Calibration of Xinanjiang model parameters using hybrid genetic algorithm based fuzzy optimal model

Wen-Chuan Wang, Chun-Tian Cheng, Kwok-Wing Chau and Dong-Mei Xu

ABSTRACT

Conceptual rainfall–runoff (CRR) model calibration is a global optimization problem with the main objective to find a set of optimal model parameter values that attain a best fit between observed and simulated flow. In this paper, a novel hybrid genetic algorithm (GA), which combines chaos and simulated annealing (SA) method, is proposed to exploit their advantages in a collaborative manner. It takes advantage of the ergodic and stochastic properties of chaotic variables, the global search capability of GA and the local optimal search capability of SA method. First, the single criterion of the mode calibration is employed to compare the performance of the evolutionary process of iteration with GA and chaos genetic algorithm (CGA). Then, the novel method together with fuzzy optimal model (FOM) is investigated for solving the multi-objective Xinanjiang model parameters calibration. Thirty-six historical floods with one-hour routing period for 5 years (2000–2004) in Shuangpai reservoir are employed to calibrate the model parameters whilst 12 floods in two recent years (2005–2006) are utilized to verify these parameters. The performance of the presented algorithm is compared with GA and CGA. The results show that the proposed hybrid algorithm performs better than GA and CGA.

Key words | chaos genetic algorithm, flood forecasting, fuzzy multi-objective optimization, simulated annealing, Xinanjiang model calibration

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ABBREVIATIONS

CRR	conceptual rainfall–runoff
GA	genetic algorithm
SA	simulated annealing
CGA	chaos genetic algorithm
FOM	fuzzy optimal model
GOM	global optimization methods
RMSE	root-mean-squared error

INTRODUCTION

Conceptual rainfall–runoff (CRR) models have been widely used for flood forecasting as basic tools for catchments basin management. As the demand for timely and accurate forecasts has increased in hydrology, the major difficulty of CRR model calibration is that these models generally have a large number of parameters that cannot be directly obtained from measurable quantities of catchments characteristics, and the accuracy of their calculations depends on how the relevant parameters are defined. In the past, manual calibrations were commonly used, which are very tedious and time-consuming tasks because of the subjectivity. Moreover, it is difficult to explicitly assess the confidence of model simulations. Owing to these shortcomings, the automation of the calibration process has to be explored. The calibration problem has been transformed into a global optimization problem, aiming to determine a set of model parameters by optimizing a number of objective functions so that the model can simulate the hydrological behaviour of the catchment as closely as possible. Thus,

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the development and implementation of automated effective global optimization methods for parameter calibration are important topics in hydrological modelling (Duan et al. 2003).

As global optimization methods (GOM), the metaheuristic techniques, such as genetic algorithm (GA), simulated annealing (SA) and other random search methods, have become increasingly important over the last two decades for CRR model parameter calibration. GA is one of the global optimization metaheuristic techniques that have gained popularity as a means to find near-optimal solutions to nonlinear optimization problems. It has become one of the most widely used techniques for model calibration (Wang 1991, 1997; Cooper et al. 1997; Franchini & Galeati 1997; Ndiritu & Daniell 2001). Recently, Cheng et al. (2002, 2006) combined a fuzzy optimal model (FOM) with GAs to solve multi-objective rainfall–runoff model calibration. Furthermore, Cheng et al. (2005) proposed a hybrid method that combines a parallel GA with a FOM in a cluster of computers. SA has been successfully employed in a number of model calibrations. Sumner et al. (1997) and Thyer et al. (1999) applied SA for optimization of a CRR model, Abdulla et al. (1999) employed SA for the estimation of base flow parameters of ARNO model and Rozos et al. (2004) combined the simplex method with SA for the calibration of a semi-distributed model for conjunctive simulation of surface and groundwater flows. The improvement in performance of these techniques can be attributed to their superior ability to navigate numerous local optima present in the response complexity of the CRR model calibration problem. However, owing to the complexities of CRR models, these methods may not always be successful in finding the global optimum (Gan & Biftu 1996; Goswami & O'Connor 2007).

It is not guaranteed that GA is able to find the global optima to solve large-scale and complex real-world problems. One of the main reasons is the problem of premature convergence of the GAs. When combined with other techniques, the individual strengths of each approach can be exploited in a collaborative manner for the construction of a powerful hybrid algorithm. A combination of global and local search methods was explored by Duan et al. (1992), which combined GA with the simplex method, with newly conceived concepts of complex partition and complex shuffling, for watershed model calibration purposes. Franchini (1996) reported a GA combined with a local search method for the automatic calibration of CRR models. In recent years, some methods, such as chaotic optimization method, SA technique and so on, were integrated with GA in order to provide a more efficient behaviour and a higher flexibility when tackling large-scale and complex real-world problems. 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. Lu et al. (2003) applied a chaotic approach to maintain the population diversity of GA in network training. Cheng et al. (2008) proposed chaos genetic algorithm (CGA) based on the chaos optimization algorithm and GA for monthly operation of a hydropower reservoir with a series of monthly inflow of 38 years. The GA and SA with improved bottom left algorithm were applied to two-dimensional non-guillotine rectangular packing problems (Soke & Bingul 2006). Chiu et al. (2007) presented a hybrid approach, combining GA with SA for optimizing reservoir operation through fuzzy programming. In the hybrid search procedure, the GA provides a global search and the SA algorithm provides local search. The GA and SA are also cooperatively used by Yoo & Gen (2007) for a real-time task in heterogeneous multiprocessors system. Consequently, it is a significant task to explore more effective hybrid approaches and improvements on GA to speed up the convergence and enhance the effectiveness of GA.

In order to avoid premature convergence and trap into poor local optima in a solution search process, the key point is to find some ways to maintain the population diversity and prevent the inbreeding leading to misleading local optima (Eshelman & Schaffer 1991). The chaos is a general phenomenon in nonlinear systems and has characteristics such as ergodicity, regularity, randomicity and acquisition of all kinds of states in a self-rule in a certain range. It can be employed to improve the performance of GA (Yuan et al. 2002; Lu et al. 2003; Cheng et al. 2008). Moreover, since GA lacks the hill-climbing capacity, it may easily fall in a trap in locating a local minimum but not the true solution. SA is an iterative improvement scheme with the hill-climbing ability, which allows it to reject inferior local solutions and find more globally near-optimal solutions. In this paper, a novel hybrid metaheuristic search algorithm is presented by taking advantage of the ergodic and stochastic properties of chaotic variables, the global search capability of GA and the local optimal search capability of SA method. The novel algorithm adopts chaotic variables to 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. SA algorithm is applied in order to jump over the local minima using Metropolis rule. It starts with a solution candidate obtained by the GA, and then repeatedly attempts to find a better solution by moving to a neighbour with higher fitness, until it finds a solution where none of its neighbours has a higher fitness. The novel method can facilitate their advantages of the GA in a collaborative manner to improve the performance of the GA and overcome their disadvantages. The new proposed algorithm is used to optimize parameter values of the Xinanjiang model for flood forecasting in Shuangpai reservoir. First, the single criterion of the mode calibration is employed to demonstrate the performance of evolutionary process of iteration. Then, the novel method together with FOM is investigated for solving the multi-objective Xinanjiang model parameters calibration. The correlative examination indicates that the hybrid method has more powerful search capabilities in order to avoid premature convergence and trap into poor local optima, and has an enhanced performance in terms of solution quality and computation efficiency.

