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PARAMETER OPTIMISATION OF RUNOFF MODEL USING PARTICLE SWARM OPTIMISATION

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OVERVIEW

- ✓ Introduction
- ✓ Objective
- ✓ Methodology
- ✓ PSO Algorithm
- ✓ Study Area
- ✓ Results
- ✓ Conclusion
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INTRODUCTION

Event-based rainfall-runoff models are effective tools in hydrological forecasting and preparedness for extreme events

Distributed models have the advantage of parameter distribution over the watershed

Parameter optimization is carried out with different hydrological models and optimization techniques

In PSO, optimisation is carried by either maximizing or minimising the objective function (fitness value)

LITERATURE REVIEW

SNo	Author	Findings
1	Alam, M. N (2016). “Particle Swarm Optimisation: Algorithm and its Codes in MATLAB”	PSO algorithm is discussed in detail in MATLAB environment
2	Chou, C-M (2012). “Particle Swarm Optimisation for Identifying Rainfall-Runoff Relationships”	PSO is applied for identifying rainfall-runoff (R-R) relationships The model is verified for daily R-R data for the u/s Kee-Lung River calibration and validation results of PSO are more accurate compared to Simple Linear Model (SLM)
3	Kouk, K.K and Chan, C.P (2012). “Particle Swarm Optimisation for Calibrating and Optimising Xinanjiang Model Parameters”	13 parameters of Xinanjiang model are calibrated and optimised Daily and Hourly runoff simulations are carried out for Bedup basin, Malaysia.
4	Wang,J-Q and Guo, X-Y (2010). “Application of Particle Swarm Optimisation in Flood optimal Control of Reservoir Group”	The combination of PSO with reservoirs cycling method has been proposed

LITERATURE REVIEW

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5	Chu,H-J and Chang,L-C (2009). “Applying Particle Swarm Optimization to Parameter Estimation of the Nonlinear Muskingum Model”	PSO is applied for parameter estimation of Muskingum Model The proposed scheme improves the accuracy of Muskingum model for flood routing
6	Gill, M.K et al.(2006). “Multiobjective Particle Swarm Optimization for Parameter Estimation in Hydrology”	PSO is used for parameter estimation of a well-known conceptual rainfall-runoff model, the Sacramento soil moisture 13 parameters were optimised for which the results are very encouraging
7	Kennedy, J and Eberhart, R. C (1995). “Particle Swarm Optimization”	PSO is extremely simple and effective algorithm for optimizing a wide range of functions The algorithm requires only specification of the problem and a few parameters to solve



OBJECTIVE

The main aim of this study is to optimise the parameters of the selected hydrological model

