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Automatic calibration a hydrological model using a master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization

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ABSTRACT

Parameter estimation for hydrological models is a challenging task, which has received significant attention by the scientific community. This paper presents a master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization (MSSE-SPSO), which combines a particle swarm optimization with self-adaptive, hierarchical and multi-swarms shuffling evolution strategies. By comparison with particle swarm optimization (PSO) and a master–slave swarms shuffling evolution algorithm based on particle swarm optimization (MSSE-PSO), MSSE-SPSO is also applied to identify HIMS hydrological model to demonstrate the feasibility of calibrating hydrological model. The results show that MSSE-SPSO remarkably improves the calculation accuracy and is an effective approach to calibrate hydrological model.

1. Introduction

The rainfall-runoff relationship is one of the most complex hydrological phenomena to comprehend, owing to the tremendous spatial and temporal variability of watershed characteristics and precipitation patterns, and to the number of variables involved in the modeling of the physical process (Kumar, Sudheer, Jain, & Agarwal, 2005). Conceptual hydrological models are popular tools for simulating major rainfall-runoff processes. Normally, a hydrological model consists of some modules with a large number of parameters. The successful application of a hydrological model depends on how well the parameters are calibrated. Calibration is the process of modifying the input parameters to a numerical model until the output from the model matches an observed set of data. Manual calibration of such models is a very tedious and daunting task, and its success depends on the subjective assessment of a particular modeler, which includes knowledge of the basic approaches and interactions in the model (Pechlivanidis, McIntyre, & Wheater, 2010). Compared to manual calibration, automatic calibration is faster while being objective and relatively easy to implement (Liu, 2009). In automatic calibration, parameters are adjusted automatically according to a specified search scheme and numerical measures of the goodness-of-fit (Liu, Khu, & Savic, 2004; Madsen, 2000). It was found that performance of model calibration depends on choice of suitable calibration strategies.

There have been various advancements in model calibration procedures in the past decades and many automatic optimization procedures have been devised to address model calibration problems. One such development is a genetic algorithm by Wang (1991), who report it is an efficient and robust means for the calibration of conceptual rainfall-runoff models. And another is the shuffled complex evolution (SCE-UA) algorithm by Duan, Sorooshian, and Gupta (1992), which combines a downhill simplex algorithm with a complex shuffling strategy. Since Gill, Kaheil, Khalil, McKee, and Bastidas (2006) utilized particle swarm optimization (PSO) for parameter estimation in hydrology, there have been various types of PSO proposed for hydrological model calibration (Jiang, Liu, Huang, & Wu, 2010; Kraue, Cullmann, Saile, & Schmitz, 2011; Kuok, Harun, & Shamsuddin, 2010; Zhang, Srinivasan, Zhao, & Liew, 2009), and recent researches have shown that PSO approach has many computational advantages over traditional evolutionary computing (Chau, 2007; Jiang, Hu, Gui, Wu, & Zeng, 2006; Jiang, Hu, Huang, & Wu, 2007).

Particle swarm optimization (PSO) is proposed by Kennedy and Eberhart (1995) based on the analogy of swarming animals, such as a flock of birds or school of fish, which is a simple and powerful heuristic method for solving nonlinear, non-differential and multimodal optimization problem (Amjady & Soleymanpour, 2010; Mandal, Basu, & Chakraborty, 2008). PSO have demonstrated good properties of fast convergence in optimal problem, but the drawback of premature degrades their performance and reduces their global search ability, which makes a local optimum highly probable.

