Calibration of Watershed Conceptual Models Using Local and Global ptimization

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Abstract:

Many issues related to water resources require the solution of optimization problems. Optimization problems can be quite difficult such as the calibration of many conceptual watershed models. Conceptual watershed models are formulated using empirical relationships between hydrological variables observed in nature or field experiments .The success of automatic calibration depends mainly on the choice of optimization method. Most early attempts to calibrate watershed models have been based on local-search optimization methods. Local optimization methods are not designed to handle the presence of multiple regions of attraction, multi-local optima, insensitivities and parameter interdependencies, and other problems encountered in the calibration of watersheds models. It is therefore imperative that global optimization procedures that are capable of dealing with these various difficulties be employed.

In this study, one local search optimization method and one global search method are used to calibrate the parameters a simple ten-parameter rainfall-runoff model. The local search method is the well known Rosenbrock's direct search method; the global search method is the newly developed Shuffled Complex Evolution (SCE) method . The results revealed that Shuffle Complex Evolution optimization method is more superior to Rosenbrok’s direct search method. The results confirmed the finding of many watershed modellers about the dependency of Rosenbrock’s method on the choice of initial search points. It further adds that Rosenbrock’s method is only effective when the initial search points are taken within 5 % or less from the true optimum parameter set. The results indicate that a proper choice of optimization methods can enhance the possibility of obtaining unique and conceptually realistic parameter estimate.

Keywords : Watershed models calibration; Rainfall-Runoff models ; Global optimization; Local optimization

معايرة نماذج أحواض التصريف التصورية باستخدام طرق الأمثلية الموضعية والعالمية

ملخص البحث :- هناك العديد من القضايا المتعلقة بالموارد المائية تتطلب الحلول المثلى. مسائل الأمثلية يمكن أن تكون معقدة مثل معايرة العديد من النماذج التصورية لأحواض التصريف. النماذج التصورية لأحواض التصريف يتم صياغتها بأستخدام العلاقات التجريبية بين المتغيرات الهيدرولوجية الملاحظة في الطبيعة أو التجارب الحقلية.

نجاح المعايرة الأتوماتيكية يعتمد في الأساس على اختيار طريقة

الأمثلية. معظم المحاولات السابقة لمعايرة أحواض التصريف أعتمدت في الأساس على طرق الأمثلية الموضعية. طرق الأمثلية الموضعية لم تصمم للتعامل مع وجود المناطق المتعددة الانجذاب والمناطق المثلى الموضعية وانعدام الحساسية والاعتماد المتبادل للوسائط ، وكذالك التعامل مع الصعوبات الأخرى التي يتم مواجهتها عند معايرة نماذج أحواض التصريف. لذا فقد بات ضروريا وملحا احلال وسائل وطرق الأمثلية العالمية القادرة على التعامل مع هذه الصعوبات المتعددة.

في هذه الدراسة احدى طرق الأمثلية للبحث الموضعي وأخرى للبحث العالمي تم استخدامها لمعايرة وسائط نموذج حوض تصريف مبسط يحتوي على عشرة وسائط. طريقة البحث الموضعية المستخدمة هي تلك المعروفة جيدا والمسماه بطريقة روسينبروك للبحث المباشر ، أما طريقة البحث العالمية فهي تلك المبتكرة حديثا والمعروفة بطريقة تحسين وخلط المجموعات.

أظهرت النتائج المستحصلة بأن طريقة تحسين وخلط المجموعات كانت أكثر تميزا وسرعة عن طريقة روسينبروك للبحث المباشر. أكدت نتائج هذه الدراسة ماجاء في تقارير الكثير من الباحثين العاملين في حقل نمذجة أحواض التصريف بأعتماد طريقة روسينبروك للبحث المباشر على القيم الأولية المختارة للبحث .

تضيف النتائج المستحصلة من هذه الدراسة بأن فعالية طريقة روسينبروك للبحث المباشر تكون فقط عند اختيار القيم الأولية للوسائط في حدود **5 %** أو أقل من القيم المثلى العالمية لتلك الوسائط. أظهرت النتائج المستحصله بأن الاختيار المناسب لطريقة الأمثلية يمكن أن يعزز من فرص الحصول على تحديد دقيق ومنطقي لقيم الوسائط لأي نموذج.

