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Optimizing hydropower reservoir operation using hybrid genetic algorithm and chaos

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Abstract. Genetic algorithms (GA) have been widely used to solve water resources system optimization. However, when applying GAs to solve large-scale and complex water reservoir system problems, premature convergence is one of the most frequently encountered difficulties and takes a large number of iterations to reach the global optimal solution and the optimization may get stuck at a local optimum. Therefore, a novel chaos genetic algorithm (CGA) based on the chaos optimization algorithm (COA) and genetic algorithm (GA), which makes use of the ergodicity and internal randomness of chaos iterations, is presented to overcome premature local optimum and increase the convergence speed of genetic algorithm. CGA integrates powerful global searching capability of the GA with that of powerful local searching capability of the COA. Two measures are adopted in order to improve the performance of the GA. The first one is the adoption of chaos optimization of the initialization to improve species quality and to maintain the population diversity. The second is the utilization of annealing chaotic mutation operation to replace standard mutation operator in order to avoid the search being trapped in local optimum. The global optimum of the Rosenbrock function is employed to examine the performance of the GA. The result indicates that it can improve convergence speed and solution accuracy. A series of monthly inflow of 38 years is employed to simulate the hydropower reservoir optimization operation. The results show that the long term average annual energy based CGA is the best and its convergent speed not only is faster than dynamic programming largely, but also overpasses the standard GA. Thus, the proposed approach is feasible and effective in optimal operations of complex reservoir systems.

Key words: chaos; genetic algorithm; optimization; hydropower system.

1. Introduction

Optimization techniques have become increasingly important over the last four decades in management and operations of complex reservoir systems. The use of these techniques has greatly aided in providing a good insight into the intricacies of various aspects of problems in water management. Yeh (1985), Wurbs (1993) and, more recently, Labadie (2004) have provided an extensive literature review, evaluation of various optimization methods and the intensive research on the optimization of reservoir system operation. As can be seen from the literature, numerous researchers have developed reservoir optimal operation during the past four decades using dynamic programming (DP), linear programming (LP), nonlinear programming (NLP), etc. Among different optimization techniques for reservoir operation, DP has enjoyed the much popularity. DP is popular in reservoir operation studies because DP can offer convenient and efficient solutions for developing complex operational strategies in the determination of optimum operating policies for hydropower station reservoir scheduling.

GA is one of the global optimization schemes that have gained popularity as a means to attain water resources optimization. Oliveira and Loucks (1997) used GA to evaluate operating rules for multireservoir systems and demonstrated that GAs can be used to identify effective operating policies. Wardlaw and Sharif (1999) employed GA to a deterministic finite horizon multi-reservoir system operation and concluded that the approach can be easily applied to non-linear and complex systems. Sharif and Wardlaw (2000) applied GA approach to optimize a three-reservoir multipurpose system over a 36 ten-day periods in the second. Chang and Chang (2001) used GAs to search the optimal reservoir operating schedule, and show that this has produced superior results compared to traditional methods. Cheng et al. (2002 & 2006) combined a fuzzy optimal model with GAs to solve multiobjective rainfall-runoff model calibration. Furthermore, Cheng et al. (2005) proposed a hybrid method that combines a parallel genetic algorithm with a fuzzy optimal model in a cluster of computers. The new method is used to improve the calibration quality and efficiency through parallelization. Chang et al. (2003) demonstrated that the optimization of rule curves through GA is effective for flushing schedules in a reservoir. Recently, in order to derive multipurpose reservoir operating rule curves, Chang et al. (2005b) investigate the efficiency and effectiveness of two algorithms. Chang et al. (2005a) applied GA for optimal reservoir dispatching. Reis et al. (2005) used hybrid genetic algorithm and linear programming to determine operational decisions for reservoirs of a hydro system throughout a planning period. However, when applying GAs to solve large-scale and complex real-world problems, premature convergence is one of the most frequently encountered difficulties and takes a large number of iterations to reach the global optimal solution and the optimization may get stuck at a local optimum. In order to overcome these flaws, it is a significant task to find some effective approaches and improvements on GA to speed up the convergence and heighten the effectiveness of GA.