In this paper, we present a novel hybrid approach through combining a self-adaptive particle swarm optimization with MSSE-SPO given in Jiang et al. (2010), called master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization (MSSE-SPSO) for calibrating hydrological model. In Jiang

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et al. (2010), a population of points sampled randomly from the feasible space is partitioned into one master swarm and several slave swarms. Each slave swarm independently executes PSO. And for the master swarm, the particles enhance themselves based on not only the social knowledge of the master swarm but also that of the slave swarms. In this paper, to overcome the premature convergence of PSO, an improved self-adaptive particle swarm optimization algorithm is proposed for evolution direction of each particle redirected dynamically by adjusting the two sensitive parameters of PSO in the master swarm and slave swarms, which makes the proposed algorithm searching around personal best solution more probably and exploring globally at the earlier stage of the evolution progress and around global best solution and locally at the latter stage. The simulation results for calibrating hydrological model show that the proposed MSSE-SPSO method possesses better ability to find the optimal solution compared to PSO and MSSE-SPO. Towards these ends, the rest of the paper is organized as follows. Section 2 presents a self-adaptive particle swarm optimization. Description of the proposed algorithm MSSE-SPSO is given in Section 3. Case study for hydrological model calibration used to illustrate the optimization performance of the proposed algorithm is given in Section 4. Finally we conclude our paper.

2. Self-adaptive particle swarm optimization

Particle swarm optimization (PSO) is a stochastic, population-based algorithm for solving optimization problems, which is initialized with a group of random particles (solutions) and then searches the optimal solution in possible space by updating its velocity and position of particles repeatedly. The algorithm ends until a user-defined stopping criterion is reached. The velocity of particle and its new position will be assigned according to the following two equations:

$$v_{id}^{t+1} = w v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 (p_{gd}^t - x_{id}^t) \quad (1)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^t \quad i = 1, 2, \ldots, N, \; d = 1, 2, \ldots, D \quad (2)$$

where v_{id}^t and x_{id}^t are the velocity and value of the d-th dimension of particle i in iteration t separately; w is a inertial factor, which is used to limit the velocity; c_1 and c_2 are positive constant parameters called acceleration coefficients which control the maximum step size; r_1 and r_2 are independently uniformly distributed random variables with range; p_{id}^t is the value of the d-th dimension of the i-th particle's precious best position in iteration t. p_{gd}^t is the value of the d-th dimension of global best position in iteration t. N is the numbers of the total populations; D is the dimension of search space.

As the suggestion of Kennedy and Eberhart (1995), $c_1 + c_2 = 4$. Generally a large c_1 make the particles flying to the personal best position more probably. Similarly, and a large c_1 makes the particles flying to the global best position more probably. For PSO, a large velocity makes the proposed algorithm explores globally, on the contrary, a small velocity will lead the algorithm searching in a local area (Lu, Sun, & Lu, 2010). So, to adequate the convergence of PSO, Wang et al. (2012) proposed an improved self-adaptive particle swarm optimization algorithm, which makes the algorithm searching around the personal best solution more probably and exploring globally at the earlier stage of the evolution progress and around the global best solution and locally at the latter stage. The new rule of updating the velocity is applied to the procedure of update and modification, the rule of each particle updating its velocity is described by:

$$\begin{aligned} w &= (w_{max} - w_{min}) \times e^{-\beta t} + w_{min} \\ c_1 &= (d_2 - d_1) \times t/T + d_1 \\ c_2 &= (d_2 - d_1) \times t/T + d_2 \end{aligned} \quad (3)$$

where w_{max} and w_{min} are initial and final inertia weigh factors, β is a shrink factor, d_1 and d_2 are constant factors, and d_1 is initialed large than d_2. T is the maximum generation number.

3. Master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization (MSSE-PSO)

It has been demonstrated that SPSO can converge fast for solving optimal problem, but the drawback of premature reduces its global search ability. When a particle in the swarm finds a local optimal position, the other particles will gather close to it rapidly. Hence the algorithm plunges into a local optima. In order to solve this problem mentioned above, a master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization (MSSE-SPSO) is proposed, which applies the strategy of population division and biological evolution to applies SPSO to keep the diversity of population and avoid premature convergence. The essence of the method is as follows.

