlation analysis is used for calibrating the measured data between cascade reservoirs, and an equation of linear regression (Eq. 7) is adopted for dealing with the calculation of the temporal-spatial variation of flow in this research. The Eq. 7 describing temporal-spatial variation of flow between cascade reservoirs, it was applied in joint optimization dispatching of Sanmenxia and Xiaolangdi reservoirs in China (Yang and Liu 2001). This equation of linear regression solves close hydraulic coupling between cascade reservoirs and improves the precision of the simulation.

Suppose inflow of upstream reservoir sequence I_t, t=1,2,…T has been obtained by historical hourly upstream reservoir inflows or hydrological forecasting. Therefore, this optimal operation is a complex problem that includes linear and nonlinear, equality and inequality constraints.

3 Genetic Algorithm for Optimal Operation of Cascade Reservoirs and its Improvement Strategy

GA can be considered to consist of the following steps (Burn and Yulianti 2001):

(1) Make the string coding of parameter.
(2) Generate the initial population of strings.
(3) Evaluate the fitness of each string.
(4) Select excellent strings from the current population to mate.
(5) Perform crossover and mutation for the selected strings.
(6) Repeat steps 3–5 for the required iteration number of generation.

In addition, the individual coding of cascade reservoirs consists of single reservoir coding from upstream to downstream. In GA, many improvement strategies have been proposed to solve problems of premature convergence and to adapt the particularity of cascade reservoirs optimization problem. In these improvement strategies, solution space generation method, chaos optimization, adaptive probabilities of crossing and mutation, annealing chaotic mutation, and simulated annealing big mutation, have shown excellent performance, thus the premature convergence in crossing and mutation operation is improved (Srinivas and Patnaik 1994; Zalzala and Fleming 1997; Cheng et al. 2008). However, the premature convergence in selecting operation still exists.

3.1 Initial Population and Individual Coding

Individual coding not only decides the performance of solution space, but also affects the crossover and mutation operations indirectly. The distribution properties of initial population affect convergence performance of GA seriously, and poor initial population may result in slow convergence or even not converge (Zalzala and Fleming 1997).

3.1.1 Individual Coding

Individual coding has evolved from binary coding conversion to real-value coding (floating-point coding, decimal coding) (Chang and Chen 1998; Chang et al. 2005). Binary strings are easy to operate on, but discretization of the decision variable apace is required. Thus it often brings redundant issues and long string, causing low search efficiency of algorithm. However, real-value coding operates directly on the phenotype of the solution and advances GA's search capabilities. Generally, for optimizing cascade reservoirs operation, real-value coded GA obtains superior results than binary-coded one, in terms of high mean objective function values. There are some advantages of real-value coding compared with binary coding.

(1) It is easy to express decision variables whose range changes large.
(2) Real-value coding is suitable for high precision operations. It is superior to binary coding, in terms of handling complex constraints of decision variable.
(3) Real-value coding improves computational complexity and advances the efficiency of the algorithm.

The real-value coding of cascade reservoirs is $(K_{i,0},K_{i,1},\ldots,K_{i,T},K_{i+1,0},K_{i+1,1},\ldots,K_{i+1,T},\ldots,K_{m,0},K_{m,1},\ldots,K_{m,T})$. Reservoir water level and real-coding can be expressed as follows

- The real-value coding

$$K_{i,t} = \mathrm{int}\left(\left(\mathrm{int}\left(\frac{Z_{\max_{i,t}} - Z_{\min_{i,t}}}{p_{opdt}}\right) + 1\right) \times rnd\right) \tag{9}$$

- Reservoir water level

$$Z_{i,t} = Z_{\min_{i,t}} + K_{i,t} \times p_{opdt} \tag{10}$$

where, p_{opdt} represents accuracy controlling parameter; and *int, rnd* denote an integral function and a random function. Water levels are chosen as the variable parameter to optimize, because objective function (generation output: $N_{i,t}$) is related to water levels. There are two reasons to support this view. On the one hand, $H_{i,t}$ is related to water levels; on the other hand, $Q_{L_{i,t}}$ is related to water levels, according to Eq. 2 and that $V_{i,t}$, $V_{i,t+1}$ are all related to water levels.

In the light of constraint Eq. 4, the initial real-value coding of a single reservoir ($K_{i,0}$) and the end real-value coding of a single reservoir ($K_{i,T}$) can be represent as

$$K_{i,0} = \mathrm{int}\left(\frac{Z_{i,0} - Z_{\min_{i,0}}}{p_{opdt}}\right) \& K_{i,T} = \mathrm{int}\left(\frac{Z_{i,T} - Z_{\min_{i,T}}}{p_{opdt}}\right) \tag{11}$$

In order to avoid the change of Z_0 and Z_T by integral function operation, the encode Eq. 10 is just used for middle water level.

After making the string coding of parameter, it is significant to calculate fitness before doing genetic evolution manipulation. Cascade reservoirs fitness function is the sum of individual reservoir, and the single reservoir fitness can be expressed as

$$f=\sum_{i=1}^{m}\left(\sum_{j=1}^{T}N\left(K_{i,j},K_{i,j-1}\right)-\alpha\frac{t_0}{T_0}\left(\beta*\sum_{i=1}^{T}A_{i,t}+\sum_{i=1}^{T}B_{i,t}\right)\right) \tag{12}$$

where, $\sum_{j=1}^{T}N\left(K_{i,j},K_{i,j-1}\right)$ is the sum of individual power generate output, 10^4 kW; α denotes penalty coefficient; β represents balance coefficient between power generate output and flow; t_0 represents current evolution generation; T_0 defines maximum evolution generation; and $A_{i,t}$, $B_{i,t}$ are flow penalty function and power generate output penalty function according to Eqs. 5–6 respectively, moreover they can be considered as

$$A_{i,t}=\begin{cases}\left|Q_{i,t}-Q_{\min_{i,t}}\right| & if\ :\ Q_{i,t}\ <\ Q_{\min_{i,t}}\\ \left|Q_{i,t}-Q_{\max_{i,t}}\right| & if\ :\ Q_{i,t}\ <\ Q_{\max_{i,t}}\\ 0 & if\ :Q_{\min_{i,t}}\le Q_{i,t}\le Q_{\max_{i,t}}\end{cases} \tag{13}$$

$$B_{i,t}=\begin{cases}\left|N_{i,t}-N_{\min_{i,t}}\right| & if: N_{i,t}<N_{\min_{i,t}}\\ 0 & if\ :N_{\min_{i,t}}\le N_{i,t}\end{cases} \tag{14}$$

