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Comparison of Automatic Calibration for a Tank Model with Optimization Methods and Objective Functions

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Abstract □ Two global optimization methods, the SCE-UA method and the Annealing-Simplex (A-S) method for calibrating a daily rainfall-runoff model, a Tank model, was compared with that of the Downhill Simplex method. The performance of the four objective functions, DRMS (daily root mean square), HMLE (heteroscedastic maximum likelihood estimator), ABSERR (mean absolute error), and NS (Nash-Sutcliffe measure), was tested and synthetic data and historical data were used. In synthetic data study, 100 % success rates for all objective functions were obtained from the A-S method, and the SCE-UA method was also consistently able to obtain good estimates. The downhill simplex method was unable to escape from local optimum, the worst among the methods, and converged to the true values only when the initial guess was close to the true values. In the historical data study, the A-S method and the SCE-UA method showed consistently good results regardless of objective function. An objective function was developed with combination of DRMS and NS, which putted more weight on the low flows.

Keywords □ Automatic calibration, Objective function, Global optimization method, Local optimization method, SCE-UA method, Annealing-Simplex method, Downhill simplex method, Tank model

I. Introduction

Hydrologic models generally are designed to approximate within their structures the hydrologic mechanism using a number of interconnected mathematical functions. In recent years, these models are becoming increasingly sophisticated, complex, and highly nonlinear to make the model behavior closely match that of the real system of interest. Environmental models that combine hydrologic models and water quality models are designed to predict not only streamflow but also sediment load, various chemical transport from watershed, soil moisture, latent and sensible heat flux, and so on. These models generally have a large number of parameters which are not directly measurable and must be estimated through model calibration. The goal of model calibration now becomes that of finding values for the model parameters such that the model-simulated fluxes match all measurement data fluxes as closely as possible.

It was reported that the manual calibration of these model parameters depending on the visual inspection of the hydrographs and the user's personal judgment is tedious, time-consuming and difficult, because manual calibration requires detailed understanding of the model and a large number of interacting parameters can result in unexpectable effects when multiple parameters are adjusted (Duan et al., 1994). The complexity of calibration, in general, depends on the number of calibration parameters. For models with only a few calibration parameters (four or less), methods such as repetitive graphical inspection or minimization of least-squares error can be used. However, for models with a large number of calibration parameters (five or more), a more systematic and automatic calibration scheme is required (Liong et al., 2001). Because of the nature of manual trial-and-error model calibration, there has been a great deal of research into the development of automatic calibration methods.

The good implementation of an automatic model calibration procedure depend on primarily the selection of the appropriate objective function and the power, effectiveness, and robustness of optimization algorithm (Diskin and Simon, 1977; Gan and Biftu, 1996; Gan et al., 1997; Gupta et al., 1999; Freedman et al. 1997;). Yapo et al. (1996) compared the performance of the DRMS (daily root mean square) and the HMLE (heteroscedastic maximum likelihood estimator) criterion, reported that the selection of an appropriate objective function depends on the intended purpose, and suggested using the DRMS criterion when the intention is better matching of flood in peaks and using the HMLE when the intention is matching of the entire range of flow events. The selection of an optimization algorithm has also been studied extensively. Until recently, local search procedure such as the downhill simplex method, pattern search method, and the Rosenbrok method have been used. However, because these methods provide parameter estimates varying with choice of starting point, they are unreliable. Therefore, in recent years, many researchers have begun to investigate the use of globally based optimization methods for model calibration (Duan et al., 1992; Gan and Biftu, 1996; Cooper et al. 1997; Freedman et al., 1998; Thyer et al., 1999; Gupta et al., 1999).

In this paper, the capability of the global optimization method, the SCE-UA method and the A-S method to which the simplex method's principle is applied for calibration of a Tank model is compared with that of the downhill simplex method using synthetic data and historical data. And, the performance of the calibrated model is investigated in detail when the different objective functions are used for model calibration and an objective function is developed and compared, which puts more weight on the low flows.

II. Optimization methods and objective functions

Automatic parameter optimization algorithm can be categorized as local search methods and global search methods. Local search methods are designed to efficiently find the minimum of unimodal functions for which any strategy that seeks to continuously proceed downhill must eventually arrive at the location of the function minimum, whereas global search methods are designed to efficiently discover the minimum of multi-modal functions, irrespective of where in the parameter space the search procedure is started.