The chaos is a general phenomenon in nonlinear system and has some special characteristics such as ergodicity, regularity, randomicity, and acquiring all kinds of states in a self-rule in a certain range. It has such sensitivity that a tiny change of initial condition can lead to a big change of the system. Based on the two advantages of the chaos, a chaos optimization algorithm (COA) was proposed that can solve complex function optimization and have a high efficiency of calculation (Li et al., 1998). The basic idea of the algorithm is to transform the variable of problems from the solution space to chaos space and then perform search to find out the solution by virtue of the randomicity, orderliness and ergodicity of the chaos variable. Although the chaos optimization method has many advantages such as sensitive to the initial value, easy to skip out of the locally minimum value, speeding up search because of reducing the search space by carrier wave, it makes no use of the experiential information previously acquired. As a result, search effect of chaos optimization has its own limitation.

In order to overcome the shortcomings of both chaotic optimization method and GA, a method is to integrate the COA with GA to fully apply their respective searching advantages. Yuan et al. (2002) employed the integration of chaotic sequence and GA with a new self-adaptive error back propagation mutation operator to solve the short-term generation scheduling of hydro system. After studying the nature of the chaotic process, Yan et al. (2003) defined a uniform mutation operation process in which each chromosome vector has exactly equal chance and proposed a chaos genetic algorithm (CGA), which integrates GA with chaotic variable to search the optimization of the operational conditions based on RBF-PLS model. Lü et al. (2003) applied a chaotic approach to maintain the population diversity of genetic algorithm in network training. Liao (2006) combined chaos search genetic algorithm and meta-heuristics method for short-term load forecasting. However, most of these algorithms just make use of the randomicity of chaos sequences to generate individuals and do not effectively combine the spatial search advantage of these two methods. Taking account of the search efficiency of the GA and the application of chaos sequences can preferably simulate chaotic evolutionary process of biology. This paper presents a novel CGA on the basis of integrating the respective characteristic of the COA and GA. The novel CGA adopts chaos optimization of the initialization to improve species quality and maintain the population diversity. Annealing chaotic mutation operation is utilized to replace standard mutation operator in order to avoid the search being trapped in local optimum. The main characteristic of this new method is that the mechanism of the GA is not changed but the search space and the coefficient of adjustment are reduced continually. This can facilitate the evolution of the next generation in order to produce better optimization individuals, which can in turn improve the performance of the GA and overcome the disadvantages of the GA. The correlative examination indicates that the CGA has fast convergent velocity and powerful search capabilities while at the same time maintaining the population diversity of the conventional GA to generate satisfactory results.

2. Mathematical model for hydropower system scheduling

Suppose the object studied is mainly on the power generation of a hydropower system in order to compromise other synthetic utilization demand of the reservoir. The objective is to maximize generation output from the power station over 12 months operating periods according to historical monthly inflows of the reservoir.

The objective function to be maximized can be written as

$$F = \max \sum_{i=1}^{T} Aq_t H_t M_t \qquad (1)$$

subject to the following constraints.

1) Reservoir storage volumes limits.

$$V_{t,\min} \le V_t \le V_{t,\max} \qquad (2)$$

2) Reservoir discharge limits.

$$Q_{t,\min} \le Q_t \le Q_{t,\max} \qquad (3)$$

3) Hydropower station power generation limits.

$$N_{\min} \le Aq_t H_t \le N_{\max} \qquad (4)$$

4) Water balance equation.