3.1.2 Initial Population

There are two methods for generating initial population, the one is a randomly generated method, and the other one is the solution space generation method. It is very difficult to search a feasible solution by using randomly generated method, because the coding of cascade reservoirs is a duplication of a single reservoir coding. And the distribution property of initial population seriously affects convergence performance of algorithm. Thus, the solution space generation method is superior to randomly generated method in terms of optimizing cascade reservoirs operation.

Chaos is a universal phenomenon in natural world. Chaos means “a state of disorder”, but it has some special properties such as ergodicity, inherent stochastic and it acquires all kinds of states in a self-rule in a certain range. The species quality of initial population can be improved by chaos optimization of the initialization (Cheng et al. 2008).

The chaotic sequence can usually be produced by the following well-known logistic map (May 1976).

$$x_i^{k+1}=4\cdot x_i^k\cdot\left(1-x_i^k\right)\qquad\forall x_i^k\in[0,1]\&\forall i=1,2,\ldots,m \tag{15}$$

where, variable x represents a chaos vector. Via this logistic map, a large difference will be caused by even a small difference in the initial value of chaos variable in its long-time behavior.

Therefore, chaos optimization of the initialization consists of the following

Step 1. Reflect to chaos variable:

$$x_i=\frac{K_i-a_i}{b_i-a_i}\qquad\forall t=1,2,\ldots,T\&\forall i=1,2,\ldots,m \tag{16}$$

in which, K_i represents real-value coding of i^{th} reservoir, and K_i=($K_{i,0}$,$K_{i,1}$,…,$K_{i,T}$); and $b_{i,}$ a_i are the bounds for real-value coding of i^{th} reservoir water lever.

Step 2. Complete iteration Eq. 12.

Step 3. Calculate fitness value f and f^{k+1}. If $f_{i,t}^{k} \leq f_{i,t}^{k+1}$ then $x_i^k = x_i^{k+1} (\forall i=1,2,\ldots,m)$ and $f^k = f^{k+1}$.

Step 4. Repeat steps 2–3 for taking adequate iteration number, (i.e. 400–500).

3.2 Genetic Evolution Manipulation

3.2.1 Selection Operation

Selection operation is one of the important aspects in the GA process. It involves randomly choosing members of the population to enter a mating pool. The selection is often based on proportion fitness or ranking fitness in GA. There are several methods for selection: Roulette Wheel Selection (RWS) method, Tournament method and Ranking selection. Among them, RWS is most commonly used (Al Jadaan et al. 2008). This method determines the reserving possibility of descendants by the size of fitness, and is based on the proportion selection. It requires that the value of fitness is higher than zero. However, the optimal operation of cascade reservoirs can not meet this requirement, because of the penalty caused by constraints. Therefore, how to improve RWS method so that it could overcome the fitness requirements of non-negative is a work worthy of further study.

The Selective Operators Based on Trigonometric Function Trigonometric selective operators are actually methods, which does nonlinear transformation on fitness. And fitness is transformed into trigonometric function $p_j(p_j \in [0,1])$. Those four trigonometric selective operators can be presented as follow

- Sine selective operator

$$p_j = \sin\left(\frac{\pi}{2} \times \frac{f_j - f_{\min}}{f_{\max} - f_{\min}}\right) \tag{17}$$

- Cosine selective operator

$$p_j = \cos\left(\frac{\pi}{2} \times \frac{f_j - f_{\max}}{f_{\max} - f_{\min}}\right) \tag{18}$$

- Tangent selective operator

$$p_j = \tan\left(\frac{\pi}{4} \times \frac{f_j - f_{\min}}{f_{\max} - f_{\min}}\right) \tag{19}$$

- Cotangent selective operator

$$p_j = \cot\left(\frac{\pi}{2} + \frac{\pi}{4} \times \frac{f_{\max} - f_j}{f_{\max} - f_{\min}}\right) \tag{20}$$

The selection operator is carefully formulated to ensure that better individuals of population have a greater probability of being selected for mating. Take Sine selective operator for instance, it can meet this requirement: x_j and $x_{j'}$ are individuals in the same population. If the fitness meets $f_j < f_{j'}$, then obviously there will be $0 \leq \theta_j < \theta_{j'} \leq \frac{\pi}{2}$, as we can see from Eq. 16. Thus we define $0 \le p_j < p_{j'} \le 1$, because the Sine function is monotone increasing in $\left[0, \frac{\pi}{2}\right]$.

Trigonometric selective operators proposed are based on the individuals' fitness, and adapt for the solution with negative individual fitness. Therefore they can be adopted to improve RWS, in order to develop GA solving cascade reservoirs optimal operation.

Sine-RWS is established by RWS combining with Sine selective operator. In addition, other selective operators can be similar developed as it.

3.2.2 Implementation Steps of Sine-RWS

Step 1. Replace f_j (fitness function) by p_j as follows

$$p_j = \sin\left(\frac{\pi}{2} \times \frac{f_j - f_{\min}}{f_{\max} - f_{\min}}\right) \tag{21}$$

Step 2. Calculate cumulative value and the cumulative proportion of p_j.

