Journal of Information Hiding and Multimedia Signal Processing ©2015 ISSN 2073-4212
Ubiquitous International Volume **6**, Number **5**, September **2015**

Study on Flood Para-Tank Model Parameters with Particle Swarm Optimization

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Received March, 2015; revised May, 2015

Abstract. *The relationship between rainfall and runoff has been the most important part of hydrological analysis. It is easier to get rainfall than to get runoff; therefore, the methods of calibration analysis regarding their relationship were actively developed in previous research to simulate the runoff with rainfall data. In this study, the concept of tank model mechanism serves as a starting point to convert the original basic type of four tank sections into a combination of aboveground and underground mechanisms to address a higher proportion of impermeable layer in cities. A concept similar to a tank is used to establish the operational mechanisms produced after rainfall on the surface. It is simulated in the underground sewer system after overland flow, and therefore, a new rainfall-runoff model is established, called the Para-Tank Model (PTM). The particle swarm optimization (PSO) from the modern stochastic optimization algorithms derived from natural biological group behaviors is employed to calculate the parameter values required by PTM. In this example, this method plots the calculated and target flows excellently according to the time axis. Its fast convergence, high calibration precision, and stable calculation results help to significantly improve the efficiency of automatic parameter calibration. Therefore, it is presented as a viable method for optimization, which can be extended to other hydrological models.*

Keywords: Tank model, Rainfall-runoff, Particle Swarm Optimization, PSO

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1. **Introduction.** In general, hydrological models simulating hydrological phenomena can be divided into black-box model, physically based model, and conceptual model according to the level of fidelity. The conceptual model is between the first two, and the tank model belongs to this model. Therefore, the original concept of the tank model is used in this study to reasonably represent the characteristics of the hydrologic system within a region with its simplified logic architecture. The runoff mechanism for both aboveground and underground scenarios is used to simulate the rainfall-runoff relationship within the region so as to develop a new hydrological model called Para-Tank Model (PTM).
In the past, the calibration of tank model parameters mainly depended on trial and error.

It is time consuming and laborious when a parameter is adjusted based on the accumulation of experiences. However, with the advancement of computer technology and mathematical optimization techniques, the parameter calibration technique based on automatic optimization has been introduced to the hydrological model. The optimization method developed on the basis of scientific observation of biological group behavior has become a new research direction. The particle swarm optimization (PSO) developed on the basis of the predatory behavior of birds by Kennedy and Eberhart [1] in 1995 is a simplified simulation model of society, which moves the individuals of the population to a better area on the basis of the level of their adaptation to the environment. In [2], Shi and Eberhart further improved the performance of PSO. Many extensions have also been proposed and can be classified as three types, 1) Discrete PSO [3], 2) Niche PSO [4] and 3) Hybrid PSO. Discrete PSO is the method that focuses on the problem of combination optimization. Niche PSO can handle premature convergence problem and slow convergence. Hybrid PSO integrates artificial intelligence technique like Genetic Algorithm, Simulate Anneal Arithmetic, Neural networks, and so forth with PSO, which includes SelPSO, BreedPSO and Simulate Anneal-PSO (SA-PSO). Bekele et al. [5] in 2005, Gill et al. [6] and Jiang Yan et al. [7] in 2006, and Chen Qiang [8] in 2010 applied PSO in parameter calibration of hydrology models and obtained good results; this proved its versatility in parameter calibration of different hydrological models. Therefore, in this paper, PSO will be used for quick, reasonable, and stable calibration of PTM parameters. The four parameters H_1 , λ_1 , H_2 , and, λ_2 , are used to calculate the ratio of calculated flow to target flow, indicating that the operating mechanism of PTM can meet the rainfall-runoff relationship. It is a good start for the development of future models.

In the following sections, we introduce the model theory in Section 2. Section 3 briefly reviews PSO and presents the method for discovering the values of model parameters. Section 4 provides an evaluation and discussion of the method. Section 5 presents the conclusions.

2. Model Theory.

In a brief rainstorm, it is difficult for a city to determine the physical meaning of 16 tank model parameters. Japanese literature recorded cases of urban flood outflow analysis with a two-stage tank, and the Chinese scholar R. S. Chen [9] studied the cases and proposed amendments to the urban tank model. Inspired by this concept, we changed the model into a dual mechanism for both aboveground and underground scenarios. A concept similar to tank is used to establish the operational mechanisms produced after rainfall on the surface. It is simulated in the underground sewer system after overland flow, and therefore, a new rainfall-runoff model is established.

2.1. Concept of catchment grid model.

The regional drainage concept dominates urban drainage system. Since urban tank is feasible, it could take the drains under main roads (i) as its mains to collect the water from street (j). Under this concept, it could consider an inter-mesh grid formed between sewers as a model unit. The sewer flow in each grid unit $q^t_{(k,i,j)}$,enters the main drains after collection. Then calculations of the sewer water system are performed. If it expands to k catchment areas, calculations of the open-channel system are performed. In Fig. 1, the entire region contains k catchments, in which main roads (i) and street (j) form many grids according to the flow and configuration of regional drainage. Each grids sewer flow is $q^t_{(k,i,j)}$. When rainwater flows through the ground into the sewers, the flows are $q^t_{(1,1,1)}$, $q^t_{(1,1,2)}$, $q^t_{(1,2,1)}$ .... , $q^t_{(k,i,j)}$ and the total flow of the drainage system in the k^{th} catchment is $\sum_1^{l,m} q^t_{(i,j)}$. Calculations of the sewer water system are then performed.