XINANJIANG MODEL

The Xinanjiang model studied is a conceptual rainfall–runoff (CRR) model with distributed parameters, which is developed by Zhao *et al*. (1980) and Zhao (1992) and has been successfully and widely applied to large basins in the humid and semi-humid regions of China for flood forecasting. The model structure is shown in Figure 1. It has 17 parameters, including seven runoff-generating component parameters (U_m, L_m, D_m, B, I_m, K, C) and 10 runoff routing parameters (S_m, E_x, K_g, K_i, C_g, C_i, C_s, K_e, X_e, L). The runoff routing component parameter L, the lag time of routing for each sub-area, an empirical value that is mainly dependent on the length and slope of a stream, can be estimated by relating to observable characteristics of the watershed. The physical descriptions of these parameters are listed in Table 1. The value of each parameter is usually within certain ranges according to physical and mathematical constraints, information about watershed characteristics and from modelling experiences. The parameters of the Muskingum method must satisfy the following constraints for each channel of the sub-basin.

$$2K_eX_e \le \Delta t \le 2(K_e - K_eX_e)$$

where K_e and X_e are the Muskingum coefficients, K_e is a storage constant having the dimension of time, X_e is a dimensionless constant for the reach of the channel and

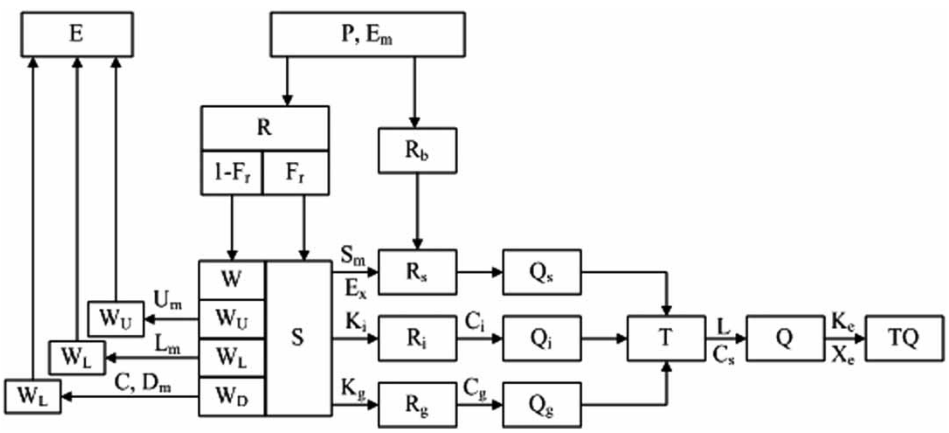

Figure 1 | Flow chart for the Xinanjiang model.

Table 1 | Parameters of the Xinanjiang model

	Parameter	Physical meaning	Unit
Runoff generating parameter			
1	U_m	Averaged soil moisture storage capacity of the upper layer	[mm]
2	L_m	Averaged soil moisture storage capacity of the lower layer	[mm]
3	D_m	Averaged soil moisture storage capacity of the deep layer	[mm]
4	B	Exponential parameter with a single parabolic curve, which represents the non-uniformity of the spatial distribution of the soil moisture storage capacity over the catchment	[–]
5	I_m	Percentage of impervious and saturated areas in the catchment	[%]
6	K	Ratio of potential evapotranspiration to pan evaporation	[–]
7	C	Coefficient of the deep layer that depends on the proportion of the basin area covered by vegetation with deep roots	[–]
Runoff routing parameter			
8	S_m	Areal mean free water capacity of the surface soil layer, which represents the maximum possible deficit of free water storage	[mm]
9	E_x	Exponent of the free water capacity curve influencing the development of the saturated area	[–]
10	K_g	Outflow coefficients of the free water storage to groundwater relationships	[–]
11	K_i	Outflow coefficients of the free water storage to interflow relationships	[–]
12	C_g	Recession constants of the groundwater storage	[–]
13	C_i	Recession constants of the lower interflow storage	[–]
14	C_s	Recession constant in the lag and route method for routing through the channel system with each sub-basin	[–]
15	K_e	Parameter of the Muskingum method	[–]
16	X_e	Parameter of the Muskingum method	[–]
17	L	Lag in time	[–]

Δt is the routing period. For a detailed description and explanation of the Xinanjiang model, please refer to Zhao (1992).

HYBRID GA WITH CHAOS AND SA

Genetic algorithm (GA)

GA is a heuristic search technique based on the mechanics of natural selection and genetics for global optimization in a complex search space (Goldberg 1989; Holland 1992). In a generation process, GA generates initial population randomly. It then evaluates the population and operates on the population using selection, crossover and mutation operators to produce new and hopefully better solutions. GA operators are briefly described as follows:

Population: It is a set of possible solutions of the problem. Because the size of the population varies with a problem, there is no clear indication how large it should be.

Selection: Selection operator is the procedure in which chromosomes are selected according to their fitness values. A popular approach is weighted roulette wheel selection, in which the probability p_i of an individual i being selected is given by

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

where f_i is the fitness of i and n is the population size.

Crossover: Crossover operator is powerful for exchanging information between chromosomes and creating new solutions. It is hoped that good parents may produce good solutions.

Mutation: Mutation operates on one parent solution and generates an offspring solution by randomly modifying the parent solution's features. It helps to preserve a reasonable level of population diversity, and provides a mechanism to escape from local optima.

CHAOS AND LOGISTIC MAPPING

Chaos is a universal phenomenon in the natural world. The chaotic sequence can usually be produced by the following well-known one-dimensional logistic map defined by May (1976):

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

in which μ is a control parameter, $0 \leq \mu \leq 4$. It can be observed that Equation (2) is a deterministic dynamic system without any stochastic disturbance. It seems that the long-term behaviour of the system in Equation (2) 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 and $x_0 \notin \{0.25, 0.5, 0.75\}$ the above system exhibits chaotic behaviour. A very small difference in the initial value of x causes a large difference in its long-term behaviour, 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 appears to be in disorder. Figure 2 shows its chaotic dynamics characteristic, where $x_0 = 0.01$, maximum value of $k = 300$. Figure 3 shows the random sample characteristic, where x is a random variable. It can be seen that the logistic map is an efficient approach for maintaining the population diversity in the problem of interest.

