Various continuous harmony search algorithms for web-based hydrologic parameter optimisation

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Abstract: This study compares five different harmony search algorithms that consider continuous variables inherently for the hydrologic parameter calibration. A rainfall intensity assessing model, which can provide stochastic rainfall sizes used for various structure designs, is optimally calibrated with the harmony search algorithms. The results showed that three different harmony search algorithms found better parameter values for the rainfall intensity model than mathematical optimisation technique (Powell method) and evolutionary computation technique (genetic algorithm) with respect to root mean square error (RMSE). Also, in order to enhance user-friendliness in utilising this technique, a web-based technique was developed, which optimally performs parameter calibration and presents its result on a digital map without requiring software installation.

Keywords: harmony search; HS; optimisation; parameter calibration; rainfall intensity modelling; VBScript; Google Maps.

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1 Introduction

So far, many phenomenon-inspired optimisation algorithms (POA), such as genetic algorithms (GA), simulated annealing (SA), tabu search (TS), ant colony optimisation (ACO) and harmony search (HS), have been originally developed to solve discrete combinatorial problems (Goldberg, 1989; Kirkpatrick et al., 1983; Glover, 1977; Dorigo et al., 1996; Geem et al., 2001). However, practical applications sometimes request modified techniques which handle continuous variables, especially in the example of model parameter calibration.

As for hydrologic models, whose results can provide stochastic size information used for the designs of various hydraulic and hydrologic structures such as storm sewer networks and flood-preventing levees, their continuous-valued parameters should be optimally calibrated in order to minimise the discrepancies between observed data and model-calculated outputs.

One of the popular hydrologic parameter calibration examples can be a non-linear Muskingum model which predicts flood-propagating characteristics along a river reach. To optimise the model parameters, Gill (1978), Tung (1985), Yoon and Padmanabhan (1993), Das (2004) and Geem (2006a) used various mathematical techniques while Mohan (1997) and Kim et al. (2001) proposed POAs. The POA models had advantages over mathematical models:

1. they could find near-optimal solutions without divergence
2. they did not require careful consideration of initial parameter values
3. they did not require complicated mathematical derivatives.

However, although POAs used for the hydrologic parameter calibration of the non-linear Muskingum model have the above-mentioned advantages, they did not consider continuous values by nature, but finely-chopped discrete values instead. It may cause a problem of numerical precision (Mohan, 1997). Thus, the first goal of this study is to propose and evaluate various new and existing continuous-variable HS algorithms and to apply the best HS algorithm to a new problem of the hydrologic parameter calibration.

The new application can be the parameter calibration of a rainfall intensity predicting model which is useful to design hydraulic structures that control storm runoff and flooding (Froehlich, 1995; Karahan et al., 2007). The rainfall intensity model calculates the average rainfall rate for certain duration under the selected return period. Once rainfall duration (for example, five, 60 or 1,440 minutes) and return period (for example, two, five, ten, 50 or 100 years) have been given for a design, the rainfall intensity amount can be obtained from various techniques: some states in the USA, such as Connecticut (2000) and Michigan (2004), use tabulated raw data that are originally sourced from National Weather Service; other states such as Illinois (2004) and Utah (2004) use rainfall-intensity-duration graph; and other states such as Florida, Kentucky, South Carolina and Virginia use various curve equations.

Florida (2004) uses third-degree polynomial equation as follows:

$$I = C_1 + C_2 \ln(t) + C_3 \ln(t)^2 + C_4 \ln(t)^3 \tag{1}$$

where I is rainfall intensity (in inch per hour) during time t (in minutes), C_1–C_4 are coefficients for the polynomial equation.

Kentucky (2000) uses second-degree exponential equation as follows:

$$I = \exp\left(C_5 + C_6 \ln(t) + C_7 \ln(t)^2\right) \tag{2}$$

where C_5–C_7 are coefficients for the exponential equation.

South Carolina (1997) and Virginia (2002) use three-coefficient integrated equation combining Talbot's and Sherman's equations (Kibler, 1982).

$$I = \frac{C_8}{(C_9 + t)^{C_{10}}} \tag{3}$$

where C_8–C_{10} are coefficients for the integrated equation.