1. Introduction

The advent of powerful desktop computer has allowed the modeling of hydrologic systems to develop to the point where sophisticated multi-parameter models are now used by many in government agencies, consulting firms and industry to decide water management issues. The complexity of these models makes meaningful calibration difficult, if not impossible, for non-expert users. The need to find the optimal solution to a problem is virtually encountered in every area of human endeavor in areas such as mathematics, engineering design, economic, medicine, telecommunication, river forecasting and many others. Two broad approaches of mathematical rainfall-runoff models for application to a given watersheds. In the first, values are estimated from available knowledge of the processes or from measurements of physical properties of the watershed. In the second approach, parameter values are found by a systematic optimization technique. The intention is to achieve the best possible reproduction of observed runoff in terms of some chosen objective function. The reliability of operational conceptual rainfall-runoff models used in forecasting is highly dependent on the adequacy of the calibration procedures employed. In many applications that are met in practice, a highly accurate solution is neither possible nor feasible. Particularly, it may be impossible because of uncertainties and inaccuracies in the underlying model or data, or it may it may be infeasible due to the unacceptable high computational effort required to attain it. Taking in view the above mention facts, this study was aimed to assess the performance and effectiveness of global and local optimization algorithm in locating global optimum starting from any population of points and also to compare their convergence speed.

2. Concept of Calibration

To obtain the best match between simulated outputs from the model and observed outputs from the watershed, the parameters of the model need to be tuned. The process of tuning model parameters is called model calibration. The calibration process requires a procedure to evaluate the success of a given calibration and another procedure to adjust the parameter estimates for the next calibration.

In general, the object of calibration is to minimize the difference between observed and simulated flows. The mathematical representation of this difference is called objective function. There are two broad approaches to watershed model calibration: manual and automatic.

2 . 1 Manual Calibration

In manual approach, trial and error procedures are used to estimate model parameters. Model knowledge and a multitude of model performance measures (i.e., objective functions) along with human judgment and visual aids combine to determine the best guesses for model parameters. This process is less prone to the effect of the noises in calibration data, but it demands a high level of understanding of the model physics.

2 . 2 Automatic Calibration

In automatic approach, model calibration problem is formulated as an optimization problem so computer based optimization methods can be employed to locate the optimal model parameters. This process takes advantage of a myriad of optimization methods available and relies on computer speed and power to perform the mundane task of finding the optimal parameters with respect to a given objective function (s). Automatic calibration procedures can be generalized for use on different models and can be easily grasped by no means a trivial exercise at all.

The automatic estimation technique consists of three elements: (1) objective function (2) optimization algorithm and (3) calibration data.

Much research has been done to study one or more of these factors (Ibbitt 1972; 1983; Kuzera 1983 a&b; Sorooshian and Gupta 1983, 1985 ; Gan and Bitfu 1996 ; among others).

3. Local Optimization

Sophisticated optimization methods have been used widely to calibrate the parameter of watershed models since the very beginning of the digital watershed-modeling era. Most early attempts to calibrate watershed models have been based on local-search optimization methods (Dawdy and O'Donnel 1965; Nash and Sutcliffe 1970; Ibbitt 1971; Jonston and Pilgrim 1976; Pickup 1977; Sorooshian and Gupta 1983; Sorooshian and Gupta 1985; Hendrickson et al. 1988; etc).

The popularity of local-search methods is mostly due to the fact that the computer capability was very limited and local search methods required relatively small computer processing units (CPU). There are two broad categories of local search methods: direct type and Gradient type.

3 .1 Direct Type

Direct type methods (e.g., the Axis-Rotating of Rosenbrock (1960), the Pattern Search (PS) method of Hooke and Jeeves (1961) and the Simplex method of Nelder and Mead (1965) all place few limitations on the form of model equations, and require only that knowledge of the objective function values be available over the feasible parameter space.