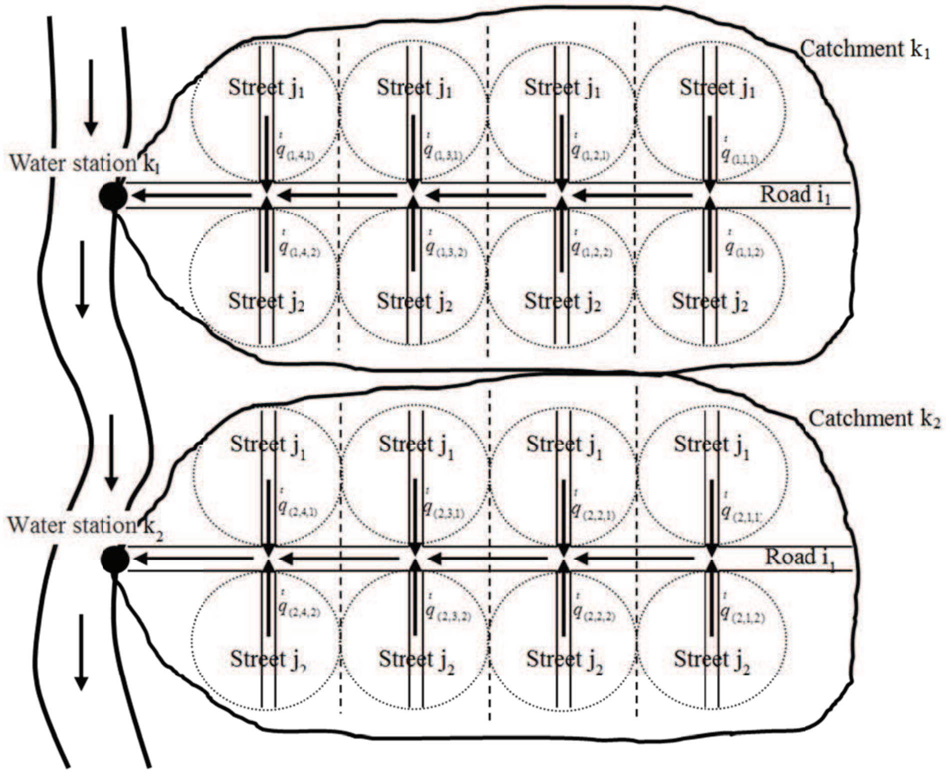

FIGURE 1. Schematic of urban-drainage grid concep.

2.2. **Model construction.** The new hydrological model system is a combination of the mechanism similar to tank and the concept of sewer system. The proposed system consists of three major parts, as shown in Fig. 2. The red-dashed range is the PTM, representing a rainfall to runoff process. The blue-dashed range shows a runoff to flood process. The green-dashed range represents flow changes within the channel.
We analyzed the case of a single model to understand model operation and carried out a four-stage discussion based on the evolution of urban rainfall:

- **Stage 1: Infiltration and depression** At the beginning of rainfall, rainwater infiltrates the soil surface layer. It is absorbed by the depressions caused by rainwater or terrain. At this time, if the head *h(t)* transformed from the cumulative rainfall *r(t)* is less than the head H_1 that the surface soil layer and the depression can carry, then the water will be infiltrated and absorbed by the depression, as shown in Fig. 2. If *h(t)* is less than H_1 , the head that the soil layer and the depression can carry is *h(t)* and the maximum head is H_1 . There is no sunshine during rainstorms, so Equation (2) omits evapotranspiration during rainfall.

  In Fig. 2, *r(t)* is cumulative rainfall (L); *h(t)* is rainfall head (L); *i(t)* is percolation (L); H_1 is infiltration and depression head (L); H_2 is sewer system head (L); y is sewer depth (L); λ_0 is percolation (%); λ_1 is terrain flooding feature outflow rate (%); λ_2 is sewer carrying capacity outflow rate (%); $q_1(t)$ is flow of runoff into the sewer (L); $q_2(t)$ is flooding depth (L); V_s is speed of surface runoff flowing into the channel (L/T).

