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A conceptual rainfall-runoff model considering seasonal variation

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Abstract:

Among various deterministic rainfall-runoff models, the tank model, which is a typical conceptual rainfall-runoff model, is often preferred for its simple concepts. On the other hand, it requires much time and effort to obtain better results owing to the need to calibrate a large number of parameters in the model. Therefore, the demand for an automatic calibration method has been increasing. In this study, three optimization algorithms were tested for automatic calibration: one nonlinear programming algorithm (Powell's method) and two meta-heuristic algorithms, i.e. a genetic algorithm and harmony search. The success of the powerful heuristic optimization algorithms enables researchers to focus on other aspects of the tank model rather than parameter calibration.

The seasonal tank model is devised from the concept that seasonally different watershed responses could be reflected by seasonally different parameter values. The powerful optimization tool used in this study enabled parameter calibration of a seasonal tank model with 40 parameters, which is a considerable increase compared with the 16 parameters of the non-seasonal tank model. In comparison, the seasonal tank model showed smaller sum of square errors than those of the non-seasonal tank model. The seasonal tank model could, therefore, be a successful alternative rainfall-runoff simulation model with its increased accuracy and convenience. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS conceptual rainfall-runoff models; tank models; Powell's method; heuristic algorithms; genetic algorithms; harmony search

INTRODUCTION

There are many deterministic models that can simulate long-term runoff, but most of them have complex structures and various data requirements. For practical purposes, the models that consider the watershed as a series of storage vessels are often preferred, since their simple structure requires only precipitation, runoff, and evapotranspiration observations. These models were first proposed by Sugawara and Funiyuki (1956), and are referred to as tank models in this article, following their notation. Dawdy and O'Donnell (1965), Jamieson and Wilkinson (1972) and others have also proposed similar models. Despite their simple structure, the tank models have proved more capable than many other models in modelling the hydrologic responses from a wide range of humid watersheds (e.g. World Meteorological Organization, 1975; Franchini and Pacciani, 1991).

On the other hand, calibration of tank models has been made difficult by the large number of model parameters used by the models. This problem has driven a lot of research on parameter calibration since the concept of tank models was first proposed. Nagai and Kadoya (1979) applied three optimization algorithms of the Powell method, the Davidon–Fletcher–Powell technique, and the combined technique of quasi-linearization and golden section methods, and proved the superiority of the standardized Powell method. Since

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Wang's (1991) application of a genetic algorithm (GA; Holland, 1975), application of heuristic algorithms to the parameter calibration has become an alternative approach to solving the problem of calibration of conceptual rainfall-runoff models. Cooper *et al.* (1997) investigated the performance of three optimization algorithms: a GA, a simulated annealing (SA; Kirkpatrick *et al.*, 1983) algorithm, and the shuffled complex evolution (SCE) method (Duan *et al.*, 1992). These algorithms were investigated based on their ability to calibrate a simple tank model that contains only two tanks. However, typical tank models have more vessels, usually four, and consequently many more parameters. There is great demand for a method to calibrate the parameters of these practical tank models; however, such a task is quite challenging.

In addition to parameter calibration, many aspects of tank models remain to be improved, one of which is their inability to consider seasonal variation. Runoff simulation with annually consistent parameters has limited application because watershed response varies remarkably from season to season. This study proposes a seasonal tank model in which parameters vary seasonally, so that the model can simulate the seasonal rainfall-runoff characteristics more precisely. However, the number of parameters needing calibration significantly increases the already large number of parameters of the typical non-seasonal tank model, thereby increasing the difficulty of the parameter calibration. Consequently, an optimization algorithm, powerful enough to calibrate many parameters of the typical tank models having more than two vessels and even more parameters of the seasonal model, is a key element to realize these ideas.

In this study, a modified harmony search (MHS) algorithm is proposed and tested for automatic calibration with three existing algorithms: a nonlinear programming (NLP) algorithm (Powell's method) and two other meta-heuristic algorithms (a GA and a harmony search (HS; Geem *et al.*, 2001) algorithm). The comparison proves the superiority of the MHS algorithm over the others in the parameter calibration. The powerful MHS optimization algorithm realizes the concept of the seasonal tank model. The advantages of the seasonal tank model over the non-seasonal model are evidently shown.

The rest of this paper is composed in the following sequence. First, brief reviews of the tank models and applied optimization algorithms are provided. Then, the proposed seasonal tank model is explained. In the section 'Applications,' the MHS algorithm is compared with the HS algorithm, followed by comparisons with Powell's method and the GA. Finally, the seasonal tank model and the non-seasonal model, commonly based on the MHS algorithm, are compared.

TANK MODELS

The tank models are intended to simulate either flood events or long-term runoff from watersheds simulated by a combination of storage vessels. These models are mostly classified as deterministic, lumped, linear, continuous, and time-invariant models. The time-invariant feature is relaxed through the seasonal model proposed in this study.

The tank models are composed of a series of vertically laid tanks. This model structure may be conceptualized as the zonal structure of the surface and subsurface water. For the model with four tanks, the outputs through the side outlets of the first (located at the top), second, third, and fourth (located at the bottom) tanks are considered as surface runoff, intermediate runoff, sub-base runoff, and base flow respectively. Similarly, the output from the bottom outlet of the first tank could be considered as infiltration, and the outputs from the bottom outlets of the other tanks could be regarded as percolation.