$$V_{t+1} = V_t + (F_t - Q_t)\Delta_t \qquad (5)$$

where

- T — total period count within a year, T = 12;
- A — coefficient of hydropower station power generation;
- Q_t — water discharge for power generation, m^3/s;
- F_t — reservoir inflow, m^3/s;
- H_t — average head at time period t, m;
- S_t — release water discharge, m^3/s;
- M_t — amount of hour at time period t;
- V_t — volume of reservoir storages at the beginning of period t, m^3;
- V_{t+1} — volume of reservoir storages at the end of period t, m^3;
- $V_{t,max}$ — maximum consent water volume of reservoir, m^3;
- $V_{t,min}$ — minimum consent water volume of reservoir, m^3;
- $Q_{t,min}$ — minimum water discharge for synthetic utilization of downstream, m^3/s;
- Q_t — water discharge of reservoir, m^3/s;
- $Q_{t,max}$ — maximum water discharge for power station, m^3/s;
- N_{max} — installed plant capacity, kW;
- N_{min} — hydro plant minimum power generation constraint, kW;

Suppose inflow sequence F_t,, t = 1, 2, ⋯, T has been obtained by historical monthly inflows of the reservoir or hydrological forecasting. The problem is a dynamic optimization problem that includes linear and nonlinear, equality and inequality constraint, and the objective function is non-linear.

3. Chaos-genetic algorithm

3.1 Chaotic sequence

Chaos is a universal non-linear phenomenon in natural world and is the highly unstable motion of deterministic systems in finite phase space. Roughly speaking, a nonlinear system is said to be chaotic if it exhibits sensitive dependence on initial conditions and has an infinite number of different periodic responses. This sensitive dependence on initial conditions is generally exhibited by systems containing multiple elements with nonlinear interactions, particularly when the system is forced and dissipative. Sensitive dependence on initial conditions is not only observed in complex systems, but even in the simplest logistic equation.

The chaotic sequence can usually be produced by the following well-known one-dimensional logistic map defined by May (1976):

$$x_{k+1} = \mu x_k (1 - x_k); \qquad x_k \in (0,1), \quad k = 0, 1, 2, \ldots \tag{6}$$

In which μ is a control parameter, $0 \le \mu \le 4$. It can be observed that Eq. (6) is a deterministic dynamic system without any stochastic disturbance. It seems that its long-time behavior of the system in Eq. (6) varies significantly with μ. The value of the control parameter μ determines whether x stabilizes at a constant size, oscillates between a limited sequences of sizes, or whether x behaves chaotically in an unpredictable pattern. For certain values of the parameter μ, of which $\mu = 4$ is one, the above system exhibits chaotic behavior. Fig. 1 shows its chaotic dynamics characteristic, where $x_k = 0.01$, $k = 300$. A very small difference in the initial value of x causes a large difference in its long-time behavior, which is the basic characteristic of chaos. The variable x is called a chaotic variable. The track of chaotic variable can travel ergodically over the whole space of interest. The variation of the chaotic variable has a delicate inherent rule in spite of the fact that its variation looks like in disorder. In general, there are three main characteristics of the variation of the chaotic variable, i.e. pseudo-randomness, ergodicity and irregularity (Li and Jiang, 1998; Ohya, 1998).

3.2 Chaotic optimization operator

Assume that the working vector of independent variables is denoted by x and consists of n elements. The elements of the working vector x are named working parameters denoted by x_1, x_2, ⋯, x_n.Thus, an optimization problem of searching minimum could be described as:

$$\min f(x_i) \qquad i = 1, 2, \cdots, n \tag{7}$$

s.t. $a_i \le x_i \le b_i$

The optimization process of the chaotic variables could be defined through the Eq. (6) when $\mu = 4$ and the system exhibits chaotic behavior (Li and Jiang, 1998; Ohya, 1998). The equation becomes

$$x_{k+1} = 4x_k(1-x_k); \qquad x_k \in (0,1), \quad k = 0, 1, 2, \cdots \tag{8}$$

Then it can be used to optimize these problems. First, using the "carrier wave" method, make optimization variables vary to chaos variables. Second, "amplify" the ergodic area of chaotic motion to the variation ranges of every variable, because the chaos system we selected has a certain ergodic area of 0-1. Finally, use the chaos search method to optimize problems. The main procedures of the algorithm are shown as follows:

Step 1. Initialization: Give *i* initial values which have very small differences to *x(n)* of Eq. (8); then *i* chaotic states can be obtained by Eq. (8).