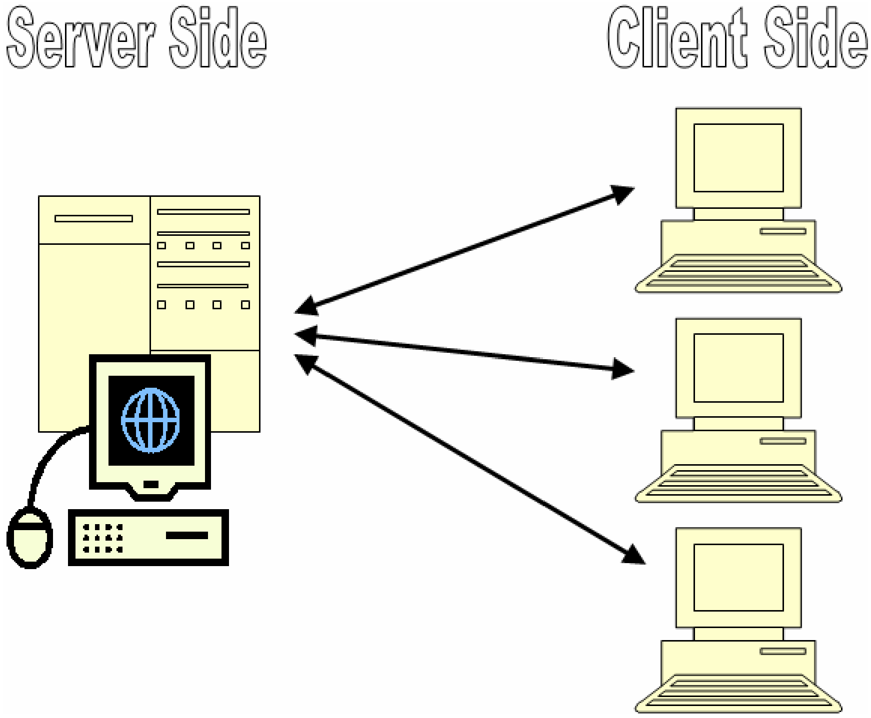
In order to use the value of the rainfall intensity in computer-based design process, equation-type is preferred to table-type or graph-type especially when interpolation between two fitted points is required. While the coefficient values for polynomial and exponential equations in equations (1) and (2) are deterministically obtained using numerical analysis techniques, the equations have more complex shape and require more precision with longer significant digits than the integrated equation. Moreover, the polynomial one in equation (1) is not valid beyond certain rainfall time because of its intrinsic structure (Florida, 2004). Thus, the integrated equation has its own merit although the values of its coefficients are not deterministically obtained. The rainfall intensity model with the integrated equation instead requires optimisation techniques to have its parameters efficiently calibrated and this study applies an improved HS algorithm to perform the parameter calibration.

Also, in order to enhance the usability of this optimisation technique for the engineers in real-world, internet-based optimising and mapping techniques are additionally developed.

Nowadays, the internet has become a major tool to obtain information. Numerous computers all over the world linked to the network can potentially store and share gigantic data and documents. The Hypertext Markup Language (HTML) usually performs the mechanism. However, the internet is also able to perform another major task, viz., computing, as the computer was originally invented for. The web-based computing occurs on two different types of computers as shown in Figure 1: one occurs on a web server which processes computing requested by a client (or user) computer and returns computing results into client's web browser; and the other occurs on a client computer using client's web browser after importing computing codes from the web server (Sridharan, 2004). For example, active server pages (ASP) can be the web-programming language for implementing the former environment and VBScript for the latter environment.

Here, the former server-side computing might become a heavy burden to the web server when multiclient computers concurrently request. Thus, client-side computing can be more stable for the huge mathematical calculation and easy-to-access even in offline situation once the computing code is previously stored in client's computer. This study is to introduce client-side web-based computing to the hydrologic parameter calibration using web scripting language, VBScript (Chandra et al., 2003; Kingsley-Hughes et al., 2004).