The tank models show variety in their number of tanks, side outlets, bottom outlets, height of side outlets, and initial storages. Parameters of the tank models are side outlet coefficients S_{ij} (for jth side outlet in the ith tank), bottom outlet coefficients B_i, heights of side outlets H_{ij}, and initial storages in tanks $h_i(1)$. There is a trade-off in determining the structure of a tank model. The simpler the structure is, the less the number of parameters becomes. This is helpful when calibrating parameters, but less general to accommodating various elements. On the other hand, a more complicated structure may be closer to the real watershed structure, but makes parameter calibration more difficult. For example, more side outlets in the first tank can more precisely represent flood response, but they increase the number of parameters to be calibrated. Therefore, the structure of a tank model should be determined based on the purpose of the model, the reliability of observations to be used for the calibration, the performance of the calibration algorithm, etc. In flood analysis, the discharge from the tanks below the second tank could be replaced by a constant, because the flows from the lower tanks form a negligible part of the large flood discharge.

This study adopts the structure of a tank model used for long-term runoff simulation by the Korea Institute of Construction Technology. This model is composed of four tanks (see Figure 1). The first tank has two side outlets and the other tanks have one side outlet.

According to the given climatologic conditions, the storage of the first tank $h_1(t)$, at time t, can either increase (due to precipitation $P(t)$) or decrease (due to evapotranspiration $E(t)$). For the other tanks, the only source of storage is the flow from the higher tank through its bottom outlet. For the ith tank, the outflow from the bottom outlet towards the $i+1$th tank is

$$I_i(t) = B_i h_i(t) \tag{1}$$

where the tank index is $i = 1$, 2, or 3. For the ith tank, the discharge from the side outlets is directly related to the storage as

$$Q_i(t) = S_{i1}(h_i(t) - H_{i1}) + S_{i2}(h_i(t) - H_{i2}) \tag{2}$$

where $i = 1$, 2, 3, or 4, $S_{i2} = 0$ for $i = 2$, 3, and 4, and $H_{i1} = 0$ for $i = 4$ (see Figure 1). When daily runoff is processed, $I_i(t)$ and $Q_i(t)$ have units of millimetres/day, $h_i(t)$ and H_{ij} are in millimetres, and B_i and S_{ij}

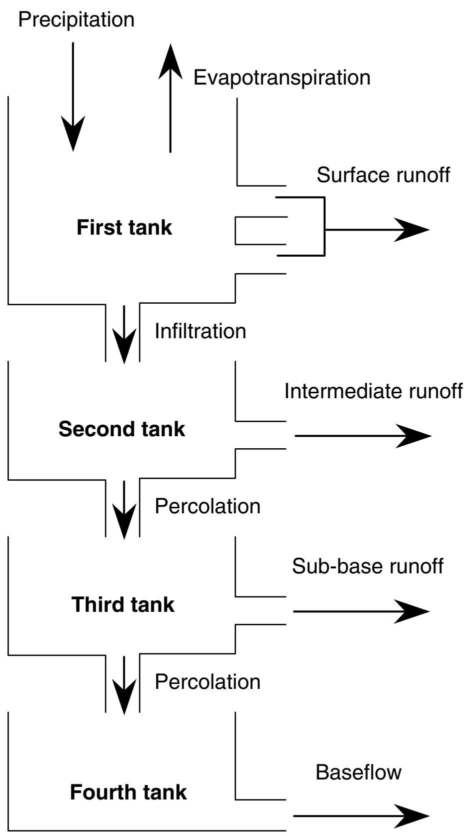

Figure 1. Schematic of the tank model used in this study

have units of reciprocal days in Equations (1) and (2). The total runoff from the watershed is the sum of discharges from each tank as

$$Q(t) = \frac{A_d}{86{\cdot}4} \sum_{i=1}^{4} Q_i(t) \quad (3)$$

where A_d (km^2) is the drainage area and $Q(t)$ (m^3 s^{-1}) is the simulated runoff. The calculations above start at the initial time ($t = 1$) with the given or calibrated initial storages $h_i(1)$, and continue. For the next time step ($t + 1$), the storages in the tanks are updated as

$$h_i(t+1) = h_i(t) + P(t+1) - E(t+1) - Q_i(t) - I_i(t) \quad \text{for } i = 1 \quad (4)$$

$$h_i(t+1) = h_i(t) + I_{i-1}(t) - Q_i(t) - I_i(t) \quad \text{for } i = 2, 3, \text{and } 4 \quad (5)$$

where $P(t+1)$ and $E(t+1)$ are in millimetres and $I_i(t) = 0$ for $i = 4$. Including initial storages, this structure has 16 parameters, which already is a large number. The seasonal model proposed here divides a year into n seasons. All parameters except initial storages have n different values due to seasonal variation. Therefore, the seasonal model has $12 \times n + 4$ parameters. This large number is what necessitates a powerful optimization algorithm for the seasonal model.

OPTIMIZATION ALGORITHMS

Powell's method

Powell's method, the abbreviated name for the conjugate direction method proposed by Powell, is a kind of direct search method that has been applied to many engineering optimization problems, and has become recognized as one of the most efficient NLP methods in unconstrained nonlinear optimization. Powell's method is much more efficient than the steepest descent method, in that the algorithm converges to the optimal solution in exactly N iterations if the function is quadratic in N variables. The method also gives good results for functions that are more complex than a quadratic form (Gue and Thomas, 1968). Furthermore, this method chooses successive directions without computation of the function's gradient. This figure reduces the total computational burden drastically (Press *et al.*, 1992).