Step 3. Select cumulative proportion of p_j by a uniform random number ([0, 1]) during each round of the selection process.

Obviously, high-fitness individual is easy to be retained in the selection process, because Sine function of high-fitness individual is larger than the low-fitness one.

3.2.3 Elitist Strategy

The best individual is expected to be preserved in each generation to advance exploration of the global solutions. Therefore, elitist strategy is widely used in GA to improve global optimal convergence speed. In this research, the top 5 % of individuals are preserved in each generation. So they would not be destroyed in the operation of crossover and mutation. Besides, the basis for the determination of excellent individuals is the value of fitness, and higher fitness means more excellent.

However, the elitist strategy reduces the diversity of the population by concentrating on some "super" individuals (Yong and Leung 2011). While, GA needs to maintain the diversity in order to find the multiple optimal solutions. Thus in the operation of crossover and mutation, the goal of maintaining the population diversity needs to realize.

3.2.4 The Operation of Crossover and Mutation

As can be seen from the literatures (Simonovic 1992; Chen et al. 2010), crossover operation reflects global search capabilities of GA, and mutation operation represents local search capabilities. For optimizing cascade reservoirs operation, multi-point crossover process and multi-point mutation process can be adopted, taking a single reservoir as a unit to do a single-point crossover or mutation operation. Crossover operation is a way to form two new individuals by exchanging some genes of each chromosome. This study adopts a restricted single-point crossover operation for each reservoir. And the crossover breakpoint takes place in *rnd* [1, *T*-2]. In which *rnd* [1, *T*-2] represents a random number belong to [1, *T*-2]. In this restricted single-point crossover operation, it is taken into account that the crossover operation should reserve too much excellent genes of each individual and should produce new individuals effectively. Moreover, the special encoding to set initial level and final level constantly is also considered in restricted single-point crossover operation. Mutation operation is an assistant method to restore genetic material. It involves the modification of the value of individual. There are two patterns of mutation operation, the one is uniform mutation, and the other is non-uniform mutation. It is bad for searching a key area in uniform mode. So this study adopts non-uniform mutation pattern, that is to say, using random disturbance to original gene. And it can be described as

$$K'_{i,t} = \begin{cases} K_{i,t} + f\left(t_0, K_{\max_{i,t}} - K_{i,t}\right) & if : rnd(0,1) = 0 \\ K_{i,t} - f\left(t_0, K_{i,t} - K_{\min_{i,t}}\right) & if : rnd(0,1) = 1 \end{cases} \tag{22}$$

$$f(t_0, y) = y^*(1 - r^{(1-t_0/T_0)^*B}) \tag{23}$$

where $K_{i,t}$ and $K'_{i,t}$ denote individual encodings before and after the operation of mutation happening in *"t"*(*t*=*rnd* [1, *T*-2]). *B* represents system parameter, which determining dependence degree of random disturbance on maximum evolution generation (T_0).

Several improvements of crossover and mutation operation have been applied for reservoirs optimal operation (Simonovic 1992; Cheng et al. 2008; Li et al. 2010). The following discusses their principles, advantages and disadvantages. And the one has superior performance in optimizing cascade reservoirs operation will be introduced.

Adaptive Probabilities of Crossover and Mutation The significance of P_c (crossover probability) and P_m (mutation probability) for controlling GA performance has long been acknowledged in literatures (Jong 1985; Goldberg 1989b). The higher value of P_c, the greater is the chance of damaging genetic pattern. As P_c decreases, however, the search can become slow. The choice of P_m is critical to GA performance, and large value of P_m transform GA into a purely random search algorithm. However, it is difficult to produce a new individual by small value of P_m. Traditional GA usually uses a constant P_c and P_m (Chang et al. 2005). It is a very tedious work to define the value of P_c and P_m by repeated experiments, for different optimization issues. And it is also a hard work to find the best value of P_c and P_m for each question. Srinivas and Patnaik (1994) proposed adaptive probabilities of crossover and mutation depending on the fitness value of individual.

$$P_c = \begin{cases} \dfrac{k_1(f_{\max} - f')}{f_{\max} - f_{avg}} & if : f \geq f_{avg} \\ k_2 & if : f < f_{avg} \end{cases} \tag{24}$$

$$P_m = \begin{cases} \dfrac{k_3(f_{\max} - f)}{f_{\max} - f_{avg}} & if : f \geq f_{avg} \\ k_4 & if : f < f_{avg} \end{cases} \tag{25}$$

where, $f_{\max}$ is the highest value of fitness in the population, 10^4 kW; f_{avg} represents average value of fitness in the population, 10^4 kW; f' denote higher fitness one in two crossover individuals, 10^4 kW; f is fitness value of mutation individual, 10^4 kW; and k_1, k_2, k_3, k_4 are adaptive parameters.

But this improvement is ineffective in early evolution, because P_c=0 and P_m=0 when the individual's fitness value is the highest one. The developed adaptive P_c and P_m are not only depending on fitness value of individual, but also depending on dispersion degree of population. They can be expressed as

$$P_c = \begin{cases} P_{c1} - \dfrac{(P_{c1} - P_{c2})\left(f' - f_{avg}\right)}{f_{\max} - f_{avg}} & if : f_{avg} \le f' \\ P_{c1} & if : f' < f_{avg} \end{cases} \tag{26}$$

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f_{\max} - f)}{f_{\max} - f_{avg}} & if : f_{avg} \le f \\ P_{m1} & if : f < f_{avg} \end{cases} \tag{27}$$

in which, P_{c1}=0.9, P_{c2}=0.6, P_{m1}=0.1, P_{m2}=0.001.