Local search methods such as Rosenbrock method, pattern search method, and simplex method have been applied to calibrating non-linear hydrologic models for their effectiveness and efficiency. Of the various direct search methods, the simplex method is more generally efficient and globally effective than the other methods, its principle is commonly applied in several global optimization algorithms.

Global optimization methods such as Uniform Random Search (URS), Adaptive Random Search (ARS), Multiple Start Simplex (MSX), Genetic Algorithm (GA), simulated annealing method, A-S method and SCE-UA are well known as global optimization method. The SCE-UA method has been tested by comparing the other methods and proved to be consistent, effective, and efficient in locating the globally optimal parameters. The simulated annealing method is based on an analogy which a thermo-dynamical process called annealing. And, the combination method of it and the downhill simplex method, A-S method, has been developed to be various types and tested by being compared with other methods (Press et al., 1992; Liu et al., 1995; Kvaniscka and Pospichal, 1997; Pan and Wu, 1998)

In this study, to compare the capability of global optimization and local optimization, the optimization methods selected are the downhill simplex method, the A-S method, and the SCE-UA method.

1. Downhill simplex method

The downhill simplex method of Nelder and Mead (1965) is one of the most popular local, direct search methods for calibrating conceptual rainfall-runoff model. This method utilizes a regular geometric figure, simplex, that spans the n dimensional space, is started with n+1 points which define an initial simplex, and takes a series of steps such as reflection, expansion, and contraction. A new point that the downhill simplex method replaces the old point by only a new point that has a lower value of the objective function and will converge to a local minimum of the function using the sequence of such steps.

2. Annealing-Simplex (A-S) Method

The A-S method is one of the effective and efficient global optimization method and combine the robustness of simulated annealing with the efficiency of downhill simplex method. The merits and faults of two methods are complementary. The simulated annealing method (Press et al., 1991) escapes from the local optimum by jumping away from them and is very easily implementable and robust, but it sacrifices efficiency; on the other hand, the downhill simplex method converge quickly to the nearest local optimum, but it has no way to escape from local optimum.

A few strategies that combine the downhill simplex method with simulated annealing method have been developed (Press et al., 1992; Liu et al., 1995; Cardoso et al., 1996; Kvaniscka and Pospichal, 1997; Pan and Wu, 1998). In this study, the A-S method proposed by Pan and Wu (1998) was applied to calibrating a rainfall-runoff model. Because the topography of the objective function of conceptual rainfall-runoff model is very complicated, several annealing procedures are needed to escape from local optimum. Therefore, only when two successive annealing procedures find the same point or the distance between the two points is less than 10^{-5}, searching the global optimum is stopped. If the global optimum is not found, the simplex is reinitialized at the best point found in previous procedure.

3. SCE-UA Method

The SCE-UA method is a new, heuristic global optimization strategy designed to handle the various response surface problems encountered in the calibration of nonlinear simulation rainfall-runoff models, particularly the nested optima problem encountered with conceptual hydrologic models. The method combines the strengths of the simplex procedure of Nelder and Mead (1965), with the concept of a controlled random search, competitive evolution, and complex shuffling (Duan et al., 1992). The method has been tested by numerous researchers on a variety models with good results, and has been reported that the method is able to find consistently and efficiently the global optimum of the problem, whereas other optimization methods either fail or provide inconsistent results (Duan et al., 1992; Gan and Biftu, 1996; Cooper et al., 1997; Freedman et al., 1998; Thyer et al., 1999; Gupta et al., 1999).

4. Objective functions

Implement of the automatic parameter optimization algorithm requires the selection of an appropriate objective function to be optimized with respective to the model parameters. In this study, the performance of the four objective functions, DRMS (daily root mean square), HMLE (heteroscedastic maximum likelihood estimator), ABSERR (mean absolute error), and NS (Nash-Sutcliffe Measure), was tested.