In spite of the above-mentioned advantages, Powell's method shares the typical drawbacks of all traditional NLP algorithms. The NLP algorithm, specifically tuned to a certain problem, may find a global optimum. However, sophisticated algorithm tuning, including the location of the appropriate initial starting point, is a very difficult task and almost impossible as the problem becomes difficult. Without proper adjustment, the NLP algorithms usually give unsatisfactory results, i.e. convergence to inferior local optima, or even numerical dispersion.

GAs

Heuristic methods have gained in popularity due to their ability to overcome the deficiencies of traditional optimization methods. Heuristic algorithms are robust, in that they provide satisfactory solutions using reasonable computational time and memory without the necessity of a careful choice of initial values. Although discovery of the global optimum is not guaranteed, the heuristic algorithms yield near-optimal solutions by searching a wide range of domains, instead of falling into a valley of a single local optimum as the NLP algorithms do. Advantages also include that there is no loss of subtle nonlinear characteristics of the model, and that solution of complex derivatives is unnecessary. The inspiration behind most heuristic algorithms is found in the paradigm of natural processes, such as the evolutionary process of Darwin's natural selection theory for the GA (Holland, 1975) and the metallic annealing process in the SA algorithm (Kirkpatrick *et al.*, 1983).

GAs are search algorithms based on the mechanics of natural selection and natural genetics. By abstracting nature's adaptation algorithm of choice in artificial form, we hope to achieve a similar breadth of performance. Recently, GAs have become known as very efficient heuristic algorithms, surmounting problems of traditional optimization algorithms, and have been applied to many engineering problems, including those involving water resources engineering. The GA applied to this study is based on the simple GA (Goldberg, 1989), but uses the strategies of multi-point crossover and promotion of the elite string to the next generation.

HS

Geem *et al*. (2001) conceptualized the musical performance process involving searching for a better harmony into a search algorithm, termed the HS algorithm. Since its conception, this young heuristic algorithm has quickly broadened its application area, including flood routing (Kim *et al*., 2001), copper dam drainage pipe design (Paik *et al*., 2001a), pipe network design (Geem *et al*., 2002), and truss structure optimization (Lee and Geem, 2004).

The HS algorithm has three basic parameters: harmony memory (HM) size, HM considering rate (HMCR), and pitch adjusting rate (PAR). Conceptually, the HM is similar to the population of GAs. The best sets of experienced harmonies are preserved in the HM. The HMCR is introduced to escape from local optima, just like the mutation probability used with GAs. The PAR is adopted to improve the solution by searching adjacent values, thus avoiding being trapped in local optima. Despite their similarity in the roles of parameter optimization, the HS algorithm differs from GAs in three respects: (1) it works with the parameters themselves, as opposed to coding the parameter set; (2) it considers each parameter independently when it generates a new harmony; and (3) it constructs a new harmony from all the existing harmonies instead of from a couple of chosen parents. In fact, these differences help the HS algorithm to have greater flexibility and produce better solutions than GAs in several applications (e.g. Geem *et al*., 2001, 2002; Kim *et al*., 2001; Lee and Geem, 2004). For further details of the HS, readers should refer to Geem *et al*. (2001) or Lee and Geem (2004).

As a young algorithm, the HS algorithm has a lot of room for improvement. We applied three strategies, i.e. the proportionate selection used in the simple GA, and two strategies devised in this study to aid the searching capability of the HS algorithm, i.e. the elimination of overlapping harmonies and the special training of elite harmonies. The elimination of overlapping harmonies is devised to increase the diversity in the limited HM. This strategy checks whether perfectly identical harmonies exist in the memory. If this happens, then this strategy leaves only one of the identical harmonies and replaces the others with new harmonies created by the standard HS algorithm.

As with most search algorithms, the HS algorithm shows rapid improvement during the initial search period, with the rate of improvement decelerating as the iteration increases. For easy problems, this may be a positive sign that global convergence is occurring. However, for hard problems, where convergence to a global optimum is unlikely, this may be a sign that the algorithm requires new stimulation. The special training of elite harmonies is the strategy that performs a very sophisticated search, with the drawback that it has a heavy computational resource requirement. This can be compared with the special training of musicians on whom the public performance is depending. This strategy is similar to dynamic programming, in that parameters are considered as stages with discrete possible states. At each stage, each parameter is adjusted until there is no more improvement while the other parameters are fixed. This strategy provides a very high chance of finding a better solution. However, the use of this strategy should be strictly limited owing to its excessive computational time.

SEASONAL TANK MODEL

The time-invariant feature of prior tank models has limited their ability to model watershed responses that vary remarkably from season to season. Since each parameter closely reflects a physical watershed property, e.g. soil moisture, model parameters are inevitably subject to variation depending on climatologic conditions.

The proposed seasonal tank model enables parameters to vary seasonally. For application to a watershed located in central South Korea, the model divides a year into three seasons here.

The first season (season 1) is from 1 February to 14 June. This season could be characterized as warm and dry, somewhat ameliorated by the influence of snowmelt. In central South Korea, melting snow contributes some runoff in the early phase of this season. The snow component takes more time to be converted to runoff than rain takes because of the additional time required for melting. Considering the snow component is important, but it involves a number of complicated tasks. Sugawara *et al.* (1984) proposed an empirical method to estimate the amount of snowmelt and added this amount to the rainfall for preparing the input data of the tank models. This method requires additional observations, e.g. spatial distribution of air temperature, and additional parameters to be estimated. These requirements have significantly weakened the prime advantage of the tank models, i.e. their low requirement of observations.