3 . 1 . 1 Rosenbrock's Method

This method has been developed by Rosenbrock's in (1960). The method aims to find the minimum or maximum of multivariable, unconstrained and constrained nonlinear functions. In this method, the coordinate system is rotated in each stage of minimization in such a manner that the first axis is oriented towards the locally estimated direction of the valley and all other axis are made mutually orthogonal and normal to the first one.

4. Optimization Methods Comparative Studies

Ibbitt (1971) conducted the first comprehensive comparative study of different optimization methods for calibration of the Stanford Watershed Model (SWM) (Crawford and Linsley 1966) and the O, Donell Model (Dawdy and O' Donnel 1965). Eight local search optimization methods and one global search method were included in the study. The local search methods included direct type methods such as the Rosenbrock's Method (Rosenbrock 1960) and gradient type methods such as Powell’s conjugate direct search method (Powell 1964); the global search method was a simple random search method (Karnopp 1963). He reported that the effectiveness of local search methods was highly dependent on the choice of initial search points, the Rosenbrock's method was the most effective among the different local search methods he tested. He pointed out that Karnopp’s random search method was unable to obtain good estimate of the global optimum, even though it might be helpful in finding good starting points for a subsequent local search.

Johnston and Pilgrim (1976) used the simplex method (Nelder and Mead 1965) and a gradient method known as the Davidon method (Fletcher and Powell, 1963) to calibrate the Bougton model. They reported that both methods failed to locate a true set of optimal parameters. Pickup (1977) was unable (using an automatic approach) to obtain the “true “values of the Bougton model’s parameters, even under ideal condition (created by assuming a perfect set of parameters and using synthetic data).

Ibbitt and O’Donnel(1971) and Johnston and Pilgrim (1976) list the following features of conceptual Rainfall-Runoff models and their automatic calibration procedures as the primary reasons for the above mention problems:

(i) Interdependence between model parameters

(ii) Indifference of the objective function to the values of “inactive” (threshold type) parameters

(iii) Discontinuities of the response surface.

(iv) Presence of local optima due to the non-convexity of the response surface.

Duan et al. (1992) conducted a detailed investigation into the problems associated with optimizing watershed model parameters.They employed an exhaustive girding method to examine the objective function and derivative surface of the SIXPAR model.

Their findings are summarized as follows:

(i) The parameter space contains several major regions of attraction into which a search strategy may converge

(ii) Each major region of attraction contains numerous local minima.

(iii)The objective function surface in the multi-parameter space is not smooth and may not even be continuous. The derivative is discontinuous and may vary in an unproductive manner throughout the parameter space.

(iv)The parameter exhibits varying degrees of sensitivity and a great deal of nonlinear interaction and compensation near the region of global optimum.

They have concluded that the combination of these features makes local-search methods inherently incapable of finding the global optimal parameters for most of watershed models.

5. Global Optimization

In practice, there are many problems that cannot be described analytically and many objective functions have multiple extrema. In these cases it is necessary to pose multi-extremum (global) optimization problem where the traditional optimization methods are not applicable. One of the approaches to solve a global optimization problem that has become popular during the recent years is the use of the so-called Shuffled Complex Evolution (SCE) method (Duan et al 1992), which is now widely use in many applications related to water resources problems. Other global optimization methods that are commonly used for calibration of watershed models are; Simulating Annealing (SA) ((Kirkpatrick et al. 1983) and Genetic Algorithm (Holland 1975). A considerable number of publications related to water resources are devoted to their use (Abdullah et al. 2000; Wang 1991; Savic & Walters 1997; Franchini & Galeati 1997).