METHODOLOGY

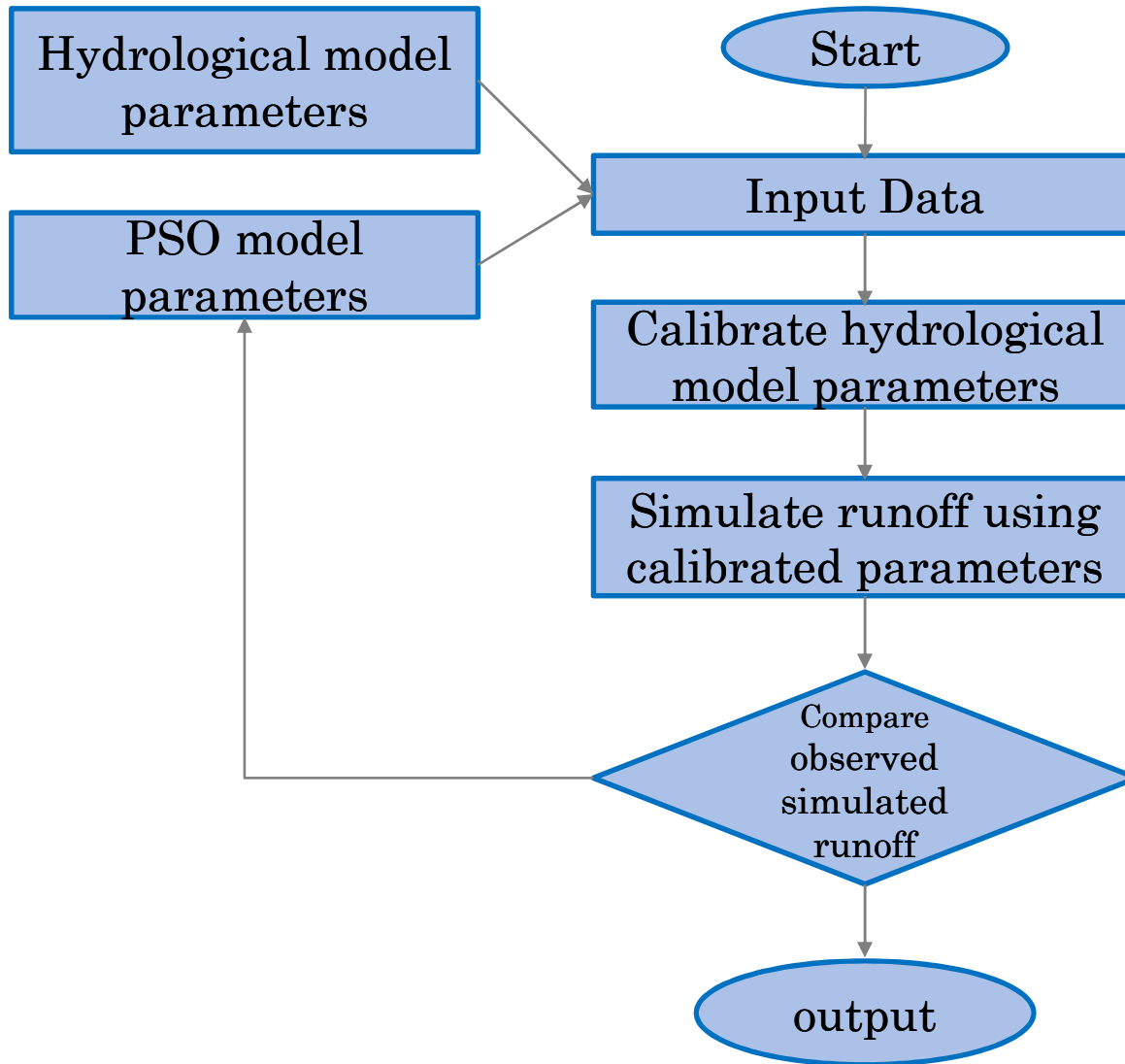


Fig 1: Flowchart for parameter optimisation using PSO

PSO ALGORITHM

Step 1: Initialising PSO parameters

Step 2: Defining the Objective Function

Step 3: Evaluation of each particle's position according to the objective function

Step 4: Comparison and updation of a particle's current position to its previous best position

Step 5: Determination of the best particle (according to the particle's previous best positions)

PSO ALGORITHM

Step 6: Updation of particles' velocities:

$$V_{i,j}^{k+1} = \omega \times V_{i,j}^k + c_1 \times r_1 \times (Pbest_{i,j}^k - X_{i,j}^k) + c_2 \times r_2 \times (Gbest_{i,j}^k - X_{i,j}^k)$$

Inertia: Makes the particle move in the same direction and with the same velocity

PI: Improves the individual. Makes the particle return to a previous position, better than the current.