This adaptive improvement not only obtains through having lower values of P_c and P_m for high fitness individuals and higher values of P_c and P_m for low fitness individuals, but also achieves to give the individual of the maximum fitness a nonzero P_c and a nonzero P_m. This developed adaptive P_c and P_m depend on fitness value of individual and the dispersion degree of population. Thus this improvement achieves the twin goals of maintaining diversity in the population and sustaining the convergence capacity of the GA. And it reduces the influence of “super” individuals concentrated by elitist strategy.

Simulated Annealing of Large Probability of Mutation The generating offspring of this improved algorithm is under control of the process in simulated annealing. And this improvement P_c and P_m decrease with annealing temperature dropping.

$$\text{Crossover probability} \quad P_c = 0.6 - \varphi / T(t_0) \tag{28}$$

$$\text{Mutation probability} \quad P_m = 0.9^{\omega} \sqrt{T(t_0)} / T_0 \tag{29}$$

where φ and ω are proportional coefficients; and $T(t_0)$ is a temperature function decreasing by evolution.

The searching of this improved algorithm is not only globally but also locally. It adopts large probability of mutation to get out of the local optimal solutions and applies simulated annealing to improve the stability of large mutation probability. The key process of this improved algorithm can be described as:

Calculate the deviation value between old fitness and the new one (in terms of offspring x'): $\Delta f = f(x') - f(x)$. If $\Delta f > 0$, then x' will be accepted as a new solution (individual); if $\Delta f < 0$, then x' will be accepted by the probability of $\min\{1, \exp(-\Delta f / T(t_0))\}$, in which $T(t_0)$ denotes the temperature of t_0^{th} generation.

That is to say, the offspring is inspected via simulated annealing after crossover and mutation operation.

Annealing Chaotic Mutation Operation This improvement takes advantage of chaotic searching to find another more excellent solution in the current neighborhood area of optimum solution. It effectively overcomes the default that algorithm searching speed obviously becomes slow when search is close to the global optimum (Cheng et al. 2008). That is to say, a heuristic gene mutation operation is developed, the main process as follow

$$x_i^{k+1} = (1 - \theta) x_i^{k*} + \theta x_i^k \tag{30}$$

where, x_i^{k*} is a chaos vector mapping to [0,1] by the current best solution ($K_1^*, K_2^*, \ldots, K_m^*$), namely the best chaos variable; x_i^k is a chaos vector formulating after k^{th} iteration; and x_i^{k+1} represents an annealing chaotic mutation vector, after joining a random perturbation. In which $0 < \theta < 1$, controlling by adaptiveness, and decreasing by evolution as follows:

$$\theta = 1 - \left|\frac{k-1}{k}\right|^n \tag{31}$$

where n is an integer, according to the optimal objective function; and k represents iteration number.

4 Case Study—Three Gorges Cascade

Three Gorges cascade reservoirs consist of Three Gorges reservoir (TG) and GeZhouBa reservoir (GZB) located on the Yangtze River in China. GZB locates in downstream and improves the navigation conditions between two dams. The Map showing the location of Three Gorges cascade reservoirs in China is represented in Fig. 1. And the basic information of Three Gorges cascade reservoirs is shown in Table 1.

From Eq. 7, hydraulically coupling constraints in Three Gorges cascade can be described as

If $Q_{sx,t}$ <16,000 m^3/s then

$$I_{gzb,t} = 0.996 Q_{sx,t} - 262.2 \tag{32}$$

If $Q_{sx,t}$ >=16,000 m^3/s then

$$I_{gzb,t} = 1.022 Q_{sx,t} + 389.9 \tag{33}$$

in which, $Q_{sx,t}$ is outflow of Three Gorges in period t, m3/s; $I_{gzb,t}$ is inflow of GZB corresponding to Q_{sx} in period t, m^3/s; and r represents correlation coefficient of linear regression. From the absolute value of r, it is known that GZB inflow may be closely related to TG outflow.

Fig. 1 Map showing the location of Three Gorge cascade reservoirs in China

Table 1 The basic information of Three Gorges cascade reservoirs

	Dead water level(m)	Normal water level(m)	Firm power(10^4 kW)	Installed capacity(10^4 kW)	Minimum discharge volume(m^3/s)
TG	145	175	499	1820	5000
GZB	65.5	66.5	76.8	271.5	3200

Firstly, in view of high-dimensional and nonlinear of cascade reservoirs, real-value coding and solution space generation method are directly applied in this study. Moreover, elitist strategy is used to ensure that the best individual can not be destroyed in each generation. Secondly, the advantages of trigonometric selective operators and chaos optimizing the initial population are analysed. Finally, "adaptive probabilities of crossover and mutation", "simulated annealing of large probability of mutation" and "annealing chaotic mutation operation" about improvement strategies introduced above are discussed.

As representation of trigonometric selective operators, Sine-RWS is contrasted with RWS. Simulate optimal operation premised on historical hourly flows is applied in order to manifest the rationality of results. In the calculation, on the one hand real-value coding, solution method and chaos optimization of the initialization are adopted. On the other hand adaptive probabilities of crossover and mutation are also applied to improve convergence speed. Besides, the size of population is 100, and p_{opdt}=0.01 m. The termination criterion of GA optimizing reservoirs operation is requiring iteration number of generation (Burn and Yulianti 2001). Besides, the maximum generation is chosen according to the performance of working computer (Chang et al. 2005). Thus 300 is adopted as the maximum generation in this research. In order to compare the performance, evolutionary generation 100, 150, 200, 250 and 300 are adopted as termination condition of genetic. Because GA is an optimization method imitating biological evolution based on stochastic theory, this research studies ten simulation operations for each selection operator in each evolutionary generation, and selects the average result as the optimal scheduling for comparison.

The contrast of initial population improvement strategies and crossover and mutation improvement strategies are studied as the same contrast mode. Three representative hydrographs are adopted in this research. Besides, the quantification criterion of inflow is historic statics hydrographs of Three Gorges.