We begin with initial search points for each agent, which is usually generated randomly within the allowable range. Then the population is partitioned into several sub-swarms (one master swarm and the others salve swarms). Each slave swarm independently executes SPSO, including the update of particles' position and velocity. For the master swarm, the particles enhance themselves based on not only the social knowledge of the master swarm but also that of the slave swarms. The resulting equation for the manipulation of the master swarm is:

$$v_{id}^{t+1} = w v_{id}^t + c_1 r_1 (p_{id}^t - x_{id}^t) + c_2 r_2 \left(p_{gd}^t - x_{id}^t\right) + c_3 r_3 \left(s_{gd}^t - x_{id}^t\right) \quad (4)$$

where, c_3 is a positive parameter called migration coefficient, and r_3 is an uniform random sequence in the range [0,1]. s_{gd} is the previous best position of the whole slave swarms. Eq. (4) comprises four components, the first term of the summation represents the inertia (the particle keeps moving in the direction it had previously moved), the second term represents memory (the particle is attracted to the best point in its trajectory), the third term represents cooperation (the particle is attracted to the best point found by all particles of master swarm) and the last represents information exchange (the particle is attracted to the best point found by the slave swarms). After a certain number of generations, the master swarm and the whole slave swarms are forced to mix and points are then reassigned to ensure information sharing. The MSSE-SPSO strategy is presented below and is illustrated in Fig. 1.

Step 1: Initializing. Select $M \geqslant 1$, $N \geqslant 1$, where, M is the number of sub-swarms (one master swarm and $M-1$ salve swarms). N is the number of points in each sub-swarm. Compute the sample size $S = M \times N$.

Step 2: Sampling. Sample S points $X_1, X_2, \ldots, X_S$ in the feasible space.

Step 3: Ranking. Compute the function value f_i at each point X_i. Sort the points in order of increasing function value and store them in an array $E = \{X_i, f_i, i = 1, 2, \ldots, S\}$.

Step 4: Partitioning. Partition E into sub-swarms $A^1, A^2, \ldots, A^M$, each containing points N, such that: $A^k = \left\{X_j^k, f_j^k | X_j^k = X_{k+p(j-1)}, f_j^k = f_{k+p(j-1)}, j = 1, 2, \ldots, N\right\}, k = 1, 2, \ldots, M$.

Step 5: Evolving. Evolve each sub-swarm A^k using SPSO.

- **Step 5.1:** Initializing. Select q, T, where q is the population size of SPSO, T is the maximal iterated generation.
- **Step 5.2:** Selecting. Choose q distinct points $Y_1^k, Y_2^k, \ldots, Y_q^k$, from A^k according to the function values to construct a sub-swarm. Better points in A^k have