Figure 1 Structure of web server and client computers (see online version for colours)



Finally, for presenting the optimisation computing results on a digital map, this study uses Google Maps API technique which allows users to add contents to an embedded digital map using JavaScript.

2 Continuous HS algorithms

The HS algorithm was first developed by mimicking a musical improvisation process (Geem et al., 2001). The original HS algorithm searches solution vectors, which have discrete variables, based upon a novel stochastic derivative rather than gradient-based mathematical derivative (Geem, 2008). It has been successfully applied to various discrete-variable optimisation problems, such as structural design (Saka, 2007), water distribution network design (Geem, 2006b) and Sudoku puzzle solving (Geem, 2007).

The HS algorithm was also applied to continuous-variable optimisation problems for hydrologic parameter calibration, such as flooding routing model (Kim et al., 2001) and rainfall-runoff model (Paik et al., 2005). However, the original HS algorithm used discrete-type variables which just mimic continuous variables by finely chopping possible value range.

In order to overcome this imperfect structure, researchers have improved the original discrete HS algorithm to handle continuous-type variables (Lee and Geem, 2005; Mahdavi et al., 2007) and applied to various continuous-variable problems, such as heat and power economic utilisation (Vasebi et al., 2007), offshore oil structure mooring (Ryu et al., 2007), aquifer parameter and structure determination (Ayvaz, 2007) and soil stability analysis (Cheng et al., 2008). However, this continuous-variable HS algorithm is also expected to be applied to hydrologic parameter calibration problems.

The optimal parameter calibration procedure using the HS algorithm consists of the following steps:

Step 1

The optimisation problem is formulated in this step. For the parameter calibration of the rainfall intensity model, the objective function is the root mean square error (RMSE) between observed rainfall data and computed one as in equation (4). This function is to be minimised.

$$\text{Minimise } RMSE = \sqrt{\frac{1}{N_d}\sum\left(I_{Observed} - \hat{f}\left(t, C_8, C_9, C_{10}\right)\right)^2} \tag{4}$$

where $I_{Observed}$ is the rainfall intensity data observed using meteorological measuring device; $\hat{f}(\cdot)$ is a rainfall intensity function which is identical to equation (3); and N_d is number of data (N_d pairs of concentration time and rainfall intensity).

Step 2

Harmony memory (HM) matrix as shown in equation (5) is randomly filled with as many solution vectors (= parameter value sets) as harmony memory size (HMS). Corresponding RMSE's are also stored in HM.

$$\left[\begin{array}{ccc|c} C_8^1 & C_9^1 & C_{10}^1 & RMSE^1 \\ C_8^2 & C_9^2 & C_{10}^2 & RMSE^2 \\ \vdots & \vdots & \vdots & \vdots \\ C_8^{HMS} & C_9^{HMS} & C_{10}^{HMS} & RMSE^{HMS} \end{array}\right] \tag{5}$$

Step 3

A new harmony vector, $(C_8^{New}, C_9^{New}, C_{10}^{New})$, is improvised based on the three rules such as random selection, memory consideration and pitch adjustment.

Random selection is the operation where the value of each coefficient for the new vector can be chosen from the value range $(\underline{C_i} \le \mathbf{C}_i \le \overline{C_i})$ with probability of freedom rate (FR) ($0 \le FR \le 1$).

$$C_i^{New} \leftarrow C_i \in \mathbf{C}_i \quad \text{w.p.} \quad FR \tag{6}$$

Memory consideration is the operation where the value of each coefficient can be chosen from any value stored in HM with probability of harmony memory considering rate (HMCR) (HMCR = 1 – FR).

$$C_i^{New} \leftarrow C_i \in \left\{C_i^1, C_i^2, \ldots, C_i^{HMS}\right\} \quad \text{w.p.} \quad HMCR \tag{7}$$

Once a value is chosen in memory consideration operation (rather than random selection operation), the value can be further adjusted to neighbouring values with a probability of *HMCR* × *PAR* (pitch adjusting rate; 0 ≤ *PAR* ≤ 1). Otherwise, the original pitch obtained in memory consideration will be just kept with probability of *HMCR* × (1 – *PAR*).