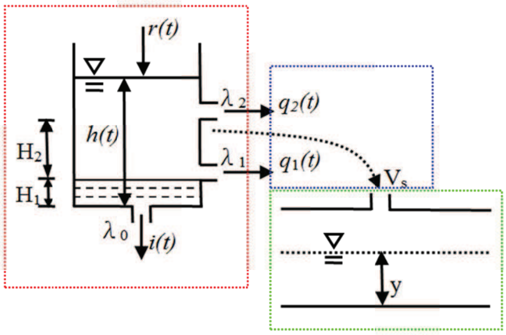

FIGURE 2. Dual model system of para-tank mechanism and sewer drainage system.

$$\Delta r(t) = r(t) - r(t-1) \tag{1}$$
$$h(t) = h(t-1) + \Delta r(t) \tag{2}$$
$$When\ h(t) \leq H_1, q_1(t) = 0 \tag{3}$$
$$q_2(t) = 0 \tag{4}$$

- **Stage 2: Percolation** When the rainfall continues increasing to the maximum head that the surface soil layer infiltration and depression can carry (H_1) , it will percolate downward to the aquifer below. In Fig. 2, *i(t)* is the downward amount of percolation, and λ_0 is the percolation proportion. At the beginning, the downward amount of percolation *i(t)* is high (the slope of percolation proportion, λ_0 , is relatively high), but when the air is squeezed under the ground, it will reduce the post-percolation, which approaches a constant value (the slope of percolation proportion, λ_0 , approaches 0). In Fig. 3, at the beginning, the downward percolation proportion, λ_0 , is high, the amount of percolation, *i(t)*, increases rapidly, but approaches a constant value at a later stage, so in the case of a quick urban storm, it is reasonable to assume that the amount of percolation *i(t)* will quickly become a constant value, which speeds up the whole model simulation by eliminating the variable λ_0 .

$$i(t) = C \tag{5}$$

Where *i(t)* is the amount of percolation (mm) and C is a constant.

- **Stage 3: Overland flow** When rainfall continues increasing, it will generate an overland flow as the rainstorm exceeds the percolation rate of the aquifer at Stage 2. The water will flow into the citys drainage system and test its capacity. We then performed the calculations of the sewer system flow. In Fig. 2, when head *h(t)* is greater than H_1 , subtract the maximum head H_1 at Stage 1 and the amount of percolation *i(t)* at Stage 2 and multiply by the outflow rate λ_1 to obtain the overland flow q_1*(t)*. When the overland flow enters the citys sewer system, there is a manhole inflow velocity, namely V_s, which can be defined as the velocity of surface runoff. After the two are multiplied, q_1*(t)* V_s will develop into a constant amount that flows into the sewer system, forming a pipe flow with a height of y, and H_2 can be regarded as the maximum head of the sewer system.

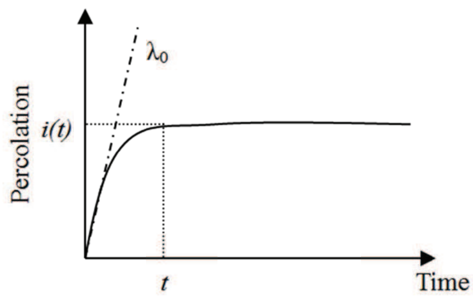

FIGURE 3. Changes in the amount of percolation *i(t)* depending on rainfall time *t*.

When H_1+H_2≥ *h(t)*> H_1,

$$q_1(t) = ((h(t) - H_1 - i(t)) \times \lambda_1 \quad (6)$$
$$q_2(t) = 0 \quad (7)$$

- **Stage 4: Flooding** After Stage 1, 2, and 3, rainfall continues increasing, and will exceed the design head of the city sewer system H_2 by which time the flooding begins. In Fig. 2, when head *h(t)* is greater than H_1+H_2 , subtract the maximum head H_1 at Stage 1, the amount of percolation *i(t)* at Stage 2 and the sewer system head H_2 at Stage 3, then multiply by the outflow rate of the sewer carrying capacity λ_2 , we will get the flow depth of the flooding q_2*(t)* . At this point, the maximum carrying capacity of the sewer system q_1*(t)* needs to be corrected to the design capacity q_c , which can be set at a constant value.

When *h(t)*>H_1+H_2,

$$q_1(t) = ((h(t) - H_1 - i(t)) \times \lambda_1 \leq q_c \quad (8)$$
$$q_2(t) = ((h(t) - H_1 - i(t) - H_2) \times \lambda_1 \times \lambda_2 \quad (9)$$

Where q_c is the sewer systems design capacity (L).
At Stage 3 and 4, after multiplied by speed V_s , the overland flow q_1*(t)* enters the sewer system, and then, we started the channel calculation process. To get the accurate velocity V and depth y, we can solve a one-dimensional Saint-Venant variable flow equation as follows:

$$q_1(t) \times V_s + \frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = 0 \quad (10)$$
$$\frac{1}{g}\frac{\partial V}{\partial t} + \frac{V}{g}\frac{\partial V}{\partial x} + \frac{\partial y}{\partial x} = S_0 - S_f \quad (11)$$

Equations (10) and (11) are the continuous equation and momentum equation of One-dimensional Gradually Varied Unsteady Flow under the assumption of no lateral flow, where Q is the flow (L^3/T) , V is the average velocity of the section (L/T) , t is the time coordinate (T), n is Manning roughness coefficient $(TL^{-1/3})$, So is the vertical gradient of the channel bottom , x is the space coordinate in the flow direction (L), y is the depth (L), g is the gravitational acceleration (L/T^2) , R is hydraulic radius (L), Sf is the energy gradient line (L/L) , and can be calculated using Manning formula, namely,

$$S_f = \frac{V^2 n^2}{R^{4/3}} \tag{12}$$

We thus built the proposed model based on the aforementioned three sections and four stages. The parameters of the model all have a certain degree of physical significance. The model is a combination of the mechanism similar to tank and the concept of sewer system. Since the model is built upon the tank model, it is called the PTM.