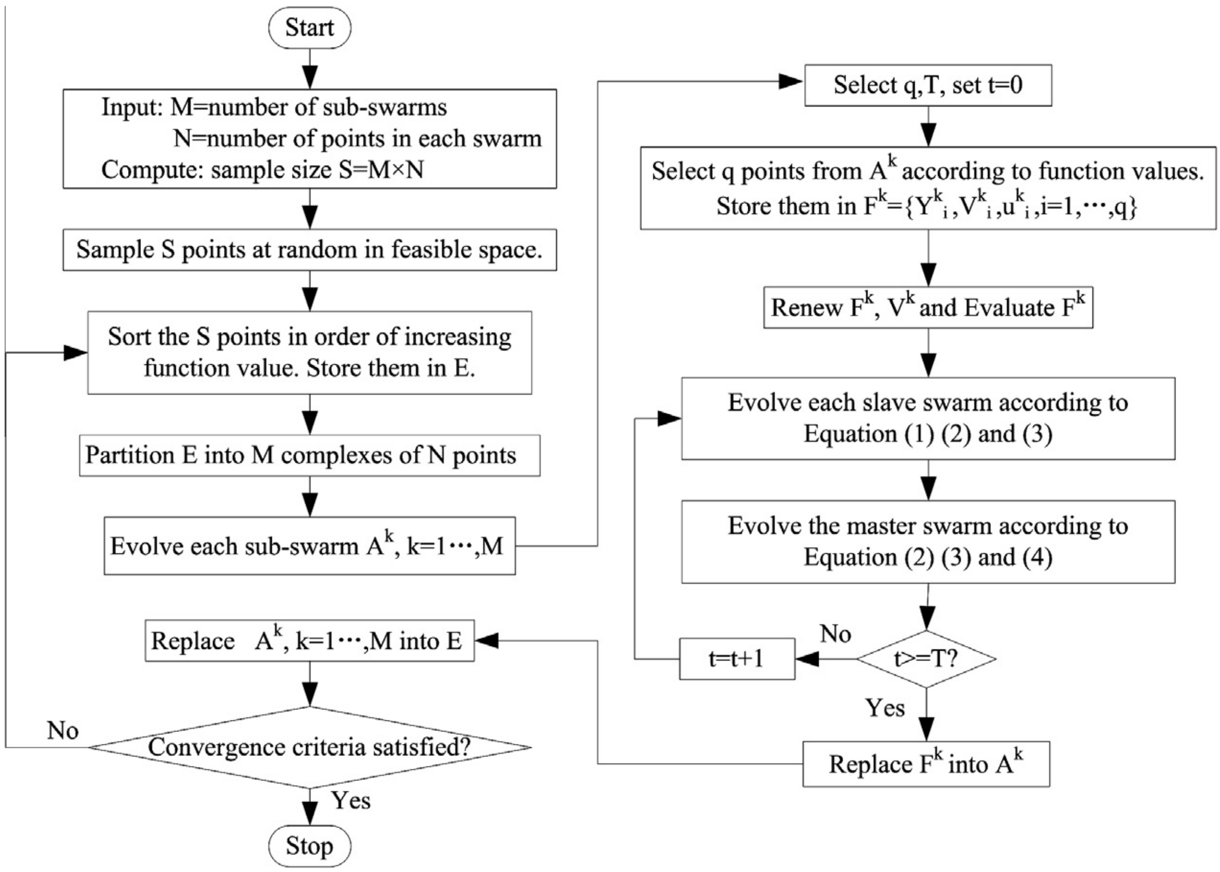

Fig. 1. Flowchart of MSSE-SPSO.

more probability to be selected. Store them in $F^k = \left\{Y_i^k, V_i^k, u_i^k | i = 1, 2 \ldots, q\right\}$, where V_i^k is the velocity for particle Y_i^k and u_i^k is the corresponding function value. Find out the best previously visited position of each particle p_i^k and the position of the best individual of the whole swarm p_g^k.

Step 5.3: Comparing. Compare the function value between each particle Y_i^k and p_i^k. If Y_i^k is better than p_i^k, then $p_i^k = Y_i^k$. Compare the function value between each particle Y_i^k and p_g^k. If Y_i^k is better than p_g^k, then $p_g^k = Y_i^k$.

Step 5.4: Renewing. Each slave swarm adapts itself according to Eqs. (1)–(3) independently. For the master swarm, it adapts itself according to Eqs. (2)–(4).

Step 5.5: Iterating. Iterate by repeating **Step 5.3** and **Step 5.4** T times, where T is a user-specified parameter which determines how fast each complex should evolve.

Step 6: Shuffling. Replace $A^1, A^2, \ldots, A^M$ into E. Sort E in order of increasing function value.

Step 7: Convergence checking. If the maximum number of generations *MaxGen* are satisfied, stop. Otherwise, return to **Step 3**.

MSSE-SPSO combines the strengths of particle swarm optimization, self-adaptive evolution, competitive evolution and sub-swarm shuffling evolution, which greatly enhances survivability by a sharing of the information gained independently by each swarm. Besides, MSSE-SPSO also uses the hierarchical idea, in which, the master swarm guides the whole group to optimal direction to enhance the performance of stability.

4. Application example

4.1. A hydrological model

Hydrological model has spread to many fields of application such as flood forecasting, water resources estimation, design flood, field drainage, water project programming, hydrological station planning, water quality accounting etc. It usually consists of a number of parameters. For any hydrological model to have practical utility, it is important to be able to identify proper values for the parameters. The procedure for doing this is called model calibration.