Step 2. Carrier way: By the carrier wave method, change *i* optimization variables to chaos variables. Furthermore, "amplify" the ergodic areas of the *i* chaotic variables to the variance ranges of optimization variables by the following equation:

$$x_i'(n+1) = a_i + (b_i - a_i)x_i(n+1) \tag{9}$$

where $x_i(n+1)$ are *i* chaotic states generated by Eq. (8), a_i and b_i are variance ranges of optimization variables. Equation (9) is an algebraic sum, $x_i'(n+1)$ are i chaotic search variables of the optimization problem.

Step 3. Iteration search by use of chaotic variables: let $x_i^* = x_{i0}$, and calculate the value of the objective function f, $f^* = f$.

Do

$n = n+1$,

$x_i = x'_i(n+1)$

calculate the value of objective function f.

if $f \le f^*$ then $f^* = f$, $x_i^* = x_i$.

Else if $f \ge f^*$ then give up the solution.

Loop f^* does not improve after *k* searches where *k* is a integer.

3.3 Chaos genetic algorithm

GA has aroused intense interest, due to the flexibility, versatility and robustness in solving optimization problems, which conventional optimization methods find difficult. However, there exist some flaws on GA, with slow convergence and premature local optimum. Difficulty lies in that it is a state-of-the-art to well balance the population diversity and selective pressure simultaneously. The following are several reasons on this difficulty.

Most important of all, diversities of an initial population are far from realized. Generally speaking, the initial individuals are taken for granted to be diversified and, in other words, distributed uniformly. Thus, conventional initialization methods such as random approach can bring problems. Even if they can guarantee that the initial population is evenly distributed in the search space, they cannot guarantee the qualities of initial population are also uniformly arranged. Indeed, an overwhelming majority of the initial chromosomes are banal and far from the global optimum which cause the slow convergence of GA.

Moreover, the diversity of population cannot be maintained under selective pressure, to say the least, the initial individuals are supposed to be fully diversified in the search space. That is why, if not well designed, the GA's searches always are found to be stuck by local traps.

Finally, conventional GA and its improvements have a common defect — complete ignorance of the individuals' experiences during their lifetime. Due to the almost randomized searches, there are no necessary connections between the current and next generations except for some controlling parameters such as crossover and mutation probabilities. In other words, the feedback information from former populations is discarded. However, many experiments show that an improved GA with resource to domain-specific heuristics information always has a good performance in evolution (Goldberg, 1989). Essentially, such good performance is attributed to the feedback information from the evolutionary system. From the viewpoint of chaos, the scheme of biological evolution can be well described as "random evolution + feedback", where randomicity is an intrinsic property of biological society and feedback part contains sufficient information for species to evolve. Only those who can successfully deal with the feedback information from evolution can survive well and keep evolving from low to higher classes.

Aiming at the above the problem, two measures are adopted to improve the GA's performance. one is the adoption of chaos optimization of the initialization to improve species quality, maintain the population diversity and finally realize the global optimization; Another is the utilization of annealing chaotic mutation operation to replace standard mutation operator in order to avoid the search being trapped in local optimum.

(1). Generating initial population by chaotic optimization: The convergence problem is relevant to initial population, because the numerous initial populations generated by random approach are far from optimal solution, which restrict algorithmic efficiency in solving the problem. The coarse-grained global search by chaotic ergodictity usually will acquire better effect than randomized search. This will improve the quality of individual of initial population and calculated efficiency.