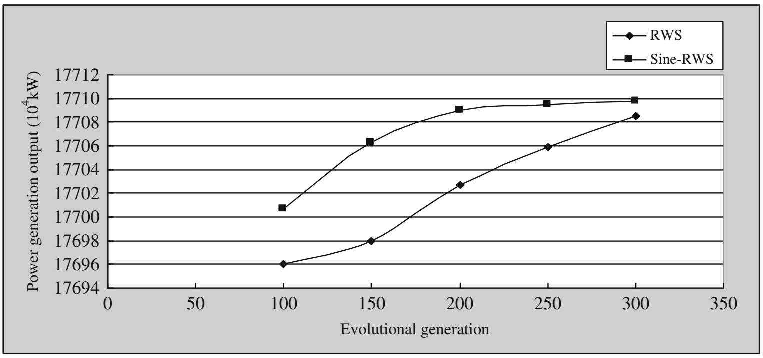

Fig. 2 The contrast of selection operation improvement strategies, case 1

Table 2 The contrast optimal operation result of selection operation improvement strategies in each evolutionary generation, case 1

Evolutionary generation	100		150		200		250		300	
Selection operator	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS
Average value	17700.7	17696.1	17706.3	17697.9	17709	17702.7	17709.5	17705.9	17709.7	17708.5
Maximum value	17718.8	17716.8	17714.4	17722.4	17726.5	17717.5	17717.3	17720.4	17718.5	17718.1
Minimum value	17654.1	17663.4	17692.8	17657.8	17685	17656.1	17702.7	17669.3	17705.6	17678.2
The difference	64.7	53.4	21.6	64.6	41.5	61.4	14.6	51.1	12.9	39.9

Unit 10^4 kW, and "the difference" denotes the difference value between maximum value and minimum value

4.1 Case 1: The Historical Hourly Inflows of Three Gorges are Small

Case 1 represents that a small hydrograph occurs in cascade system. Figure 2 shows the contrast of selection operation improvement strategies and Table 2 represents the contrast optimal operation result of selection operation improvement strategies in each evolutionary generation. Meanwhile, Fig. 3 shows the contrast of initial population improvement strategies and Table 3 represents the contrast optimal operation result of initial population improvement strategies in each evolutionary generation. Moreover, Fig. 4 shows the contrast of crossover and mutation improvement strategies and the Table 4 describes the contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300.

4.2 Case 2: The Historical Hourly Inflows of Three Gorges are Medium

Case 2 represents that a medium hydrograph occurs in cascade system. Figure 5 represents the contrast of selection operation improvement strategies and Table 5 shows the contrast optimal operation result of selection operation improvement strategies in each evolutionary generation. Meanwhile, Fig. 6 shows the contrast of initial population improvement strategies and Table 6 represents the contrast optimal operation result of initial population improvement strategies in each evolutionary generation. Besides, Fig. 7 shows the contrast of crossover and mutation improvement strategies and the Table 7 describes the contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300.

4.3 Case 3: The Historical Hourly Inflows of Three Gorges are Large

Case 3 represents that a large hydrograph occurs in cascade system. Figure 8 shows the contrast of selection operation improvement strategies and Table 8 represents the contrast optimal operation result of selection operation improvement strategies in each evolutionary generation; Meanwhile, Fig. 9 shows the contrast of initial population improvement strategies and Table 9 represents the contrast optimal operation result of initial population improvement strategies in each evolutionary generation; In addition, Fig. 10 shows the contrast of crossover and mutation improvement strategies and the Table 10 describes the contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300.

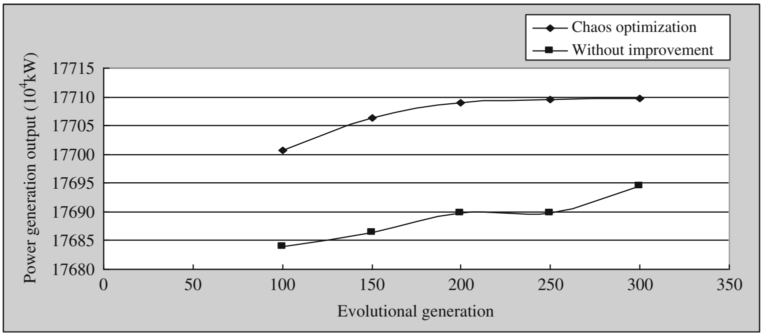

Fig. 3 The contrast of initial population improvement strategies, case 1

Table 3 The contrast optimal operation result of initial population improvement strategies in each evolutionary generation, case 1

Evolutionary generation	100		150		200		250		300	
Initial population	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without
Average value	17700.7	17684	17706.3	17686.3	17709	17689.7	17709.5	17689.9	17709.7	17694.5
Maximum value	17718.8	17708.4	17714.4	17704.4	17726.5	17704.8	17717.3	17703.7	17718.5	17707.9
Minimum value	17654.1	17658	17692.8	17650.6	17685	17670.7	17702.7	17681.8	17705.6	17685.4
The difference	64.7	50.4	21.6	53.8	41.5	34.1	14.6	21.9	12.9	22.5

Unit 10^4 kW, “Chaos” represents chaos optimization, “without” denotes without improvement, and “the difference” means the difference value between maximum value and minimum value