The seasonal tank model is very convenient, in that it considers the snow component without additional observations and parameters. In the seasonal tank model, the attenuation effect of the snow component could be reflected in the existing model parameters having unique values for the snow season.

The season from 15 June to 30 September (season 2) is regarded as the rainy season in central South Korea, and about two-thirds of the annual precipitation is concentrated in this season. This season contains the monsoon period, the most severe rainy period in the year, with most typhoons visiting central South Korea during this season. During this season, high soil moisture and short watershed response time can be observed. The attenuation effect of the basin becomes weak and precipitation causes high runoff in a short time.

Finally, the remaining period from 1 October to 31 January (season 3) involves cold and dry conditions. The humidity and soil moisture content is low and the amount of precipitation is small. As snowmelt does not occur during this season, it is different from season 1. To illustrate the different seasonal characteristics, the hyetograph and hydrograph of Daecheong dam watershed in central South Korea, observed in the year 1982, are shown in Figure 2 as an example. The precipitation and runoff patterns of these three seasons are clearly distinguished.

In this seasonal tank model, all parameters except initial storages are calibrated differently for each season, which yields 40 ($= 12 \times 3 + 4$) parameters to be calibrated. The upper and lower bounds of each parameter are set following recommendations from previous studies about Korean and Japanese watersheds (e.g. Sugawara *et al.*, 1984; Kim and Park, 1986). For the GA and the HS/MHS algorithm, these feasible regions for each parameter are divided into 201 partitions. This yields the total number of possible parameter combinations as 201^{16} for the non-seasonal tank model and 201^{40} for the seasonal one.

To reduce sudden changes of parameter values, which may occur at the boundary days between adjacent seasons, transitional periods of 10 days are inserted into the three seasonal boundaries. In these transitional periods, the parameters are linearly interpolated between the values of the two adjacent seasons. Therefore, technically, the model has six seasons for each year.

APPLICATIONS

Study area

The tank model linked to the optimization algorithms was applied to the Daecheong dam basin, which occupies about half of the Geum river basin with its drainage area of 4134 km^2 (see Figure 3). Daily runoff data are observed at the Daecheong multipurpose dam, located 150 km above the Geum river estuary, 16 km northeast of Daejeon, and 16 km south of Cheongju. Daily precipitation, pan evaporation, relative humidity, and wind speed were collected at the five nearby stations of Boeun, Cheongju, Daejeon, Geochang, and Jeonju, operated by the Korea Meteorological Administration. Observation data for 17 years (from 1981 to 1997) were used in this study. From these observations, the daily actual evapotranspiration $E(t)$ is estimated and the water budget over a year is balanced (Paik *et al.*, 2001b).

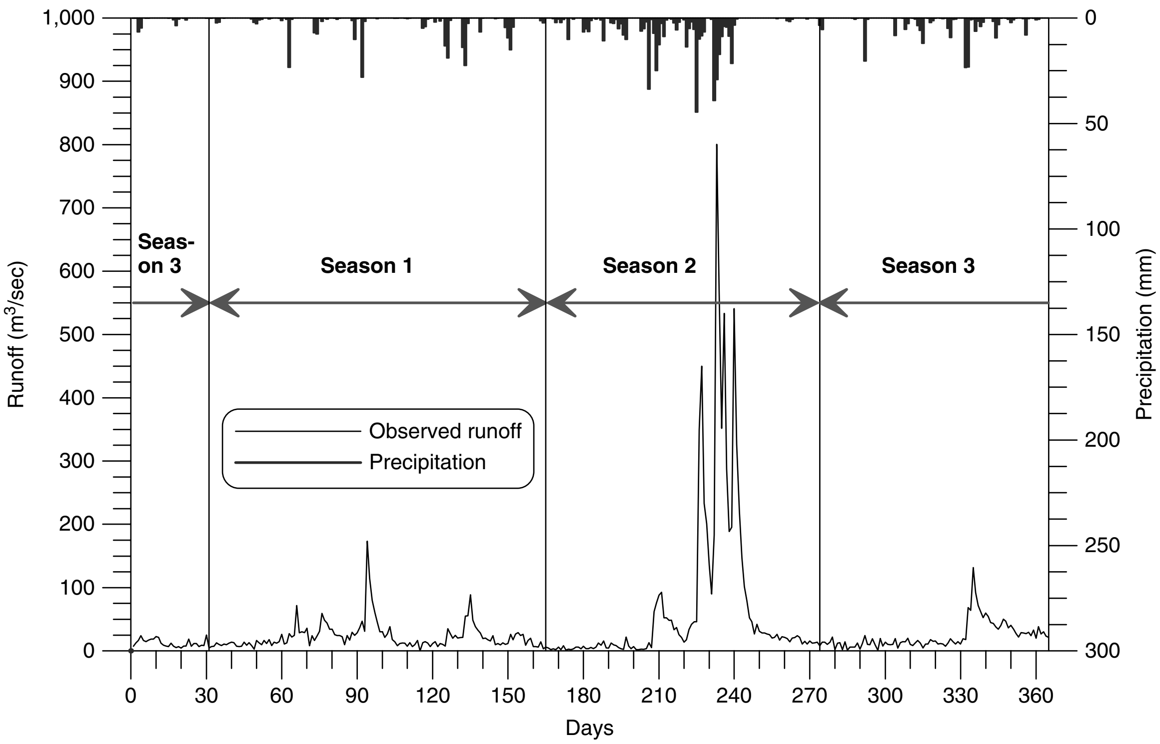

Figure 2. Classification of seasons adopted in this study

Sensitivity analysis of optimization parameters

In the case of the GAs and the HS/MHS algorithm, users have to specify values for various optimization parameters. The population size, the crossover probability, and the mutation probability are the main optimization parameters in the GAs, whereas the HM size, the HMCR, and the PAR are the optimization parameters in the HS/MHS algorithm. Since these optimization parameters greatly influence the efficiency of the optimization algorithms, the sensitivity of these parameters was analysed to determine the best value for each optimization parameter for fair comparison of the optimization algorithms. The sensitivity was evaluated by the criterion of the sum of the squares (SSQ), which is given as