5.1 Shuffled Complex Evolution Method

The shuffled complex evolution (SCE) method is a heuristic global optimization scheme that became quickly one of the most popular among water resources engineers. According to the algorithm, a random set of points is sampled and partitioned into complexes. Each of them is allowed to evolve in the direction of global improvement, using competitive evolution techniques based on the downhill simplex method. At periodic stages, the entire set of points is shuffled and reassigned to new complexes, to enable information sharing. The combination of competitive evolution and shuffling ensures that the information gained by each of the individual complexes is shared through the entire population. SCE method is based on a synthesis of four concepts**:**

(a) Combination of deterministic and probabilistic approaches

(b) Systematic evolution of a complex of points spanning the parameter space, in the direction of the global improvement

(c) Competitive evolution

(d) Complex shuffling

The first three concepts are drawn from existing methodologies that have been proven successful in the past including GA, simplex and CRS methods (Price 1983,1987; Nelder and Mead 1965; Holland 1975), while the last concept is newly introduced by Duan (1992).

6. Conceptual Rainfall-Runoff Model

The model used was a simple ten-parameter conceptual rainfall-runoff (Abdulnoor , 2003). The model is based in on water balance of the land phase, the he major input requirements for this model are the hourly rainfall, potential evaporation and streamflow record and the main output from the model are hourly stream flow and peak flow rate. The general structure for this model is shown in Fig. 1.

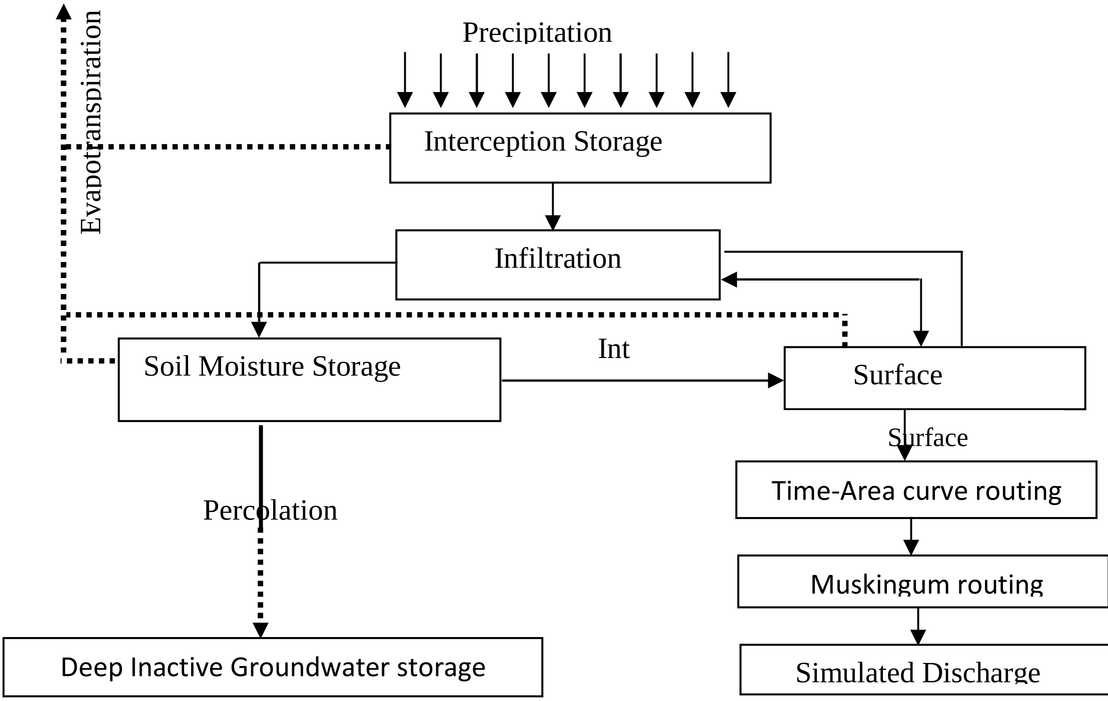

Fig. 1. Structure of the model used in this study

The model has ten parameters all are fitted by employing optimization technique. These parameters are; Holtan equation parameters, namely the intercept a, the slope n and the steady state constant infiltration rate fc, interflow coefficient Sc, maximum surface depression storage capacity Dmax, recession coefficient Kr; the Muskingum equation two parameters, x and k, Initial soil moisture storage capacity Sa and the number of catchment wetted areas NA. These parameters are all shown with their upper and lower bound in table 1.