SI: Makes the particle follow the best neighbors direction

PSO ALGORITHM

Sep 7: Updation of particles' position

$$X_{i,j}^{k+1} = X_{i,j}^k + V_{i,j}^{k+1}$$

Step 8: Step 3 to Step 7 are repeated until stopping criteria is satisfied

PSO APPLICATION

The objective function of PSO: Minimise

$$E = 1 - \frac{\sum_{i=1}^n (Q_f^i - Q_o^i)^2}{\sum_{i=1}^n (Q_o^i - \bar{Q}_o)^2}$$

where Q_f^i : forecasted discharge, Q_o^i : observed discharge, \bar{Q}_o : mean of observed discharge,

In this study, commonly used parameters of PSO algorithm are set as

Inertia weight (w_{\max} , w_{\min}): 0.9 to 0.4

Acceleration factor ($c1$, $c2$): 2 to 2.05

Population size: 50

Maximum iterations (Max): 100

Initial velocity: 10 % of position

RUNOFF ESTIMATION BY KW-FEM

A computationally well-organized KW-FEM model is adopted for rainfall-runoff simulation

Reddy (2011) developed the model based on application of kinematic-wave theory for surface runoff and Finite Element Method

Prominent hydrological processes like infiltration, overland flow and channel flow have been considered in this model

infiltration $f_p = K_s [1 + \frac{Ms_c}{F}]$

overland flow $[C]\{h\}^{t+\Delta t} = [C]\{h\}^t - \Delta t[B]\{(1-\omega)q^t + \omega q^{t+\Delta t}\} + \Delta t\{f\}((1-\omega)(r_s^t) + \omega(r_s^{t+\Delta t}))$

channel flow $[C]\{A\}^{t+\Delta t} = [C]\{A\}^t - \Delta t[B]\{(1-\omega)Q^t + \omega Q^{t+\Delta t}\} + \Delta t\{f\}((1-\omega)q^t + \omega q^{t+\Delta t})$