The one most commonly used objective functions for calibrating the rainfall-runoff model is a simple daily root mean square (DRMS) estimation criterion as

$$\underset{\theta}{Minimize} \quad DRMS(\theta)=\sqrt{\frac{\sum_{i=1}^{n}\{q_i^{sim}(\theta)-q_i^{obs}\}^2}{n}} \qquad (1)$$

where n is the number of the data points and q_i^{obs}, q_i^{sim} are the measured and simulated flows at time i, respectively. The DRMS implicitly assume the presence of Gaussian with a zero mean, independent homogeneous variance error. The HMLE criterion was proposed by Sorooshian (1983) for the case where errors are assumed to be uncorrelated and non-homogeneous. In the HMLE, the error variance is assumed to vary with the magnitude of the flows in a manner to be common in stream flow data. The HMLE in simplified form is

$$\underset{\theta,\lambda}{Minimize}\quad HMLE(\theta,\lambda)=\frac{\frac{1}{n}\sum_{i=1}^{n}w_i(\lambda)\{q_i^{sim}(\theta)-q_i^{obs}\}^2}{\{\prod_{i=1}^{n}w_i(\lambda)\}^{1/n}} \tag{2}$$

where $w_i=f_i^{2(\lambda-1)}$, weight assigned to time i, $f_i=q_i^{true}$, expected true flow at time i, approximated using q_i^{obs}. The mean absolute error (ABSERR) and the Nash-Sutcliffe Measure (NS) are measures of dispersion of the model residual around zero. The ABSERR means the absolutely relative magnitude of the residual variance as

$$\underset{\theta}{Minimize}\quad ABSERR(\theta)=\frac{1}{n}\sum_{i=1}^{n}|q_i^{sim}(\theta)-q_i^{obs}| \tag{3}$$

The NS is the modified form of the Nash-Sutcliffe efficiency (NSE) which means the relative magnitude of the residual variance to the variance of the observed flows and the optimal value is 1.0. In this study, the form was modified to search the minimum value, 0.0, as

$$\underset{\theta}{Minimize}\quad NS(\theta)=\left|\frac{\sum_{i=1}^{n}(q_i^{obs}-\overline{q^{obs}})^2-\sum_{i=1}^{n}(q_i^{sim}(\theta)-q_i^{obs})^2}{\sum_{i=1}^{n}(q_i^{obs}-\overline{q^{obs}})^2}-1\right| \tag{4}$$

III. Performance Evaluation

1. Tank model

Tank model demonstrated its capability for modeling the hydologic responses from a wide range of catchments among the more popular conceptual rainfall-runoff models (WMO, 1975; Franchni and Pacciani, 1991). The model represents the catchment as a system of interconnected tanks with additional outlets and uses physically sound structure and simple equations. In spite of the simplicity of equations used in the model, a series of combinations of the tank components results in a highly nonlinear integral operation and has may local optima. In many countries, the model has been applied to flood forecasting, watershed management, reservoir operation, etc. (Copper et al., 1997; Lee and Singh, 1999). For the characteristics of its structure and wide application, it was chosen as the model for investigation.

The Tank model selected in this study is one of the modified versions of Sugawara's model and consists of three tanks in series with four drainage outlets (Huh et al., 1993; Sugawara, 1995). The model has nine parameters and three initial state variables. a_{11}, a_{12}, a_2, and a_3 are, respectively, the runoff coefficients of each tank; h_{11}, h_{12}, and h_2 are, respectively, the height of runoff orifice of each tank; b_1 and b_2 are, respectively, the infiltration coefficients of each tank. The amount of runoff throughout the outlet of each tank is linearly proportional to the head of water at the outlet and can be described as

$$q_{11}=a_{11}\cdot(ST_1-h_{11});\ q_{12}=a_{12}\cdot(ST_1-h_{12});$$
$$q_2=a_2\cdot(ST_2-h_2);\ q_3=a_3\cdot ST_3 \tag{5}$$

where ST_1, ST_2, and ST_3 are, respectively, the head of water of each tank. The amount of infiltration from the upper tank to lower tank is linearly proportional to the head of water of each tank and can be expressed as

$$f_1=b_1\cdot ST_1;\ f_2=b_2\cdot ST_2 \tag{6}$$

The daily runoff from a given watershed can be expressed as

$$q_t = q_{11} + q_{12} + q_2 + q_3 \quad (7)$$

2. Synthetic data test

To compare the capability of the downhill simplex method, the A-S method, and the SCE-UA method, we used the synthetic streamflow data. Because the synthetic data are error free, we can verify if the parameter optimization method can search the global optimal parameters of the model or not. Synthetic streamflow data were generated using real hydrometeorological data and parameters considered as true values. The input data series to the Tank model comprised one year of daily rainfall and evaporation measured on a weather station. This sequence of streamflow was treated as the observed streamflow for the synthetic calibration test. The precision associated estimation is expressed by the average relative bias (ARB) as

