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Automatic Calibration of Lumped Conceptual Rainfall-Runoff Model Using Particle Swarm Optimization

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Abstract: The main objective in Conceptual Rainfall-Runoff (CRR) model calibration is to find a set of optimal model parameter values that provides a best fit between observed and estimated flow hydrographs, where the traditional trial and error manual calibration is very tedious and time consuming. Recently in multi dimensional combinatorial optimization problems, meta-heuristic algorithms have shown an encouraging performance with a low computational cost. In this study as a new application of Particle Swarm Optimization (PSO) algorithm, it is applied to automatic calibration of HEC-1 lumped CRR model and the methodology is tested in two example applications: a synthetic hypothetical example and a real case study for the Gorganrood river basin in the north of Iran. The results show encouraging performance of the proposed automated methodology.

Key words: Lumped conceptual rainfall-runoff model, auto-calibration, particle swarm optimization, Gorganrood river

INTRODUCTION

Water quantity and quality mathematical modelling in water resources systems is an essential tool for effective planning, design, operation and maintenance of such systems. In recent years, due to the affordability of computing power and the increasing competency in mathematical modelling, numerical simulation models have improved in terms of sophistication and complexity and this poses a challenge for both software developers and users to provide reliable model set-up and results. The rainfall–runoff process is very complex considering the space–time variability of rainfall, soil moisture and evapotranspiration. Other relevant factors involved include land use, vegetation cover, land and channel slopes and soil drainage properties. The lack of adequate data and model imperfections has been found to limit the application of models for flood forecast. Conceptual Rainfall-Runoff Models (CRRM), aiming at predicting streamflow from the knowledge of precipitation over a catchment, have become basic tools for flood forecasting. Due to the complexity of the system studied and because of the inevitable simplifications of mathematical models that describe them, some parameters can be experimentally determined, while others may have little physical meaning. Therefore, model parameters can not be specified a priori, but have to be estimated through the comparison with field observations. This problem, referred to as model calibration, can be stated as: find a set of parameters that maximise/minimise some criteria that express the degree of agreement between simulated model outputs and measured data sets. Recent years have testified the shift from an inefficient manual trial-and-error approach usually involve making small changes to each parameter, one at a time, to more advanced automated calibration approaches for hydrologic models (Duan *et al*., 1993; Liong *et al*., 1995a; Clemens, 2001; Cooper *et al*., 1997; Franchini *et al*., 1998; Zakermoshfegh *et al*., 2008). At the same time, as a surrogate to reliability of model performance there is a need to quantify the goodness-of-fit of the calibrated model beyond pure visual graphical comparison of model output. Early optimization methods range from expert systems (Manohar *et al*., 1999; Ibrahim and Liong, 1993), Stochastic search methods such as Shuffled Complex Evolution (SCE) algorithm (Duan *et al*., 1992) and Evolutionary Algorithms (EA) (Tang *et al*., 2007) have been proven to be efficient in several applications. Within

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the water resources systems community, EA and in particular Genetic Algorithms (GA), have been applied to numerous engineering problems (Rauch and Harremoes, 1999), such as management of water systems (Cai *et al*., 2001), design of water distribution networks (Savic and Walters, 1997), optimization of sewer networks (Parker *et al*., 2000), calibration and improvement of urban drainage systems (Liong *et al*., 1995b; James *et al*., 2002). The Particle Swarm Optimization (PSO) is a newer evolutionary technique and very recently, has been shown to be a powerful optimization algorithm which was first introduced by Eberhart and Kennedy (1995), Kennedy and Eberhart (1995) and Kennedy (1997), which is motivated from the simulation of social behavior. Since no application of PSO in rainfall-runoff model calibration is addressed, in this study, as a new application of the PSO algorithm, it is applied to automatic calibration of the HEC-1 lumped conceptual rainfall-runoff model. In this regard, firstly a synthetic hypothetical example and also a historical rainfall-runoff event in the Gorganroud watershed which is located in the north of Iran are set up and then the problem of model calibration is transformed into an optimization problem. The developed PSO optimization code and the HEC-1 model are linked together in the MATLAB environment so that the PSO minimizes the error function calculated by comparing observed and simulated hydrographs.

