Int. J. Advance. Soft Comput. Appl., Vol. 3, No. 3, November 2011
ISSN 2074-8523;
www.i-csrs.org

Comparison of Particle Swarm Optimization and Shuffle Complex Evolution for Auto-Calibration of Hourly Tank Model's Parameters

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Abstract

The famous Hydrological Tank Model is always preferred for runoff forecasting. This main reason is Tank Model not only simple in term of its structures, but able to forecast runoff accurately using only rainfall and runoff data. However, much time and effort are required to calibrate a large numbers of parameters in the model for obtaining better results through trial-and-error procedure. Therefore, there is an urgent need to develop an auto-calibration method. Two types of global optimization methods (GOMs), named as Particle Swarm Optimization (PSO) and Shuffle Complex Evolution (SCE) are selected. The selected study area is Bedup basin, Samarahan, Sarawak, Malaysia. Input data used for model calibration are hourly rainfall and runoff only. The accuracy of the simulation results are measured using Coefficient of Correlation (R) and Nash-Sutcliffe Coefficient (E^2). The robustness of the model parameters obtained are further analyzed with boxplots analysis. Peak errors are also evaluated to determine the difference between the observed and simulated peaks. Results revealed that the performance of simple PSO method is slightly better than the famous and complicated SCE method. PSO is able to obtain optimal values for 10 parameters fast and accurate within a multidimensional parameter space that could provide the best fit between the observed and simulated runoff.

Keywords: Hydrological Tank Model, particle swarm optimization (PSO), shuffle complex evolution (SCE), rainfall-runoff model.

1 Introduction

There are many deterministic and conceptual models that are able to simulate daily and hourly runoff accurately. However, most of them have complex structures and required various types of data. Thus, Hydrological Tank Model that considered the watershed as a series of storage vessels is selected in this study. This simple structure requires only rainfall and runoff data for model calibration.

Tank Model was first proposed by Sugawara and Funiyuki (1956). According to Paik *et al.* (2005), despite the simple structure, Tank Model has proven more capable than many other models in modeling the hydrologic responses from a wide range of humid watersheds (World Meteorological Organization, 1975; Franchini and Pacciani, 1991).

However, the major work in applying this hydrological model is fitting the model parameters. In early days, the most common procedure for searching the model parameters is through trial-and-error procedure. This manual calibration process is tedious and time consuming owing to the large numbers of model parameters involved in the four-layered Tank Model. Sometimes, the simulation results may be uncertain due to the subjective factors involved. Therefore, this study is carried out to determine a more efficient automatic calibration procedure. Recently, various optimization techniques have been developed (Shuchita and Richa, 2009; Rahnama and Jahanshai, 2009; Premalatha and Natarajan, 2010a)

Past studies claimed that the most effective and efficient GOM for auto-calibration of Tank Model is shuffle complex evolution (SCE) (Cooper *et al*., 1997; Chen *et al*., 2005). Cooper *et al*. (2007) extended the SCE optimization technique by including hydrologic process-based parameter constraints to improve the accuracy and efficiency of calibration procedures. Meanwhile, the most frequent algorithm investigated is GA where Cooper *et al*. (1997), Paik *et al*. (2005), Chen and Barry (2006) have compared the performance of GA with other algorithms even though GA is not always the best algorithm. Other algorithms such as simulated annealing (SA), Standardized Powell Method (SP), Marquardt algorithm, Multistart Powell, modified harmony search algorithm (MHS), Rosenbrock algorithm and simplex technique are rarely used by the researchers.

Due to the superiority and popularity of SCE methods, this method is selected to auto-calibrate the Tank Model parameters in humid region that consists of four storage vessels. The performance of SCE method is then compared with particle swarm optimization method (PSO), a simple and newly developed optimization algorithm, but has proven it realization and promising optimization ability in solving various problems (Song and Gu, 2004).

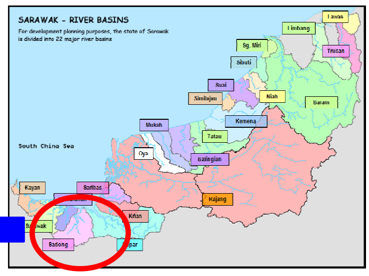
Currently, the application of PSO method in hydrology is still rare. Alexandre and Darrel (2006) applied multiobjective particle swarm optimization (MOPSO) algorithm for finding nondominated (Pareto) solutions when minimizing deviations from outflow water quality targets. Bong and Bryan (2006) used PSO to optimize the preliminary selection, sizing and placement of hydraulic devices in a pipeline system in order to control its transient response. Janga and Nagesh (2007) used multiobjective particle swarm optimization (MOPSO) approach to generate Pareto-optimal solutions for reservoir operation problems. Subashini and Bhuvaneswari (2011) applied non-dominated sorting particle swarm optimization (NSPSO) to combine the operations of NSGA–II for scheduling tasks in a heterogeneous environment. Premalatha and Natarajan (2010b) hybrid PSO and Genetic Algorithm (GA) approaches for solving the document clustering problem.

2 Study Area

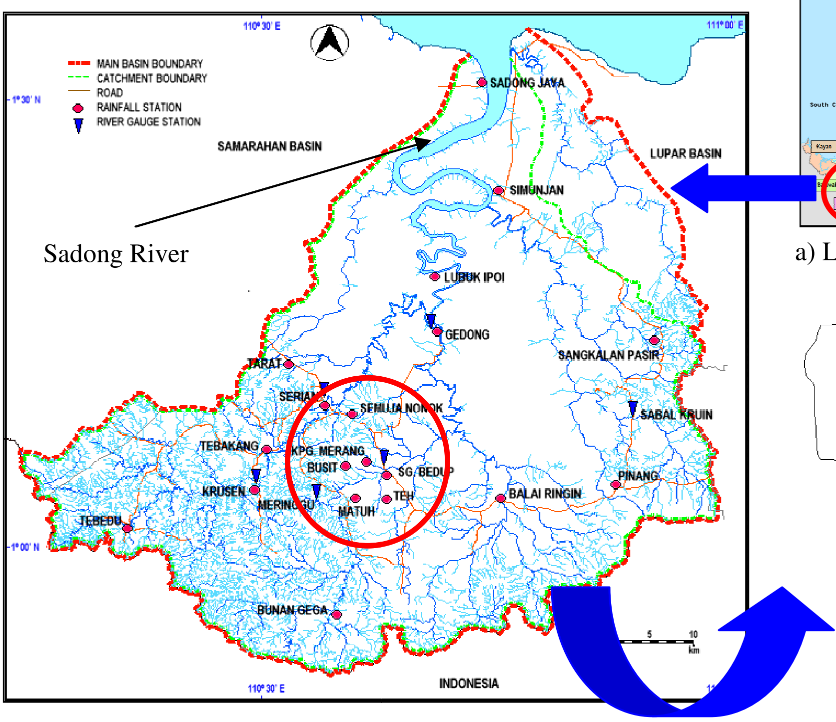
The selected study area is Bedup basin, located approximately 80km from Kuching City, Sarawak, Malaysia. It is non-tidal influence river basin, located at upper stream of Batang Sadong. The basin area is approximately about 47.5km^2 and the elevation varies from 8m to 686m above mean sea level (JUPEM, 1975). Vegetation cover is mainly shrubs, low plant and forest. The development and land use changes are not really significant in this rural watershed for the past 30 years. Sungai Bedup's basin has a dendritic type channel system. Maximum stream length for the basin is approximately 10km, which is measured from the most remote area point of the stream to the basin outlet.