$$C_i^{New} \leftarrow \begin{cases} C_i \pm \Delta & \text{w.p.} \quad HMCR \times PAR \\ C_i & \text{w.p.} \quad HMCR \times (1 - PAR) \end{cases} \tag{8}$$

where pitch-adjustment amount (Δ) can be calculated using the following equation:

$$\Delta \leftarrow (\overline{C} - \underline{C}) \times PWR \tag{9}$$

where pitch width rate (PWR) can be calculated using one of the following five different techniques. While PWR in equation (10) was already proposed by Lee and Geem (2005), PWR's in equations (11)–(14) are first proposed in this study:

$$PWR \leftarrow FPWR \times u(0,1) \tag{10}$$

$$PWR \leftarrow PWR_1 + \left(PWR_2 - PWR_1\right) \frac{Iter - 1}{Iter^{\max} - 1} \tag{11}$$

$$PWR \leftarrow \frac{PWR_3}{1 + \dfrac{Iter - 1}{Iter^{\max} - 1}\left(\dfrac{PWR_3}{PWR_4} - 1\right)} \tag{12}$$

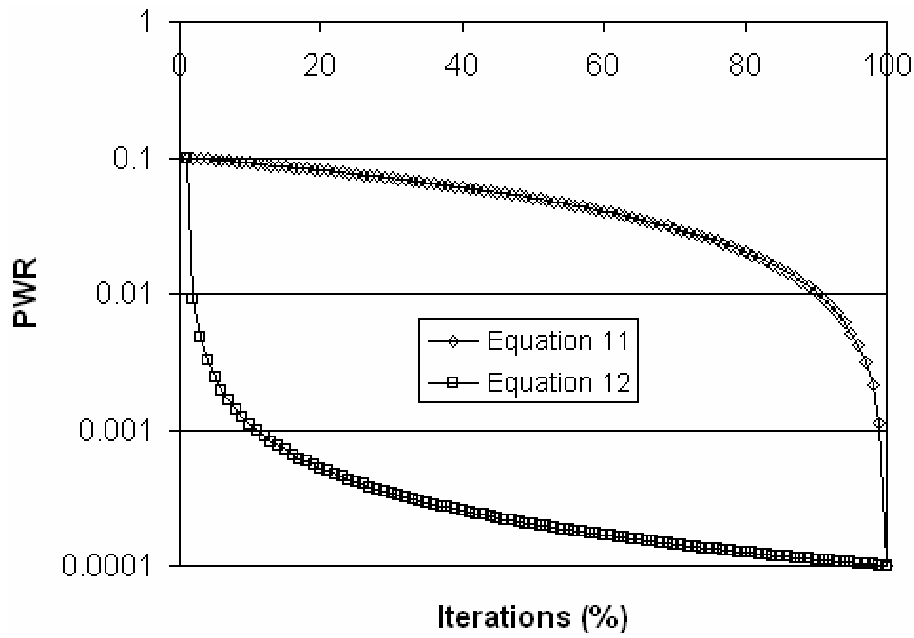
$$PWR \leftarrow \begin{cases} VPWR & \text{if } Iter^{Ct} \le Iter^{\max Ct} \\ VPWR / 2 & \text{otherwise} \end{cases} \tag{13}$$

$$PWR \leftarrow \begin{cases} VPWR \times u(0,1) & \text{if } Iter^{Ct} \le Iter^{\max Ct} \\ VPWR / 2 \times u(0,1) & \text{otherwise} \end{cases} \tag{14}$$

where $FPWR$ is fixed pitch width rate; $u(0,1)$ is a uniform random number between 0 and 1; PWR_1 and PWR_3 are starting pitch width rate; PWR_2 and PWR_4 are ending pitch width rate; $VPWR$ is variable pitch width rate; $Iter$ is the current number of computing iterations (or function evaluations); $Iter^{\max}$ is maximum number of computing iterations; $Iter^{Ct}$ is the number of iterations where no HM update occurs consecutively; $Iter^{\max Ct}$ is a maximum allowable number of no HM update. If $Iter^{Ct}$ is greater than $Iter^{\max Ct}, VPWR$ is bisected.