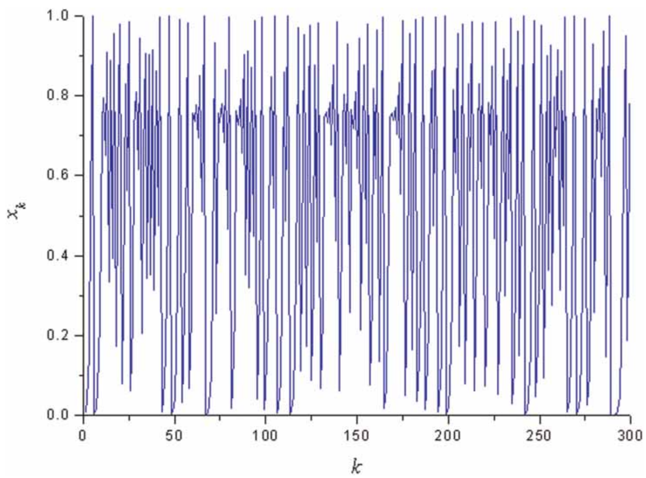

Figure 2 | Dynamics of logistic map.

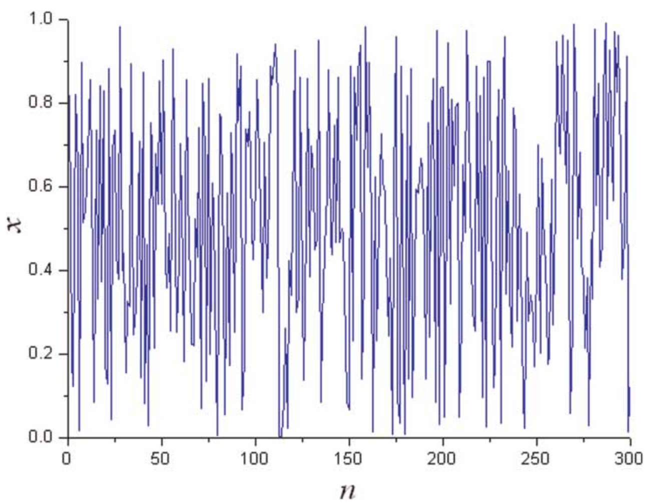

Figure 3 | Random variable.

SIMULATED ANNEALING (SA)

SA is probabilistic hill-climbing technique that imitates the natural process of metals annealing (Kirkpatrick *et al.* 1983). The SA carries out a random search in the range of values based on the Metropolis criterion (Metropolis *et al.* 1953). In each step of the approach, an atom is displaced through a random perturbation of its current state, and the consequential change ΔE in the energy of the system is calculated. If $\Delta E \leq 0$, the change is accepted deterministically because it represents a perturbation and results in a lower energy of the system, and the new configuration of system constitutes the starting point for the next step. If $\Delta E > 0$, it indicates an uphill move to a higher energy state and the proposed change is accepted with a probability given by the Boltzmann distribution:

$$P(\Delta E) = \exp(-\Delta E / k_B T) \tag{3}$$

where k_B is Boltzmann's constant and T corresponds to the current temperature. The use of $P(\Delta E)$ forces the system to evolve into thermal equilibrium, i.e. after a large number of perturbations, the probability distribution of the states approaches the Boltzmann distribution (van Laarhoven & Aarts 1987).

HYBRID GA WITH CHAOS AND SA (CGASA)

Literature review shows that GA is a versatile and effective search technique for solving optimization problems. However, there are still some situations, such as slow convergence and premature local optimum, where GA on its own does not perform particularly well to solve large-scale and complex real-world problems. The population diversity is an important factor for successful application of GA. If GA cannot hold its diversity well before the global optimum is reached, it may prematurely converge to a local optimum.

In order to maintain diversity of population, the initial individuals are taken for granted to be diversified and, in other words, distributed uniformly. The 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, during the searching process the population variety falls and chromosomes of individuals tend to coincide under selective pressure. As such, in many cases, the GA's searches are found to be stuck by local traps. Thus, the hybrid technique ought to be explored to maintain diversity of evolution population and improve performance of GA.

In the randomized searches process of conventional GA, 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. The individuals' experiences are completely ignored during their lifetime. 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. The scheme of biological evolution can be well described as 'random evolution + feedback' from the viewpoint of chaos, where randomicity is an intrinsic property of biological society and the feedback part contains sufficient information for species to evolve. SA is an iterative improvement scheme with the hill-climbing ability, which allows it to reject inferior local solutions and find more globally near-optimal solutions. SA allows occasionally an uphill move to solutions with lower fitness by using a temperature parameter to control the acceptance of the moves (with a probability) to avoid getting trapped in poor local optima. Only those who can successfully deal with the feedback information from evolution can survive well and keep evolving from low to higher classes. Consequently, a novel hybrid GA with chaos and SA is presented in this paper.

THE IMPLEMENTATION OF CGASA

In initial implementation of GA, the variables were encoded as strings of binary alphabets, i.e. zero and one. A major drawback of binary GAs is that they face difficulties when applied to problems having large search space and seeking high precision, because they encode parameters as finite length strings and therefore spend a considerable time performing encoding and decoding processes. To overcome this problem, real coded GA, in which variables are encoded as real numbers, is now becoming popular. Experiments have shown that real coded GAs are superior to binary coded GAs for optimization problems (Janikow & Michalewicz 1991). In this study, a real coded GA is applied, and some measures are adopted to improve its performance, such as generating initial population by chaotic sequence, utilization of annealing chaotic mutation operation to replace standard mutation operator and SA technique providing neighbour local search.

To implement the hybrid algorithms 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}, the evolution number of generation G_{max}, the initial temperature T of SA, Boltzmann's constant k_B etc. need to be selected.

1. *Generation of initial population by chaotic sequence:* The variable solutions of initial population are generated by the Logistic Equation of chaos, which usually will have a better effect than randomized generation. This will improve the diversity of the initial population and calculated efficiency.

   The m initial values of very small difference x_k ($0 \le x_{k,i} \le 1$, $i = 1, 2, 3, \ldots, m$) are given in Equation (2) and $x_{0,i} \notin (0.25, 0.5, 0.75)$ to assure the evolution process proceeds correctly. It will generate m chaotic variables $x_{k,i}$ ($x_{k,i}$, $i = 1, 2, \ldots m$) of different trajectory. The m chaotic variables are mapped to variable space of optimization and translated into chaotic variable $x^*_{k,i}$ according to Equation (4):

$$x^*_{k,i} = a_i + (b_i - a_i)x_{k,i} \tag{4}$$

   For fixed k, $x^*_k = (x^*_{k,1}, x^*_{k,2}, \ldots, x^*_{k,m})$ represents a feasible solution. The n feasible solutions generated, which can satisfy variable space of optimization, become the initial population.
2. *Computation of fitness value:* According to the objective function or the properly transformed objective function, the fitness value of individuals is determined.
3. *Selection:* The fitness value selection adopts the weighted roulette wheel approach, in which the probability P_i of an individual i being selected is given by Equation (1). In order to ensure that good chromosomes have a 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 a variable with higher fitness has a higher probability of being selected.
4. *Crossover:* The crossover operation can create new individuals. It is responsible for the global search property of the GA. The common crossover operations are single point, two points and uniform arithmetic crossover. For the real numbers encoding individuals, uniform arithmetical crossover is usually used. Suppose two parent individuals that have been selected from the ith generation population are $x_{iv} = (v_1, v_2, \ldots, v_n)$, $x_{iw} = (w_1, w_2, \ldots, w_n)$, respectively, offspring individuals that are produced by the linear combination of the parent individuals are