The model used in this study is HIMS (HydroInformatic Modeling System) rainfall-runoff model (Liu, Wang, Zheng, Zhang, & Wu, 2008) with 9 parameters needed to be calibrated. The structure of the model is shown in Fig. 2. A brief description of calibration parameters used is given in Table 1. In HIMS hydrological model, the basin is divided into a set of sub-basins, the outflow hydrograph from each of which is first simulated and then routed down the channels to the main basin outlet. The inputs to the model are rainfall P, maximum temperature T_{max}, minimum temperature T_{min} and the output is the outlet discharge TQ from the whole basin.

In order to evaluate the validity of the proposed method MSSE-SPSO for hydrological model calibration, HIMS model is applied to the Liu River catchment, located in Hebei Province, China. This catchment has an area of 626 km^2, dominated by sand soils. The

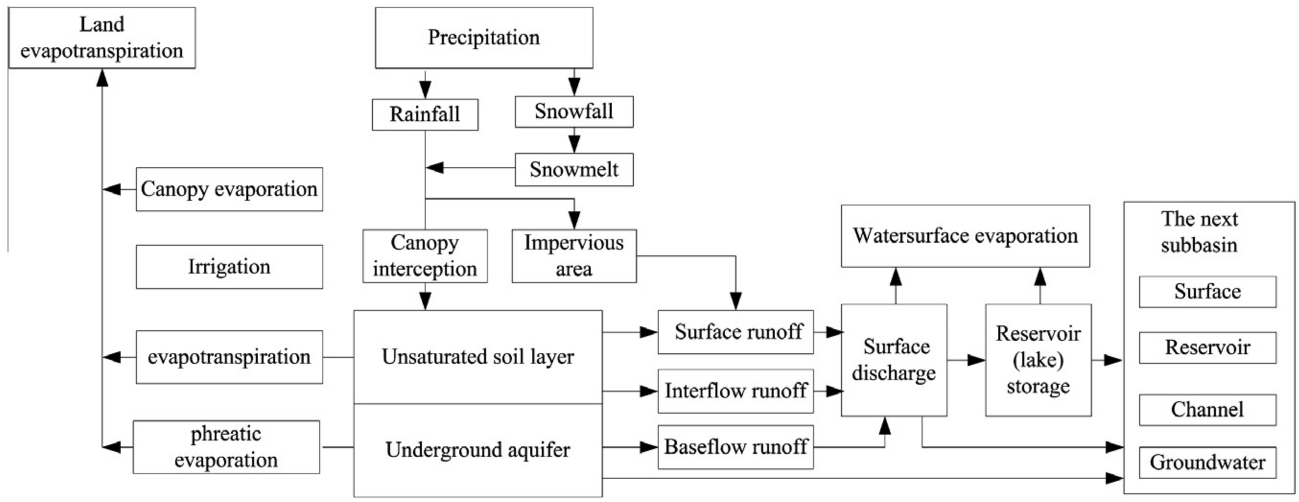

Fig. 2. Flowchart of HIMS hydrological model.

Table 1
The range and physical meaning of parameter for HIMS hydrological model and its best optimal value obtained by MSSE-SPSO.

Parameter	Description	Min[a]	Max[b]	Opt.[c]
W_{sm}	The maximum storage capacity of the soil layer	50	1000	137.07
R	The infiltration coefficient	0.1	2	1.75
r	The infiltration coefficient	0.1	1	0.93
C	The evapotranspiration coefficient	0.01	20	12.00
La	The interflow coefficient	0.1	1	1.00
Rc	The groundwater recharge coefficient	0.01	1	0.36
Kb	The baseflow coefficient	0.01	1	0.01
KE	The Muskingum coefficient	0.05	0.9	0.32
XE	The residence time of water	0.05	0.9	0.58

[a] The minimal parameter value.
[b] The maximal parameter value.
[c] The best parameter value calibrated for 10 runs.