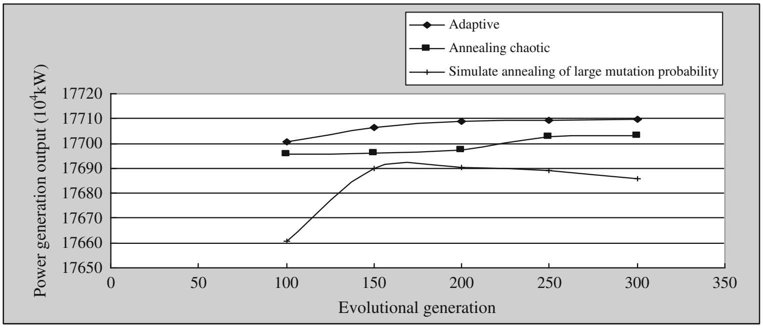

Fig. 4 The contrast of crossover and mutation improvement strategies, case 1

Table 4 The contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300, case 1

Generation power output of cascade system (Unit 10^4 kW)			
Improvement	Adaptive	Annealing chaotic	Simulate annealing of large mutation probability
Average value	17709.7	17703.3	17685.8
Maximum value	17718.5	17714.8	17719.1
Minimum value	17705.6	17696.2	17647.5
The difference	12.9	18.6	71.6

"The difference" denotes the difference value between maximum value and minimum value

Figures 2, 5 and 8 show Sine-RWS has a better performance in the same evolutionary generation than RWS. From "the difference" represented in Tables 2, 5 and 8, it is obviously that the stability of GA is improved. Only in low evolutionary generation, Sine-RWS sometimes has a worse stability. However, GA often adopts high evolutionary generation as the requiring iteration number of generation for optimizing cascade reservoirs operation. That is to say, the improved selection operator accelerates convergence speed and the stability of GA optimizing cascade reservoirs operation. The reason of producing a better performance is contributed to using trigonometric selective operators to do nonlinear

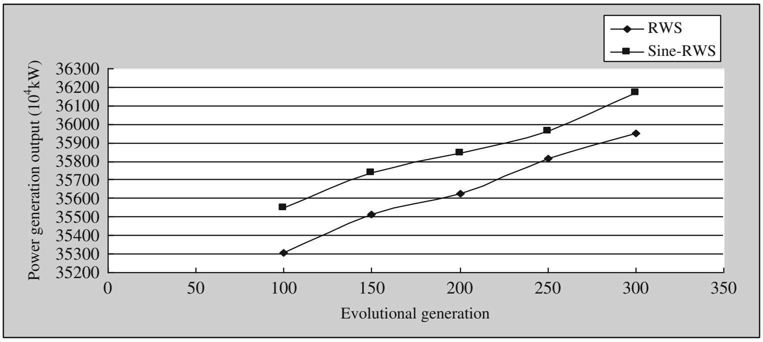

Fig. 5 The contrast of selection operation improvement strategies, case 2

Table 5 The contrast optimal operation result of selection operation improvement strategies in each evolutionary generation, case 2

Evolutionary generation	100		150		200		250		300	
Selection operator	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS
Average value	35548.5	35307.6	35739.2	35513.7	35841.8	35624.8	35960.4	35815.5	36171.8	35953
Maximum value	36027.8	35942.4	36182.2	36196.1	36312.8	36250.2	36238.1	36403.8	36557.8	36573.9
Minimum value	35221.6	34418.6	35347.51	34377.8	35372.1	34687.7	35711.8	34900.3	35916.9	35485.6
The difference	806.2	1523.8	834.69	1818.3	940.7	1562.5	526.3	1503.5	640.9	1088.3

Unit 10^4 kW, and “the difference” denotes the difference value between maximum value and minimum value

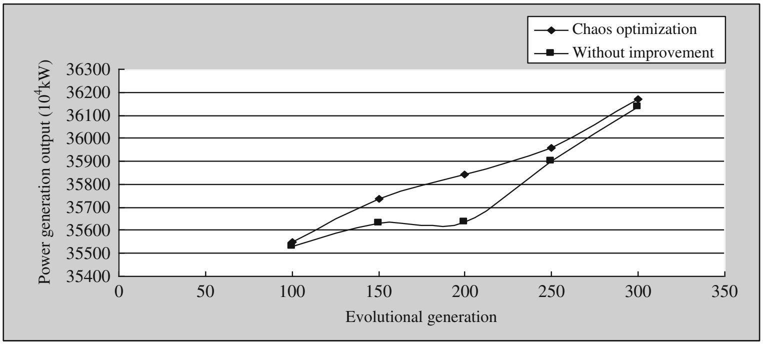

Fig. 6 The contrast of initial population improvement strategies, case 2

transformation on fitness. This nonlinear transformation is equal to adding noise in fitness, thus the fitting degree of fitness needs further study.

The above studies show that trigonometric selective operators are feasible and effective to overcome the fitness requirement of non-negative. They are superior in maintaining diversity in the population and improving the problem of slow convergence speed, and they are suitable to optimizing cascade reservoirs operation.

Figures 3, 6 and 9 and Tables 3, 6 and 9 demonstrate that chaos optimization of the initialization obviously improves stability and convergence speed of GA. The chaos has special characteristic such as ergodicity, regularity, and it has such sensitivity that a tiny change of initial condition can lead to a big change of the system. Chaos accelerates convergence speed of GA, undoubtedly. For cascade reservoirs optimal operation, the distribution property of initial population seriously affects convergence performance of GA, thus it is significant to adopt chaos optimization of the initialization.