where

f_p -infiltration capacity,

K_s -saturated hydraulic conductivity,

M -Initial moisture deficit,

s_c -Capillary suction at the wetting front,

F -cumulative infiltration,

$[C]$ -Global capacitance matrix,

h -Depth of flow in the vertical direction,

t -time, Δt -time step,

$[B]$ -global gradient matrix,

$\{f\}$ -Global forcing term vector,

q -lateral inflow per unit width of flow plane,

r_e -excess rainfall rate,

ω -factor which depends on type of finite difference scheme,

A -area of flow in channel

STUDY AREA

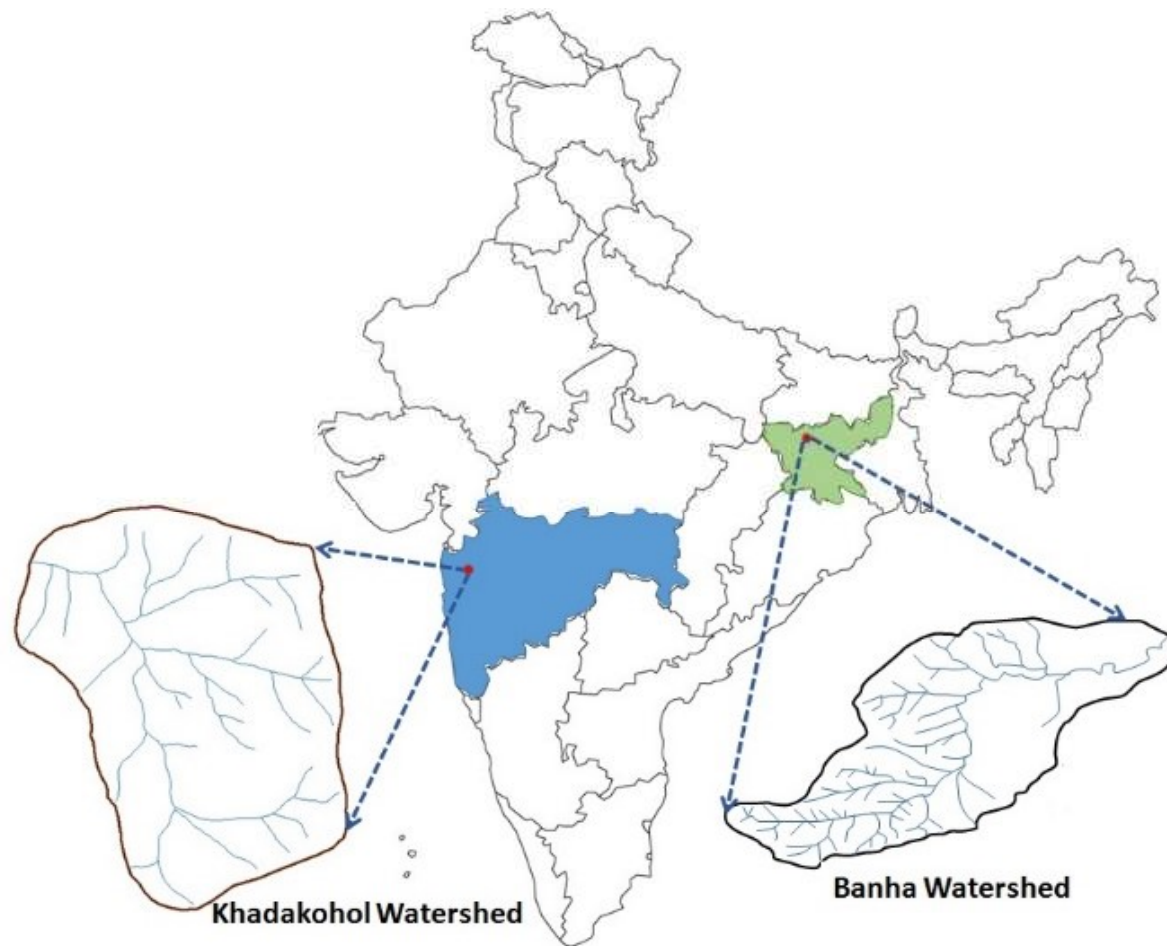


Fig 2: Location map of Watersheds

FEM GRIDS

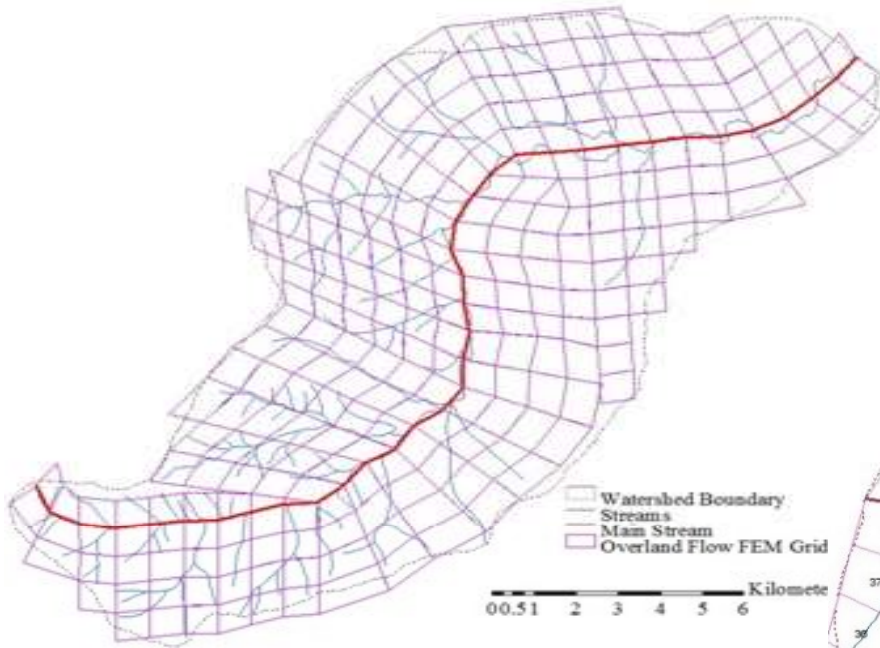


Fig 3: FEM grid map of Banha Watershed

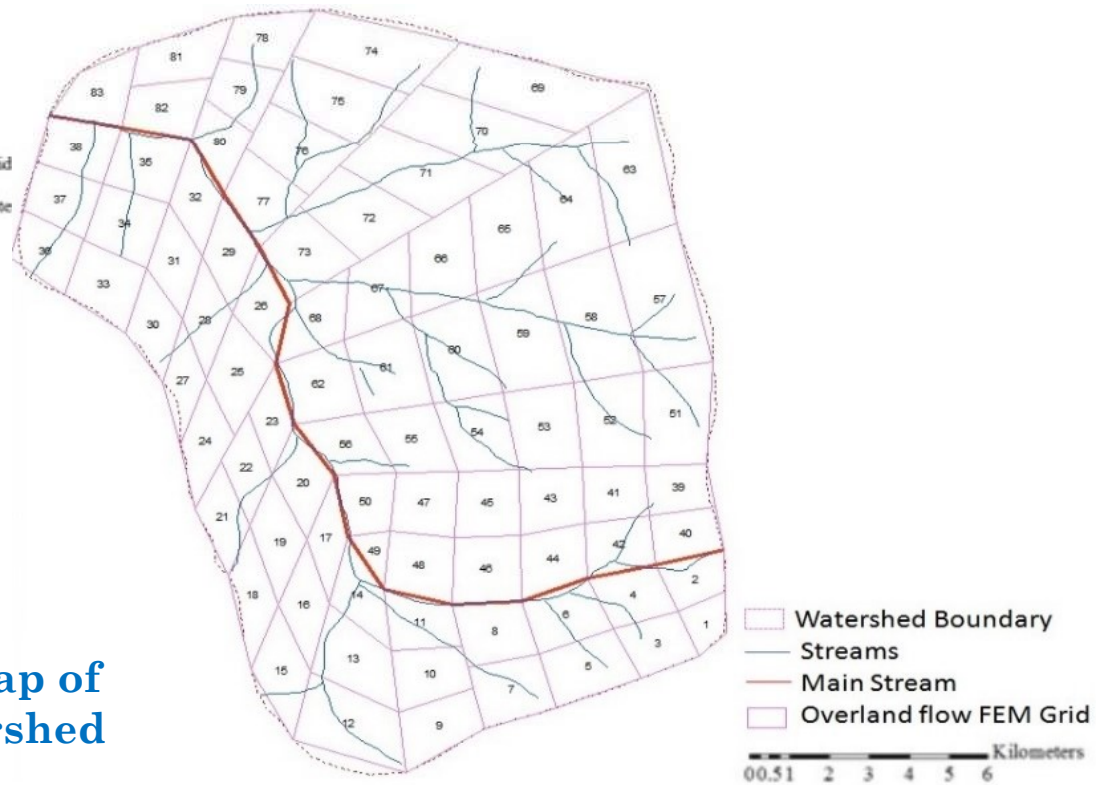


Fig 4: FEM grid map of Khadakohol Watershed

FEM Grids

Name	Banha	Khadakohol
District (State)	Chatra (Jharkhand)	Nashik (Maharashtra)
FEM (Reddy, 2007)	256 overland flow elements, 324 overland flow nodes and 35 channel flow elements	83 overland flow elements, 112 overland flow nodes and 15 channel flow elements