average annual temperature is 7.6 °C, and the maximum is 41 °C and the minimum is −18 °C. The average annual precipitation is 670 mm, of which 70–80% happens in flood season between June and September. The annual average runoff depth is 82.7 mm. For the calibration, a 5-year period (1 January 1995 to 31 December 2000) is used where daily data of precipitation, maximum and minimum temperature, and catchment flow are available. In order to evaluate the performance of the calibrated model, validation data covering the periods 1 January 2001 to 31 December 2006 were used. The first 3 months of the calibration period were discarded in the calculation of the objective functions in order to minimize the influence from the initial conditions.

4.2. Objective function and model performance assessment

In general terms, the objective of model calibration can be stated as follows: Selection of model parameters so that the model simulates the hydrological process of the catchment as closely as possible. Different objective function describes the different characteristics of hydrological processes. Normally the only available information for evaluating this objective is the total catchment discharge. In this paper, in order to obtain a successful calibration by using automatic optimization routines, it is necessary to formulate the calibration objective for comprehensive consideration of error of water balance and fitting degree between measured and simulated discharge. Hence the following function is selected as the objective function as formula (5) and it is designed to have the minima.

$$f(x) = \frac{1}{N}\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2\left(1 + \frac{|\overline{Q}_{obs} - \overline{Q}_{sim}|}{\overline{Q}_{obs}}\right) \tag{5}$$

where, the variable x is parameters needed to be calibrated. $Q_{obs,i}$ and $Q_{sim,i}$ are the measured and simulated discharge in the period of calibration respectively. $\overline{Q}_{obs}$ and $\overline{Q}_{sim}$ are the average value of measured and simulated discharge in the period of calibration respectively. N is the number of time series.

The variables restraint for the problem is: $X_{min} \leqslant x \leqslant X_{max}$. Where, X_{min},X_{max} are the lower and upper bound of the variables given in Table 1.

The first criterion used in the present study to evaluate the performance of the model is the Nash–Sutcliffe efficiency criterion (Nash & Sutcliffe, 1970), which is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{N}(Q_{obs,i} - \overline{Q}_{obs})^2} \tag{6}$$

where, $\overline{Q}_{obs}$ is the mean value of the observed discharge in the calibration period. The value of R^2 is always expected to approach unity for a good simulation of the observed discharge series.

The second efficiency criterion used is the relative error of the volumetric fitness between the observed discharge and the simulated series, which is defined as:

$$RE = \frac{|\overline{Q}_{obs} - \overline{Q}_{sim}|}{\overline{Q}_{obs}} \times 100\% \tag{7}$$

where, $\overline{Q}_{sim}$ is the mean value of the simulated discharge in the calibration period. The value of RE is expected to be close to zero for a good simulation of the total volume of the observed runoff series.

4.3. Calibration and validation results

To validate the feasibility of proposed algorithm, MSSE-SPSO is compared with PSO and MSSE-PSO for the same test system, where PSO is implemented by classic PSO and MSSE-PSO strategy is available from (Jiang et al., 2010). The relevant experiment parameters of the three algorithms for this test system are shown in Table 2.

4.4. Experimental setup

The general flow chart for the calibration process using MSSE-SPSO, MSSE-PSO and PSO for HIMS hydrological model is presented in Fig. 3. The calibration process can be performed via an automatic process. And this process is continued until a satisfied condition is met. The termination criterion for the iterations is determined according to whether the max iteration is reached. The all three algorithms take 10 trials to get the optimal solution for avoiding the influence of randomicity. And in each trial the population size takes 100.

Table 2
The parameter of the three algorithm.