When tested with $PWR_1 = PWR_3 = 0.1$ and $PWR_2 = PWR_4 =$ 0.0001 (these values are only for demonstration purpose; real values can be much smaller), the PWR from equation (11) is gradually varying in early iterations and rapidly varying in late iterations while PWR from equation (12) is rapidly varying in early iterations and gradually varying in late iterations, as shown in Figure 2.

Figure 2 Comparison of differently varying PWR's



Step 4

If the new harmony vector $(C_8^{New}, C_9^{New}, C_{10}^{New})$ is better than the worst harmony in the HM in terms of RMSE, the new harmony is included in the HM, the existing worst harmony is excluded from the HM and $Iter^{Ct}$ is set to zero. Otherwise, $Iter^{Ct}$ is increased by one.

Step 5

If the HS algorithm reaches the maximum number of harmony improvisations $(Iter^{\max})$, the computation is terminated. Otherwise, Steps 3 and 4 are repeated.

3 Applications

The proposed five continuous-variable HS algorithms are applied to the parameter calibration of rainfall intensity model with the data from the city of Incheon, South Korea. Because other researchers have already performed the parameter calibration using Powell method (Song and Seoh, 2000) and GA (La et al., 2001), the HS algorithms are also applied for comparing their performance and effectiveness.

For the area, the rainfall data was obtained as shown in Table 1.

Table 1 Rainfall-duration-frequency data for Incheon City

Time (min) \ Period (yr)	2	5	10	50	100	500
10	88.00	111.60	124.20	147.00	153.60	171.60
20	66.30	89.10	103.50	132.90	143.10	170.70
30	54.40	75.40	89.60	119.60	130.20	159.80
40	47.25	65.70	78.45	106.35	116.25	144.45
50	42.84	60.60	72.96	100.20	109.80	137.52
60	39.70	56.40	68.10	93.70	102.80	128.90
90	33.27	47.47	57.33	78.87	86.53	108.40
120	28.95	41.75	50.40	69.15	75.70	94.40
180	22.40	32.40	39.30	54.43	59.77	75.03
240	18.75	27.10	32.85	45.40	49.83	62.48
300	16.06	23.38	28.58	40.26	44.44	56.48
360	14.40	21.13	26.00	36.97	40.92	52.33
1,440	4.95	7.80	10.08	15.55	17.58	23.56

For the HS optimisation, the values of the HS parameters are chosen as follows (extensive sensitivity analysis needs to be performed in the future): HMS = 10; HMCR = 0.95; PAR = 0.8; $FPWR = 0.01$; $PWR_1 = 5\text{e-}4$; $PWR_2 = 5\text{e-}7$; $PWR_3 = 0.1$; $PWR_4 = 5\text{e-}5$; starting $VPWR = 0.01$; $Iter^{\max} = 50{,}000$; and $Iter^{\max Ct} = 120$. The minimum and maximum values for three coefficients are $350 \le C_8 \le 10{,}000$; $2 \le C_9 \le 100$; and $0.2 \le C_{10} \le 1.0$.

Table 2 shows the results (RMSE's that are objective functions in this study) from various continuous-variable HS algorithms as well as Powell (Song and Seoh, 2000) and GA (La et al., 2001). HS^1 is the results using equation (10); HS^2 using equation (11); HS^3 using equation (12); HS^4 using equation (13); and HS^5 using equation (14).

Table 2 Comparison of RMSE's among different algorithms

Return period (year)	*Powel*	*GA*	HS^1	HS^2	HS^3	HS^4	HS^5
2	1.305	0.969	0.948	0.986	1.053	0.965	0.947
5	1.522	1.217	1.202	1.214	1.209	1.204	1.202
10	1.609	1.137	1.140	1.140	1.140	1.139	1.139
50	NA	1.103	1.004	1.004	1.004	1.004	1.004
100	NA	1.496	1.490	1.599	1.923	1.495	1.490
500	NA	3.966	3.763	3.775	3.775	3.767	3.765

As seen in Table 2, all continuous-variable HS algorithms have performed better than Powell method in terms of RMSE. When compared with GA, HS^1, HS^4 and HS^5

performed better than GA in five cases while they performed worse in one case of ten-year return period. The reason why GA performed better than HS's in the specific case is presumably that GA found the solution which is very close to optimal one [different trial of HS^1 found the better solution (1.136) for the case]. HS^2 and HS^3 found better solutions in three cases and worse ones in three cases.