The locality plan of Bedup basin is presented in Fig. 1. Fig. 1a shows the location of Sadong basin. Main boundary of the Sadong basin, rainfall and river stage gauging stations within Sadong basin, are shown in Fig. 1b. Fig. 1c shows the 5 rainfall gauging stations available in Bedup basin, namely, Bukit Matuh (BM), Semuja Nonok (SN), Sungai Busit (SB), Sungai Merang (SM) and Sungai Teb (ST), and one river stage gauging station at Sungai Bedup located at the outlet of the basin.

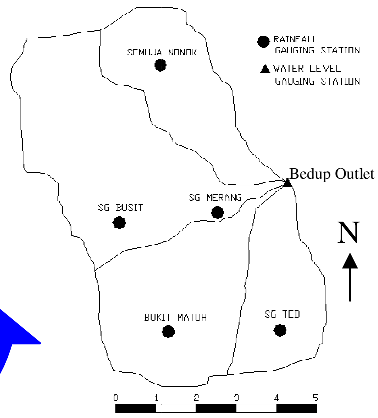
Soil map of Bedup basin is presented in Fig. 2. In general, Bedup basin is mostly covered with clayey soil, such as Merit (Mrt), Malang (Mlg), Tarat (Trt), Kerait (Krt), Bijat (Bjt) and Anderson (And). Clayey soil has low infiltration rate (minimum infiltration rate of 0.04 inches/hr), where most of the precipitation fails to infiltrate, runs over the soil surface and thus produces surface runoff. Part of Bedup basin is covered with Nyalau (Nyl), Triboh (Trh), Semilajau (Sml) soils, which are coarse loamy soil. This group of soil has higher infiltration rate (minimum infiltration rate of 1.02 inches/hr) and therefore has moderately low runoff potential.



a) Location map of Sadong basin



b) Sadong basin and river network (DID, 2004)



c) Bedup basin

Fig 1: Locality map of Bedup basin, Sub-basin of Sadong basin, Sarawak

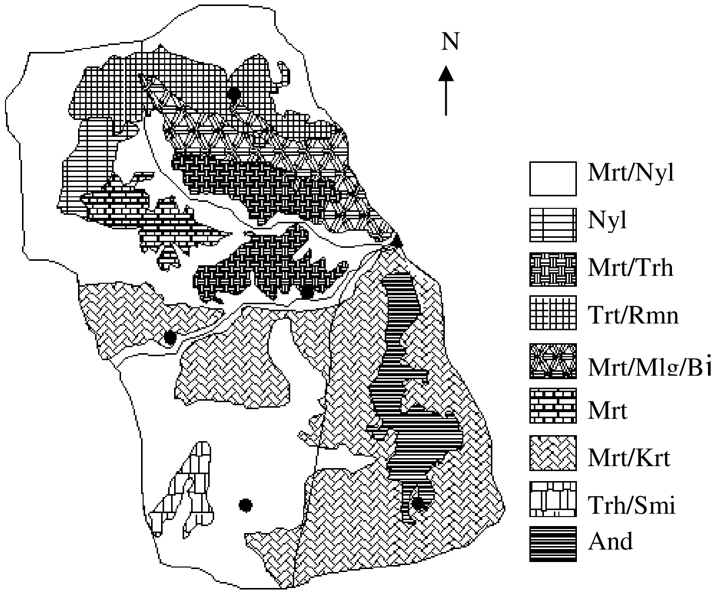


Fig. 2: Soil Map of Bedup basin, Sarawak (DOA, 1975)

The input data used is hourly rainfall data from the 5 rainfall stations. Data series used for model calibration and verification are hourly rainfall and runoff from year 1990 to year 2003 obtained from Thiessen Polygon Analysis. The area weighted precipitation for BM, SN, SB, SM, ST are found to be 0.17, 0.16, 0.17, 0.18 and 0.32 respectively. The average areal hourly rainfall data for that time step is then fed into the Tank Model. The calibrated Tank Model will then carry out computations to simulate the hourly discharges for Bedup outlet. Observed runoff data are converted from water level data through a rating curve given by Equation 1 (DID, 2004).

$$Q=9.19(H)^{1.9} \tag{1}$$

where Q is the discharge (m^3/s) and H is the stage discharge (m). These observed runoff data were used to compare the model runoff.

3 Global Optimization Methods (GOMs)

Two types of GOMs namely SCE and PSO methods are selected for auto-calibration of hourly Tank Model's parameters. The details of these two algorithms are described below.

3.1 Particle Swarm Optimization (PSO) Method

Particle swarm optimization (PSO) was developed by Kennedy and Eberhart (1995). PSO is initialized with a group of random particles (trial solutions), which are assigned with random positions and velocities. The algorithm then searches for optima through a series of iterations where the particles are moved through the hyperspace searching for potential solutions. These particles "learn" over time in response to their own experience and those of other particles in their group (Ferguson, 2004).

According to Eberhart and Shi (2001), each particle keeps track of its best fitness position in hyperspace that it has achieved so far. This best position value is called personal best or "pbest". The overall best value obtained by any particle so far in the population is called global best or "gbest". During each iterations, every particle is accelerated towards its own "pbest" as well as in the direction of the "gbest" position. This is achieved by calculating a new velocity term for each particle based on the distance from its "pbest" as well as its distance from the "gbest" position. These two "pbest" and "gbest" velocities are then randomly weighted to produce the new velocity value for this particle, which will affect the next position of the particle in next iteration (Van den Bergh and Engelbrecht., 2000). The basic PSO procedure is presented in Fig. 3.