Parameter	Description	Value
S	The population size	100
d_1	Constant factor	2.8
d_2	Initial inertia weigh factor	1.2
w_{max}	Initial inertia weigh factor	0.9
w_{min}	Final inertia weigh factor	0.4
β	Shrink factor	0.001
c_1	Acceleration coefficient only for PSO and MSSE-PSO	2.0
c_2	Acceleration coefficient only for PSO and MSSE-PSO	2.0
c_3	Migration coefficient	0.8
M	The number of sub-swarms	4
T	The maximal iterated generation of each sub-swarm	20
$MaxGen$	The total iterations	1000

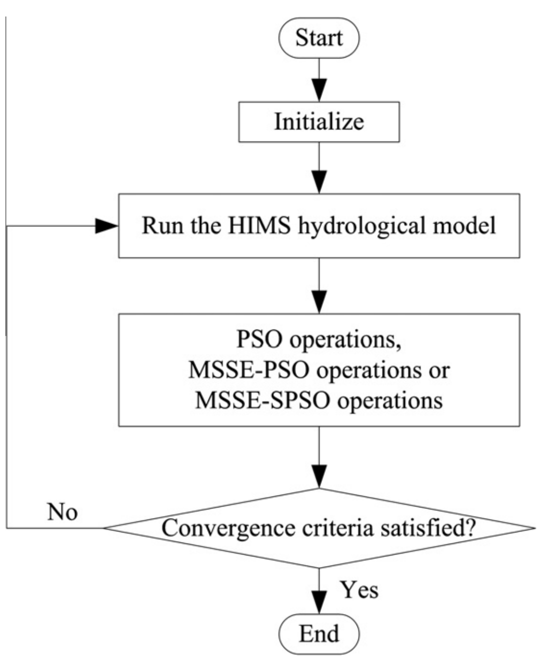

Fig. 3. Outline of PSO, MSSE-PSO and MSSE-SPSO for HIMS hydrological model calibration.

The best optimal parameter values with minimum objective function value obtained by MSSE-SPSO are showed in Table 1. Fig. 4 shows the optimal function values of the best particles for PSO, MSSE-PSO and MSSE-SPSO. It can be seen that the performance of MSSE-SPSO is better than PSO and MSSE-PSO. Table 3 compares the performance of PSO, MSSE-PSO and MSSE-SPSO. From Table 3, it can be seen that PSO, MSSE-PSO and MSSE-SPSO can control water balance error in the allowed range (less than 5%) except for PSO in the calibration period, but MSSE-SPSO has larger Nash–Sutcliffe efficiency than PSO and MSSE-PSO in the calibration and validation period, which means that MSSE-SPSO has higher simulation accuracy than PSO and PSSE-PSO. Therefore, MSSE-SPSO performs better than PSO and MSSE-PSO for HIMS hydrological model calibration. Figs. 5 and 6 shows the simulated

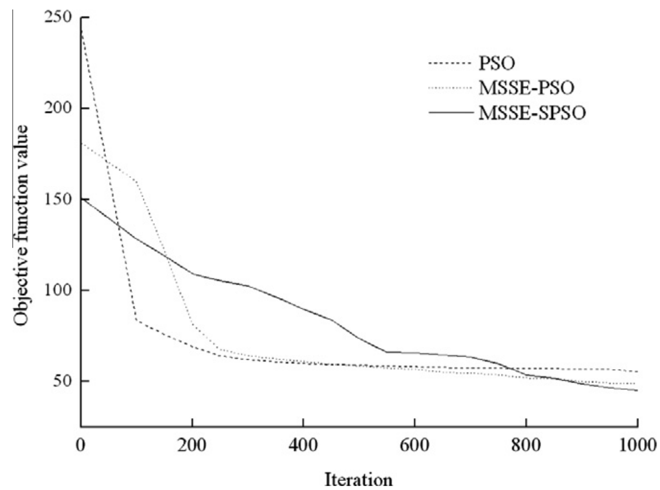

Fig. 4. Convergence progress of PSO, MSSE-PSO and MSSE-SPSO.

Table 3
Comparison of performance for PSO, MSSE-PSO and MSSE-SPSO.