$$\begin{aligned} x_{(i+1)v} &= \partial x_{iv} + (1 - \partial)x_{iw}, \\ x_{(i+1)w} &= \partial x_{iw} + (1 - \partial)x_{iv} \end{aligned} \tag{5}$$

   where ∂ is a constant between 0 and 1.
5. *Annealing chaotic mutation operation*: Mutation operator changes the characteristics of genetic material in a chromosome to sustain population diversity, and bring the individual of higher fitness value and guide evolution of the whole population. A large scale of mutation is good for acquiring the optimum solution in an 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 trapped at a local optimum or take too long to converge. In order to overcome these flaws, this paper adopts the annealing chaotic mutation operation. It can preferably simulate the chaotic evolutionary process of biology. Simultaneously, it is quite easy to find another better solution in the current neighbourhood area of optimum solution and let GA possess ongoing motivity all along. It directly adopts the chaotic variable to carry through an ergodic search of solution space and the process of search goes along according to the rule of chaos movement. Accordingly, it effectively overcomes the default that speed obviously becomes slow by feedback information when search is close to the global optimum. The main process is shown as follows:

The nth generation population $(y_{n1}, y_{n2}, \ldots, y_{nm})$ of current solution space (a, b) is mapped to chaotic variable interval $[0, 1]$ to form chaotic variable space Y^*_n, $Y^*_n = (y^*_{n1}, y^*_{n2}, \ldots, y^*_{nm})$

$$y^*_{ni} = \frac{y_{ni} - a}{b - a}, \quad i = 1, 2, \ldots, m; n = 1, 2, \ldots, G_{max} \tag{6}$$

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

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

$$Z^*_{ni} = y^*_{ni} + \partial x_{k,i} \tag{7}$$

in which ∂ is the annealing operation

$$\partial = 1 - \left|\frac{n-1}{n}\right|^k \tag{8}$$

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, which completes a mutative operation,

$$Z_{ni} = a + (b-a)Z^*_{ni} \tag{9}$$

As we can see from Equations (8) and (9), the annealing chaos mutation operation is processed according to definitive probability of mutation and generates offspring generation. It simulates the process of species evolution of nature. Usually appearing with more evolutionary attempts 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.

6. Using SA for neighbour local search: GA is good at generating populations which have high average fitness value, but it is short of the means that can generate the optimum individual of higher fitness value. SA strategy may help obtain the optimum individual solutions of higher fitness value associated with local optima of the fitness function.
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 2 and go on next time iterative operation. The framework flow chart of CGASA is shown in Figure 4.

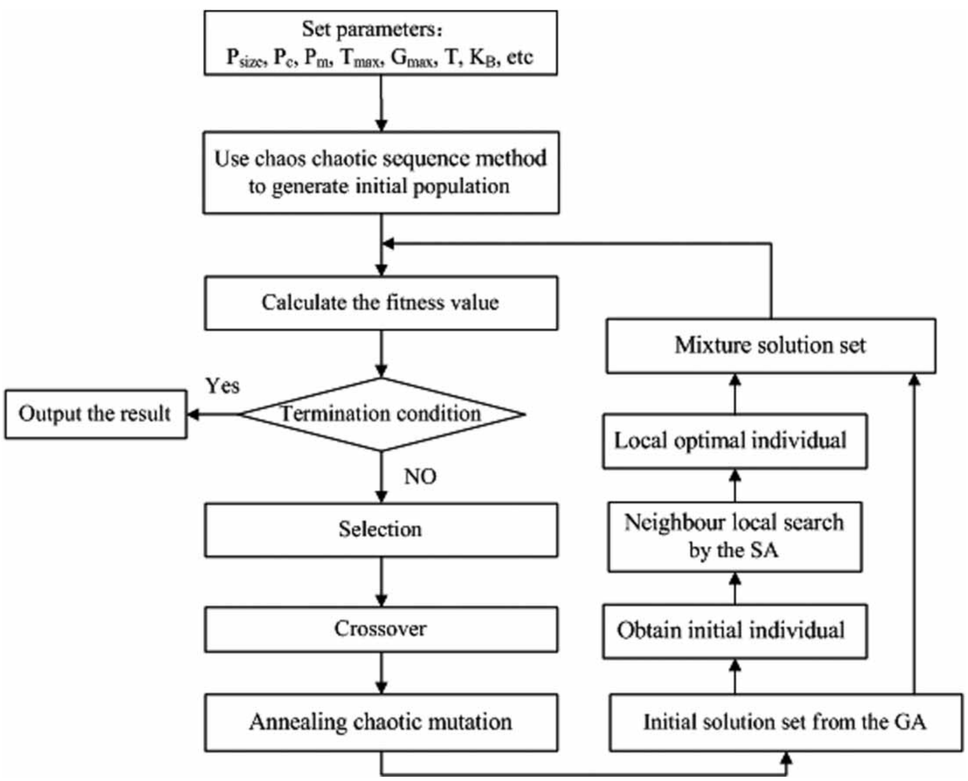

Figure 4 | The flow chart of the GA implemented with chaos and SA.

CASE STUDY

Study area

The proposed algorithm in this paper is used to estimate parameter values of the Xinanjiang model for flood forecasting in Shuangpai reservoir (Figure 5), which is located in Hunan Province of southern China and downstream of the Xiaoshui Stream, which is one of the tributary rivers in the Xiangjiang River. The reservoir, with a drainage area of 10,594 km^2 and a water holding capacity of up to 373.8 million cubic metres, is used for power generation and flood control, as well as for irrigation purposes. The length of the main stream is 154.9 km with an average slope of 0.61%. The area is in a sub-tropical monsoon zone with rich rainfalls and good vegetation cover. The annual rainfall is 1,500 mm; the average depth of runoff is 893 mm and the average discharge is 300 m^3/s. However, the temporal distribution of the rainfall during a given year is significantly heterogeneous in this area. The flood events in this area are mainly due to thunderstorms. 45.9% of the total rainfall falls between April and June, and 34% of the total rainfall between September and October, which are referred to as the high-flow periods. The region is divided into 12 sub-areas, each of which has the same set of model parameters. Each sub-area is represented by a rain gauge station. Table 2 summarizes the rain gauge stations covered in this study, including the representing area and the corresponding