3. Optimization Method.

3.1. Particle Swarm Optimization (PSO).

In this study, the optimization of parameter calibration uses PSO, developed on the basis of the discovery of an evolutionary advantage of the population regarding information sharing from the observation of the social behaviors of animals. The principle moves the individuals of the population to a good area based on the level of their adaptation to the environment. It does not apply an evolution operator to the individuals, instead it views each individual as a particle without volume in d-dimensional search space, flying at a certain speed that is determined according to its own flying experience and that of the other particles. The i^{th} particle is represented as $X_i = (X_{i1}, X_{i2}, \ldots, X_{id})$. The best position that it has experienced, namely the position with the best fitness, is denoted by $P_i = (P_{i1}, P_{i2}, \ldots, P_{id})$, also known as P_{best} . The index number of the best-experienced position of all the particles in the group is denoted by g, namely Pg, also called G_{best} . The velocity of Particle i is represented by $V_i = (V_{i1}, V_{i2}, \ldots, V_{id})$. The d^{th} dimension of each generation varies according to the following equations:

$$V_{id}^{t+1} = \omega V_{id}^{t} + c_1 r_1^t (P_{id}^t - x_{id}^t) + c_2 r_2^t (P_{gd}^t - x_{id}^t) \tag{13}$$

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} t \tag{14}$$

Where w is inertia weight, c_1 and c_2 are acceleration constants, r_1 and r_2 are two random values changing in the range [0,1]. If the velocity of a particle that is accelerated in some dimension $V_i d$ exceeds the maximum velocity $V_{max,d}$, then the dimensional velocity is set to the maximum velocity for that dimension $V_{max,d}$.

In Equation (13), the first part is the previous behavior inertia of particle; the second part is a cognition part, which means the self-reflection of particle; and the third part is a social part, which means the information sharing and mutual cooperation between particles. The PSO algorithm is like a psychological assumption: in the cognitive process of seeking consistency, individuals tend to take into account the faith of their coworkers while maintaining their own beliefs. When perceiving that the faith of their coworkers is better, they will adjust adaptively. As shown in Fig.4, the particle has its original velocity V_{id}^t and X_{id}^t, together with its past experience. It finally moves to the best position after referring to the current local optimal solution P_{best} (cognition part) as well as the information sharing and mutual cooperation of the current global optimal solution G_{best} (social part).

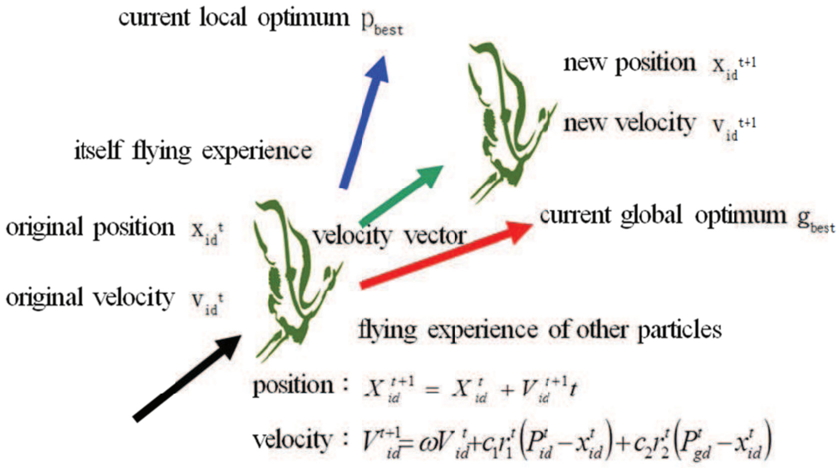

FIGURE 4. Schematic diagram of PSO.

3.2. **Parameter optimization of the proposed model system.** Every grid in the city represents a catchment. To start with, we analyzed and studied just one single grid model in order to verify its feasibility. The improvements have been made to PSO in the last 20 years, but the basic principle remains the same, so this study still selects the parameters based on a combination of the basic PSO and PTM operation while using Matlab programming language as a development tool. The design process consists of a main program as shown in Fig. 5 and a subroutine as shown in Fig. 6.
The basic input data include the number of particles (m), dimension count (d), unknown variables (X_{id}), i=1-m, position range ($X_{id,max}, X_{id,min}$), the number of times (t_{max}), speed correction (R), inertia weight (w), global acceleration constants (c_1, c_2), and randomly generated numbers (r_1), (r_2). Historical hydrographic data require target flow $Q_o(t)$ and target number (N, with 1 hour as the unit) to establish the speed range of each particle. Generally, we assume that $X_{id,max} = X_{id,max} - X_{id,min}$, $V_{id,min} = -V_{id,min}$. Since there was no set value to begin with, we first started initialization by assuming that $V_{id,high} = V_{id,max} \times R$, $V_{id,low} = 0$, $V_{id} = rand \times (V_{id,high} - V_{id,low})V_{id,low}$, $X_{id} = rand \times (X_{id,min} - X_{id,min})X_{id,min}$. With the initial values, we then established the target function and used the historical hydrological data to optimize the parameters. It is best when the difference between the calculated flow and the target flow is at its minimum. Considering the possibility that positive and negative values can cancel out each other, the target function uses the Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Q_C(t) - Q_O(t))^2}{N}} \tag{15}$$

Where: $Q_c(t)$ stands for the calculated flow; $Q_c(t)$ stands for the targeted flow and; N stands for the number of data points.