Range of parameters

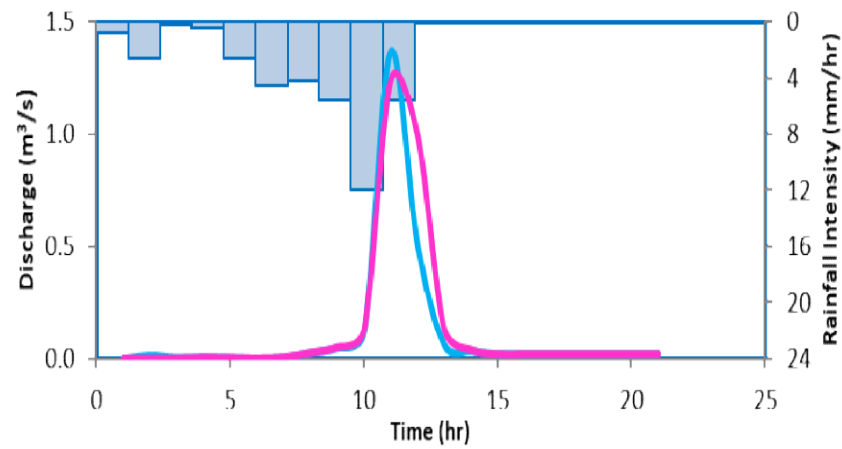
Parameter	Khadakohol	Banha
K_s	0.65 (0.075-3.0)	1.09 (1.0-10)
S_{av}	16.68 (2.92-95.4)	11.01 (2.67-45.5)
Θ_s	0.486 (0.394-0.578)	0.412 (0.283-0.541)
Θ_i	0.186 (0.124-0.378)	0.152 (0.103-0.241)

RESULTS

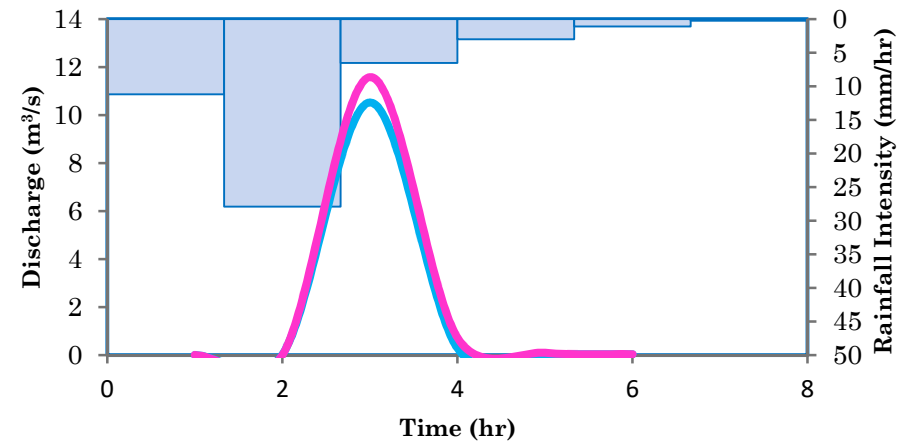
8 historical rainfall events from literature (Reddy 2007 and Reddy et al. 2011) are considered for present study

Table 1: Results of runoff forecasting

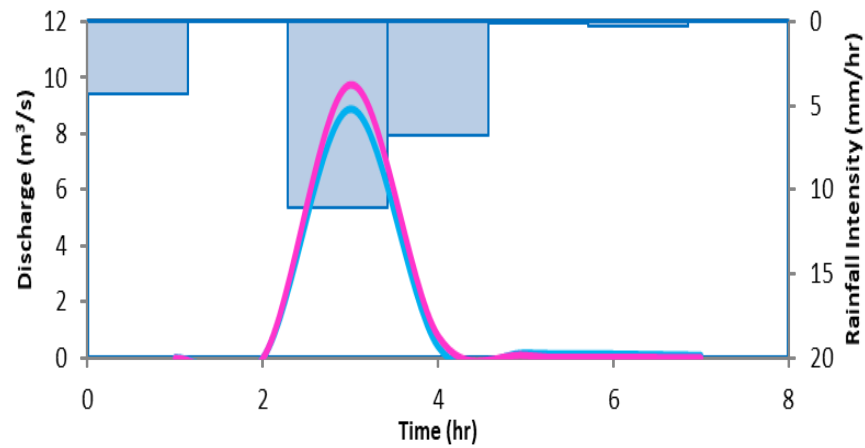
Watershed	Event Date	E
Khadakohol	August 25, 1997	0.85
	September 24, 1997	0.98
	August 22, 1997	0.98
	September 26, 1997	0.86
Banha	July 24, 1996	0.86
	August 23, 1996	0.96
	August 30, 1996	0.81
	August 18, 1995	0.97