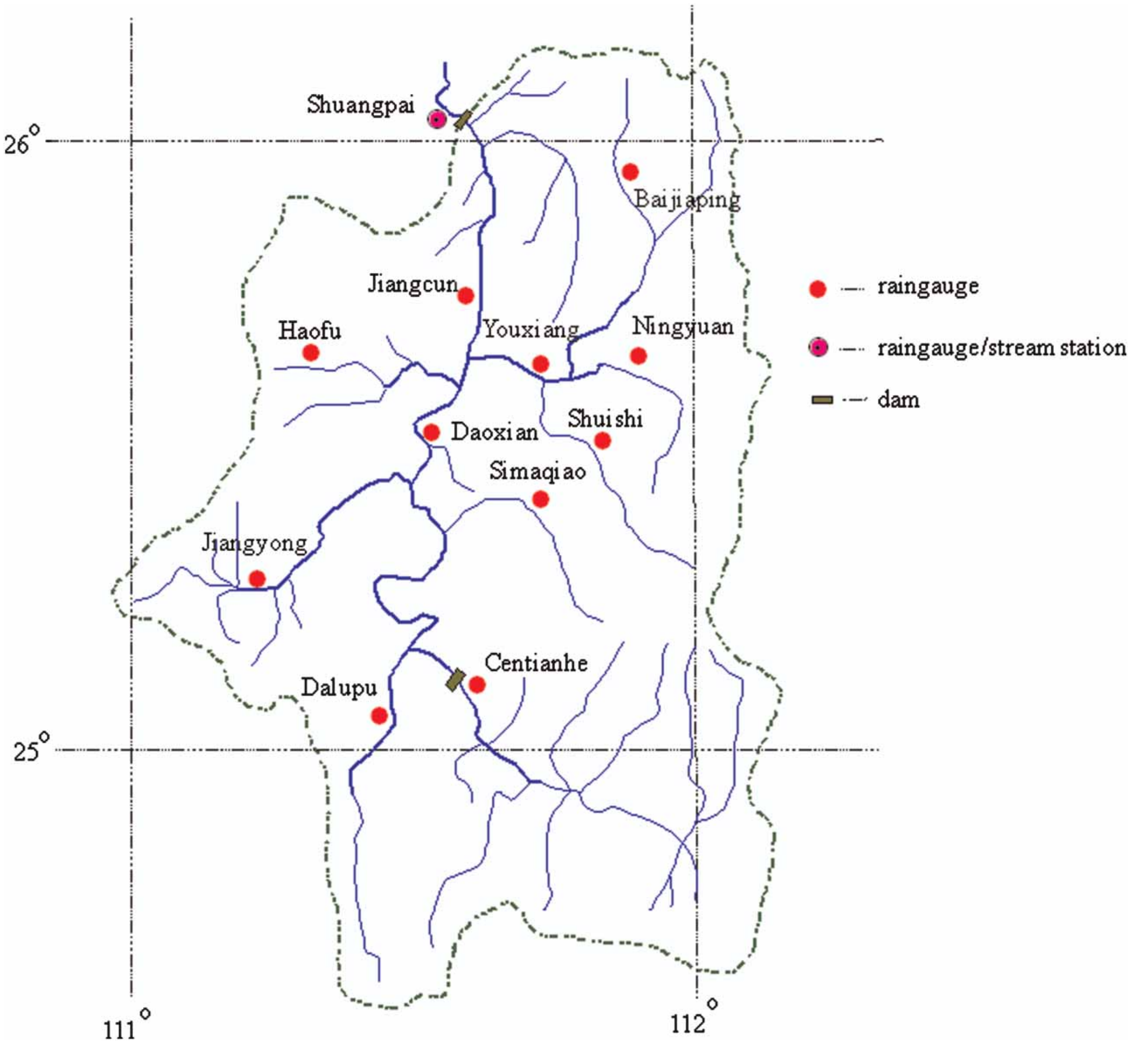

Figure 5 | Map of the Shuangpai area with locations of rain gauge stations.

Table 2 | Details of rain gauge stations in the study area

Station	Type of station	Station name	Weighting	Area (km^2)
01	Rainfall	Jiangcun	0.0915	745
02	Rainfall	Daoxian	0.0846	691
03	Rainfall	Haofu	0.0689	562
04	Rainfall	Jiangyong	0.1134	926
05	Rainfall	Dalupu	0.1200	979
06	Rainfall	Centianhe	0.0326	266
07	Rainfall	Simaqiao	0.0651	531
08	Rainfall	Youxiang	0.0762	622
09	Rainfall	Ningyuan	0.0911	744
10	Rainfall	Shuishi	0.0651	532
11	Rainfall	Baijiaping	0.1210	988
12	Rainfall/streamflow	Shuangpai	0.0705	576

weighting for each rain gauge. A total of 36 historical floods with one-hour routing period between 2000 and 2004 are employed to calibrate the model parameters whilst 12 floods between 2005 and 2006 are utilized to verify these parameters. Table 3 lists the initial ranges of parameter values for the Shuangpai reservoir.

CALIBRATION CRITERIA

CRR model calibration is a highly complex nonlinear problem. A successful calibration depends not only on effective optimization methods, but also on calibration objective. This situation is because the performance evaluation and parameter adjustment procedures are objective, in the sense that they establish explicit rules by which the actual sequence of parameter adjustments is made in an automatic calibration process. The single criterion selected to measure the closeness of the model output and data has been devoted to identifying the 'best' criterion and the 'best' optimization. In general, the criterion most commonly used in the literature has been the root-mean-squared error (RMSE) evaluated on either the streamflows or the log of the streamflows (Boyle *et al.* 2000):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Q_s(i) - Q_0(i)\right)^2} \tag{10}$$

where $Q_0(i)$ and $Q_s(i)$ are, respectively, the observed and simulated streamflow or log streamflow and N is the number of data points considered.

However, according to the national criteria for flood forecasting in China (NCHI 2000), the three statistical ratios of acceptable criteria relative to the peak discharge, peak time and total runoff volume among the calibrated and validated historical flood events, respectively, are used to evaluate the parameter calibration performance for rainfall–runoff model. They are expressed as $r_{\mathrm{peak\_discharge}}$, $r_{\mathrm{peak\_time}}$ and r_{runoff}:

$$\text{Maximize } r_{\mathrm{peak\_discharge}} = \frac{M_{\mathrm{pd}}}{N} \times 100\% \tag{11a}$$

$$\text{Maximize } r_{\mathrm{peak\_time}} = \frac{M_{\mathrm{pt}}}{N} \times 100\% \tag{11b}$$

$$\text{Maximize } r_{\mathrm{runoff}} = \frac{M_{\mathrm{r}}}{N} \times 100\% \tag{11c}$$

where M_{pd}, M_{pt} and M_{r} represent the total number of floods that satisfy the acceptable criteria relative to the peak discharge, peak time and total runoff volume, respectively, and N is the total number of the calibrated or validated floods. When all three ratios are greater than 85%, the performances of parameter calibration satisfy the first level standard of flood forecasting calibration or validation. When all three ratios are greater than 75% and one is less than 85%, the performances of parameter calibration satisfy the second level standard of flood forecasting calibration or

Table 3 | The initial ranges of parameter values

Parameter:	U_m	L_m	D_m	B	I_m	K	C	S_m	E_x	K_g	K_i	C_g	C_i	C_s	K_e	X_e
Lower	10	50	10	0.1	0.0	0.1	0.1	10	1.1	0.1	0.2	0.7	0.1	0.01	0.5	0.01
Upper	40	90	80	0.9	0.1	1.2	0.3	50	1.4	0.4	0.6	0.99	0.99	0.4	2	0.5

validation. Otherwise, the results of the performances of parameter calibration are unsatisfactory for online flood forecasting.