Jones (2005) specified two equations used in PSO, named as movement equation (Equation 2) and velocity update equation (Equation 3). Movement equation provides the actual movement of the particles using their specific vector velocity while the velocity updates equation provides for velocity vector adjustment given the two competing forces ("gbest" and "pbest"). Besides, inertia weight (ω) was introduced to improve the convergence rate (Shi and Eberhart, 1998).

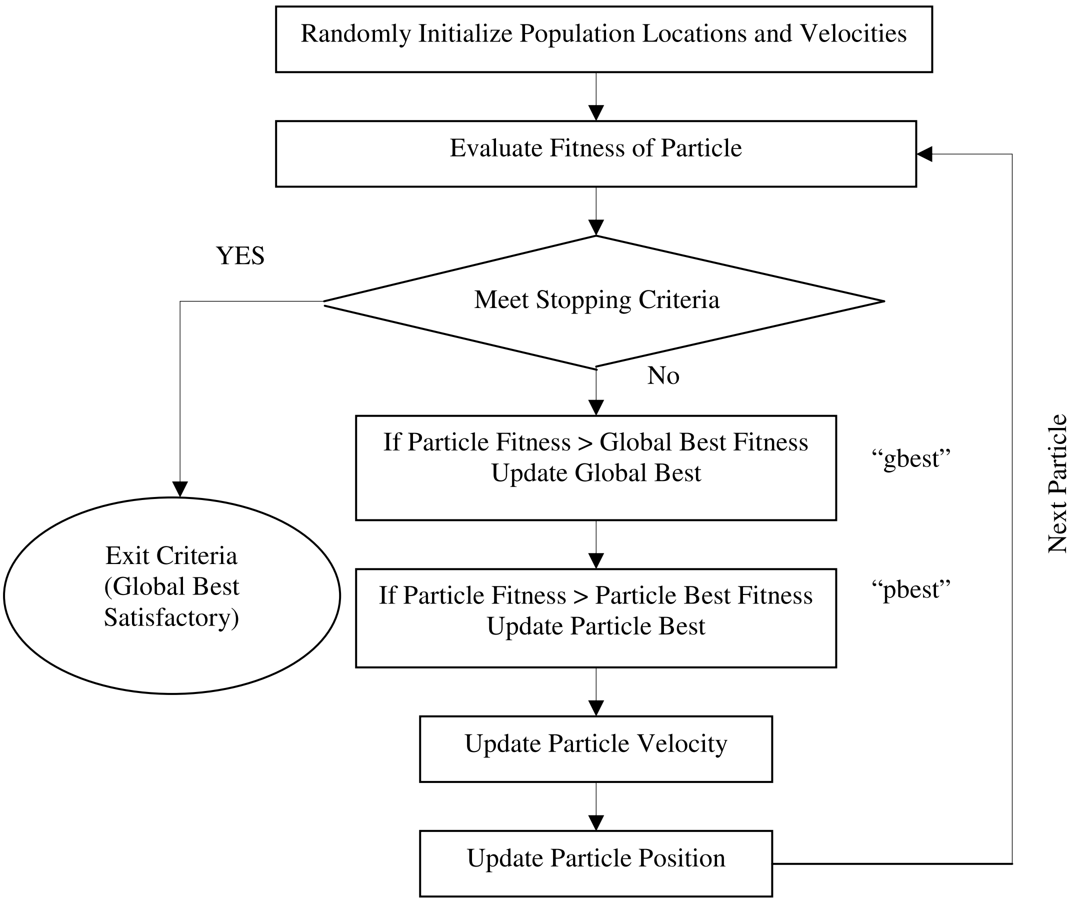


Fig. 3: Basic PSO procedure

$$presLocation = prevLocation + V_i \Delta t \qquad (2)$$

$$V_i = \omega V_{i-1} + c_1*rand()*(pbest-presLocation) + c_2*rand()*(gbest-presLocation) \qquad (3)$$

where V_i is the current velocity, Δt defines the discrete time interval over which the particle will move, ω is the inertia weight, V_{i-1} is the previous velocity, *presLocation* is the present location of the particle, *prevLocation* is the previous location of the particle and *rand()* is a random number between 0 and 1, c_1 and c_2 are the acceleration constants for "gbest" and "pbest" respectively.

3.2 Shuffle Complex Evaluation (SCE) Method

The SCE method is a global optimization algorithm that based on a synthesis of four concepts that have proved to be effective automatic calibration tool for optimization problems (Duan *et al*., 1992). These four concepts are a) combination of random and deterministic approaches, b) the concept of clustering, c) the concept of a systematic evolution of a complex of points spanning the space, d) the concept of competitive evolution. The combination of these concepts made the SCE known as a powerful, effective and flexible method. SCE method consists of two parts, SCE and competitive complex evolution (CCE).