MATERIALS AND METHODS

Case study and dataset: The methodology is demonstrated on two example applications: a synthetic hypothetical example and the case study of Gorganrood river at Tamar hydrometric station in the North of Iran, calibrated for flood hydrograph. The synthetic example was created and a flood hydrograph calibration was performed using synthetically generated data. Since predefined parameters were used to create the synthetic data set, the expected calibration results were known before calibration. In this example a 250 mm rainfall event was temporally distributed over a 1000 km^2 watershed with a 50 m^3 sec^{-1} base flow. The exponential loss rate method with four variables (STRKR, DLTKR, RTIOL and ERAIN) and the Clark unit hydrograph method with two parameters (T_c and R) were used to create the example. The second application is performed for a real rainfall-runoff event occurred on May 5-6, 2005 in the Gorganrood river basin at Tamar hydrometric station, north of Iran with a 2205.2 km^2 basin area. Eight daily rain-gauges (PD_1, ..., PD_8) and three recording rain-gauges (PR_1, PR_2 and PR_3) have recorded the rainfall event and the flood hydrograph has been recorded at the Tamar hydrometric station which are shown in Fig. 1. The SCS curve number loss method and the Clark unit hydrograph method was applied for model calibration. Therefore, 15 calibration parameters (eight weighting factors for daily rain-gauges, three weighting factors for recording rain-gauges, two parameters related to the SCS curve number loss method and two parameters related to the Clark unit hydrograph method) were used to model auto-calibration. In both applications, the Sum of Absolute Errors (SAE) is calculated and the PSO algorithm has tried to minimize this objective function which is calculated as follows:

$$\mathrm{SAE} = \sum_{i=1}^{n} \left| Qt_i - Qc_i \right| \tag{1}$$

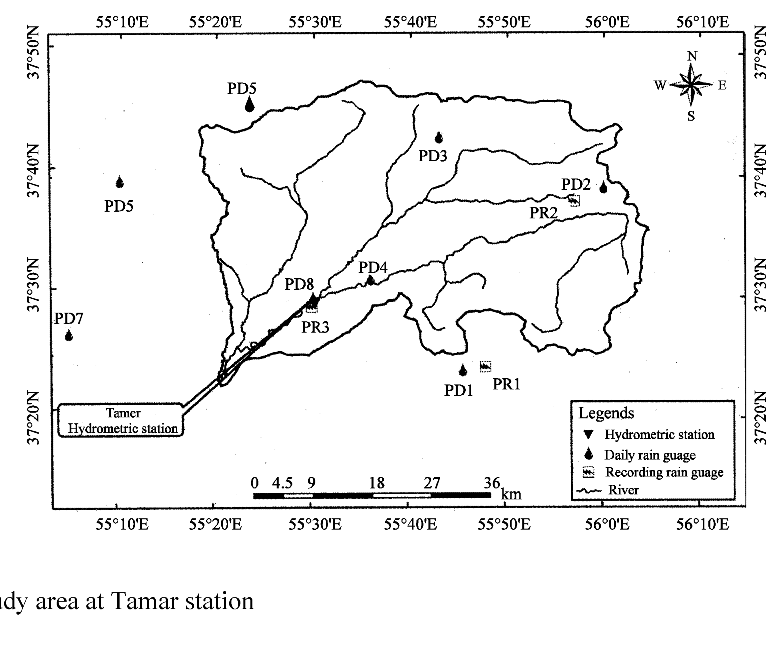

Fig. 1: Gorganrood study area at Tamar station

where, Qt is the target discharge, Qc is the computed discharge and n is the number of hydrograph ordinates.

Lumped conceptual rainfall-runoff model: The HEC-1 model is designed to simulate the surface runoff response of a river basin to precipitation by representing the basin as an interconnected system of hydrologic and hydraulic components. Each component models an aspect of the precipitation-runoff process within a portion of the basin, commonly referred to as a sub-basin. A component may represent a surface runoff entity, a stream channel or a reservoir. Representation of a component requires a set of parameters which specify the particular characteristics of the component and mathematical relations which describe the physical processes. The result of the modeling process is the computation of streamflow hydrographs at desired locations in the river basin (USACE, 1998). Figure 2 represents the typical watershed runoff procedure in HEC-1 model.

The total storm precipitation for a sub-basin may be computed as the weighted average of measurements from several gages. The Soil Conservation Service (SCS), U.S. Department of Agriculture, has instituted a soil classification system for use in soil survey maps. Based on experimentation and experience, it has been able to relate the drainage characteristics of soil groups to a curve number, CN. The SCS provides information on relating soil group type to the curve number as a function of soil cover, land use type and antecedent moisture conditions. Precipitation loss is calculated based on supplied values of CN and I_a (where I_a is an initial surface moisture storage capacity in units of depth). CN and I_a are related to a total runoff depth for a storm by the following relationships:

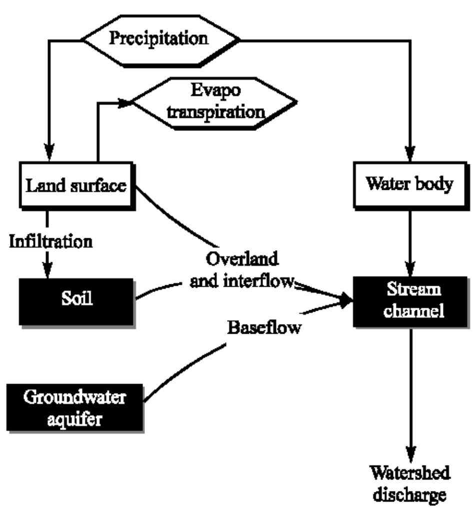

Fig. 2: Typical HEC-1 representation of watershed runoff (USACE, 1998)

$$Q = \frac{(P - I_a)^2}{(P - I_a + S)} \quad (2)$$

$$S = \frac{25400 - 254 \times CN}{CN} \quad (3)$$

where, Q is the accumulated excess rainfall in mm, P is the accumulated rainfall depth in mm and S is the currently available soil moisture storage deficit in mm.

The Clark unit hydrograph method is applied in this study as the excess rainfall transformation method. It requires three parameters to calculate a unit hydrograph: T_c, the time of concentration for the basin, R, a storage coefficient and a time-area curve. A time-area curve defines the cumulative area of the watershed contributing runoff to the sub-basin outlet as a function of time (expressed as a proportion of T_c).

Particle swarm optimization: Particle Swarm Optimization (PSO) was originally designed and introduced by Eberhart and Kennedy (1995). The PSO is a population based search algorithm based on the simulation of the social behavior of birds, bees or a school of fishes. This algorithm originally intends to graphically simulate the graceful and unpredictable choreography of a bird folk. A vector in multidimensional search space represents each individual within the swarm. This vector has also one assigned vector, which determines the next movement of the particle and is called the velocity vector. The PSO algorithm also determines how to update the velocity of a particle. Each particle updates its velocity based on current velocity and the best position it has explored so far and based on the global best position explored by swarm (Engelbrecht, 2005, 2007; Sadri and Suen, 2006). The PSO process then is iterated a fixed number of times or until a minimum error based on desired performance index is achieved. It has been shown that this simple model can deal with difficult optimization problems efficiently.

A detailed description of PSO algorithm is presented by Eberhart and Kennedy (1995). A short description of the PSO algorithm is given. Assume that our search space is d-dimensional and the i-th particle of the swarm can be represented by a d-dimensional position vector X_i $(x^1_i, x^2_i,...,x^d_i)$. The velocity of the particle is denoted by V_i $(v^1_i, v^2_i,..., v^d_i)$. Also consider best visited position for the particle is P_{ibest} $(p^1_i, p^2_i,...,p^d_i)$ and also the best position explored so far is P_{gbest} $(p^1_g, p^2_g,...,p^d_g)$. So, the position of the particle and its velocity is being updated using following equations:

$$v_i(t+1) = w.v_i(t) + c_1\varphi_1(p_i(t) - x_i(t)) + c_2\varphi_2(p_g(t) - x_i(t)) \quad (4)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (5)$$

where, c_1 and c_2 are positive constants and φ_1 and φ_2 are two uniformly distributed number between 0 and 1. In Eq. 4, W is the inertia weight which shows the effect of previous velocity vector on the new vector. The inertia weight W plays the role of balancing the global and local searches and its value may vary during the optimization process. A large inertia weight encourages a global search while a small value pursues a local search. Mahfouf *et al.* (2004) have proposed an Adaptive Weighted PSO (AWPSO) algorithm in which the velocity formula of PSO is modified. Another application of AWPSO algorithm is addressed by Shakiba *et al.* (2008).

RESULTS AND DISCUSSION

The PSO algorithm is linked to the HEC-1 rainfall-runoff model in the MATLAB environment so that the PSO minimizes the error function calculated by comparing observed and simulated hydrographs.

Synthetic hypothetical example: The six parameters (i.e., initial value of loss coefficient, initial loss, loss coefficient recession constant, exponent of precipitation, time of concentration and storage coefficient) were involved in the optimization process as independent variables. The PSO algorithm with twenty particles and one hundred epochs was performed in such a way that each independent variable could vary in its feasible domain (variable range). The result of model auto-calibration is shown in Table 1 in which the sum of absolute errors between target and computed hydrographs is 230 m^3 sec^{-1}.

Figure 3 shows the graphical agreement between target and auto-calibrated hydrographs beside the rainfall hyetograph. These results show that the proposed methodology is able to find the near optimal solution in a multi-dimensional search space. Hence, it can be confidently applied for real rainfall-runoff model calibration cases.