$$ARB = \frac{1}{n} \sum_{i=1}^{n} \frac{|\theta_i - \theta_i^*|}{\theta_i^*} \quad (8)$$

where n is the number of parameters and θ_i and θ_i^* are the estimated and true optimum values, respectively, of the parameters (Isabel and Villeeneuve, 1986).

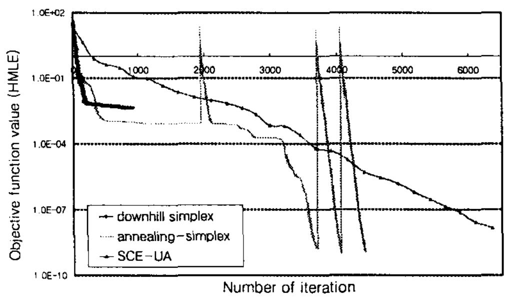
Table 1 and 2 show that the results of synthetic calibration tests as to the optimization methods and objective functions. The synthetic calibration test demonstrates a 100 % success rate for the A-S method regardless of objective functions when calibrating the Tank model under ideal conditions. Among the optimization method, the A-S method was most robust, efficient, and effective, followed by the SCE-UA method, and then simplex method. By comparison, the

Table 2 Comparison of synthetic calibration tests with optimization methods using ARB

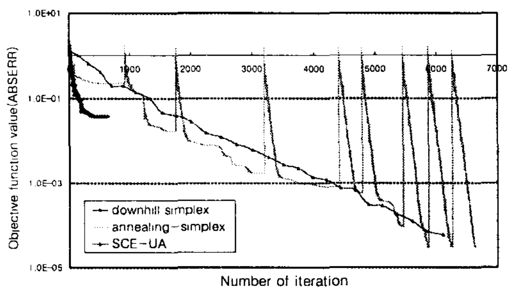
Opt. method	Initial ARB	Objective function			
		HMLE	DRMS	ABSERR	NS
Downhill Simplex	1.1234	0.1559	0.1559	0.1514	0.1559
Downhill Simplex	0.1158	0.0000	0.0000	0.0146	0.0000
A-S	1.1234	0.0000	0.0000	0.0000	0.0000
SCE-UA	1.1234	0.0001	0.0002	0.0000	0.0001

Table 1 Results of synthetic calibration tests using the A-S method

True value		Initial value	Bounds		Estimates			
			Lower	Upper	HMLE	DRMS	ABSERR	NS
a11	0.0810	0.1000	0.0500	0.5000	0.0810	0.0810	0.0810	0.0810
a12	0.1220	0.3000	0.0500	0.5000	0.1220	0.1220	0.1220	0.1220
a2	0.0085	0.0500	0.0010	0.1000	0.0085	0.0085	0.0085	0.0085
a3	0.0026	0.0050	0.0010	0.1000	0.0026	0.0026	0.0026	0.0026
b1	0.4520	0.5000	0.1000	0.5000	0.4520	0.4520	0.4520	0.4520
b2	0.0800	0.0500	0.0100	0.1000	0.0800	0.0800	0.0800	0.0800
h11	8.6000	5.0000	0.0000	10.0000	8.6000	8.6000	8.6000	8.6000
h12	59.0000	10.0000	0.0000	150.0000	59.0000	59.0000	59.0000	59.0000
h2	37.3000	5.0000	0.0000	50.0000	37.3000	37.3000	37.3000	37.3000
ARB	0.0000	1.1234	0.7913	6.5775	0.0000	0.0000	0.0000	0.0000



(a) HMLE criterion



(b) ABSERR criterion

Fig. 1 Optimization method's objective function value against number of function evaluation

A-S method converged to the true value in all cases. Regardless of objective function, this ranking was generally the same except the SCE-UA method in conjunction with the ABSERR that demonstrates a 100 % success rate. The downhill simplex method was unable to exactly locate the true parameter values even with more neighboring parameters to true values parameter than these of other methods (Table 2). The success of this method depends on the starting position of its search relative to the global optimal parameter set and the global optima might be its location in a relatively flat area of the simplex method's response surface. Only when the initial guess was close to the true value the downhill simplex method converged to the global optimum.