The m initial values of punily difference x_k ($0 \leqslant x_k \leqslant 1$, $i = 1, 2, 3, \cdots m$) are endowed in Eq. (8) and $x_k \notin (0.25, 0.5, 0.75)$ to assure the evolution process going on properly. it will generate m chaotic variable $x_{k,i}$ ($x_{k,i}$, $i = 1, 2, \cdots m$) of different contrail. The m chaotic variable are mapped to variable space of optimization and translated into chaotic variable $x^*_{k,i}$ according to Eq. (10).

$$x^*_{k,i} = a_i + (b_i - a_i) x_{k,i} \tag{10}$$

For fixed k, $x^*_k = (x^*_{k,i}, x^*_{k,i}, \cdots x^*_{k,m})$ represents a feasible solution. The fitness value of every feasible solution is calculated and n individuals of the highest fitness value are sought to become initial population. In order to guarantee that chaotic variable can be fully ergodic, the chaotic sequence ought to take adequate iterated time (i.e. 400- 500) in the process of chaos generation of initial population.

(2). Annealing chaotic mutation operation: Mutation is an effective operator to increase and retain the population diversity, and is meanwhile an efficient method to escape the local optimum solution and to overcome the premature convergence. The purpose of mutation can ceaselessly bring the individual of higher fitness value and guide evolution of the whole population. The GA is good at generating populations which have the high average fitness value, but it is short of the means which can generate the optimum individual of higher fitness value. A large scale of mutation is good for acquiring the optimum solution in extensive search, but the search is rough and the solution precision is poor. On the other hand, if the precision is satisfactory, the solution will be got stuck at a local optimum or take too long time to converge. In view of overcoming these flaws, this paper adopts the annealing chaotic mutation operation. It can preferably simulate chaotic evolutionary process of biology. Simultaneously, it is quite easy to find another more excellent solution in the current neighborhood area of optimum solution and let GA possess ongoing motivity all along. It directly adopts chaotic variable to carry through ergodic search of solution space and the process of search go along according to oneself rule of chaos movement. Accordingly, it effectively overcomes the default that speed obviously become slow by feedback information when search is close to the global optimum. The main process as follow:

The nth generation population（y_{n1}, y_{n2}, …, y_{nm}) of current solution space (a,b) are mapped to chaotic variable interval [0,1] and formed chaotic variable space Y^*_n, Y^*_n =（y^*_{n1}, y^*_{n2}, …, y^*_{nm})

$$y^*_{ni} = \frac{y_{mi} - a}{b - a}, i = 1, 2, \cdots, m. n = 1, 2, \cdots, G_{max} \quad (11)$$

where, G_{max} is the maximum evolutional generation of the population.

The ith chaotic variable $x_{k,}$ is degenerated and summed up to individual mapped y^*_{mi}, and the chaotic mutation individual are mapped to interval [0, 1] (Wang et al., 1999).

$$Z^*_{mi} = y^*_{mi} + \partial x_{k,i} \quad (12)$$

in which ∂ is the annealing operation

$$\partial = 1 - \left| \frac{n-1}{n} \right|^k \quad (13)$$

where, n is iterative time and k is an integer.

At last, the chaotic mutation individual obtained in interval [0,1] is mapped to the solution interval (a, b) by definite probability, and completes a mutative operation,

$$Z_{ni} = a + (b - a)Z^*_{ni} \quad (14)$$

As we can see from Eq. (13) and (14), the annealing mutation operation simulates process of species evolution of nature. Usually appearing with more evolutionary attempt because of higher mutative probability, it results in diversity of population in the initial stage of the evolution. However, with the increase of evolutionary generation, the population gradually becomes stable as the function of mutation operation becomes slower and the function of crossover operation becomes increasingly important. Integrating crossover operation with selection operation can perform accurate search in local solution space.

3.4 Implementation steps of chaotic genetic algorithm

(1) Encoding & parameter selected.

Since the hydropower station optimization operation is a complex nonlinear constrained optimization problem, the application of the floating point numbers encoding technique is appropriate. In this representation method, each chromosome vector is coded as a vector of floating point number of the same length as the solution vector. Each element is initially selected to be within the desired domain. In addition, the floating-point numbers representation is capable of representing quite a large domain. Also, it is easier to handle constraints. To implement the chaos genetic algorithm technique, parameters such as the population size P_{size}, the probability of crossover P_c, the probability of mutation P_m, the chaos iteration time T_{max} and the evolution number of generation G_{max} etc. need to be selected.