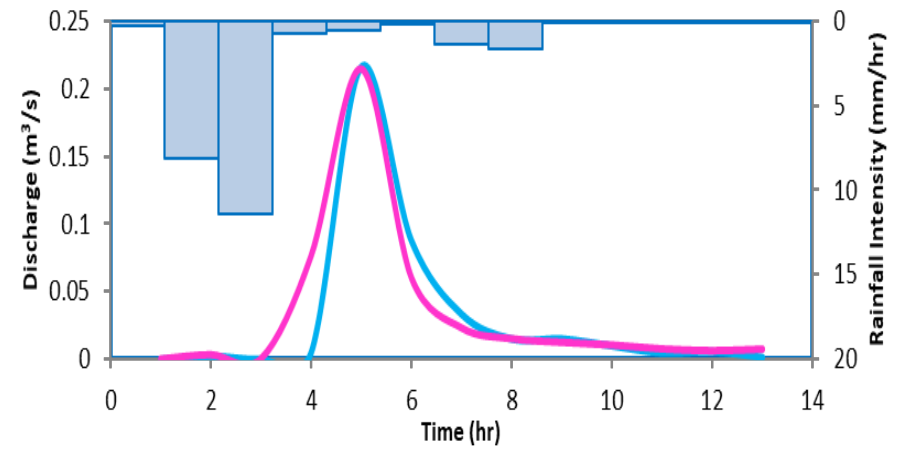
(a)



(c)



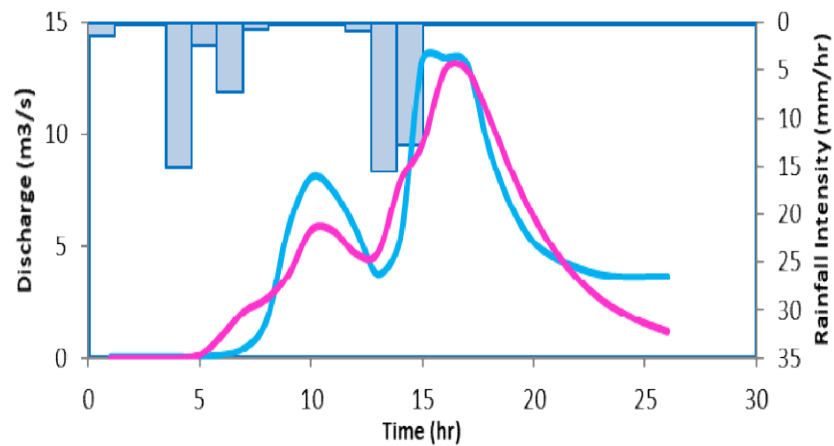
(b)



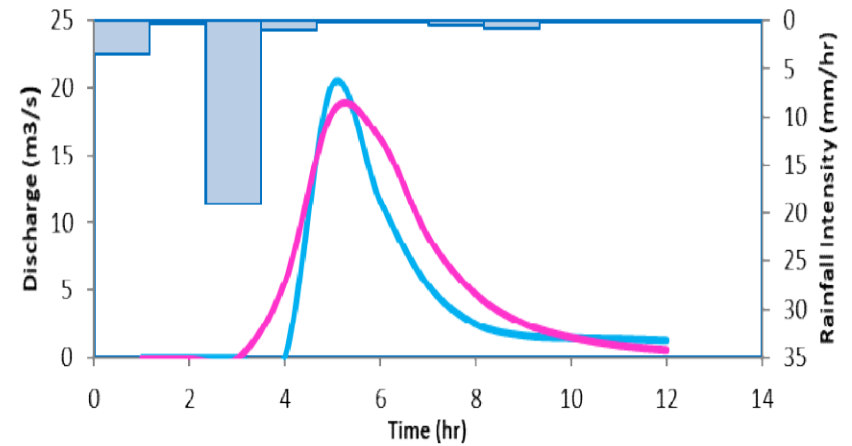
(d)