Fig. 1 shows the convergence dynamics of the three optimization method plotted the value of the objective function versus the number of iterations for each methods. The A-S method is converged to the minimum value of the objective function in all cases and the number of iterations of it is smaller than that of the SCE-UA method except the ABSERR. Unlike the downhill simplex method which always moved downhill, the A-S method sometimes moved uphill. The reannealing of the A-S method enhanced the minimum procedure with enlarging the simplex to initial size and raising the temperature, which increased the chance of escaping from the local minimum. Fig. 1 also shows that only when two successive reannealing process find the same best point, the process of the A-S method is stopped.

3. Historical data test

The watershed to which the model is applied is the Balan watershed, which has been investigated extensively by Department of Agricultural Engineering, Seoul National University in Korea. The downhill simplex method, the A-S method, and the SCE-UA method were used to calibrate the Tank model using historical data from the Balan watershed as to the objective functions. Data from April 1, 1996, to December 31, 1996, were used for calibration and data from January 1, 1997, to December 31, 1997, were used for verification.

(1) Statistical error measurements

To compare the result of the parameter estimates, the five statistical error measurements CC (Correlation Coefficient), SE (Standard Error), NSE (Nash-Sutcliffe Efficiency), PBIAS

(Percent BIAS), PME (Persistence Model Efficiency), RE (Relative Error), were selected, where

$$CC=\frac{\sum_{i=1}^{n}(q_i^{sim}-\overline{q^{sim}})(q_i^{obs}-\overline{q^{obs}})}{\sqrt{[\sum_{i=1}^{n}(q_i^{sim}-\overline{q^{sim}})^2][\sum_{i=1}^{n}(q_i^{obs}-\overline{q^{obs}})^2]}};$$

$$SE=\sqrt{\frac{\sum_{i=1}^{n}(q_i^{sim}-q_i^{obs})}{n}} \quad (9)$$

$$NSE=1-\frac{\sum_{i=1}^{n}(q_i^{sim}-q_i^{obs})^2}{\sum_{i=1}^{n}(q_i^{obs}-\overline{q^{obs}})^2};$$

$$PME=1-\frac{\sum_{i=1}^{N}(q_i^{sim}-q_i^{obs})^2}{\sum_{i=1}^{N}(q_i^{obs}-q_{i-1}^{obs})^2} \quad (10)$$

$$PBIAS=\frac{\sum_{i=1}^{N}(q_i^{obs}-q_i^{sim})}{\sum_{i=1}^{N}q_i^{obs}}\times 100\%;$$

$$RE=\frac{1}{n}\sum_{i=1}^{n}\frac{|q_i^{sim}-q_i^{obs}|}{q_i^{obs}} \quad (11)$$

The CC measures the extent of the correlation of the observed and simulated values. The optimal value is 1.0, and the value around 1.0 indicates that the observed and simulated values are highly correlated. The SE measures the standard deviation of the model prediction error, and a smaller value of it indicates a better model performance. The NSE measures the relative magnitude of the residual variance to the variance of the observed flows. The optimal value is 1.0 and values should be larger than 0.0 to indicates that the mode is a better predictor than the mean observed flow. The PBIAS measures the tendency of the simulated flows to be larger or smaller than observed values. The positive value indicates a tendency to underestimation, and negative value indicate a tendency to overestimation. The PME measures the relative magnitude of the residual variance to the variance of the errors obtained by the use of a simple persistence model which assumes that the best estimate of streamflow at the next time step is given by the observed flow at the current time step. The optimal value is 1.0, and values should be larger than 0.0 to indicate minimally acceptable performance (Gupta et al., 1999). The RE measures the absolute magnitude of the residual variance to the observed flows. The larger is the difference of the observed and simulated flows, the larger is the RE and the poorer is the estimation.