From the above comparison results, the HS^5 appears to perform best for this hydrologic parameter calibration. Thus, the HS^5 was further applied with the rainfall data from Fairfax County, Virginia in USA. While the original parameter values are $C_8 = 41.820$, $C_9 = 8.250$ and $C_{10} = 0.780$ and corresponding RMSE is 0.031 (Virginia, 2002), those obtained by the HS^5 are $C_8 = 40.7791$, $C_9 = 8.0864$ and $C_{10} = 0.7775$ and corresponding RMSE is 0.0055. HS found less-error parameter values in terms of RMSE.

4 Web-based computing and mapping

In order to enhance the usability of the continuous-variable HS model for the hydrologic parameter calibration, web-based optimising and mapping (WOM) model is further developed. Figure 3 shows the structure of WOM. The WOM model consists of five components: web server, client web browser, HS calibration module, digital mapping interface and rainfall database. In the model, the hydrologic parameter calibration is performed on client's web browser without requiring any optimisation and GIS software.

Figure 3 Schematic of WOM model (see online version for colours)

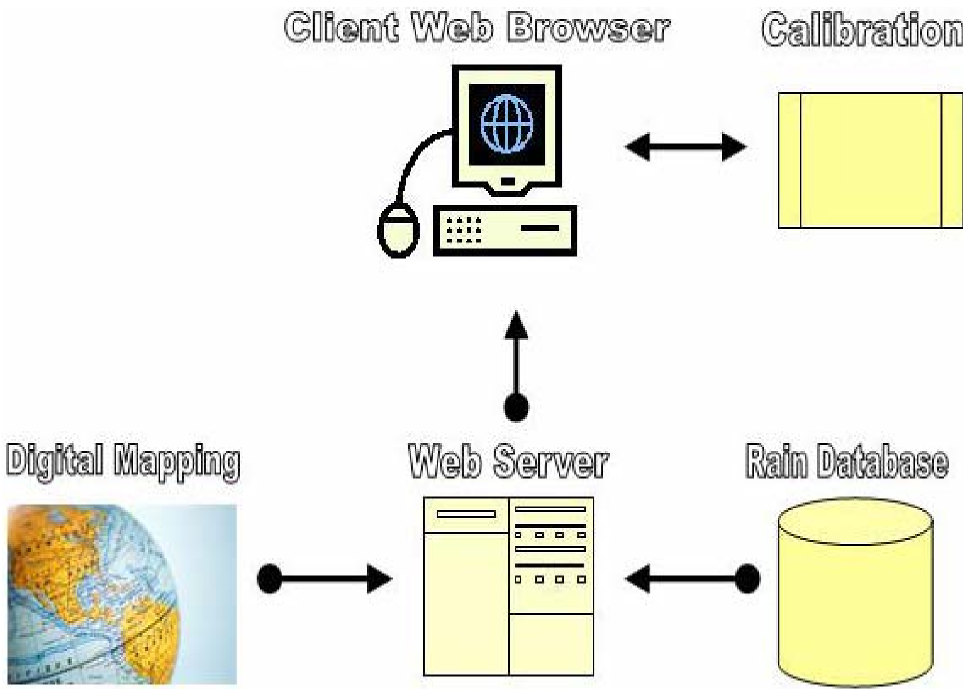


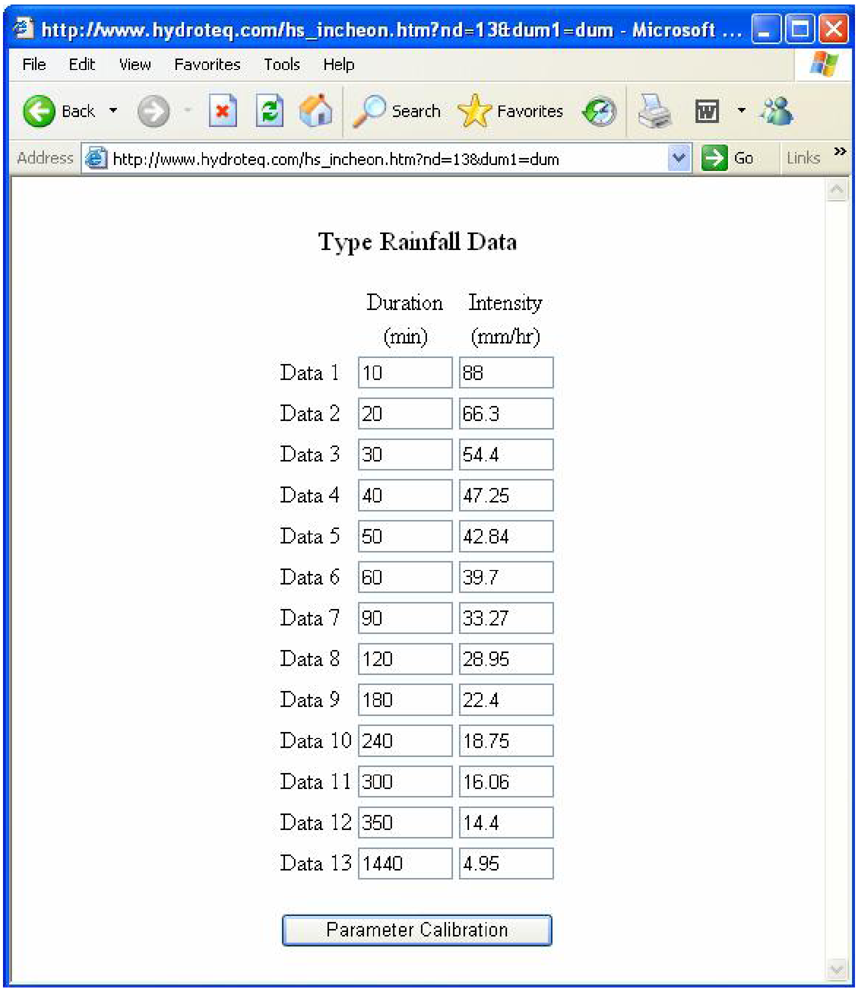
Figure 4 Illustration of HTML code containing VBScript code

```
<HTML>
<HEAD>
<TITLE>Web Page Title</TITLE>
<SCRIPT LANGUAGE="VBScript">
<!--

... VBScript Code ...

-->
</SCRIPT>
</HEAD>
```

Figure 5 Rainfall data entry screen (see online version for colours)



The HS parameter calibration is performed using VBScript, which has been so far applied mostly to information processing rather than scientific computing (Lambert, 1999; Tang et al., 2003; Roudsari et al., 2004). In order to run the VBScript code, it is added to existing HTML code without either