(2) Generating initial population by chaos optimization.

(3) Calculating fitness value. According to the objective function or the properly transformed objective function, the fitness value of individual will be determined.

(4) Selection. The fitness value selection adopts weighted roulette wheel approach, in which the probability P_i of an individual i being selected is given by

$$p_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \tag{15}$$

In order to ensure that good chromosomes have higher chance of being selected for the next generation, ranking schemes are always used. Ranking schemes operate by sorting the population on the basis of fitness values and then assigning a probability of selection based upon the rank. So string with higher fitness has a higher probability of being selected.

(5) Crossover. New parent individual are produced by crossover operation. Uniform arithmetical crossover is usually used for the floating-point numbers encoding individuals, i.e. the offspring individuals are produced by the linear combination of the parent individuals. Suppose two parent individuals that have been selected from the ith generation population are x_{iv} =(v_1, v_2, …, v_n), x_{iw} = (w_1, w_2, …, w_n), respectively, offspring individuals that are produced by parent individuals are

$$x_{(i+1)v} = \partial x_{iv} + (1-\partial)x_{iw}, \quad x_{(i+1)w} = \partial x_{iw} + (1-\partial)x_{iv} \tag{16}$$

where ∂ is a constant between 0 and 1.

(6) Mutation. According to Eq. (12) and Eq. (13), annealing chaos mutation operation is processed according as definitive probability of mutation and generates offspring generation.

(7) Termination condition. The algorithm will be stopped, if it arrives at a total generation of evolution or the optimum individual does not improve after n iterative search. Or else, return to step 3 and go on next time iterative operation. The framework flow chart of CGA is described in Fig. 2.

4. Case study

Two examples are used to test the performance of the proposed algorithms in this paper. Example 1 is a famous benchmark test function, example 2 is a case study about hydropower optimization scheduling with long term historical inflow.

4.1 Example 1

This example investigates the convergence speed and solution accuracy of the proposed approach and its performance is compared with that of GA. The optimum searching of the test function does not depend on any knowledge of special domain and can be used to illustrate the performance of approach clearly. The Rosenbrock function is employed in Eq. (17),

$$\min f = 100(x_1 - x_2)^2 + (1 - x_1)^2; \quad -2.048 \le x_i \le 2.048\,,\ i = 1,2\,. \tag{17}$$

The global optimum of the Rosenbrock function resides inside a long, narrow, and parabolic-shaped flat valley, which is difficult to follow.
Fig. 3 shows the evolutionary process of iteration. It can be seen that the CGA converges to the global optimum speed faster than the classical GA. Its objective function value is better than that of the GA.

4.2 Example 2

The Chaishitan reservoir, which is located upstream of Nanpan River in the Yunnan province of China and the first reservoir of series of power stations of Nanpan River (Fig. 4), with a total reservoir storage of 4.37×10^8 m^3 and watershed area of 4556 km^2, is selected as a case study. The normal and dead levels of the reservoir are 1640.5 m. and 1605.5 m, respectively. Efficiencies range from 80% to 90%, and for this study, an average value is chosen, i.e. 85%. The installed capacity of the hydropower is 60 MW, with an average annual energy of 1.83×10^8 kWh.

The simulation was done on a monthly basis, with a series of monthly inflow of 38 years. The long term average annual energy is calculated by annual power generation maximum, Table 1 lists the optimal results of three methods: DP, GA and CGA. The results indicate that the long term average annual energy based on CGA is the best and its convergence speed is not only faster than

DP largely but also overpasses the standard GA. Results indicate that using chaotic optimization improves the quality of individual of initial population and the annealing chaos mutation operation can preferably simulate chaotic evolutionary process of biology to improve performance.