From Figs. 4, 7 and 10, it is remarkable that adaptiveness ("adaptive probabilities of crossover and mutation") is the best improvement for crossover and mutation operation. To maintain diversity in the population, in adaptive improvement strategy, P_c and P_m increase as fitness value of population got to become equal or got to local optimization value. However, P_c and P_m decrease as fitness value of population became disperse. Meanwhile, the higher fitness individuals are corresponding to larger P_c and P_m, and lower fitness individuals are corresponding to smaller P_c and P_m. The adaptive improvement strategy keeps diversity in the population and advances convergence speed by taking advantage of fitness value of individuals and dispersion degree of population. However, annealing chaotic ("annealing chaotic mutation operation") just takes advantage of chaotic searching to find another more excellent solution in the current neighborhood area of optimum solution. Simulated annealing of large mutation probability ("simulated annealing of large probability of mutation") adopts large probability of mutation to get out of the local optimal solutions and uses simulated annealing to improve the stability of large mutation probability. Fitness value of individuals is considered in annealing chaotic and simulated annealing of large mutation probability improvement strategies. But dispersion degree of population is still not taken into account. That is why adaptive improvement strategy has a better performance than others. Tables 2, 5 and 8 also show that adaptiveness is the best improvement for crossover and mutation operation. It helps to find the best solution and to have a better stability of GA. However, even though simulated annealing is used to improve the stability of large mutation probability, but the effect is still not perfect, because the difference between maximum value

Table 6 The contrast optimal operation result of initial population improvement strategies in each evolutionary generation, case 2

Evolutionary generation	100		150		200		250		300	
Initial population	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without
Average value	35548.5	35530.9	35739.2	35630.9	35841.8	35634.1	35960.4	35901	36171.8	36136.6
Maximum value	36027.8	36059.5	36182.2	36324.3	36312.8	36247.1	36238.1	36271.5	36557.8	36989.8
Minimum value	35221.6	35146.4	35347.5	34988.8	35372.1	34970.6	35711.8	35334.6	35916.9	35744.9
The difference	806.2	913.1	834.7	1335.5	940.7	1276.5	526.3	936.9	640.9	1244.9

Unit 10^4 kW, “Chaos” represents chaos optimization, “without” denotes without improvement, and “the difference” means the difference value between maximum value and minimum value

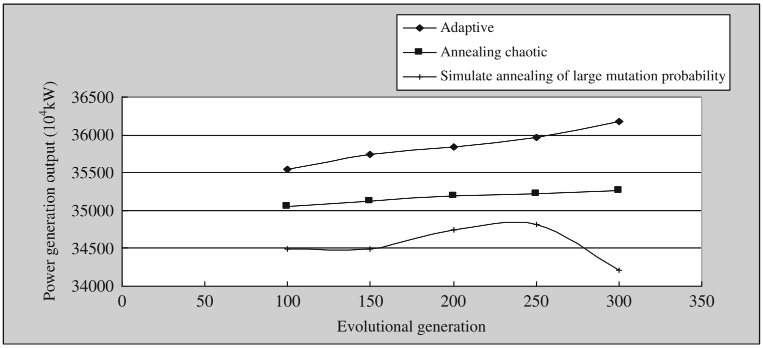

Fig. 7 The contrast of crossover and mutation improvement strategies, case 2

and minimum value in evolutionary generation 300 is still large (Tables 4, 7 and 10). Besides, the performance of annealing chaotic mutation operation is also not perfect.

The above comparisons show that the proposed new selection operators are feasible and effective to improve the performance of GA. From the comparisons, we can draw the conclusion that the respective advantages of five improvement strategies (solution space

Table 7 The contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300, case 2

Generation power output of cascade system (Unit 10^4 kW)			
Improvement	Adaptive	Annealing chaotic	Simulate annealing of large mutation probability
Average value	36171.8	35261.6	34214.4
Maximum value	36557.8	36264.6	36427.7
Minimum value	35916.9	34556.7	29842.3
The difference	640.9	1707.9	6585.4

"The difference" denotes the difference value between maximum value and minimum value

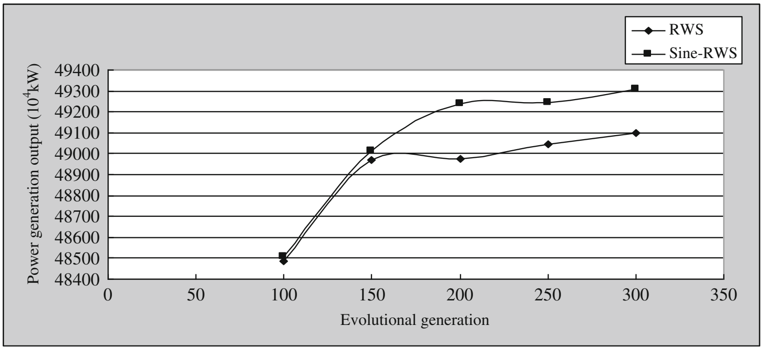

Fig. 8 The contrast of selection operation improvement strategies, case 3

Table 8 The contrast optimal operation result of selection operation improvement strategies in each evolutionary generation, case 3

Evolutionary generation	100		150		200		250		300	
Selection operator	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS	Sine-RWS	RWS
Average value	48508.7	48486.5	49014.4	48967.3	49241.2	48977.2	49244.9	49042.9	49310.7	49098
Maximum value	49539	49149.5	49936.2	49811.2	49936.2	49686.2	49660.6	49618.6	50196	50000.3
Minimum value	49307.2	48028	47848.6	46610.5	48295.5	47398.4	48833.4	48272.4	48644.1	48446.2
The difference	231.8	1121.5	2087.6	3200.7	1640.7	2287.8	827.2	1346.2	1551.9	1554.1

Unit 10^4 kW, and "the difference" denotes the difference value between maximum value and minimum value

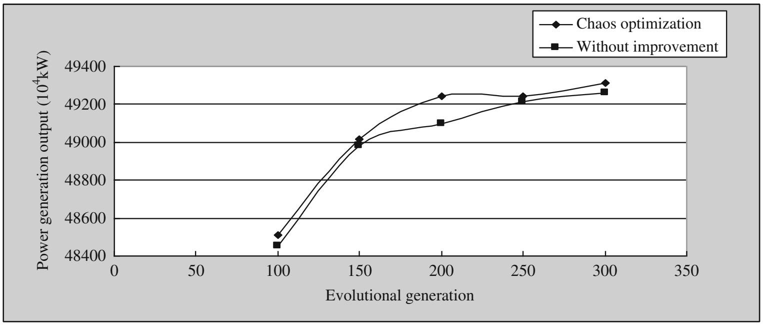

Fig. 9 The contrast of initial population improvement strategies, case 3

generation method, chaos optimization of initial population, trigonometric selective operators, adaptive probabilities of crossing and mutation, and elitist strategy) can be found application effectively. Therefore, the hybrid architecture jointed these improvement strategies has excellent performance, and it is suitable to optimizing cascade reservoirs operation.