(2) Single objective function

To compare the ability of the optimization methods and objective functions, each objective function, DRMS, HMLE, NS, and ABSERR is combined with optimization method, respectively. Table 3 shows the calibration and validation results. In calibration, the downhill simplex method, the A-S method, and the SCE-UA method generally provide similar statistic performance for the each objective functions, with the SCE-UA method slightly superior, followed by the A-S method, and then the downhill simplex method. The CC of the each optimization method is 0.98~0.99, which indicates that the observed and simulated value is highly correlated. The SE of the each optimization method is 0.01～0.02, which indicate that the residual variance is small. The calibrated model tends to be quite efficient with NSE

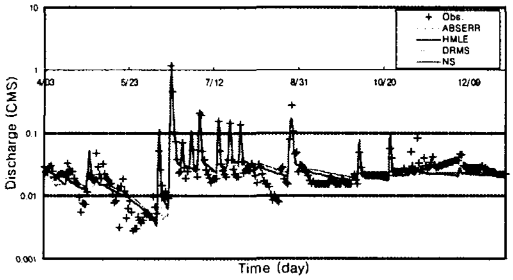
Table 3 Calibration and validation result of the model calibrated using each optimization methods and objective functions

Opt. method	Obj. function	Calibration						Verification					
		CC	SE	NSE	PBIAS	PME	RE	CC	SE	NSE	PBIAS	PME	RE
Downhill Simplex	DRMS	0.98	0.02	0.95	4.0	0.96	0.30	0.89	0.21	0.49	38.7	0.67	0.43
	HMLE	0.98	0.02	0.95	4.0	0.96	0.30	0.89	0.21	0.49	38.7	0.67	0.43
	ABSERR	0.98	0.02	0.96	0.9	0.97	0.31	0.94	0.20	0.53	35.0	0.70	0.51
	NS	0.98	0.02	0.95	4.0	0.96	0.30	0.89	0.21	0.49	38.7	0.67	0.43
A-S	DRMS	0.99	0.01	0.98	1.4	0.97	0.25	0.92	0.20	0.52	35.9	0.69	0.44
	HMLE	0.99	0.01	0.98	1.4	0.97	0.25	0.92	0.20	0.52	35.9	0.69	0.44
	ABSERR	0.98	0.02	0.97	1.3	0.97	0.28	0.91	0.21	0.50	36.0	0.68	0.48
	NS	0.99	0.01	0.98	1.4	0.97	0.25	0.92	0.20	0.52	35.9	0.69	0.44
SCE-UA	DRMS	0.99	0.01	0.97	1.4	0.98	0.25	0.92	0.20	0.52	35.9	0.69	0.44
	HMLE	0.99	0.01	0.97	1.4	0.98	0.25	0.92	0.20	0.52	35.9	0.69	0.44
	ABSERR	0.99	0.01	0.97	2.1	0.98	0.27	0.92	0.20	0.52	35.2	0.69	0.47
	NS	0.99	0.01	0.97	1.5	0.98	0.25	0.92	0.20	0.52	35.9	0.69	0.44

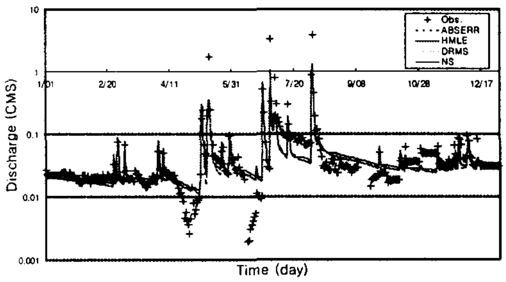
statistic value larger than 0.95 and is able to provide a forecast that is superior to that of persistence model with PME statistic value larger than 0.96. The A-S and SCE-UA method provide similar PBIAS statistic performance, and the simulated values are a definite tendency to underestimation. The RE of the each method is 0.25~0.31, and the RE of the A-S method and the SCE-UA method are smaller than that of the downhill simplex method, which indicate the A-S method and the SCE-UA method are slightly superior to the downhill simplex method. In verification, the each optimization method has a different value of the statistic performance, CC, NSE, PBIAS, and the A-S method and the SCE-UA method are effective, efficient, and consistent. Compared to the statistic performance of the calibration, the result of the verification test is poorer than that of the calibration test, especially the comparison of the PBIAS statistic value represent that the simulated values of the verification test is more underestimated than that of the calibration test. This results from that the location of the global optimum of conceptual rainfall-runoff model is greatly influenced by a combination of factors such as the model structure representation, data measurement error, and imperfect representation of the physical process by the model. Fig. 2 shows the comparison of the observed and simulated hydrograph as to objective function using the SCE-UA method. The difference of each optimization methods is little, the ABSERR tends to match flood peaks, and the values simulated by the model calibrated using it were larger than that using other objective functions in low flow season.