Algorithm	Opt.[a]	The calibration period		The verification period	
		RE (%)	R^2	RE (%)	R^2
PSO	55.328	5.02	0.720	2.54	0.812
MSSE-PSO	48.913	4.33	0.768	1.66	0.824
MSSE-SPSO	45.124	4.29	0.776	0.62	0.903

[a] The best objective function value for 10 runs.

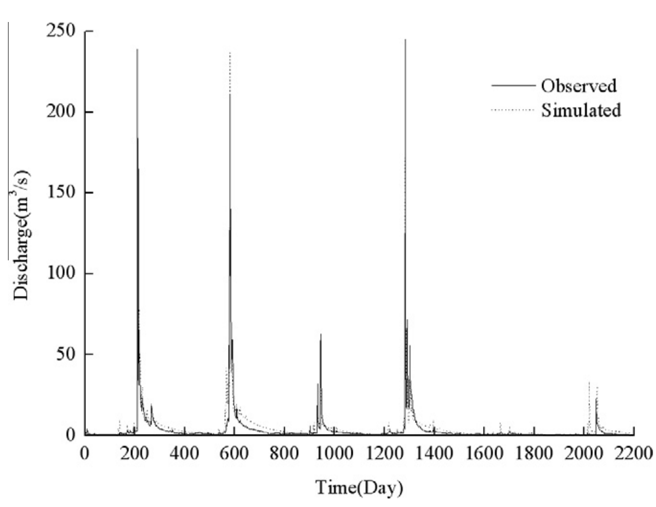

Fig. 5. Observed and simulated discharge of MSSE-SPSO in the calibration period.

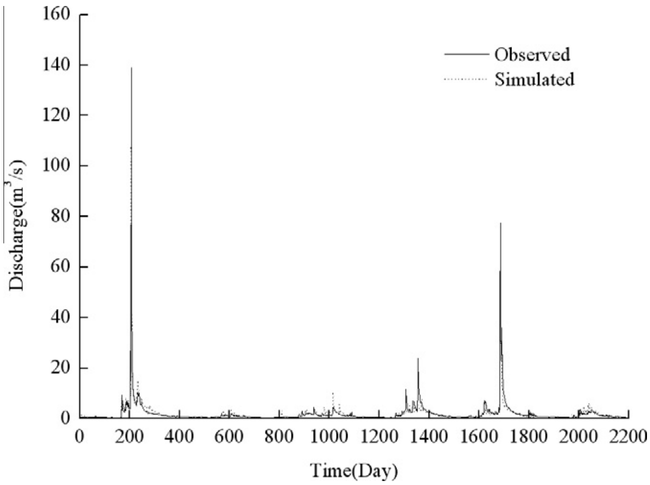

Fig. 6. Observed and simulated discharge of MSSE-SPSO in the verification period.

discharge versus observed data using the best optimal parameters obtained by MSSE-SPSO for the calibration period and validation periods, respectively. These figures show that there is very similar match between simulated and observed values. Therefore MSSE-SPSO is an effective method to calibrate hydrological model.

5. Conclusions

In this paper, we propose a master–slave swarms shuffling evolution algorithm based on self-adaptive particle swarm optimization (MSSE-SPSO), which combines particle swarm optimization with self-adaptive, hierarchical and complex shuffling evolution strategies. A dynamic adjustment on the two sensitive acceleration coefficients of PSO is imported to control the searching direction of each particle. Additionally, in order to handle premature convergence, the population is partitioned into several sub-swarms (one master swarm and other slave swarms). Each slave swarm independently executes SPSO. For the master swarm, the particles enhance themselves based on the social knowledge of master swarm and that of slave swarms. At periodic stage in the evolution, the master swarm and the whole slave swarms are forced to mix and points are reassigned to sub-swarms to ensure information sharing. Finally, the MSSE-SPSO developed in this paper is applied to calibrate HIMS hydrological model for verifying its feasibility. The experiment results show that the proposed MSSE-SPSO can remarkably improve the simulation accuracy in the calibration and verification period compared with PSO and MSSE-PSO. So, it is an effective approach to calibrate hydrological model.

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