$$\mathrm{SSQ} = \sum_{t=1}^{T} [q(t) - Q(t)]^2 \tag{6}$$

where $q(t)$ and $Q(t)$ ($\mathrm{m}^3\ \mathrm{s}^{-1}$) are the observed and the simulated runoff respectively and T is the number of records at evenly spaced time intervals.

For the GA, a crossover probability between 0·5 and 0·8 (especially 0·65), and a low mutation probability of 0·01, produced good results. The population size showed little correlation with performance. This result agrees well with the previous experiments of De Jong (1975). For the HS algorithm, high HMCR, especially from 0·9 to 0·95, contributed to excellent outputs, whereas the HM size and the PAR showed little influence on performance improvement. This result matches Geem *et al.*'s (2001) sensitivity analysis of the HMCR. The optimization parameter values determined, used in the following analysis, are summarized in Table I. The parameter values determined for the HS algorithm are also used for the MHS algorithm, since they share the same basic structure in which the influence of these optimization parameters is limited.

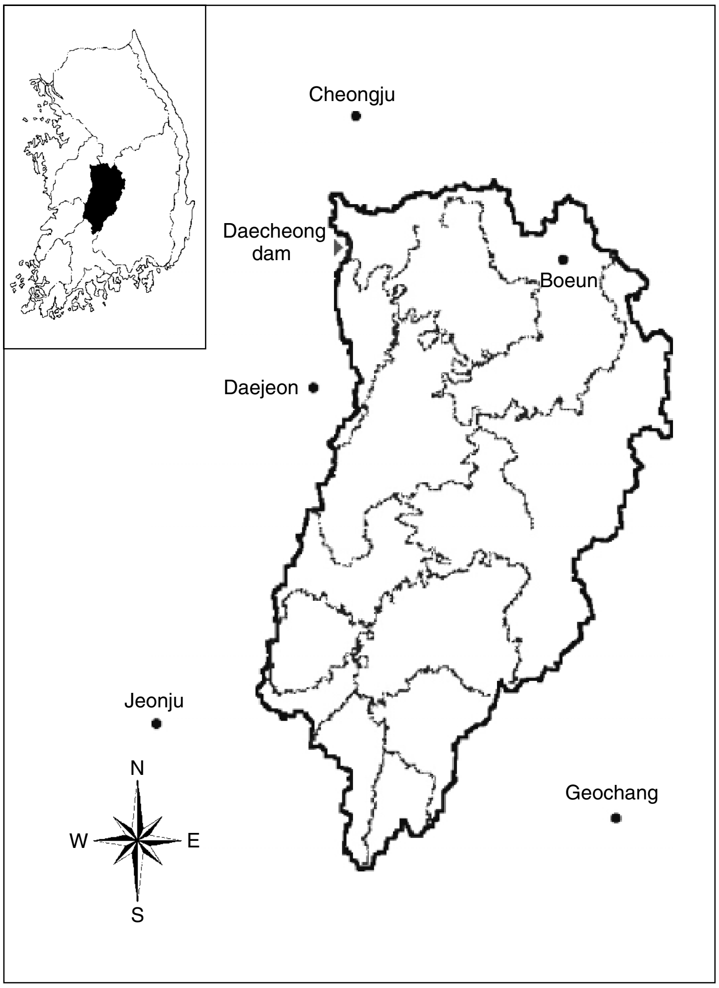

Figure 3. Location map of Daecheong dam basin

Table I. Optimization parameter values determined

GA	
Population size	60
Crossover probability	0·65
Mutation probability	0·01
HS/MHS	
HM size	60
HMCR	0·95
PAR	0·3

MHS

As an effort to improve the performance of the HA algorithm, the three strategies of proportionate selection, elimination of overlapping harmonies, and special training of elite harmonies were evaluated by the SSQ criterion in the parameter calibration of the non-seasonal tank model. Calibration was performed for each of the 16 different periods using optimization parameter values in Table I. Each of these periods is 2 years in length. Each strategy is combined with the HS algorithm and calibrated until 10 000 iterations.

To prevent excessive computational burden, the use of the special training of elite harmonies is limited to those cases when the relative SSQ of the worst harmony to the best one in the HM, defined in Equation (7), becomes less than a parameter C, or when only several iterations are left until the termination of the calibration. Initially, the parameter C is given as 2% and decreases by 0·1% each time the strategy is used.

$$\text{Relative SSQ of A to B (\%)} = \frac{\text{SSQ of A} - \text{SSQ of B}}{\text{SSQ of B}} \times 100 \tag{7}$$

The results showed that elimination of overlapping harmonies and the special training of elite harmonies enhances the performance of the HS algorithm, whereas proportionate selection undermines the performance. Two beneficial strategies of the elimination of overlapping harmonies and the special training of elite harmonies were simultaneously applied to the HS algorithm, and this combination is termed the MHS algorithm. Based on the relative SSQ of MHS to HS as the criterion, this combined algorithm performed better (showed negative values of relative SSQ) than the standard HS algorithm, as shown in Figure 4.