Table 1. The model parameters with their upper and lower Bound

Parameter	Lower Bound	Upper Bound
a	0.08	0.9
n	0.1	1.5
fc (mm/hr)	1.27	3.8
Sc	0.0	0.9
Dmax (mm)	10.0	30.0
Kr	0.1	0.99
K (hr)	0.0	7.0
X	0.0	0.5
Sai (mm)	0.0	141.3
NA	1.0	9.0

The data for the simulation example in this study are collected from one ephemeral semi arid catchment located at the central part of Jordan. These data were considered to some extent sufficient for fitting the model parameters at the test catchment. The available hourly rainfall data and streamflow record along with other climatic variables were obtained for a period (1990 to 2001). Ten different storms are selected for fitting the model parameters . The storms are divided into two parts; the first for calibration and the second for validation. The storms used in calibration are inserted into the model continuously so that the resulted optimal parameters will represent the average for all events. The model was fitted to the runoff time series of the five selected events using the least square objective function.

7. Model Calibration Using Rosenbrock's Direct Search Method

The program code for unconstrained Rosenbrock's optimization method is taken from Kuester (1973). Some modification is made to restrict the parameters within the given limits so that upper and lower bounds of the parameters can not be violated.

The input requirements for this program are : number of independent variables, maximum number of times program is to evaluate objective function, maximum number of time axis are to be rotated, number of successive failures encountered in all directions before termination, error in objective function to be reached before program terminates, control variable determining step size to be used after each rotation of axis, scaling factor for step size increases (α), scaling factor for step size reduction (β) and control variable to change the operation mode to optimization or evaluation.The program starts by picking a set of initial values already assigned for each parameter. These values are within the specified bounds. Initial step size of 0.1 and 0.01 are used in operation of the program. The chosen values of α and β were 3.0 and 0.5.

The program terminates when the following condition are met:

(1) The difference between current and previous objective function is equal to or less than convergence criteria, which is here (10-4).

(2) Number of successive failure encountered is equal to or greater than maximum allowable number of failure (here, it is taken as 100).

(3) Number of times the objective function is evaluated is equal to or greater than maximum allowable number (it is taken here equal to 10000 iterations).

To test the ability of Rosenbrock's direct search method in locating the global optima from a set of initial search points we chose sex different sets and we use theme as an initial input values for the model parameters. An equal number of program runs were also carried out for all the selected parameter sets.

In the first run of the program , the parameter set was taken closer to the lower bound of parameters. In the second run initial parameter set was taken equal to the output set resulted from the first run. This process is followed consequently in both third and fourth runs. In the fifth run the chosen parameter set was taken closer to the upper parameters bound whereas, in the last run the initial parameter set was taken equal to the intermediate values of the upper and lower bounds of the parameters. These procedures are clearly illustrated in table 2.

8. Model Application Using Shuffle Complex Evolution Global Optimization Method

The computer code for this optimization method has been provided by Dr.Q.Duan (the developer of this method).

The input requirements for this program are as follows :

(1)Maximum number of trials allowed (adopted equal to 90000 trials).

(2)Number of shuffling loop in which the criterion must improve by the specified percentage (taken equal to 19 shuffling loop).

(3)Percentage by which the criterion value must change in the specified number of shuffling loops (adopted equal to .001).

(4)Number of complexes used for optimization search (adopted equal to 8 complexes).

(5)Random seed used in optimization search (adopted equal to 10).

(6)Flag for setting the control variables of the SCE algorithm

(adopted equal to 0 for optimization and 1 for validation).
(7)Number of points in each complex (adopted equal to 21).
(8)Number of points in each sub-complex (adopted equal to 11).
(9)Number of evolution steps taken by each complex before next shuffling (adopted equal to 21).
(10) Minimum number of complexes required for optimization search, if the number of complexes is allowed to reduce as the optimization search proceeds (adopted equal to 8).
(11) Flag on weather to include the initial points in the starting population (equal to "1" if initial points are to be included and "0" if initial point is not to be included; here it is adopted equal to "1").
(12) Print-out control flag (equal "0" to print out the best estimate of the global optimum at the end of each shuffling loop, or equal to "1" to printout every point in the entire sample [here it is adopted equal to "0"]).
(13) Initial estimates of the parameters to be optimized with their upper and lower bounds.