installing any special software or referring back to the web server. Once the HTML and VBScript code is transferred from the web server to client's web browser, it can be easily handled like other HTML codes. VBScript code is written within paired <SCRIPT> tags in the <HEAD> section of the HTML code as illustrated in Figure 4.

The HS calibration is performed on internet using the HTML and VBScript code. If a user clicks the hyperlink of the WOM model on its web-browser, an initial screen appears. Once the number of data is entered, next screen for rainfall data entry appears, as shown in Figure 5. Although Figure 5 shows the example of manual data entry, this process can be automated by interfacing with rainfall database as shown in Figure 3. After all data is manually entered, the user needs to click the button (parameter calibration) to obtain calibration results. The result screen includes the optimised values of three parameters and corresponding RMSE.

For presenting the calibration results on digital map, an application programming interface (API) technique of Google Maps is adopted. Figure 6 shows the screen of HS parameter calibration with Google Maps. When user opens a HS calibration page with web browser, six markers, that point six different locations where obtainable rainfall data is constructed on the database, appear on the map and six geographical names are listed in right-hand column. If user clicks any name in the list, another text box, which points corresponding marker, appears and shows location information. If user clicks the link 'run calibration' in the text box, web browser performs parameter calibration and returns computational results. Table 3 shows the computational results for six different locations on the map.