5 Conclusions and Future Work

5.1 Conclusions

a. Optimal operation of cascade reservoirs can improve the efficiency of water resource utilization and benefit. In this research, the hydraulically coupling constraint in cascade reservoirs is described well in mathematical model for cascade reservoirs daily scheduling. And the solution methodology of optimizing cascade reservoirs operation, an improved adaptive genetic algorithm, is proposed. The simulating optimal operation of Three Gorges demonstrates that the proposed method is feasible and effective to optimizing cascade reservoirs operation. In terms of water resources point, the proposed method finds effective storage and discharge status changing process of cascade reservoirs. Water utility efficiency of cascade reservoirs is promoted.
b. GA overcomes the “curse of dimensionality”, that is to say, GA is more suitable for solving optimal operation of cascade reservoirs. There are a lot of improvement strategies on GA for cascade reservoirs optimal operation: (1) Generating initial population concerned: real-value coding and solution space generation method can ensure the convergence of GA to optimize cascade reservoirs operation, and chaos optimization of the initialization can improve the stability and the convergence of GA by the fine structure of chaos. (2) Selection operation highly depends on non-negative value of fitness. However various constraints of optimizing cascade reservoirs operation usually give rise to negative fitness. Thus traditional selection operator has its limitation for GA optimizing cascade reservoirs operation and causes GA premature. Trigonometric selective operators are superior in maintaining diversity in the population and improving the problem of slow convergence speed by doing nonlinear transformation on fitness. And they are feasible and effective for optimizing cascade reservoirs operation. (3) There are lots of improvement strategies for crossover and mutation, and the most excellent one is “adaptive probabilities of crossover and mutation”, which takes advantage of fitness value of individuals and dispersion degree of population. However, the

Table 9 The contrast optimal operation result of initial population improvement strategies in each evolutionary generation, case 3

Evolutionary generation	100		150		200		250		300	
Initial population	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without	Chaos	Without
Average value	48508.7	48455.1	49014.4	48982.8	49241.2	49098.7	49244.9	49213.9	49310.7	49259.8
Maximum value	49539	49569.6	49936.2	49710.5	49936.2	49987.2	49660.6	49743.4	50196	49865.9
Minimum value	49307.2	46206.3	47848.6	47519.5	48295.5	48142	48833.4	48592.3	48644.1	48711.1
The difference	231.8	3363.3	2087.6	2191	1640.7	1845.2	827.2	1151.1	1551.9	1154.8

Unit 10^4 kW, "Chaos" represents chaos optimization, "without" denotes without improvement, and "the difference" means the difference value between maximum value and minimum value

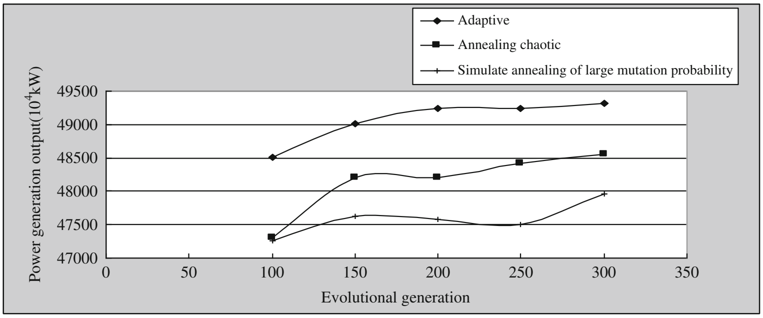

Fig. 10 The contrast of crossover and mutation improvement strategies, case 3

performance of "annealing chaotic mutation operation" and "simulated annealing of large probability of mutation" are not as excellent as adaptive one, because they just take advantage of fitness value. And "simulated annealing of large probability of mutation" has a poor stability.

5.2 Future Work

a. The new selective operators, trigonometric selective operators, actually are methods doing a nonlinear transformation of fitness function. After transformation, the value of fitness is changeable, that is to say the noise is added in fitness value. However, the proposed new operators could improve the problem of slow convergence speed and they are more feasible and effective in maintaining diversity in the population than traditional selective operators. Therefore the noise added in fitness value needs research further.
b. Optimal operation of cascade reservoirs is a complex problem. Firstly, the natural water inflow, it itself indeterminate and must be forecast. So the uncertainty and risk of cascade reservoirs optimal operation needs research further. Secondly, the close hydraulic coupling between cascade reservoirs makes it more difficult. Hydraulically coupling constraints vary over daily scheduling period. In the case of daily optimal operation, the last scheduling period discharge volume of upstream reservoir affects the next day's first scheduling period inflow of downstream reservoir. However, it can not be represented by specific mathematical equations in a daily optimal operation model, it needs research further.

Table 10 The contrast optimal operation result of three crossover and mutation improvement strategies in evolutionary generation 300, case 3

Generation power output of cascade system (Unit 10^4 kW)			
Improvement	Adaptive	Annealing chaotic	Simulate annealing of large mutation probability
Average value	49310.7	48551.2	48061.08
Maximum value	50196	49464.8	48544.8
Minimum value	48644.1	47570.4	46314.8
The difference	1551.9	1894.4	2230

"The difference" denotes the difference value between maximum value and minimum value

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