In this study, first, the single criterion is employed to demonstrate the performance of the proposed algorithms in this paper. Then the combination of a FOM with the proposed algorithms is used to optimize multi-objective Xinanjiang models for real-time flood forecasting and flood simulation. Cheng *et al.* (2002) introduced a FOM with limited alternatives and multiple criteria for CRR model parameter calibration. Except for the specific fitness value calculated below, the multiple criteria CGASA presented in this section is basically the same as the single criteria CGASA presented earlier. It is assumed that the total number of criteria for a chromosome evaluation is m, and the alternative set consisting of n alternatives is denoted by $A = \{A_1, A_2, \ldots, A_n\}$. The decision matrix is represented by $X = (x_{ij})_{m\times n}$ where x_{ij} is the ith criteria value of the alternative A_j $(j = 1, 2, \ldots, n)$. In determining the relatively optimal decision among n alternatives, the decision matrix X should be transformed into the matrix of membership degree by the following equations:

$$r_{ij} = x_{ij}/x_{i\max} \tag{12}$$

$$r_{ij} = (1 - x_{ij})/x_{i\max} \tag{13}$$

where $x_{i\max} = \overset{n}{\underset{j=1}{\vee}} x_{ij}$. If the maximum value represents more optimum membership degree, Equation (12) should be adopted; otherwise, Equation (13) should be applied. After the transformation, the matrix of membership degree is represented as:

$$R = (r_{ij})_{m\times n} \tag{14}$$

Here, only the final equation is given:

$$u_{ij} = \left[1 + \frac{\sum_{i=1}^{m}[w_i(1 - r_{ij})]^2}{\sum_{i=1}^{m}(w_i r_{ij})^2}\right]^{-1} \tag{15}$$

where $i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$. For details, please refer to Cheng *et al.* (2002).

Generally, the weights of criteria are determined from experience depending on the individual problem. In this study, the weights of the peak value, peak time and total runoff volume are 0.333, 0.333 and 0.333, respectively, i.e. $w = (0.333, 0.333, 0.333)^T$, because they are equally important according to the national criteria for flood forecasting in China. The value of u_j is obtained from Equation (15). By sorting the values of membership degree of n alternatives in descending order, the optimal order of alternatives can be obtained. Comparing with the procedure reproducing offspring in CGASA for the next generation, the membership degree of alternative u_j can defined as the fitness of the jth chromosome.

APPLICATION AND PERFORMANCE COMPARISON

In this study, GA and CGA are employed as a yardstick to gauge the performance of the proposed CGASA algorithms. Some parameters of algorithms need to be chosen in order to obtain good performance of GA and its improvement, such as the choice of a moderate population size (P_{size}), a high crossover probability (P_c) and a low mutation probability (P_m). P_{size} critically affects the efficiency and solution quality of the GAs. Generally, P_{size} is set to be a value between 150 and 300. P_c controls the frequency of crossover operation. Generally, P_c is chosen between 0.5 and 0.8. P_m is a critical factor in extending the diversity of the population. Generally, P_m is often chosen between 0.001 and 0.1. The same $P_{size} = 300$, $P_c = 0.8$, $P_m = 0.1$ are employed for GA, CGA and CGASA in order to examine their performance. The weighted roulette wheel approach and the ranking schemes are adopted for GA, CGA and CGASA. The initial value of temperature $T = 100$ and the value of Boltzmann's constant $k_B = 0.99$ are set for CGASA.

Figure 6 demonstrates its evolutionary process of iteration using a single criterion (RMSE) to optimize parameters of the complex Xinanjiang model where the evolution number of generation $G_{max} = 2000$. Obviously, CGASA can obtain better objective value than the classical GA and CGA. The convergence speed of CGASA is faster than the classical GA and CGA. CGASA can give a solution

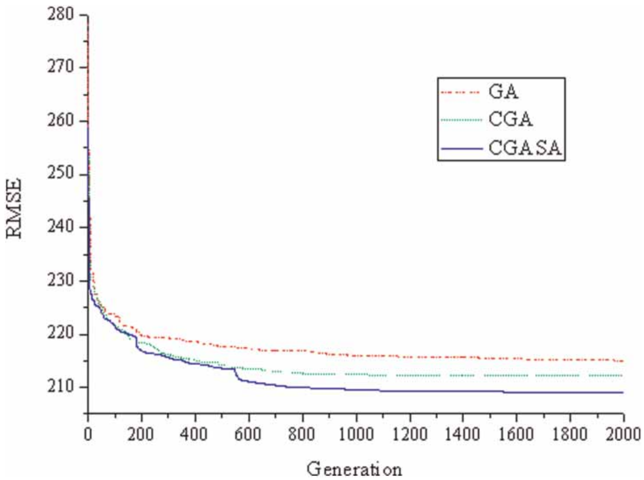

Figure 6 | Evolutionary process of iteration.

near 400 generations, which surpasses the final one from GA when the iteration number of GA is near 2000. Furthermore, the solution of CGA almost halts at 600 generations and CGASA continues to converge. This demonstrates that generating initial population by chaotic sequence and annealing chaotic mutation operation can improve the diversity of population and performance of GA. Moreover, SA strategy can help obtain the optimum individual solutions of higher objective value by neighbour local search.

In order to simulate all the important characteristics of the flood forecasting system according to national criteria in China, the combination of a FOM with CGASA is used to calibrate multi-objective Xinanjiang model parameters. Table 4 shows the results of parameter calibration. Table 5 lists the performances of the calibrated parameters. Table 6 lists performances of the validated parameters. Table 7 presents statistical comparisons of results by CGASA, GA and CGA during calibration and validation stages. The performances of all simulated hydrographs of rainfall–runoff process by different calibration methods from 2000 to 2004 during the calibration and from 2005 to 2006 during the validation are shown in Figures 7 and 8, respectively. As can be seen from Figures 7 and 8, using CGASA calibration parameters of the Xinanjiang model have better fitting ability between the simulated and observed flows hydrograph than by using GA and CGA.

From Table 7, using the CGASA method calibration, the values of three criteria: $r_{peak\_discharge}$, r_{peak_time} and $r_{runoff,}$ are 86.11, 91.67 and 86.11%, respectively, for the calibrated result, and 100, 91.67 and 91.67% for the validated result. The qualificatory ratios of the peak discharge, peak time and runoff total volume are all more than 85%. Whilst the results calibrated by GA are 83.33, 91.67 and 80.56%, the validated results are 100, 91.67 and 75%. The results calibrated by CGA are 83.33, 91.67 and 83.33% whilst the validated results are 100, 91.67 and 83.33%. The qualificatory ratios of peak time of the three methods are the same, while in the calibration phase the qualificatory ratios of the peak discharge and runoff total volume by CGASA calibration are 2.78 and 5.55% higher by GA calibration, respectively. During the validation phase, the qualificatory ratio of the runoff total volume by CGASA calibration is 16.67% more than that by GA calibration. Thus the results of this analysis indicate that using CGASA calibration parameters of the Xinanjiang model enables better forecasting results to be obtained than by using GA and CGA.