Gorganrood catchment case study: As described in the material and methods section, a rainfall-runoff event has been occurred on May 5-6, 2005 over the Gorganrood river basin and the flood hydrograph is recorded at Tamar hydrometric station. Fifteen model parameters were introduced in the material and methods were mentioned as independent variables to minimize the calibration objective function which is the sum of absolute errors. Table 2 shows the results of lumped conceptual rainfall-runoff model auto-calibration. In Table 2, the feasible domain and optimized values of model parameters are listed whereas the calibration error is 916 m^3 sec^{-1}. In Fig. 4, good agreement between observed and calibrated hydrographs in both peak discharge and hydrograph shapes is seen and it is concluded that the proposed methodology also has a reliable performance in a real case study.

Table 1: Results of model auto-calibration in synthetic example

Parameters	Description	Variation range	Predefined value (Target)	Optimized value	Error (SAE)
STRKR	Initial value of loss coefficient (mm h^{-1})	1-20	5	8.70	
DLTKR	Initial loss (mm)	300-400	350	341.40	
RTIOL	Loss coefficient recession constant	0.5-5	2	2.55	230
ERAIN	Exponent of precipitation	0.1-2	0.5	0.52	
T_c	Time of concentration (h)	1-20	6	6.10	
RTIOL	Storage coefficient	0.1-10	1	0.10	

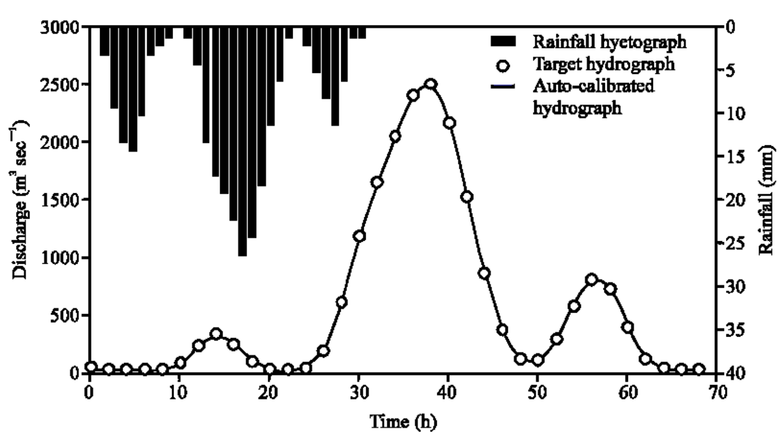

Fig. 3: Target and auto-calibrated hydrographs in synthetic example

Table 2: Results of model auto-calibration in Gorganrood river case study

Parameter	Description	Variation range	Optimized value (auto-calibrated)	Error (SAE)
[WPD_i]	Daily rain-gauge weighting factor	0-1	[0.39,0,0,0.07,1, 0.41,0.29,1]	
[WPR_i]	Recording rain-gauge weighting factor	0-1	[1,0,0.71]	
CN	Curve No.	50-90	71.6	916
I_a	Initial abstraction (mm)	5-50	23.1	
T_c	Time of concentration (h)	2-15	2.0	
RTIOL	Storage coefficient	0.1-20	0.1	

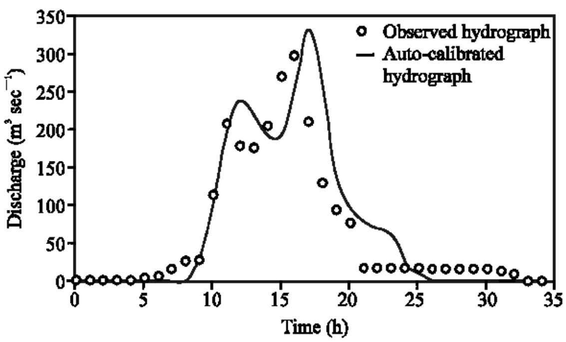

Fig. 4: Target and auto-calibrated hydrographs in Gorganrood river case study

CONCLUSION

Lumped Conceptual Rainfall-Runoff (LCRR) models have a variety of parameters which most of them have no physical sense and therefore the manual trial and error calibration of these models is often a time consuming and boring task. A methodology for automatic calibrating of the HEC-1 LCRR model is presented. The calibration procedure is firstly transferred to an optimization problem and then as a new application of the PSO algorithm, it is linked to the LCRR model for parameter optimization. Two examples, a synthetic hypothetical with six calibrating parameters and a real case study for the Gorganrood river basin in the north of Iran with fifty calibrating parameters are implemented. In both cases the hydrograph shape and peak discharge are beneficially achieved and it is concluded that the proposed methodology is able to find the near optimal solution so that it can be applied as a powerful tool for model auto-calibration.

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