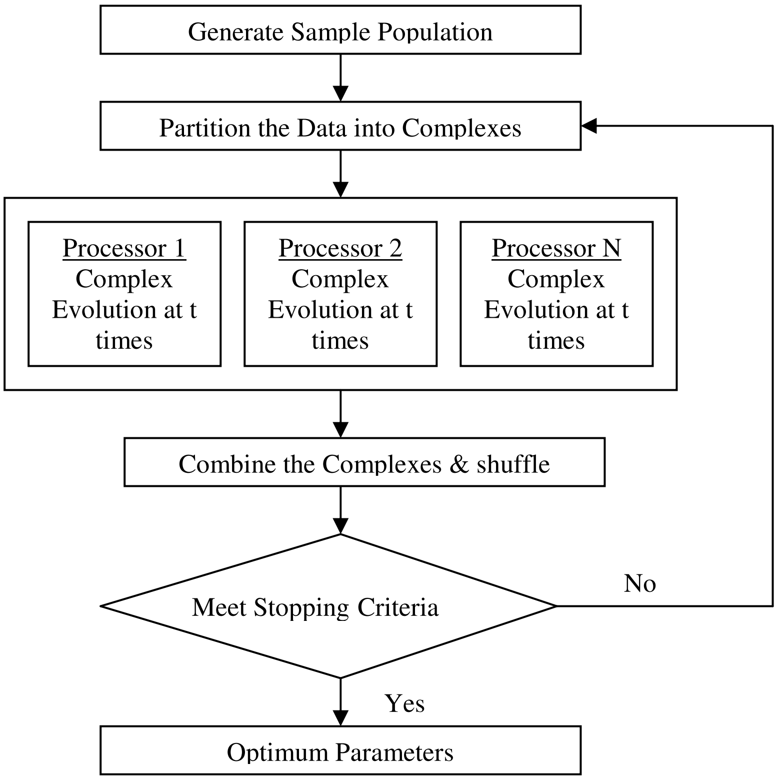


Fig. 4: SCE Calibration Process

For SCE method, the search within the feasible region is conducted by first dividing the set of current feasible trial solutions into several complexes, each containing equal number of trial solutions. Concurrent and independent searches within each complex are conducted until each converges to its local optimal value. For each of the complexes, that are now defined by new trial solutions is collated into a common pool, shuffled by ranking according to their objective function value and then further divided into new complexes. The procedure is terminated when none of the local optima found among the complexes can improve on the best current local optimum. The SCE method used the Nelder and Mead (1965) downhill simplex method to accomplish local searches. The flow chart of SCE calibration process was shown in Fig. 4.

The competitive complex evolution (CCE) algorithm is required for the evolution of each complex. Each point of a complex is a potential 'parent' with the ability to participate in the process of reproducing offspring. A subcomplex functions like a pair of parents. Use of a stochastic scheme to construct subcomplexes allows the parameter space to be searched more thoroughly. The idea of competitiveness is introduced in forming subcomplexes where the stronger survives better and breed healthier offspring than the weaker. Inclusion of the competitive measure expedites the search towards promising regions.

4 Tank Model Parameters

Since Tank Model is developed in 1956, it has been adopted by many water resources development or management agencies all over the world. This is not only due to the model is simple and easily to understand, but also it is able to indicate accurately the response for surface runoff (Kawasaki, 2003).

The response of surface runoff system is explained by vertically connected plural tanks. The model consists of four storage vessels (4-Tank) that lay vertically. Each tank has one or more outlets on its side and bottom. First storage tank (TS1) represents surface tank; second storage tank (TS2) represents intermediate tank; third tank (TS3) represents sub-base tank and the forth tank (TS4) represents base tank. Each outflow from side outlet will only occur when the water level in each tank is higher than the height of side outlet. The output from the bottom outlet of the first tank is used to model infiltration, the outputs from the bottom outlets for the rest of the tanks could be regarded as percolation. The total discharge, Q was calculated using Equation 4. A schematic diagram of Tank Model is presented in Fig. 5.

$$Q = C1Q1 + C2Q2 + C4Q3 + C6Q4 + C8Q5 \tag{4}$$

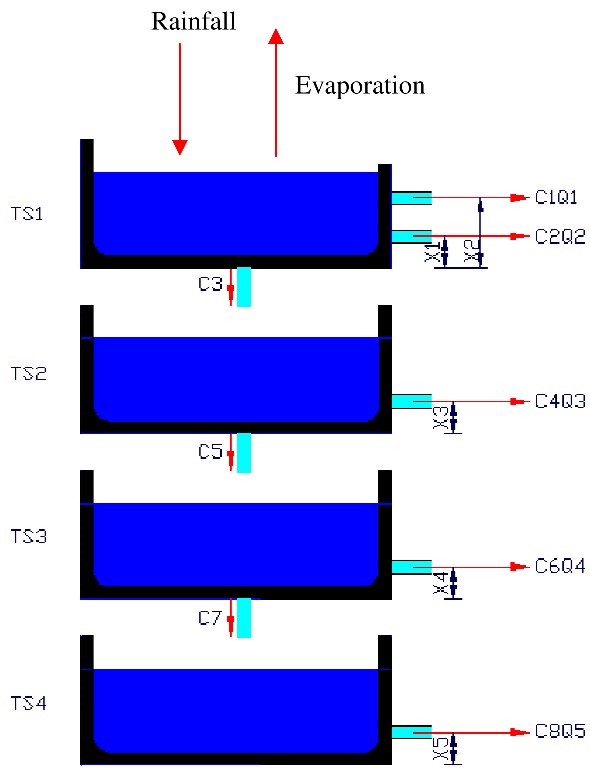


Fig. 5: Schematic of Tank Model used in this study

Parameters of Tank Model are side outlet coefficients (C1, C2, C4, C6 and C8), bottom outlet coefficients (C3, C5 and C7), height of side outlets (X1, X2, X3, X4 and X5) and initial storages in tanks (TS1, TS2, TS3 and TS4). The descriptions of 10 parameters are tabulated in Table 1. Prior to calibration, parameters X3, X4 and X5 are set to 0, This is because these parameters have little impact to model output and the values obtained are always near to 0. Hence, the remaining 10 parameters that calibrated automatically using PSO and SCE algorithms are C1, C2, C3, C4, C5, C6, C7, C8, X1 and X2. The models calibrated by PSO and SCE algorithms are denoted as PSO-Tank-H and SCE-Tank-H respectively.

Table 1: The description of the 10 parameters for Tank Model

No	Coeff	Identification	Description
1	C1	Side outlet coefficients No.1 for TS1	Surface runoff coefficient No.1
2	C2	Side outlet coefficients No.2 for TS1	Surface runoff coefficient No.2
3	C3	Bottom outlet coefficient from TS1 to TS2	Infiltration coefficient from surface tank to intermediate tank
4	C4	Side outlet coefficients for TS2	Intermediate runoff coefficient
5	C5	Bottom outlet coefficient from TS2 to TS3	Infiltration coefficient from intermediate tank to sub-base tank
6	C6	Side outlet coefficients for TS3	sub-base runoff coefficient
7	C7	Bottom outlet coefficient from TS3 to TS4	Infiltration coefficient from sub-base tank to base tank
8	C8	Side outlet coefficients for TS4	Base runoff coefficient
9	X1	Height of side outlets No.2 for TS1	Height of surface runoff No.2 from surface tank
10	X2	Height of side outlets No.1 for TS1	Height of surface runoff No.1 from surface tank

5 Model Calibration

The input data to Tank Model comprised of hourly average areal rainfall calculated using Thiesen Polygon method. In order to find the most robust parameters, Tank Model is calibrated using 11 sets of hourly rainfall-runoff data and the learning mechanism depends on the type of algorithm applied. Each set of parameters obtained is further validated with other 11 storm hydrographs. Hence, there are 121 repetitions for each set of experiments calibrated with PSO and SCE respectively. Table 2 presents the storm hydrographs used for finding the optimal Tank Model's parameters of PSO-Tank-H and SCE-Tank-H.