CONCLUSIONS

To improve GA convergence and performance, a novel hybrid GA that combines chaos and SA algorithm is proposed to exploit their advantages in a collaborative manner in this paper. Chaos, as a primary mode of nature motion, is ergodic, internal stochastic and sensible to initial conditions. A chaotic system applied to GA can significantly enhance GA's potential in terms of maintaining the

Table 4 | Results of the calibrated model parameters by CGASA

Parameter:	U_m	L_m	D_m	B	I_m	K	C	S_m
Value	21.2192	65.0837	49.3368	0.998	0.0574	0.6548	0.1436	39.9985
Parameter:	E_x	K_g	K_i	C_g	C_i	C_s	K_e	X_e
Value	1.1863	0.2902	0.3803	0.9867	0.1	0.2031	2	0.1498

Table 5 | Performance of the calibrated parameters by CGASA

Floods	Observed (m^3/s^{-1})	Simulated (m^3/s^{-1})	Percentage (error/%)	Observed peak time (yyyy-mm-dd hh)	Simulated peak time (yyyy-mm-dd hh)	Error (number)	Total volume (error/%)
20000426	718.5	665.1	−7.43	2000-04-26 22	2000-04-26 23	1	**34.33**
20000430	737.7	799.5	8.37	2000-04-30 12	2000-04-30 09	−3	12.44
20000510	691.3	730.3	5.64	2000-05-10 07	2000-05-10 07	0	18.30
20000527	1,343.4	1,257.6	−6.39	2000-05-27 07	2000-05-27 08	1	1.07
20000528	2,445.3	2,513.7	2.80	2000-05-28 16	2000-05-28 18	2	17.18
20001022	1,569.4	1,387.0	−11.62	2000-10-22 09	2000-10-23 16	**31**	17.71
20010406	1,494.3	1,116.0	−**25.32**	2001-04-06 17	2001-04-06 16	−1	−8.96
20010417	732.7	550.7	−**24.84**	2001-04-17 00	2001-04-16 23	−1	13.68
20010418	899.8	740.6	−17.70	2001-04-19 01	2001-04-18 23	−2	−13.78
20010421	1,298.1	1,123.3	−13.47	2001-04-20 21	2001-04-20 23	2	10.41
20010509	1,249.6	1,170.3	−6.35	2001-05-09 23	2001-05-09 22	−1	4.47
20010613	4,976.6	4,543.2	−8.71	2001-06-13 20	2001-06-13 17	−3	19.63
20010707	1,896.2	1,462.8	−**22.86**	2001-07-07 19	2001-07-07 23	**4**	7.22
20020313	2,347.1	2,037.1	−13.21	2002-03-13 21	2002-03-13 21	0	11.78
20020411	1,656.6	1,192.6	−**28.01**	2002-04-11 02	2002-04-11 02	0	−10.83
20020426	1,556.6	1,448.5	−6.94	2002-04-26 04	2002-04-26 03	−1	6.85
20020510	1,222.6	1,078.4	−11.80	2002-05-10 06	2002-05-10 04	−2	**42.39**
20020514	2,615.5	2,063.6	−**21.10**	2002-05-14 20	2002-05-14 20	0	8.83
20020618	3,184.9	2,715.6	−14.73	2002-06-18 12	2002-06-18 10	−2	−6.45
20020701	6,245.8	6,128.3	−1.88	2002-07-01 23	2002-07-01 21	−2	−3.77
20020721	1,132.1	1,065.0	−5.92	2002-07-21 06	2002-07-21 07	1	16.11
20020726	3,532.1	2,954.6	−16.35	2002-07-26 13	2002-07-26 14	1	−3.84
20020807	5,230.2	5,443.4	4.08	2002-08-08 00	2002-08-08 00	0	10.01
20020819	3,365.2	2,874.9	−14.57	2002-08-19 21	2002-08-19 21	0	17.79
20021030	3,226.5	3,089.9	−4.23	2002-10-30 08	2002-10-30 06	−2	5.45
20030420	2,196.2	2,226.3	1.37	2003-04-20 16	2003-04-20 17	1	9.68
20030513	1,650.9	1,752.7	6.16	2003-05-13 22	2003-05-13 23	1	19.48
20030515	4,490.6	4,438.0	−1.17	2003-05-15 22	2003-05-15 21	−1	16.35
20030607	3,171.1	2,884.8	−9.03	2003-06-07 04	2003-06-07 00	−**4**	16.44
20030629	1,079.3	899.1	−16.69	2003-06-29 03	2003-06-29 01	−2	6.13
20040508	1,267.9	1,258.4	−0.75	2004-05-08 07	2004-05-08 07	0	**24.77**
20040513	1,783.0	1,545.2	−13.34	2004-05-13 04	2004-05-13 03	−1	−11.79
20040517	2,879.7	2,705.6	−6.05	2004-05-16 18	2004-05-16 17	−1	18.13
20040531	1,101.9	1,119.2	1.57	2004-05-31 19	2004-05-31 17	−2	**21.45**
20040616	2,710.3	3,218.5	18.75	2004-06-16 21	2004-06-16 21	0	**35.68**
20040712	2,364.2	1,960.9	−17.06	2004-07-12 17	2004-07-12 16	−1	8.54

Notes: The total number of floods is **36**. **31** of them are qualificatory relative to the error of peak discharge and the ratio of qualifying simulation is **86.11%**. **33** are qualificatory relative to the error of peak time and the ratio of qualifying simulation is **91.67%**. **31** are qualificatory relative to the error of total runoff volume and the ratio of qualifying simulation is **86.11%**.

Table 6 | Performances of validated parameter by CGASA

Floods	Observed (m^3/s^{-1})	Simulated (m^3/s^{-1})	Percentage (error/%)	Observed peak time (yyyy-mm-dd hh)	Simulated peak time (yyyy-mm-dd hh)	Error (number)	Total volume (error/%)
20050215	1,775.5	1,890.8	6.50	2005-02-15 18	2005-02-15 18	0	19.92
20050420	627.4	583.5	−7.01	2005-04-20 06	2005-04-20 05	−1	**40.79**
20050506	1,041.5	889.2	−14.62	2005-05-06 08	2005-05-06 06	−2	11.54
20050527	1,552.4	1,440.6	−7.20	2005-05-27 22	2005-05-27 20	−2	12.49
20050606	1,579.1	1,677.3	6.22	2005-06-06 04	2005-06-06 03	−1	17.83
20050622	2,776.0	2,870.0	3.39	2005-06-22 02	2005-06-22 01	−1	18.86
20060527	2,366.0	2,339.5	−1.12	2006-05-27 05	2006-05-27 05	0	7.78
20060601	971.9	944.0	−2.87	2006-06-01 09	2006-06-01 09	−1	16.47
20060608	2,641.5	2,642.2	0.03	2006-06-08 01	2006-06-08 01	0	15.15
20060615	2,329.1	2,089.4	−10.29	2006-06-15 02	2006-06-15 02	−1	14.06
20060716	5,020.2	4,405.1	−12.25	2006-07-16 05	2006-07-15 13	**16**	−4.37
20060805	1,877.4	2,114.9	12.65	2006-08-05 01	2006-08-05 01	0	6.34

Notes: The total number of floods is **12**. All of them are qualificatory relative to the error of peak discharge and the ratio of qualifying simulation is **100%**. **11** are qualificatory relative to the error of peak time and the ratio of qualifying simulation is **91.67%**. **11** are qualificatory relative to the error of total runoff volume and the ratio of qualifying simulation is **91.67%**.