Comparison of optimization algorithms

The MHS algorithm, which showed its superiority over the standard HS algorithm, was compared with Powell's method and GA. In the comparison, minimization of SSQ is adopted as the objective function, while percent error in volume (PEV), defined as Equation (8), is used as an inspector to check the adequacy of the calibrated parameters. This is to reduce the risk of resulting in physically meaningless parameter values despite excellent fitting, the problem of blind automatic calibration having single criterion.

$$\text{PEV (\%)} = \left| \frac{\text{Total simulated runoff volume} - \text{Total observed runoff volume}}{\text{Total observed runoff volume}} \right| \times 100 \tag{8}$$

The same 16 periods that were used in the previous evaluation of the MHS algorithm, and the optimization parameter values in Table I, were used for the calibration. Comparison of the three algorithms showed that the GA and the MHS algorithm have much smaller SSQs than those obtained using Powell's method. The

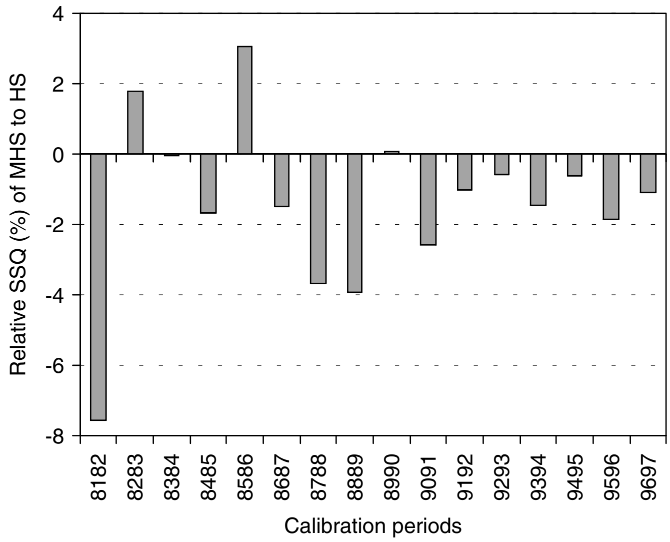

Figure 4. Comparison between MHS and HS

MHS algorithm after 30 000 iterations showed the best results followed by the GA after 10 000 iterations. The MHS algorithm after 10 000 iterations gave SSQs slightly bigger than the GA after 10 000 iterations, but much better than Powell's method. This comparison result was also confirmed by the PEV comparison, in that the rank of algorithms based on the PEV agreed exactly with the rank determined by the objective function of minimizing SSQ (Table II).

Powell's method is regarded as the weakest algorithm in this comparison due to the largest SSQ among the three algorithms, as well as the numerical dispersion. In this comparison, 9 among 16 cases resulted in numerical dispersion. The convergence is highly related to the initial values of parameters, which should be provided by the user. In fact, there is no specific rule in choosing initial values for Powell's method, whereas this effort is not required for the GA and the HS/MHS algorithm. These problems associated with Powell's method are, in a sense, common in traditional NLP algorithms. The handicaps of Powell's method further support the choice of the heuristic algorithms. Since the focus of this study is not on customizing Powell's method, no further effort is made to improve the results through adjusting the initial values.

For the evaluation of the heuristic algorithms, the computational time is equally as important as the objective function value. In the case of hard problems, where the global optimum is seldom expected, if time allows, the heuristic algorithms often keep making progress, although their performance is significantly decelerated over time. Therefore, a fair comparison should imply checking which algorithm yields better results in a limited time.

Until 30 000 iterations, the actual computational time was measured for the GA, the HS algorithm, and the MHS algorithm (Figure 5). Owing to its simple structure, the HS algorithm is the fastest among these. The strategies of elimination of overlapping harmonies, and particularly of the special training of elite harmonies, make the MHS algorithm consume more computational time than the HS algorithm for the same iterations, but this is still much less than the GA. The average computational time for 10 000 iterations used by the MHS algorithm was only 5·75% of the GA's. The large computational time required for the GA is mostly due to the GA's binary coding/encoding and the proportionate selection. Consequently, the MHS algorithm after 30 000 iterations takes less time and gives better results (compare SSQ and PEV in Table II) than the GA after 10 000 iterations.

Note that the focus by far has been on the comparison of various algorithms, rather than runoff simulation. The non-seasonal tank model was used simply as an apparatus for the comparison. Using the MHS algorithm, proven in this comparison, the real runoff simulation is focused on in the following analysis.

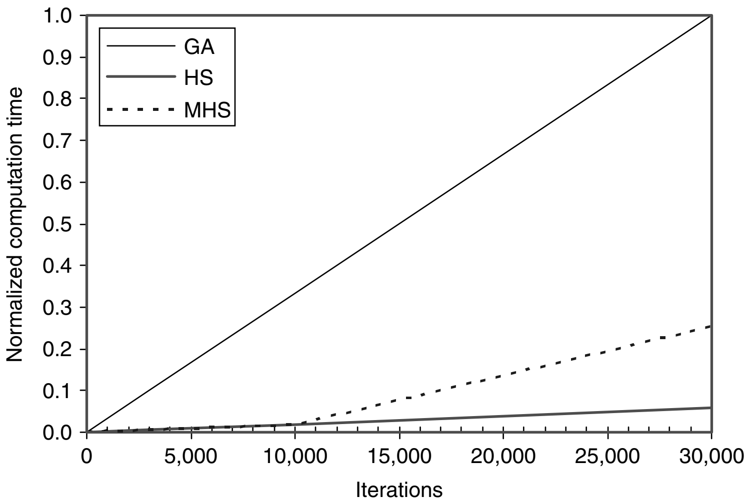

Figure 5. Normalized computational time versus number of iterations

Table II. Comparison of optimization algorithms[a]