Figure 6 Screen of parameter calibration results on Google Maps (see online version for colours)

HS parameter calibration for rainfall intensity model

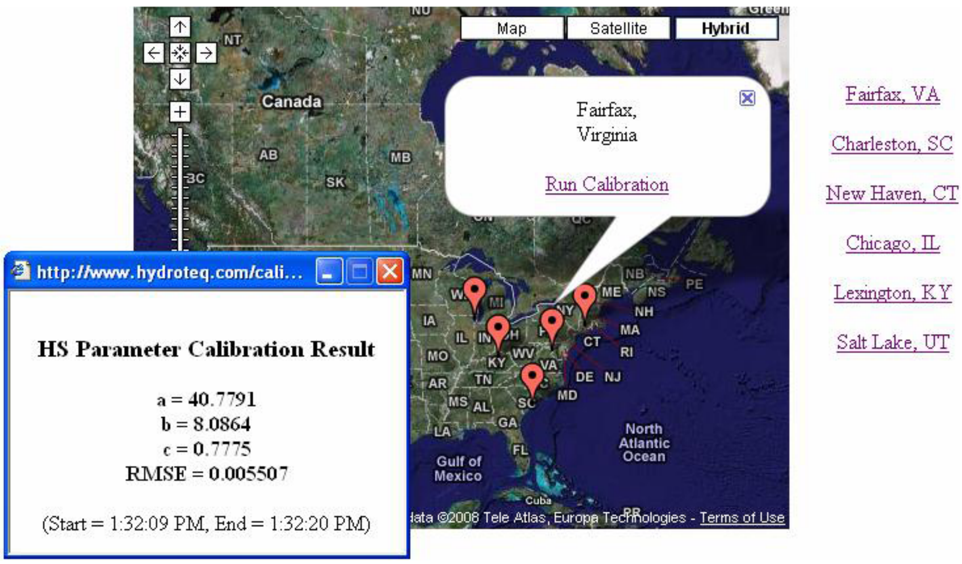


Table 3 Parameter values and corresponding RMSE

Location	C_8	C_9	C_{10}	*RMSE*
Fairfax, VA	40.7791	8.0864	0.7775	0.0055
Charleston, SC	160.9458	29.9518	0.9278	0.0023
New Haven, CT	23.3467	5.0004	0.7062	0.0179
Chicago, IL	124.9562	22.9533	1.0010	0.1116
Lexington, KY	68.4336	5.0001	0.8865	0.1687
Salt Lake, UT	13.1608	9.9579	0.8017	0.0163

5 Conclusions

This study proposed a parameter calibration technique for rainfall intensity model using five different continuous-variable HS algorithms. Also, web-based computing and mapping technique was implemented for the hydrologic parameter calibration.

For the parameter calibration, this study proposed four new modifications of the original HS algorithm which considers discrete variables by nature. The improved HS algorithms could consider continuous variables by nature, which gives much flexibility in finding solutions of the hydrologic parameter calibration while original HS and GA can find only the solutions that variable precision allows. If the value range is coarsely divided in discrete algorithms, the algorithms hardly find good solutions.

The continuous HS algorithms were applied to the rainfall intensity data from real-world. The computing results showed that three continuous HS algorithms could find less-error parameter values than mathematical technique (Powell method) and evolutionary algorithm (GA) in most cases in terms of RMSE.

Also, web-based computing and mapping techniques may give engineers friendliness in utilising this optimisation technique for their design process. While the internet has gathered great popularity nowadays, it is mostly used for information distribution rather than scientific computation. Thus, this study more focused on a kind of cloud computing, which can be defined as a concept of using the internet to allow users to access technology-enabled services. The web-based calibrating and mapping model is easy-to-use and does not require any software installed on user's computer. The web-computing time is also relatively prompt (each run took around ten seconds). Thus, the author hopes to see further applications of this web-based technique to various model parameter calibrations in the future.

In addition, because the proposed algorithms use more user-defined empirical values of the parameters, it may not enhance the robustness of the algorithm. In order to overcome this situation, future study should include parameter-value-setting-free algorithms.

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