5. Conclusions

The CGA presented in the paper integrates the advantages of the powerful global searching capability of the GA with that of the powerful local searching capability of the COA. Chaos optimization of the initialization is adopted to improve species quality, maintain the population diversity and finally realize the global optimization. The current optimum value obtained by annealing chaotic mutation operation of each generation in the CGA converges to a certain individual of the current generation. An exact solution exists in the neighborhood of this individual, which brings powerful searching capability of CGA for small space domain into full play, thus resulting in a better overall searching capability. The proposed CGA is applied to the global optimum of the Rosenbrock function and the optimal operation of hydropower station reservoir. The experimental results indicate that the proposed algorithm not only retains the virtue of GA, but also can improve the computational efficiency and produce more satisfactory output.

A new annealing chaotic mutation operation is employed in the evolutionary process of GA, and it not only avoid the search being easily trapped in a local optimum, but also overcomes the problem of slow convergence speed. The proposed CGA is applied to optimal operation of hydropower station reservoir. Simulation results demonstrate that the proposed CGA is more feasible and effective in searching optimum than the traditional GA.

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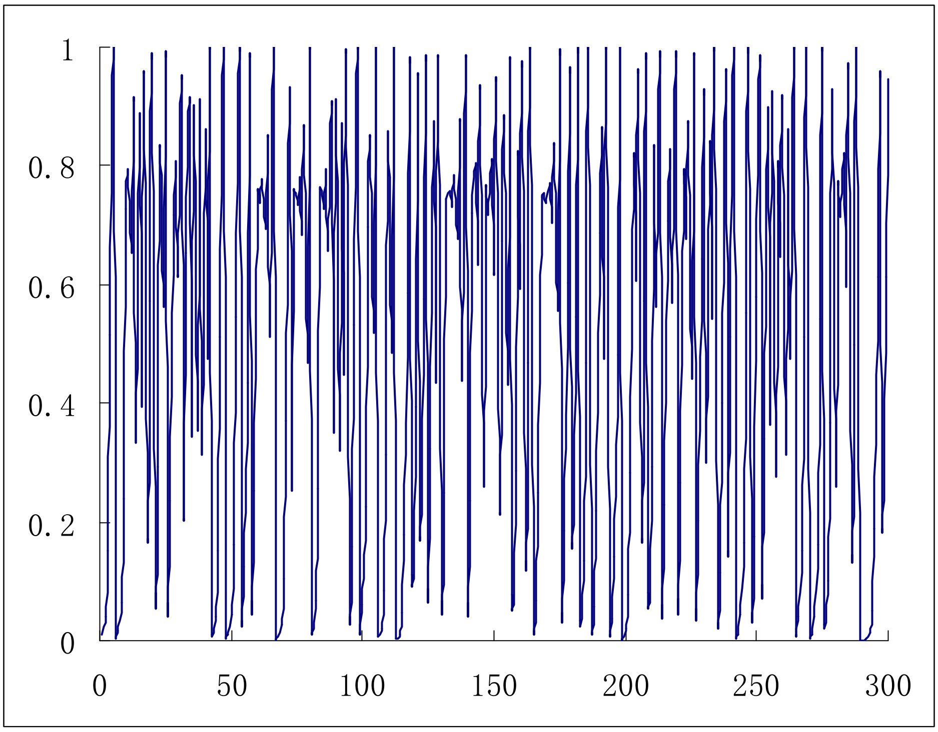