■ Rainfall — Observed — Simulated

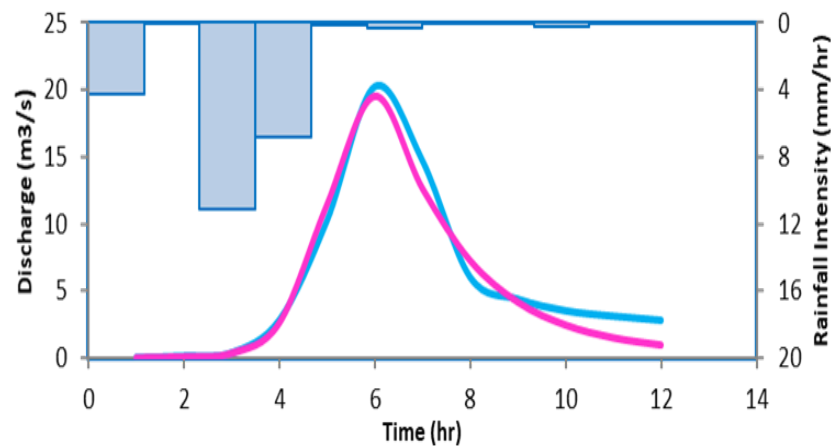
Fig 5: Runoff forecasting for Khadakohol Watershed
 (a) August 25,1997; (b) September 24,1997; (c) August 22,1997; (d) September 26,1997



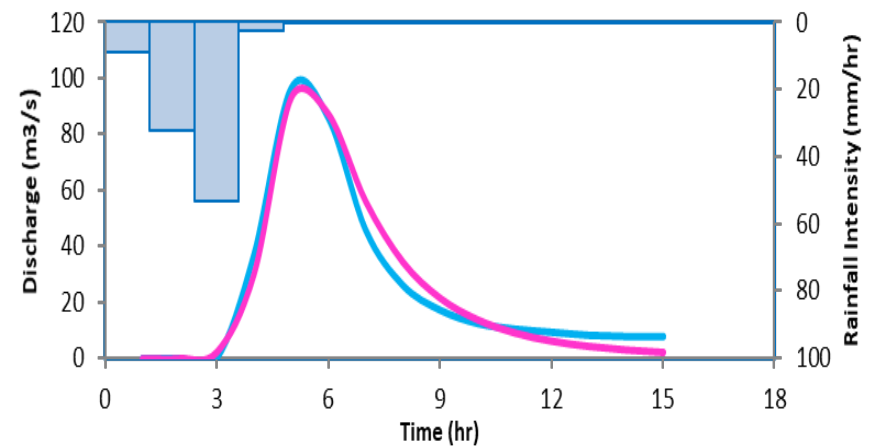
(a)



(c)



(b)



(d)

Rainfall
 Observed
 Simulated

Fig 6: Runoff forecasting for Banha Watershed
(a) July 24, 1996; (b) August 23, 1996; (c) August 30, 1996; (d) August 18, 1995

SUMMARY AND CONCLUSIONS

Parameter optimisation improves the hydrograph

Optimisation of parameters reduces the number of iterations to be performed, thereby increasing the computational speed

The manual intervention is avoided and the optimisation process stops after the simulated flow approaches observed flow

PSO optimization method is a simple, robust, efficient and effective algorithm in searching optimal rainfall-runoff model parameters

Automatic calibration of the rainfall-runoff model parameters using PSO algorithm is being applied for Banha and Khadakohol watersheds.

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THANK YOU