Three stopping criteria are used to terminate SCE-UA these are as follows :
(1) The objective function does not change by 0.01 % in 19 consecutive shuffling loops.
(2) The change in objective function and parameters values is less 0.0001.
(3) The number of iterations is greater than 90000 iterations.

To investigate the effectiveness and efficiency of SCE method, procedures similar to those implemented under the application of Rosenbrock's direct search method were conducted. This is clearly presented in table 2.

A detailed investigation on the effect of selecting different initial random seed incorporated with numerous consecutive number of program runs was conducted. The average number of function evaluations that is required by the program to converge toward the global optimum was also estimated for each consecutive program run, the values are all provided in table 3. The values of objective function associated with each run of the program are also provided in the same table.

A detailed study on interdependence between the model parameters was conducted. The effect of varying the initial random seed on the final optimum set of the parameter was also studied. Ten consecutive program runs were carried out. The global optimum parameter set resulted from each run was obtained and is presented in table 4. for the seek of comparison.

Table 2. Performance and Effectiveness of Rosenbrock's and shuffle complex evolution optimization

Initial parameter set at the start of run	Rosenbrock's direct search optimization method		Shuffle complex evolution global optimization method	
	Objective function (m3/s)	Number of function evaluations	Objective function (m3/s)	Number of function evaluations
(1) Values are taken closer to the lower bound .	8663.31	2177	6240	12532
(2) The output from the first run is taken as initial set for the current run.	8662.19	11	6240	12532
(3) The output from the second run is taken as initial set for the current run.	8662.19	11	6240	12532
(4) The output from the third run is taken as initial set for the current run.	8662.19	11	6240	12532
(5) Values are taken closer to the upper bound.	185313	2	6240	12532
(6) Values are taken intermediate of the upper and lower bound.	185313	2	6240	12532

9. Results Discussions

Generally, the experimental results revealed that the performance of SCE optimization method has proven to be more effective, efficient and robust than Rosenbrock's direct search method. This interested fact is clearly illustrated in table 2.

Unlike Rosenbrok's direct search, Shuffle Complex Evolution optimization method was found insensitive to any change in the values of initial search points, since at all runs the resulted objective function remains unchanged. Rosenbrock's direct search optimization method has been found more dependent on the choice of initial search points. In all program runs Rosenbrock's direct search failed to locate the global optimum objective function and the corresponding global optimum parameter set, it is found likely to climb at local minima.

Rosenhrock's direct search method was found capable in locating the global optimum only when the initial search points were taken very close to optimum parameters values (i.e., the initial search points values are within 5 % or less of the optimum parameter set).

The effectiveness of SCE method is measured by its capability to locate the global optimum starting from any initial population of points. Table 3. Illustrate that in most of consecutive program run, there has been very minor variation in the final value of objective function, and hence we can observe that changing the initial sets of random seed would have a very slight effects on the final global optimum. Table 3. Shows another performance indicator for SCE method called; the reliability or robustness of optimization algorithm, which is measured by the number of successes in finding the global optimum, or at least approaching it sufficiently closely. In all consecutive run, the number of success in finding the global optimum was much greater than number of failure. The efficiency of SCE algorithm is measured also by the number of function evaluations needed, the SCE method was capable to locate the global optimum with a minimum number of iteration or function evaluations, the global optimum was approached in most of run with a number of iteration equal to one sixth of the maximum number of iteration fixed by the author see table 3.

Parameters correlation was also studied when Shuffle Complex Evolution optimization is used in calibration. Table 4. shows the results of several consecutive model runs incorporated with different set of initial random seeds. It has been found that nearly all parameters have got very close values, and the effects of changing initial parameter set on the final optimal parameter set was very minor. It has been noted that slight improve could be achieved to the objective function obtained using SCE method. This could be realized when the optimum parameter set obtained by SCE method is taken as initial search points for Rosenbrock's direct search method.