Fig. 1. Dynamics of logistic map

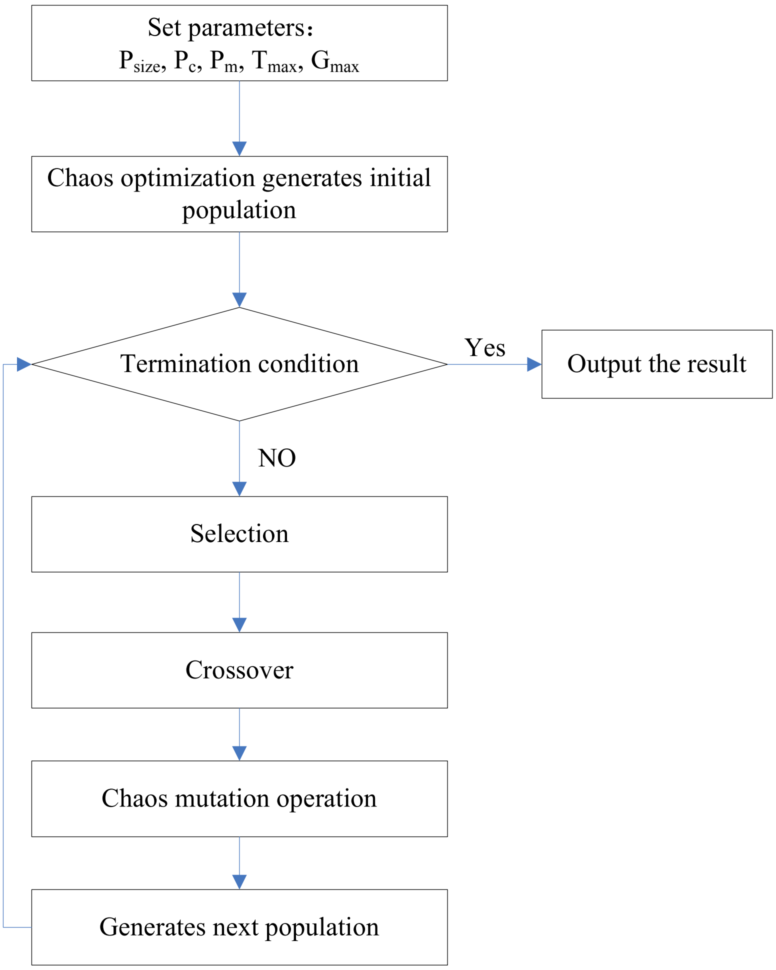

Fig. 2. The framework flow chart of CGA

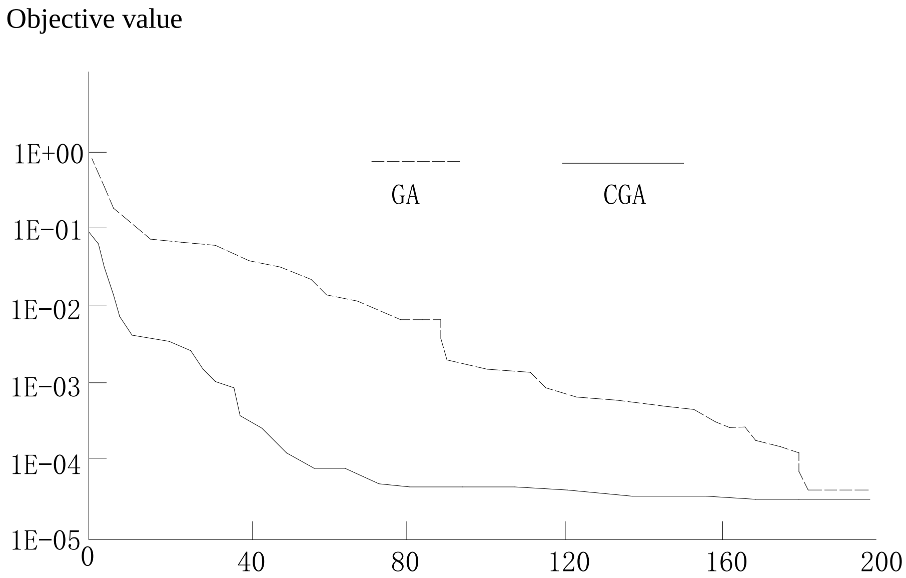

Fig.3. Evolutionary process of iteration.

Fig. 4. Location of the Chaishitan Hydropower

Table 1. The results from different optimal methods

Methods	Design	DP	GA	CGA
The long term average annual energy（10^8kWh）	1.83	1.893	1.928	2.039
Average execution time（second）		175	14	10