After initialization, we can get the local optimum P_{best} [X_{id} and $(F_n)_i$] and the group optimum G_{best} [X_{id} and $(F_n)_i$] of the target function between the particles, and then adjust the speed and position through Equations (13) and (14) according to the PSO principle to get better local optimum P_{best} and group optimum G_{best}.

We then calculated the flow value $Q_c(t)$ in the subroutine. For the PTM after the rainfall, parameters such as the previous residual head h_0 and cumulative rainfall r_0 need to be taken into account. According to the PTM rainfallrunoff process within the red dashed-line square in Fig. 2, we used four dimensions X_{i1}, X_{i2}, X_{i3}, and X_{i4}, of $(H_1)_{id} = X_{i1}$, $(\lambda_1)_{id} = X_{i2}, (H_2)_{id} = X_{i3}$, and $(\lambda_2)_{id} = X_{i4}$ to represent four parameters H_1, λ_1, H_2, and λ_2. We then calculated rainfall $r(t)$, amount of percolation $i(t)$, sewer design capacity (q_c), and basin area (A_b) hourly to get the calculated flow $Q_c(t)$, which was then fed back into the main program to continue the search of optimal PSO parameter. When the number of search attempts reaches t_{max} , the optimization process is terminated. The four particles X_{i1}, X_{i2}, X_{i3}, and X_{i4} corresponding to the obtained target function $(F_n)_i$ are the desired results.

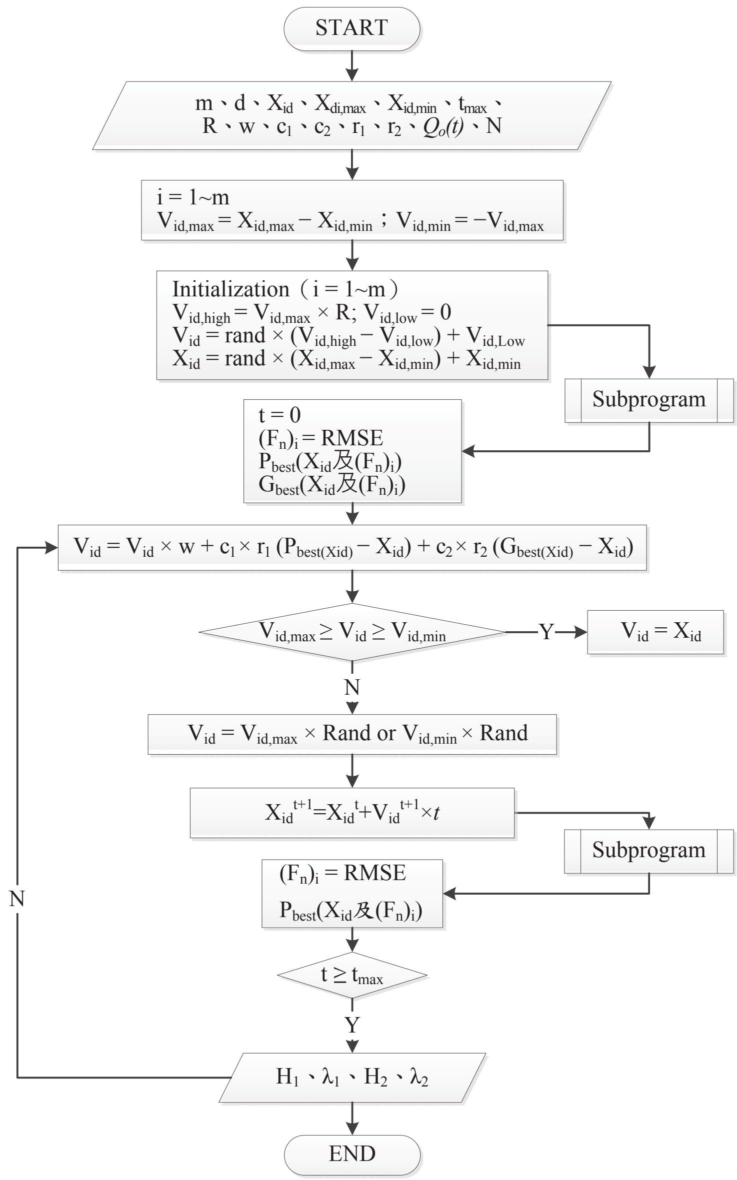

FIGURE 5. Flowchart of the main program for obtaining PTM parameters through PSO.