Table 2: Calibration data for PSO-Tank-H and SCE-Tank-H

Description	Storm Date
PSOSetHA, SCESetHA	1-7 Jan 99
PSOSetHB, SCESetHB	5-8 Apr 99
PSOSetHC, SCESetHC	5-8 Feb 99
PSOSetHD, SCESetHD	8-12 Aug 98
PSOSetHE, SCESetHE	9-12 Sep 98
PSOSetHF, SCESetHF	15-18 Mac 99
PSOSetHG, SCESetHG	20-24 Jan 99
PSOSetHH, SCESetHH	26-31 Jan 99
PSOSetHI, SCESetHI	16-20 Apr 03
PSOSetHJ, SCESetHJ	18-21 Jan 00
PSOSetHK, SCESetHK	9-12 Oct 03

The robustness of the optimal parameters obtained will be further evaluated with different sets of validation data. 11 single storm hydrographs are used to validate the hourly simulation model. The validation data sets used for hourly runoff simulation are presented in Table 3.

Table 3: Validation data for hourly runoff

Description	Storm Date
Hydrograph 1	1-7 Jan 99
Hydrograph 2	5-8 Apr 99
Hydrograph 3	5-8 Feb 99
Hydrograph 4	8-12 Aug 98
Hydrograph 5	9-12 Sep 98
Hydrograph 6	15-18 Mac 99
Hydrograph 7	20-24 Jan 99
Hydrograph 8	26-31 Jan 99
Hydrograph 9	16-20 Apr 03
Hydrograph 10	18-21 Jan 00
Hydrograph 11	9-12 Oct 03

The robustness of the validated data for hourly runoff simulation is then measured with boxplots whiskers analysis. The objective function selected is ordinary least squares (OLS). OLS always provide better approximations of the model parameters due to its algebraic formulations where each of these formulations consists of a summation of the least squares differences for every point in the flow series (Cooper *et al.*, 1997). The objective function will evaluate the performance of the GOMs in calibrating Tank Model and it will ensure that the learning error is getting lesser with the increase of number iterations. The accuracy of simulation results is measured using the coefficient of correlation (R) and Nash-Sutcliffe coefficient (E^2).

6 Performance Evaluation

Boxplots is applied to determine the robustness of parameters investigated. In its simplest form, the boxplot presents five sample statistics namely the minimum, the lower quartile, the median, the upper quartile and the maximum, in a visual display.

Peak runoff is evaluated for each storm hydrograph simulated by optimal configuration of Tank Model's parameters. Observed and simulated peaks generated by optimal configuration of PSO-Tank-H and SCE-Tank-H approaches are compared for 11 validation data sets. The objective is to evaluate how successful the simulated runoff in approaching the observed peak. Error between observed peak and simulated peak is calculated using Equation 5.

$$Error = \left(\frac{simulated\_peak - observed\_peak}{observed\_peak} \right) x100\% \tag{5}$$

The simulated results obtained are evaluated to determine the differences between observed and predicted values. The accuracy of model performance is measured by Coefficient of Correlation (R) and Nash-sutcliffe coefficient (E^2). According to Lauzon *et al.* (2000), the R and E^2 are measuring the overall differences between observed and estimated flow values. The closer R and E^2 to 1, the better the predictions are. The formulas of these two coefficients are presented in Table 4.

Table 4: Formulas for R and E^2

Concept	Name	Formula
Coefficient of Correlation	R	$\dfrac{\sum(obs-\overline{obs})(pred-\overline{pred})}{\sqrt{\sum(obs-\overline{obs})^2\sum(pred-\overline{pred})^2}}$
Nash-Sutcliffe Coefficient	E^2	$E^2 = 1-\dfrac{\sum_i^j(obs-pred)^2}{\sum_i^j(obs-\overline{obs})^2}$

Note : obs = observed value, pred = predicted value, $\overline{obs}$ = mean observed values, $\overline{pred}$ = mean predicted values and j = number of values.

7 Results and Discussion

7.1 Particle Swarm Optimization (PSO)

The results revealed that the best parameter set is obtained using single storm event on 5 to 8 April 1998 (PSOSetHC), with optimum R and E^2 values of 0.962 and 0.8935 respectively. The optimal configuration for PSO algorithm was found to be using 100 numbers of Particles (D), 200 maximum iterations and c_1 and c_2 of 1.4. The optimal parameters obtained using PSO are C1=0.1165, C2=0.00001, X1=0.1593, C3=0.00001, X2=0.00001, C4=0.1158, C5=0.00001, C6=0.1208, C7=0.00001 and C8=0.0212. The best storm hydrograph calibrated by the optimal configuration of PSO algorithm is presented in Fig. 6.

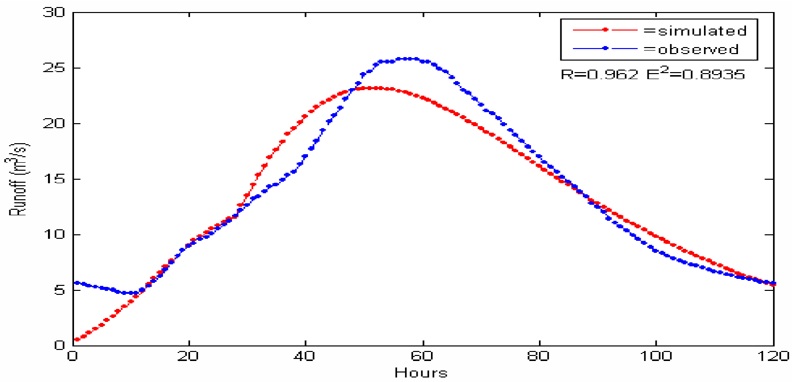


Fig. 6: Comparison between observed storm hydrograph and optimal simulated storm hydrograph using PSO

The trend of simulated hydrograph is very close with observed runoff. However, the simulated peak is slightly lower than observed peak. Five parameters including C1, C4, C6, C8 and X1 are the dominance parameters that affect the hourly runoff generation. Other parameters such as C2, C3, C5, C7 and X2 have little impact to hourly runoff simulation. All the infiltration coefficient values C3, C5 and C7 are found to be 0.00001. This indicates the infiltration rate for Bedup basin, which mostly covered by clayey soil is very low. The performance of PSOSetHC when validating 11 storm events is presented in Table 5.