Table 7 | Result comparison of GA, CGA and CGASA algorithms

Algorithm	Ratio of qualificatory in calibration/% Peak discharge	Peak time	Total runoff	Ratio of qualificatory in validation/% Peak discharge	Peak time	Total runoff
GA	83.33	91.67	80.56	100	91.67	75
CGA	83.33	91.67	83.33	100	91.67	83.33
CGASA	86.11	91.67	86.11	100	91.67	91.67

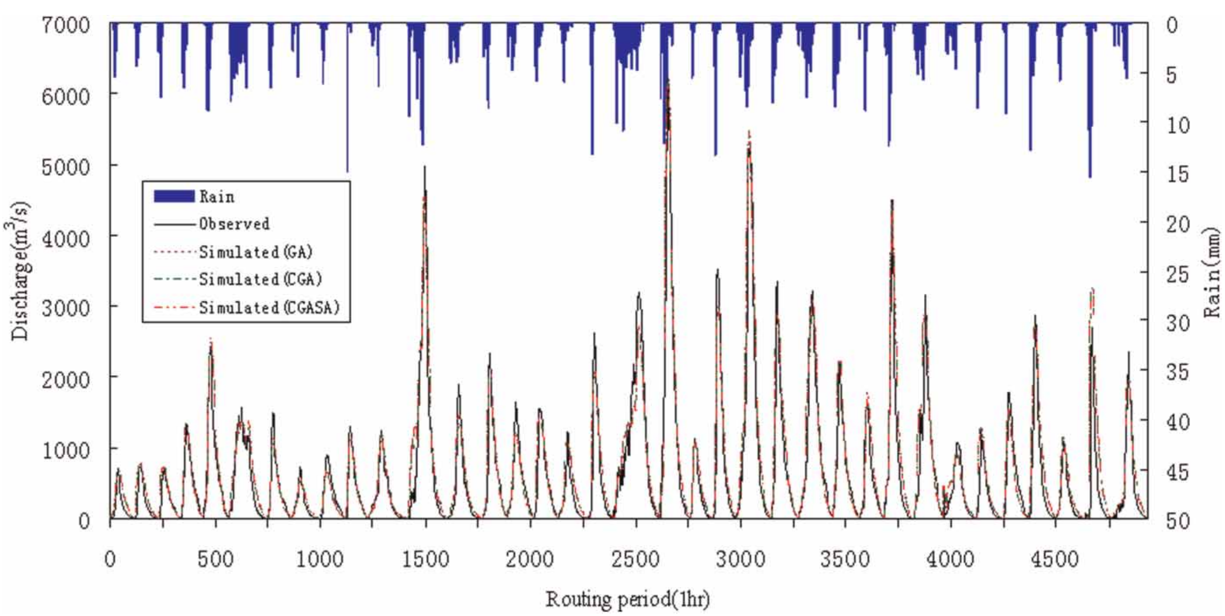

Figure 7 | The rain, observed hydrographs and simulated hydrographs (GA, CGA, CGASA) for 2000–2004 during calibration.

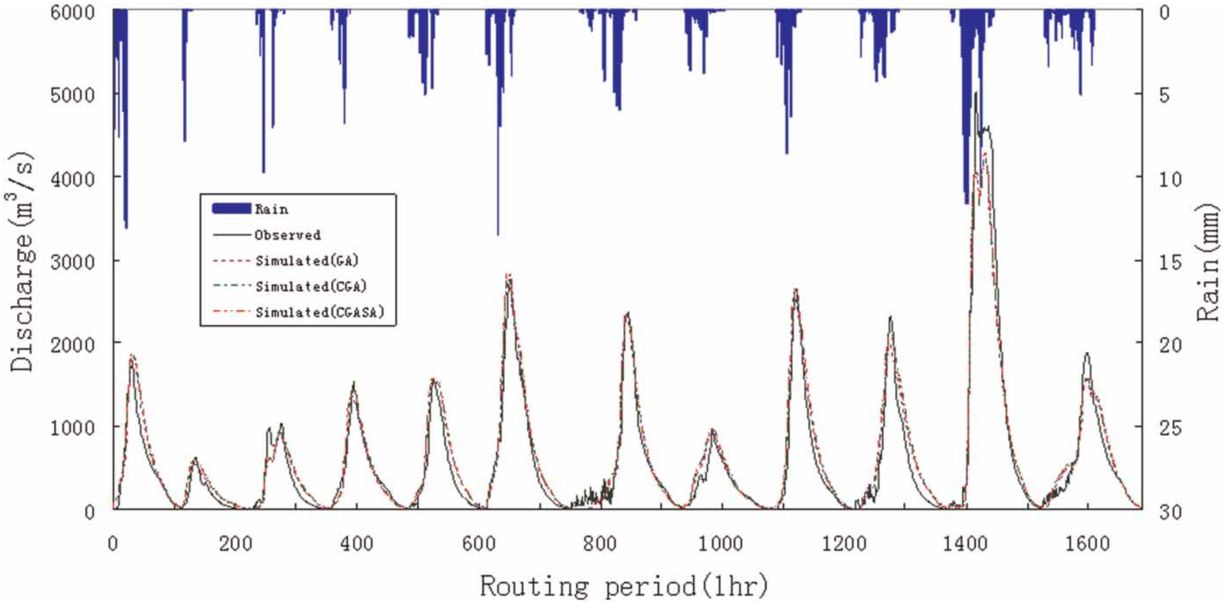

Figure 8 | The rain, observed hydrographs and simulated hydrographs (GA, CGA, CGASA) for 2005–2006 during validation.

population diversity during the evolutionary process. An annealing chaotic mutation operation is employed to replace the standard mutation operator in the evolutionary process of GA. SA strategy can jump over the local minima using the Metropolis rule and improve the hill-climbing capacity of GA. The new proposed algorithm is used to optimize parameter values of the Xinanjiang model for flood forecasting in Shuangpai reservoir. First, the single criterion of the mode calibration is employed to compare the performance of the evolutionary process of iteration with GA and CGA. It shows that the proposed CGASA outperforms the GA and CGA. Then, the novel method together with the FOM is investigated for solving the multi-objective Xinanjiang model parameters calibration. The resulting comparisons obtained from case applications indicate that the CGASA is capable of dealing with large and complex problems, and is a new, promising hybrid metaheuristic algorithm for optimization of CRR models.

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