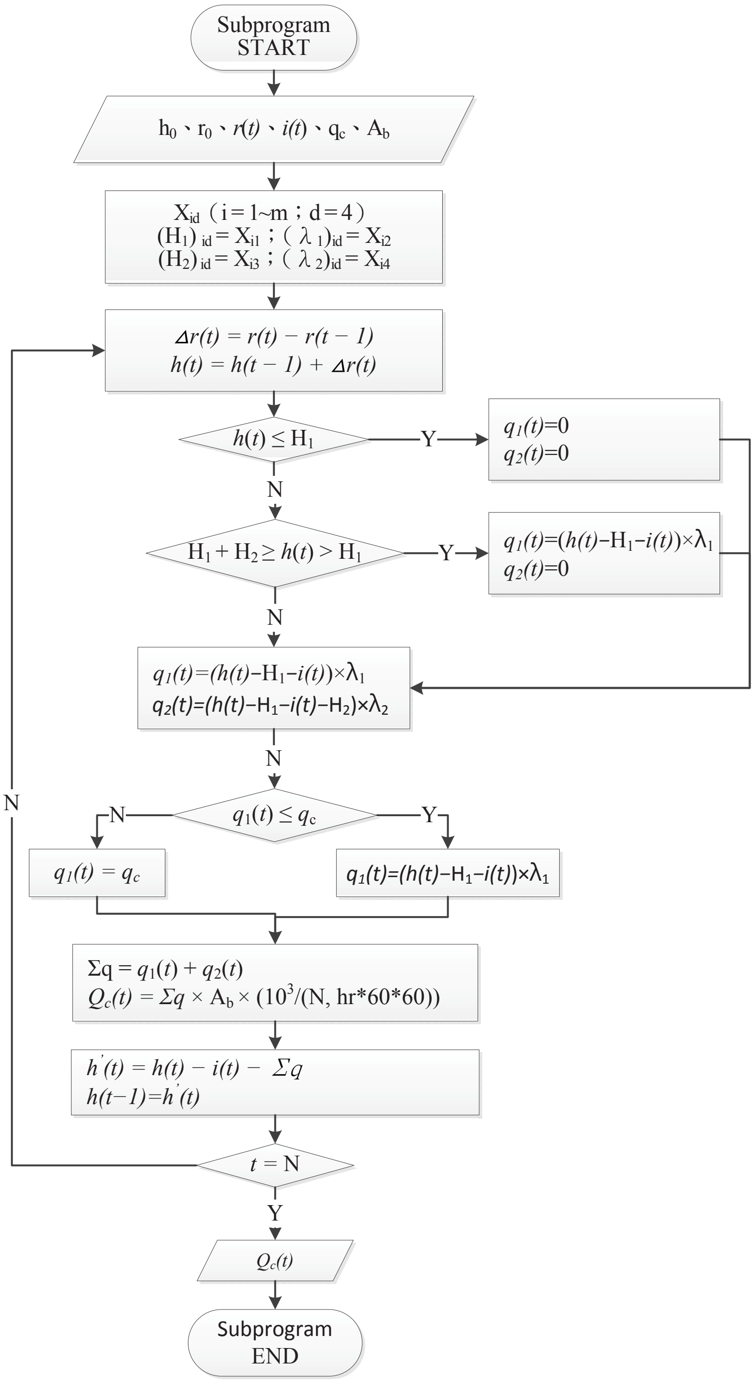

Figure 6. Flowchart of the subroutine for obtaining PTM parameters through PSO.

4. Results of Parameter Calibration and Discussion.

4.1. **Overview of the Regions Under Study.** The study is carried out in the metropolitan area of Kaohsiung. The report of the Flood Control and Drainage Plan of Kaohsiung noted [10] that at 5:00 pm on July 11, 2001, the strong southwest flow introduced by Tropical Storm Trami set off 10 consecutive hours of heavy rain in Kaohsiung area. According to the records of Cianjhen and Zuoying weather stations of the citys

Weather Bureau, the cumulative rainfall totals of these two areas are respectively 525 mm (the highest single-day rainfall since 1962) and 493 mm. The 1-hour maximum rainfall recorded at Zuoying Station is 126.5 mm, approaching the 130 mm standard for a 100-year storm, and the 3-hour maximum rainfall is 329 mm, higher than the 300 mm standard for a 200-year storm. The 1-hour maximum rainfall recorded at Cianjhen Station is 119.5 cm, and the 3-hour maximum rainfall is 239 mm. The rainfall records of both stations are much higher than the flood control and drainage design standards of Kaohsiung (5-year drainage and 20-year flood control). The drainage experienced further blocking caused by the tidal surge at the Love River estuarine, as a result, although the implementation rate of urban stormwater sewer system reached over 90 percent, the system still failed to put the flood under control, resulting in severe flooding of 300 hectares of low-lying areas of Yancheng District, Benguanli, Benheli, Baozhugou, No.2 Canal and Cianjhen District. For a comparative analysis of PTM operation, PTM rainfall data and the average of Kaohsiung, Zuoying and Fongshan rainfall stations during the 711 Flood from the Flood Control and Drainage Plan of Kaohsiung are taken as the rainfall *r(t)* values in the model for calculation, with the rainfall data shown in Table 1.

TABLE 1. Observed rainfall data during the 711 Flood.