Table 5: Results of PSOSetHC for validating 11 single storm events

Description	SCE	
	R	E^2
Storm Hydrograph 1	0.747	0.6139
Storm Hydrograph 2	0.905	0.9512
Storm Hydrograph 3	0.962	0.8935
Storm Hydrograph 4	0.876	0.9590
Storm Hydrograph 5	0.961	0.6097
Storm Hydrograph 6	0.855	0.8032
Storm Hydrograph 7	0.832	0.6961
Storm Hydrograph 8	0.935	0.9312
Storm Hydrograph 9	0.902	0.719
Storm Hydrograph 10	0.968	0.6587
Storm Hydrograph 11	0.901	0.8780
Average	**0.8949**	**0.7921**

7.2 Shuffle Complex Evolution (SCE)

The best set of parameters is obtained using single storm event on 5 to 8 April 1998 (SCESetHC), with nsp1 of 75 where R and E^2 yielded to 0.917 and 0.8154 respectively. The optimal 10 parameters optimized by SCE algorithm are C1=0.57876, C2=0.374059, X1=14.7853, C3=0.311226, X2=6.49865, C4=0.047421, C5=5.90424e-007, C6=0.695887, C7=0.000155 and C8=0.017274. The optimal calibrated storm hydrograph using SCE algorithm was shown in Fig. 7. Result reveals that the simulated peak is slightly underestimated than observed peak.

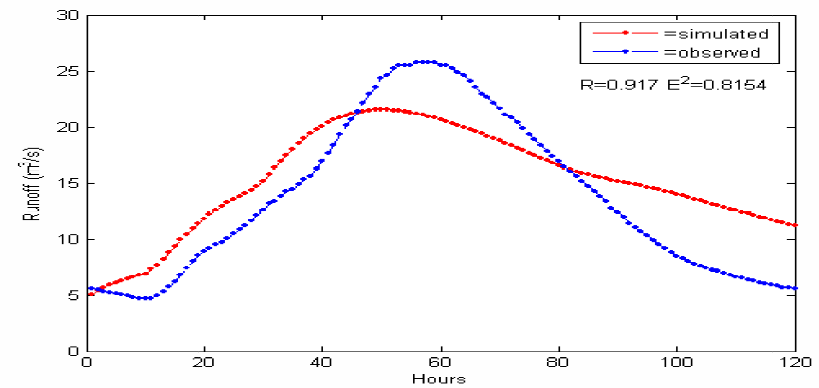


Fig. 7: Comparison between observed storm hydrograph and optimal simulated storm hydrograph using SCE

Infiltration coefficient values C3, C5 and C7 are found to be 0.311226, 5.90424e-007 and 0.000155 respectively. This revealed that the infiltration rate from first to second tank is high. Thereafter, there is only little infiltration for the subsequent tanks. The calibration results revealed that 8 parameters calibrated by SCE algorithm including C1, C2, C3, C4, C6, C8, X1 and X2 are controlling the hourly runoff generation. In contrast, C5 and C7 have minor effect to hourly runoff simulation. Table 6 presents the R and E^2 obtained when validating 11 storm events using the SCESetHC optimal parameters.

Table 6: Results of SCESetHC for validating 11 single storm events

Description	SCE	
	R	E^2
Storm Hydrograph 1	0.765	0.7285
Storm Hydrograph 2	0.933	0.9291
Storm Hydrograph 3	0.917	0.8154
Storm Hydrograph 4	0.785	0.5138
Storm Hydrograph 5	0.860	0.8418
Storm Hydrograph 6	0.930	0.6462
Storm Hydrograph 7	0.788	0.5302
Storm Hydrograph 8	0.933	0.8846
Storm Hydrograph 9	0.894	0.6390
Storm Hydrograph 10	0.964	0.7557
Storm Hydrograph 11	0.953	0.8254
Average	**0.8838**	**0.7372**

7.3 Comparison of Two GOMS

Fig. 8 shows the average R and E^2 values produced by the optimal configuration of SCE and PSO algorithm for validating 11 storms hydrograph. The average R and E^2 values obtained by PSO algorithm are 0.8949 and 0.7921 respectively. For SCE algorithm, the average R and E^2 values obtained after validating 11 storm events are 0.8838 and 0.7372 respectively. This indicates that the parameters calibrated using PSO is more accurate than SCE when validating 11 storm events.

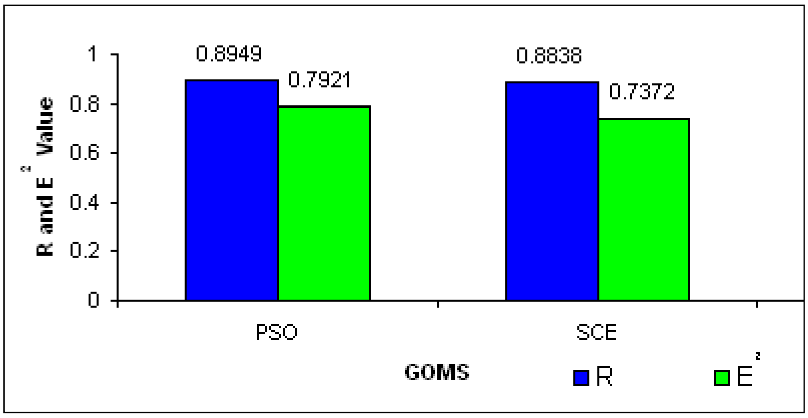


Fig. 8: Comparison of optimal PSO and SCE algorithms

7.4 Comparison Between Observed Peak and Simulated Peak

The simulated peak for optimal configuration of each GOMs was compared with observed peak. Table 7 presents the peak error (%) between observed and simulated peak flow for PSOSetHC and SCESetHC when validating 11 storms hydrograph.