10. Conclusions

When the region of the parameters response surface contains one or more local optima just like the multiple extrema function of the model used in this study, Rosenbrock’s direct search optimization method has failed to locate the global optimum corresponding to the lowest objective function. It was found more dependent on the choice of the initial search points. Rosenbrock’s direct search method was found more effective, when initial search points are taken within 5 % or less from the true optimum. Shuffle Complex Evolution SCE optimization method has been found very successful in locating the true optimum points corresponding to the lowest objective function. More-over, it was found insensitive to the choice of initial search points. Unlike Rosenbrock’s direct search method, which is also failed in obtaining the true global optimum parameters set, Shuffle Complex Evolution method was found more able to obtain true global optimum parameters set. The true global optimum parameters set obtained using SCE optimization method has been found slightly effected when a change is made to the values of initial search points. SCE found more reliable than Rosenbrock's direct search since the number of successes encountered in all program runs was greater than the number of failure encountered during the same runs. After extended analysis, the SCE algorithm was proved more effective, efficient and reliable than Rosenbrock's direct search algorithm. The findings obtained in this study are found identical with other findings obtained by numerous researchers which all concluded that global optimization algorithms are more powerful and superior than traditional local optimization algorithms. This has made a global optimization algorithm such as SCE is now becoming the most widely used among hydrologists and water resources engineers.

Table 3. Effect of using different set of initial random points on the final value of objective functio obtained using SCE optimization method

Number of consecutive Program Runs	Initial Random Seeds used	Objective function Obtained with each run (m3/s)										Ave Num Fun Evalu duri r
		First Run	Second Run	Third Run	Forth Run	Fifth Run	Sixth Run	Seventh Run	Eighth Run	Ninth Run	Tenth Run	
1	2	6240										12
2	2,3	7320	6240									16
3	2,3,5	7320	6240	6240								15
4	2,3,5,7	7320	6240	6240	6240							15
5	2,3,5,7,11	7320	6240	6240	6240	6240						15
6	2,3,5,7,11,13	7320	6240	6240	6240	6240	7330					15
7	2,3,5,7,11,13,17	7320	6240	6240	6240	6240	7330	6240				15
8	2,3,5,7,11,13,17,19	7320	6240	6240	6240	7320	7330	6240	6240			14
9	2,3,5,7,11,13,17,19,23	7320	6240	6240	6240	7320	7330	6240	6240	6240		15
10	2,3,5,7,11,13,17,19,23,29	7320	6240	6240	6240	7320	7330	6240	6240	6240	6240	15

Table 4. Effects of varying the initial random seed on the final optimum parameter set obtained using SCE optimization method

Program Runs	Initial Seed used with each run	Optimum parameters values										Number function evaluatio
		a	n	fc	Sc	Dmax	Kr	K	x	Sai	NA	
First	2	0.136	0.482	1.376	0.485	29.998	0.914	3.639	0.064	0.05	4.051	17768
Second	3	0.499	0.624	1.405	0.499	10.021	0.902	3.289	0.002	15.275	5.24	15327
Third	5	0.9	0.568	1.405	0.412	10	0.902	3.288	0.002	10.884	5.883	14731
Fourth	7	0.654	0.393	1.432	0.772	18.757	0.908	2.751	0	11.08	6.105	12653
Fifth	11	0.9	0.448	1.405	0.51	10.001	0.902	3.287	0.002	15.205	5.033	16440
Sixth	13	0.478	0.432	1.377	0.442	27.029	0.914	3.636	0.065	0.004	4.695	13938
Seventh	17	0.321	0.803	1.406	0.447	10.003	0.902	3.285	0.002	13.884	5.929	14324
Eighth	19	0.265	0.598	1.406	0.639	10.001	0.902	3.285	0.002	19.372	5.97	11862
Ninth	23	0.633	0.404	1.406	0.62	10.056	0.902	3.285	0.002	18.486	5.125	19675
Tenth	29	0.454	0.481	1.406	0.608	10.002	0.902	3.285	0.002	18.756	5.499	18145

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