Period	SSQ				PEV (%)			
	Powell	GA 10 000	MHS		Powell	GA 10 000	MHS	
			10 000	30 000			10 000	30 000
1981–82	ND	828	828	827	ND	2·76	3·04	2·79
1982–83	ND	887	891	867	ND	3·54	0·27	2·95
1983–84	ND	1476	1463	1462	ND	0·01	0·15	0·00
1984–85	2844	2133	2136	2104	25·5	2·24	1·77	1·53
1985–86	3042	2091	2164	2087	23·1	0·65	1·64	0·57
1986–87	4881	3725	3692	3720	19·0	0·10	0·38	0·07
1987–88	ND	3293	3318	3284	ND	0·42	0·53	0·86
1988–89	1568	1049	1049	1048	27·5	0·86	0·52	0·11
1989–90	1855	1484	1471	1468	19·8	0·23	0·24	0·13
1990–91	ND	975	988	967	ND	5·14	4·75	4·85
1991–92	981	615	631	657	24·9	4·63	3·66	3·97
1992–93	1662	878	885	860	26·0	0·59	5·63	0·33
1993–94	ND	689	674	670	ND	7·72	7·60	7·66
1994–95	ND	885	877	876	ND	1·09	1·13	1·56
1995–96	ND	1943	1954	1939	ND	1·15	3·75	1·38
1996–97	ND	6012	5954	5910	ND	0·21	0·25	0·10
Average	2405	1810	1811	1797	23·69	1·96	2·21	1·80
Rank	Worst	Second place	Third place	First place	Worst	Second place	Third place	First place

[a] ND: numerical dispersion.

Comparison of the seasonal and the non-seasonal tank models

For physically meaningful long-term runoff simulations, we should consider the lag time and low discharges. The lag time might be defined as the average time that the net precipitation (equal to precipitation minus evapotranspiration) of the entire basin takes to contribute to the runoff at the outlet. In general, the lag time increases as the drainage area increases. Owing to the flow velocity dependence on the stream discharge (e.g. Leopold and Maddock, 1953), the lag time of a watershed is directly related to the discharge, i.e. higher discharges or effective rainfalls yield shorter lag times. To find the adequate lag time for the Daecheong dam basin, lag times ranging from 0 to 2 days were tested at intervals of 0·1 days. The test revealed a lag time of 0·8 days, indicating that applying 20% of the net precipitation of a day to the tank model during that day, with the remaining 80% delayed to the next day, yields the minimum SSQ. This strategy is adopted here.

In the long-term runoff simulation, modelling low discharge (e.g. drought) is as important as modelling high discharge (e.g. flood). To prevent the parameters from being biased to large-magnitude events, the observed runoff data are logarithmically transformed in the calculation of SSQ in the following analysis, i.e. $q(t)$ and $Q(t)$ in Equation (6) are substituted by $\ln q(t)$ and $\ln Q(t)$ respectively.

With the lag time of 0·8 days and the optimization parameter values in Table I, the MHS algorithm is used to calibrate parameters of both the seasonal and the non-seasonal tank models using the logarithmically transformed runoff data. In this comparison between the seasonal and non-seasonal tank models, calibration is commonly implemented for 10 000 iterations and data for 16 years (1982–97) are used. Based on the partition of this period, five cases are classified as follows: the whole period is (1) divided into 16 partitions and each partition is a year long, (2) divided into eight partitions and each partition is 2 years long, (3) divided into four partitions and each partition is 4 years long, (4) divided into two partitions and each partition is 8 years long, and (5) is not divided.

As shown in Figure 6, the seasonal tank model outperformed the non-seasonal tank model for every case without exception. This is a big advantage of the seasonal tank model because it can successfully simulate

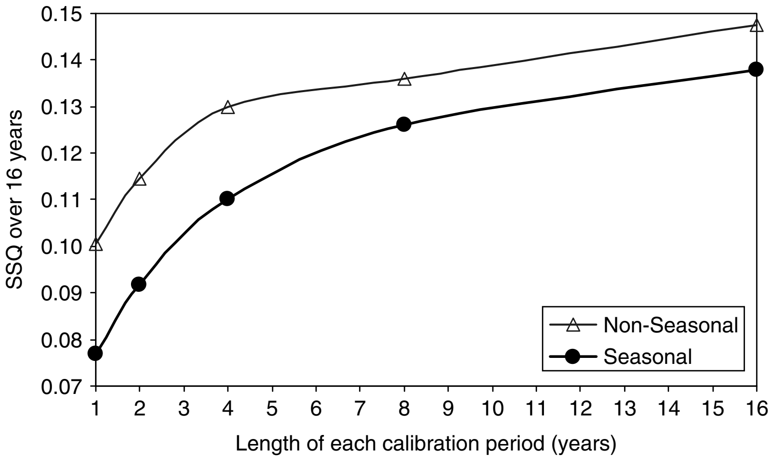

Figure 6. Comparison of the seasonal tank model with the non-seasonal tank model

runoff with little error and general watershed characteristics can be represented by calibrated parameters for longer periods.