(3) Combination of objective functions

The comparison of the statistic performance and the hydrograph for each optimization method showed that the difference of each method is just a little. To develop the objective function that



(a) calibration



(b) verification

Fig. 2 Comparison of the observed and simulated hydrograph of each objective function in conjunction with the SCE-UA method

provides different parameter estimates which results in different simulated hydrograph, we combined the two objective functions into a single objective function in the form as

$$\underset{\theta}{Minimize} \quad F(\theta) = \sqrt{f_1(\theta)^2 + f_2(\theta)^2} \tag{12}$$

where $F(\theta)$ is the combined objective function, $f_1(\theta)$ and $f_2(\theta)$ are, respectively, one of the single objective functions such as the DRMS, the HMLE, the NS, the ABSERR. This problem can be easily solved using single optimization method. We estimated the global parameters of the model and found the results of the NA (the combination of the Nash-Sutcliff measure and the mean absolute error) and DN (the combination of the daily root mean square error and the Nash-Sutcliff measure) are better than that of the objective functions, where

$$\underset{\theta}{Minimize} \quad NA(\theta) = [\{\frac{\sum_{i=1}^{n}(q_i^{sim}(\theta) - q_i^{obs})^2}{\sum_{i=1}^{n}(q_i^{obs} - \overline{q^{obs}})^2}\}^2 + \{\frac{1}{n}\sum_{i=1}^{n}\frac{|q_i^{sim}(\theta) - q_i^{obs}|}{q_i^{obs}}\}^2]^{1/2} \tag{13}$$

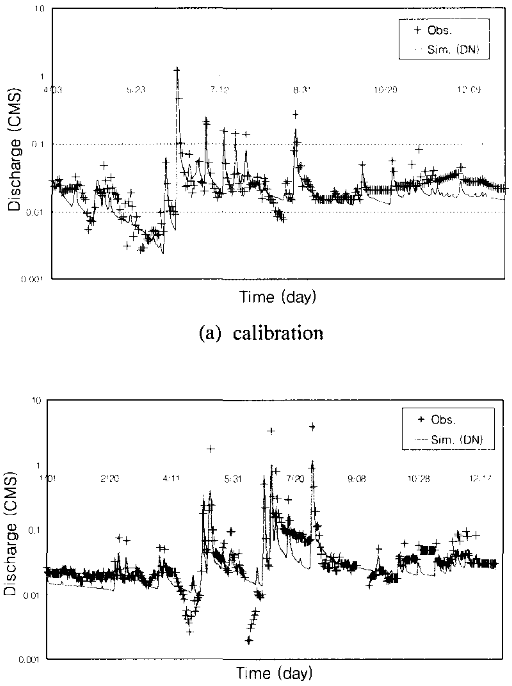
$$\underset{\theta}{Minimize} \quad DN(\theta) = [\{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\frac{q_i^{sim}(\theta) - q_i^{obs}}{q_i^{obs}})^2}\}^2 + \{\frac{\sum_{i=1}^{n}(q_i^{sim}(\theta) - q_i^{obs})^2}{\sum_{i=1}^{n}(q_i^{obs} - \overline{q^{obs}})^2}\}^2]^{1/2} \tag{14}$$

Because the units of the ABSERR and the NS in the NA and the DRMS and the NS in the DN are not the same, the ABSERR and the DRMS were divided by q_i^{obs} to reduce the influence of the unit before equation (12) is applied for optimization.