Time		Rainfall (mm)				Time		Rainfall (mm)			
Day	Hour	K.siung	Zuoying	Fongshan	Average	Day	Hour	K.siung	Zuoying	Fongshan	Average
11	5	1.5	0.0	0.0	0.50	12	1	29.0	42.5	45.5	39.00
	6	2.5	0.0	0.0	0.83		2	25.0	48.5	41.0	38.17
	7	5.0	1.5	0.0	2.17		3	18.5	20.0	17.5	18.67
	8	3.5	1.5	1.0	2.00		4	7.5	11.0	16.0	11.50
	9	0.5	0.0	8.5	3.00		5	1.5	6.0	1.0	2.83
	10	0.0	1.5	3.5	1.67		6	1.0	1.5	6.0	2.83
	11	0.5	0.0	0.5	0.33		7	0.0	0.5	0.0	0.17
	12	0.0	0.5	0.0	0.17		8	0.0	9.5	0.0	3.17
	13	0.0	0.0	0.0	0.00		9	0.0	2.0	1.0	1.00
	14	0.0	0.0	0.0	0.00		10	2.0	0.0	0.5	0.83
	15	0.0	0.0	0.0	0.00		11	0.0	0.0	2.5	0.83
	16	2.0	0.5	4.5	2.33		12	0.0	0.0	0.0	0.00
	17	8.5	1.0	8.0	5.83		13	0.0	0.0	0.0	0.00
	18	26.0	3.0	39.0	22.67		14	0.0	2.0	0.0	0.67
	19	72.5	95.0	44.5	70.67		15	2.5	5.5	3.0	3.67
	20	43.0	107.0	29.5	59.83		16	0.0	0.0	2.0	0.67
	21	54.0	126.5	92.0	90.83		17	0.0	0.0	0.0	0.00
	22	65.5	22.0	81.0	56.17		18	0.0	0.0	0.0	0.00
	23	119.5	32.5	89.0	80.33		19	1.5	0.0	0.0	0.50
	24	66.0	44.0	64.0	58.00		20	0.0	0.0	0.0	0.00

In this study, the hydrological model PTM focuses on the impact of rainstorm on metropolitan areas with a higher proportion of impermeable layer. The 711 Storm event can be used as a perfect case to discuss the parameter optimization of the model for urban rainfallrunoff pattern. Kaohsiung area is mainly in the Love River basin. According to the distribution of the flooded area in the 711 Flood, the basin is divided into nine catchments depending on the terrain, as shown in Fig. 7. Catchment 3 is selected for the optimization of PTM parameter calibration, as it has no differentiated subareas such as a and b. We calculated the rainfallrunoff in the catchment (HEC-1) using the measured rainfall records as the sidestream boundary of channel flood routing model (NETSTARS) and the tide level hydrograph of Kaohsiung Port as the downstream water boundary to generate the water level and discharge hydrograph of each Love River section. The flow value thus acquired is regarded as true in the PTM model and taken as the target of parameter calibration. The calculation model has a backwater effect, resulting in a small portion of negative flow values, so the backwater effect will not be considered for the current stage of the study.

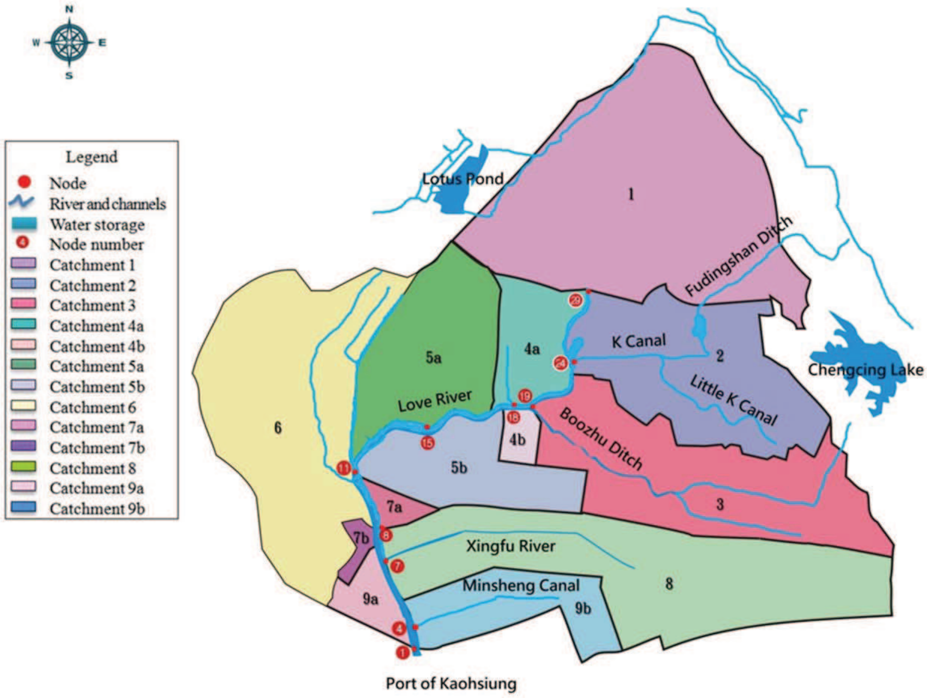

FIGURE 7. Catchments in Love River basin.