Note that the calibration error increases as the calibration period of each partition increases for both the seasonal and the non-seasonal tank models in Figure 6. Calibration with a long period might help reduce the effect of the error in the initial storages for the case where the initial storages are neglected or assumed as uncertain values. However, for the case where the initial storages are also calibrated, such as in this study, calibration with the shortest period (1 year in this study) is most efficient in reducing error. Although calibration with a long period is certainly required to represent general watershed characteristics over entire years, this study shows that calibration with a long period solely to reduce the error of initial storage estimation should be avoided.

It is noteworthy that the distinctive watershed characteristics in each season are reflected in the seasonal variation of parameters. Throughout the five cases of calibration periods, the rainy season (season 2) tended to have higher S_{11}, S_{12}, and S_{21} than the dry seasons (seasons 1 and 3). This is believed to be a result of the increased runoff ratio due to the high soil moisture content of this rainy season. High S_{11}, S_{12}, and S_{21} assist the quick transition of rainfall to runoff by directly increasing the discharge from the first and the second tanks. On the other hand, season 1 had parameter values, except S_{41}, generally smaller than season 3. This reflects the delayed contribution to runoff caused by snow.

In conclusion, the seasonal tank model helps in understanding the temporal variation of the physical watershed characteristics, and gives much less calibration error than the non-seasonal model. As an example to demonstrate that the calibrated seasonal tank model accurately generates hydrographs close to the observed hydrographs, the calibrated results for the year 1993 using the seasonal tank model are shown in Figure 7.

CONCLUSIONS

To relax the time-invariant feature of the tank models, a popular conceptual rainfall-runoff model, the seasonal tank model, is proposed. Since this idea can be realized only by a powerful optimization algorithm, efforts are made to suggest the appropriate algorithm for the calibration of the seasonal model. We compared existing algorithms, such as Powell's method, the GA, and the HS algorithm, as well as the MHS algorithm developed in this study. The MHS algorithm is a combination of the standard HS algorithm and two strategies for elimination of overlapping harmonies and special training of elite harmonies. In the comparison of these algorithms, the superiority of the heuristic algorithms, such as the GA, the HS, or the MHS algorithm, over

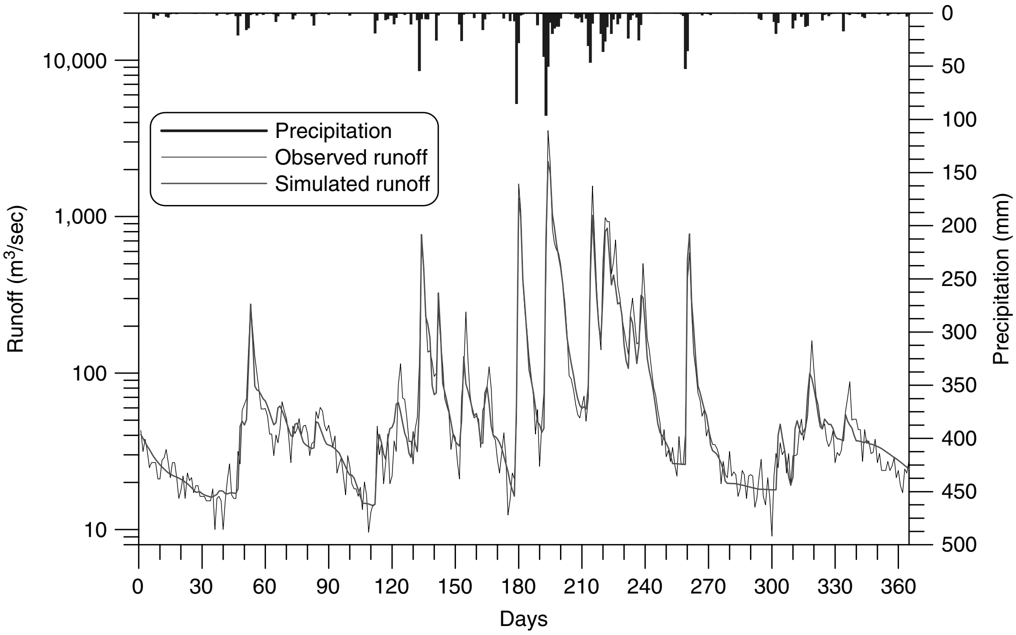

Figure 7. Simulated results of the seasonal tank model for the year 1993

Powell's method was demonstrated in terms of less erroneous parameter calibration, needlessness of setting initial parameter values, and freedom from numerical dispersions. In particular, the MHS algorithm was proven to be an adequate optimization algorithm for the parameter calibration of the tank model, in consideration of both objective function value and computational time.

The powerful MHS algorithm enabled the derivation of the seasonal tank model through its ability to handle a larger number of parameter combinations. The performance of the seasonal tank model was compared with that of the non-seasonal tank model and the effect of the calibration period was also analysed. In comparison, the seasonal tank model showed smaller calibration errors than those of the non-seasonal model regardless of the length of each calibration period. In addition, the seasonal tank model offers great convenience, in that the snow component can be reflected by the model without any additional parameter requirement.

The seasonal tank model was devised based on the concept that seasonally different watershed responses could be reflected in seasonally different parameter values. Calibrated parameter values followed distinctive seasonal trends, which is physically interpretable. This feature is important, in that this model helps in understanding the physical characteristics of a target watershed based on the calibrated parameters. Conclusively, the seasonal tank model could, therefore, be a successful alternative conceptual rainfall-runoff simulation model due to its improved accuracy, convenience, and physical implications.

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