Table 7: Peak flow Error for PSOSetHC and SCESetHC

	SCE-Tank-H			PSO-Tank-H		
Storms	**Observed Peak**	**Simulated Peak**	**Error (%)**	**Observed Peak**	**Simulated Peak**	**Error (%)**
1998 Aug 8-12	25.75	27.61	7.24	25.75	22.73	11.71
1999 Jan 1-7	34.63	27.36	20.97	34.63	23.68	31.62
1999 Apr 5-8	18.37	16.03	12.74	18.37	13.65	25.74
1999 Feb 5-8	14.26	18.58	30.30	14.26	15.28	7.14
1998 Sep 9-12	40.40	23.20	42.57	40.40	30.21	25.22
1999Mac 15-18	13.20	16.37	23.97	13.20	13.61	3.09
1999 Jan 20-24	20.36	22.38	9.92	20.36	19.35	4.98
1999 Jan 26-31	28.37	25.05	11.72	28.37	21.71	23.48
2000 Apr 5-8	22.45	19.50	13.12	22.45	19.69	12.30
2000 Jan 18-21	22.18	20.85	5.98	22.18	16.86	23.98
2003 Oct 9-12	19.36	21.22	9.62	19.36	17.27	10.78
Average Error			**17.10**			**16.37**

It was found that average error (%) between simulated and observed peak for optimal configuration of SCE and PSO are 17.10% and 16.37% respectively. The results revealed that PSO approach has produced simulated peaks that are closer to observed peak than SCE approach. These simulated peaks can be used as early warning flow forecaster to take necessary flood protection measures before a severe flood occurs.

7.5 Boxplots Analysis

To ensure the parameters obtained is the most optimal and accurate, 11 sets of storm hydrographs are calibrated and optimized by PSO and SCE algorithms. Each set of parameter obtained is then validated with another 11 sets of storm events. The resulting parameters obtained using PSO and SCE calibration methods for different dataset are presented in Table 8 and 9 respectively.

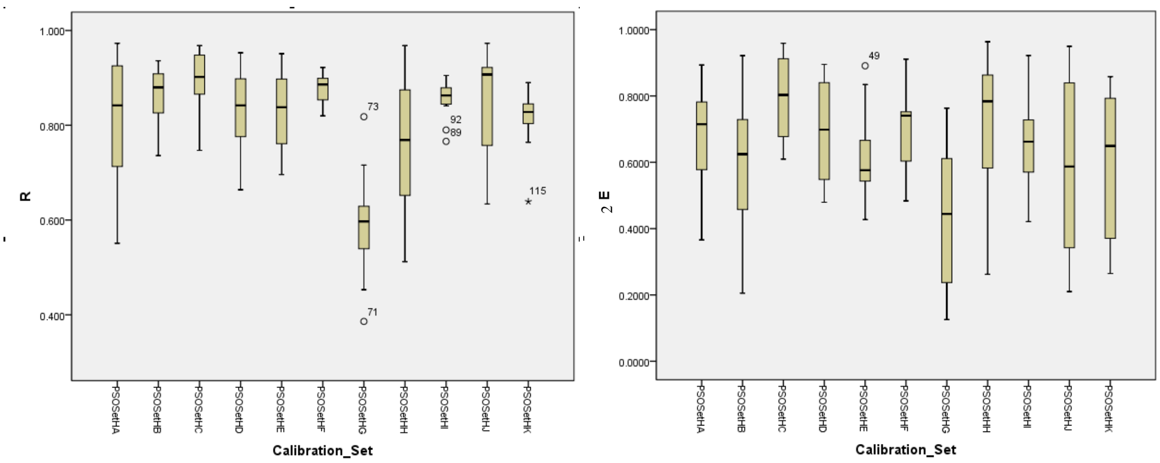
Table 8: Optimal parameters obtained using PSO algorithm with different dataset

	C1	C2	X1	C3	X4	C4	C5	C6	C7	C8
PSOSetHA	0.1165	0.00001	0.1593	0.00001	0.00001	0.1158	0.00001	0.1208	0.00001	0.0212
PSOSetHB	1.1435	1.1448	0.3693	0.2980	0.3232	2.4044	0.3188	0.0260	0.00001	0.0351
PSOSetHC	1.0688	1.0113	0.1393	0.00001	0.00001	1.8834	1.6107	0.0337	0.00001	0.0352
PSOSetHD	0.1087	0.00001	0.3801	0.00001	0.00001	1.3865	0.9869	0.1004	0.00001	0.0160
PSOSetHE	0.6970	0.0061	0.0011	0.00001	0.0321	2.3341	0.4037	0.0868	0.00001	0.0150
PSOSetHF	0.1561	0.00001	0.0504	0.00001	0.0003	1.8585	0.00001	0.1666	0.00001	0.0143
PSOSetHG	1.8862	0.6467	0.0744	0.00001	0.00001	1.0000	0.7005	1.0000	0.0924	0.0053
PSOSetHH	1.1934	0.00001	0.3576	0.00001	0.00001	2.3606	0.7823	0.0323	0.00001	0.0414
PSOSetHI	0.9851	0.3346	0.00001	0.0592	0.00001	1.2972	0.7070	0.0979	0.00001	0.0138
PSOSetHJ	0.1422	0.00001	0.00001	0.0008	0.00001	0.9962	1.7252	0.1686	0.00001	0.0242
PSOSetHK	0.9440	0.4144	1.0077	0.3297	0.6356	1.0000	0.6417	0.0981	0.00001	0.0127