Table 4 shows that the calibration and verification results of the NA and the DA. The statistic performance of the optimization methods is similar to that of the single optimization methods. But, the PBIAS of calibration and verification is larger than that of single objective function. This indicates that the NA and DN put more weight on the low flows than other objective function. Fig. 3 shows the ability of the model to match the observed hydrograph, using the A-S method with the DN. The comparison of the Fig. 2 and the Fig. 3 represents that the parameter optimization result using the DN and the NA tends to be more consistent performance across all flow range. The scattergrams showing simulated values using the ABSERR against the

Table 4 Result of model calibration and verification using the NA and the DN as objective function

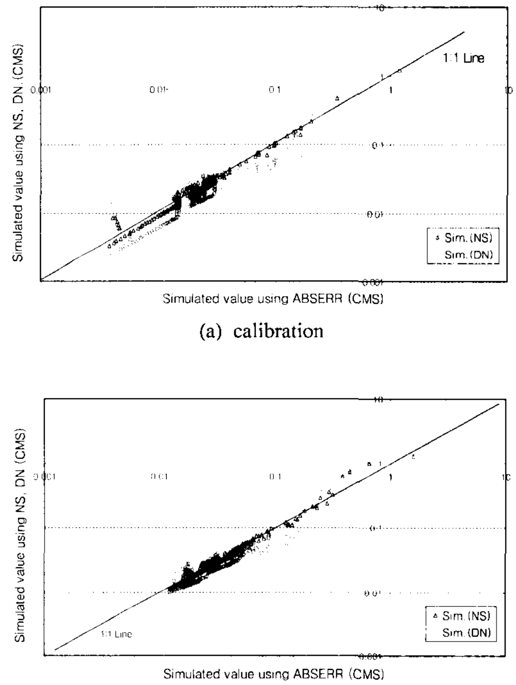
Opt. method	Obj. function	Calibration						Verification					
		CC	SE	NSE	PBIAS	PME	RE	CC	SE	NSE	PBIAS	PME	RE
Downhill -Simplex	NA	0.98	0.02	0.95	15.2	0.96	0.26	0.90	0.20	0.53	38.9	0.53	0.45
	DN	0.98	0.02	0.96	18.4	0.97	0.24	0.91	0.21	0.49	42.6	0.67	0.44
A-S	NA	0.98	0.02	0.96	14.9	0.97	0.22	0.92	0.21	0.51	40.9	0.68	0.41
	DN	0.99	0.01	0.97	16.8	0.97	0.22	0.91	0.21	0.50	42.9	0.68	0.41
SCE-UA	NA	0.97	0.02	0.94	16.0	0.96	0.22	0.94	0.21	0.49	43.7	0.67	0.42
	DN	0.98	0.02	0.96	16.4	0.97	0.22	0.91	0.21	0.50	42.7	0.68	0.41



(a) calibration

(b) verification

Fig. 3 Comparison of the observed and simulated hydrograph of the DN in conjunction with the A-S method



(a) calibration

(b) verification

Fig. 4 Comparison of the simulated value of the ABSERR, the NS, and the DN in conjunction with the A-S method

NA and the DN are displayed in Fig. 4(a) and (b). The ABSERR tends to emphasize mini--mization of peak flow error and the simulated values of it is larger than these of the NA and the DN in low flow season. This indicates that the NA and the DN tend to provide the parameter estimates matching the simulated and observed values in the entire range of flow.

V. Conclusion

In this paper, the capability of the global optimization methods, the SCE-UA method and the A-S method for calibrating a conceptual rainfall-runoff model, a Tank model was compared with that of the downhill simplex method, one of the local optimization methods. The performance of the four objective functions, DRMS (daily root mean square), HMLE (heteroscedastic maximum likelihood estimator), ABSERR (mean absolute error), and NS (Nash-Sutcliffe Measure), was tested and synthetic data and historical data were used.

In synthetic data study, a 100 % success rate that the average relative bias between true values and estimated values is 0.0 % was obtained using the A-S method regardless of objective function, and the objective function value of it is the smallest among the methods. However, the SCE-UA method was also consistently able to obtain good estimates, especially, the SCE-UA method in conjunction with the ABSERR was able to locate the true values. The downhill simplex method was unable to escape from local optimum, the worst among the methods, and converged to the true values only when the initial guess was close to the true values.

In the historical data study, the A-S method and the SCE-UA method obtained consistently the values of statistical error measurements, regardless of objective function, and the downhill simplex method provided parameter estimates varying the choice of starting point. Compared with objective functions, the ABSERR tends to match flood peaks, and the simulated-values by the model calibrated using it were larger regardless of optimization methods. The single objective functions were combined to develop the objective function which puts more weight on the low flows, and the DN, combination of the DRMS and the NS, provided the parameters that tend to be more consistent performance across all flow ranges.

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