4.2. **Results of parameter calibration.** We then fed the rainfall and flow of a catchment into the PTM analysis program. We assumed that the global acceleration constants c_1 and c_2 are both 0.1, the inertia weight $w = 0.8$, the particle count $m = 30$, the dimension count $d = 4$, the previous residual head $h_0 = 3\ mm$, the cumulative rainfall $r_0 = 1\ mm$, and the amount of percolation $i(t)$ is 1 mm. The sewer design capacity qc refers to the standard of the urban stormwater sewer system in Taiwan. The stormwater sewer system of Kaohsiung was designed in 1976 by the former Bureau of Public Works of Taiwan Provincial Government, primarily based on the rainfall regression analysis for 19481974, and the 1-hour 5-year storm intensity, 70.9mm/hr, is the drainage-section design standard. Position range X_{i1} represents the head of infiltration and depression H_1 and is set between 1 and 100, X_{i2} represents the outflow rate of the terrain flooding feature λ_1 and is set between 0 and 1, X_{i3} represents the head of the sewer system H_2 and is set between 50 and 100, X_{i4} represents the outflow rate of the sewer carrying capacity λ_2 and is set between 0 and 1, and number t_{max} is set to 1000 for the actual calculation. The calculation results are H_1= 3.745365, λ_1 = 0.591964, H_2 = 52.16278, and $\lambda_2 = 0.240281$; the target function $(F_n)_i$ reaches 3.66. The four parameters were then fed back into PTM for hourly calculation to get the comparative results of the calculated flow $Q_c(t)$ and the target flow $Q_o(t)$, as shown in Fig. 8, which shows that it is feasible to obtain the PTM parameters by means of PSO.

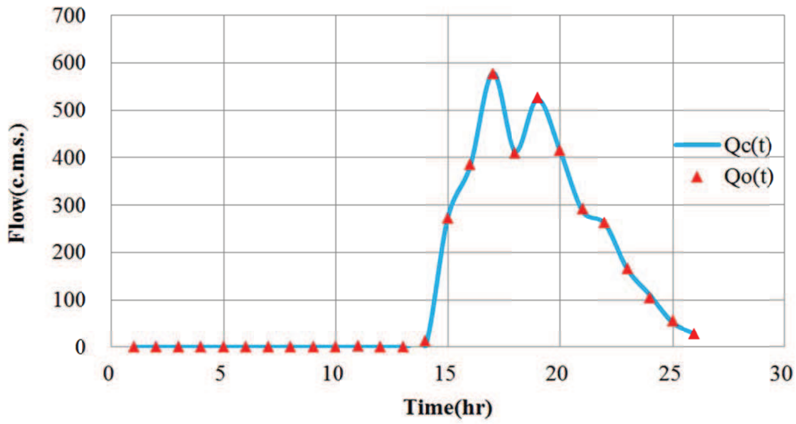

FIGURE 8. Comparison of the calculated flow and the target flow.

4.3. **Discussion.** PSO is applied in this study to select the PTM parameters. In the Flood Control and Drainage Plan of Kaohsiung, the impact of the 711 Trami on Baozhugou of Kaohsiung can be shown by the fact that the parameters in this area are $H_1 = 3.745365$, $_1 = 0.591964$, $H_2 = 52.16278$, and $_2 = 0.240281$. After assessment of the model indicators, considering the time axis factor, we select the root mean squared error (RMSE), coefficient of efficiency (CE), and percent error of total volume (VER) of total data-point count for evaluation. The evaluative results depend on the error evaluation; when the closest RMSE value approaches 0, the better the model performs, and the more CE approaches 1 or VER approaches 0, the better applicability the model has for the rainfallrunoff process.

In this example, RMSE reaches 3.66. This is because the sudden rainfall prevents the PTM with only four parameters from showing the variations immediately, but the comparison of the calculated flow and the target flow in Fig. 8 shows excellent adaptation. CE is 0.999, almost equal to 1, indicating almost the same rainfallrunoff simulation of PTM in this area. VER is -0.92%, close to 0, indicating that the total volume is close to error-free, and the calculated flow and the target flow are almost the same. The results of the three model assessment indicators show that the PTM selection of local parameters through PSO can achieve good accuracy, thus demonstrating the applicability of PSO to the parameter selection for hydrological models.

5. **Conclusions.** This paper proposes the concept of PTM, the parameters of which have corresponding physical meanings, and introduces four model parameters via the rapid calculation of basic PSO. According to the RMSE, CE, and VER assessment, the obtained RMSE value is 3.66, while the results of CE and VER are 0.999 and -0.92%, respectively, thus demonstrating that this model is suitable for simulating the urban rainfallrunoff process. The study results have important significance to future model development.

Calculating hydrological model parameters via PSO is a good choice. Scholars have developed new PSO methods, but they are essentially unchanged. The algorithm, featuring quick convergence, high accuracy, and stable results can significantly improve the efficiency of automatic parameter calibration. It is a general optimization method, suitable for extending to other hydrological models for better choices.

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