Table 9: Optimal parameters obtained using SCE algorithm with different dataset

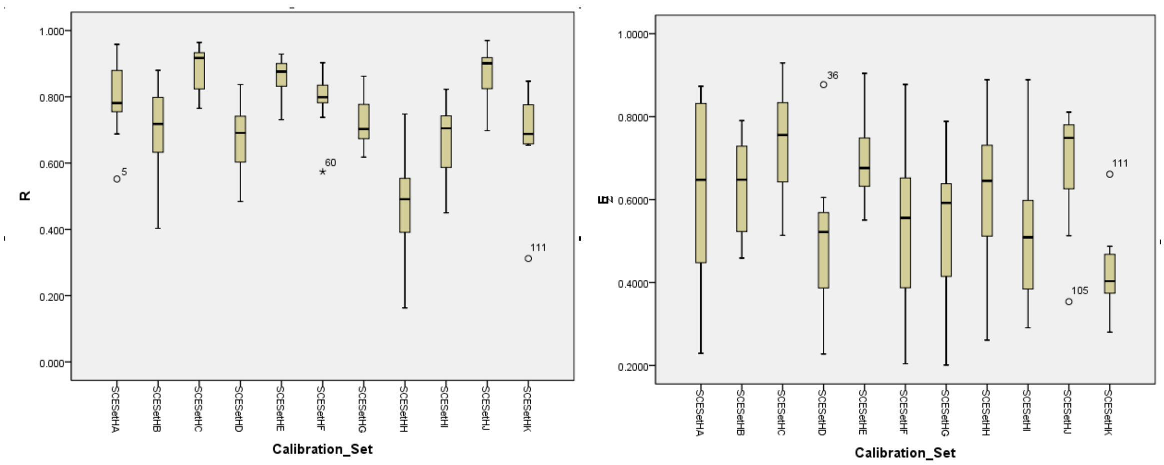
	C1	C2	X1	C3	X4	C4	C5	C6	C7	C8
SCESetHA	0.57876	0.374059	14.7853	0.311226	6.49865	0.047421	5.90E-07	0.695887	0.000155	0.017274
SCESetHB	0.239367	0.000152	19.9981	0.00404	4.21419	0.99953	0.142576	0.999998	0.651766	0.01605
SCESetHC	0.382111	0.013735	13.3852	0.000111	10.9231	0.073761	9.38E-07	0.850929	0.00194	0.024017
SCESetHD	0.73823	0.073409	3.3418	3.13E-05	7.1593	0.42368	3.52E-06	1.000000	0.39497	0.009329
SCESetHE	0.835835	0.289136	13.3096	0.255264	12.7314	0.115417	6.29E-08	0.759014	3.18E-08	0.015798
SCESetHF	0.137185	1.65E-05	9.46114	0.880488	19.9992	0.787643	0.000103	0.716401	0.004526	0.010075
SCESetHG	0.278742	0.531293	19.3113	0.234886	19.9882	0.710385	0.000219	0.999999	0.935953	0.009887
SCESetHH	0.548313	0.480161	10.9885	0.534595	9.90657	0.999945	0.15776	0.99975	0.316135	0.018535
SCESetHI	0.660371	0.349439	15.1549	0.168425	4.16672	0.928385	2.80E-05	0.999984	0.138532	0.01006
SCESetHJ	0.113613	0.001223	19.9952	0.459864	19.1121	0.204836	1.07E-05	0.926352	0.493893	0.018574
SCESetHK	0.27012	0.164622	19.9984	0.062928	11.568	0.999998	0.152339	0.999982	0.99596	0.008362

The selection of a GOM for a particular application is governed by GOM's accuracy of its solution to the global optimum. Accuracy was expressed as R and E^2 of the simulated flow series generated by the parameter set found in the search. The R and E^2 obtained are analyzed with boxplots. The boxplots in Fig. 9 and 10 show the quartile distributions of the R and E^2 performances using SCE and PSO optimization methods respectively. These two GOMs are compared according to their robustness and accuracy, where the robust method is one which has little variability.



a) Boxplots of R for PSO-Tank-H b) Boxplots of E^2 for PSO-Tank-H.

Figure 9: Boxplots of PSO-Tank-H for validating 11 storms hydrograph



a) Boxplots of R for SCE-Tank-H b) Boxplots of E^2 for SCE-Tank-H

Fig. 10: Boxplots of SCE-Tank-H for validating 11 storms hydrograph

The boxplots also proclaimed that PSOSetHC produced highest median with R=0.902 and E^2=0.8032 among the 11 calibration sets (refer Fig. 9). Upper quartile R of 0.961 and lower quartile R of 0.855 are obtained for PSOSetHC. Meanwhile, PSOSetHC also produced upper and lower quartile E^2 of 0.9312 and 0.6587 respectively. The maximum R recorded for PSOSetHC is 0.968, and 0.747 is obtained for minimum R. Meanwhile, the maximum and minimum of E^2 were found to be 0.9590 and 0.6097 respectively. Thus, the best set of calibration parameters is obtained using PSOSetHC for PSO algorithm.

Fig. 10 presents the boxplots produced by SCE algorithm. The results clearly indicated that the best calibration set for SCE algorithm is SCESetHC among the 11 calibration sets, with median R of 0.917 and median E^2 of 0.7557. The upper and lower quartile recorded for R is 0.933 and 0.788 respectively for SCESetHC, where else 0.8418 and 0.6390 are obtained for E^2. The maximum and minimum of R are found to be 0.964 and 0.765 respectively, while maximum and minimum values recorded for E^2 are 0.9291 and 0.5138 respectively.

Between the two GOMs, PSO method appeared to consistently give a remarkable performance and is considered as more robust and accurate than SCE method. PSO still consider more reliable that SCE, even though the median of R=0.902 provided is slightly lower than SCE method (R=0.917). This is because PSO method has produced median of E^2=0.8032, which is much better than SCE method (E^2=0.7557). Besides, boxplots also revealed that PSO method has smaller variability for both R and E^2 than SCE approach. Moreover, average R and E^2 obtained for PSO when validating 11 storms hydrograph are higher than SCE approach (refer Fig. 8). Therefore, PSO approach performs better than SCE for hourly runoff simulation in this study.

8.0 Conclusion

The new PSO algorithm and the famous SCE are compared to determine their suitability and accuracy for calibration of Tank Model, under various modeling scenarios. Both GOMs had confirmed their abilities to calibrate and optimize 10 parameters of Hydrologic Tank Model. Optimal PSO calibration method had achieved average R=0.8949 and E^2=0.7921 with the model configuration of c_1=1.4, c_2=1.4, 100 of number of particles, 200 max iteration when validating 11 storms hydrograph. Meanwhile, the performance of SCE method is slightly lower than PSO with average R and E^2 of 0.8838 and 0.7372 respectively for validating 11 storms hydrographs.

These results proved that the newly developed PSO algorithm has the ability to calibrate and optimize 10 parameters of Tank Model accurately. Besides, PSO had shown its robustness by simulating accurately the 11 single storms hydrograph during the validation period. This indicates that PSO optimization search method is a simple algorithm, but found to be robust, efficient and effective in searching optimal Tank Model parameters. This was totally revealed by the ability of PSO methods in searching the optimal parameters that provide the best fit between observed and simulated flows.

The methodology has been tested for rural catchment in humid region. The results revealed that Hydrologic Tank Model clearly manage to demonstrate the ability to adapt to the respective lag time of each gauge through calibration. Rainfall and runoff as inputs are sufficient to develop an accurate hourly rainfall-runoff model. Inclusion of more parameters such as temperature, moisture content, evaporation will make the Tank Model unnecessarily complex in nature without any significant improvement in performance.

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