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Investigation of effect of optimal time interval on the linear Muskingum method using particle swarm optimization algorithm

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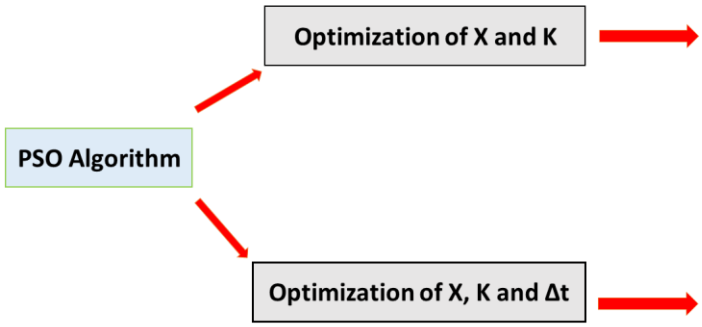
GRAPHICAL ABSTRACT



Flood	MRE % (Total flood)	MRE % (Peak zone)
First flood	6.03	8.34
Second flood	4.07	2.24
Third flood	3.13	1.99

Flood	MRE % (Total flood)	MRE % (Peak zone)
First flood	5.80	5.14
Second flood	3.35	0.44
Third flood	2.80	1.08

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ABSTRACT

In engineering works, calculation of the peak zone of the flood is very important. Therefore, in the present study, a method was presented to increase the accuracy of the flood routing of the peak zone of the inflow hydrograph. The recorded data in the Ahwaz and Farsiat hydrometric stations were used, both of which are related to the Karun river, Iran. In contrast to previous studies, in addition to calculating the coefficients of linear Muskingum method (X, K), the time interval (Δt) parameter was also optimized in the present study using the PSO algorithm. The results showed that if only the X and K coefficients were calculated, the mean relative error (MRE) of the peak zone for the first, second and third floods were equal to 8.34, 2.24, and 1.99 %, respectively. However, by using the optimized Δt value, the corresponding error decreased to 5.14, 0.44, and 1.08 %.

1. Introduction

Floods are one of the natural disasters and preventing economic, social, socio-economic and other damage to floods has been a concern for humans (Dutta et al. 2010; Farzin et al. 2018; Fotovatikhah et al. 2018; Kadam and Sen 2012; Vafaei and Harati 2010; Vatankhah 2018). In particular, peak flood calculation is of great importance for the construction of flood control structures and reducing natural hazards and economic and social costs (Gholami et al. 2015; Reggiani et al. 2016; Wu and Chau 2011). Hirpurkar and Ghare (2014) analyzed three different nonlinear forms of the parameter (m) in the nonlinear Muskingum method using Microsoft Excel. Their results confirms higher accuracy of the nonlinear Muskingum when using the form presented by Chow (1959) a $S=K[XI+(1-X)O]^m$. Hamedi et al. (2016) improved the accuracy of the proposed models for the nonlinear Muskingum method presented by Bozorg Haddad (2015), Gill (1978) and Hamedi (2014). Instead of using a constant value for the initial storage volume (S_0), they optimized this parameter as a variable parameter in the Weed Optimization Algorithm (WOA). Niazkar and Afzali (2017) investigated non-linear Muskingum method using 14 new models and Optimization performed through MHBMO algorithm and the results suggest that using three variable – parameter model is more accurate. The PSO algorithm used in engineering works such as researches (Afshar et al. 2011; Abozari et al. 2019; Chau 2005; Lu et al. 2002; Nagesh Kumar and Janga Reddy 2007; Qasem et al. 2017; Shourian et al. 2008). Use of the PSO algorithm in the optimization of the parameters of the nonlinear Muskingum method is accurate (Bazargan and Norouzi 2018; Chu and Chang. 2009; Moghaddam et al. 2016; Norouzi and Bazargan. 2020). Farahani et al. (2019) proposed a new model for the Four-Parameter Nonlinear Muskingum (FPNM), also used the Shark Algorithm (SA) for

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optimization. Okkan and Kirdemir (2020) they used a combination of PSO with the Levenberg–Marquardt (LM) algorithms to optimize the parameters of the Muskingum method. Pashazadeh and Javan (2020) compared the gene expression programming method, the artificial neural network (ANN), and equivalent Muskingum inflow models in branched. Increasing the number of the parameters of the Muskingum method, causes the increase of the algorithm calculation time, while the accuracy of results does not change significantly (Farahani et al. 2018).

Some of the previous researchers have considered the parameter Δt equal to the time interval of reading inflow and outflow hydrographs. However, optimization results for the first, second, and third floods are not the same. In other words, optimization of the parameter Δt leads to an increased accuracy of the linear Muskingum method in estimating the outflow hydrograph. It is worth noting that the PSO algorithm was used for the optimization.

2. Materials and methods

2.1. Study area

In the present study, data from two hydrometric stations of Ahwaz and Farsiat of Karun River was used. It was tried to use both the inflow and outflow hydrographs of all three floods (Fig.1) in the desired river reach in calculation of the parameters (X, K, Δt) and estimation of the downstream hydrograph (outflow hydrograph). Flood data with an inflow discharge of 311-551 (m^3/s), 265-634 (m^3/s) and 203-451 (m^3/s) were used as the first flood (occurred on 27/02/2012 to 01/03/2012), second flood (occurred on 15/11/2012 to 17/11/2012), and third flood (occurred on 02/02/2012 to 06/02/2012), respectively.

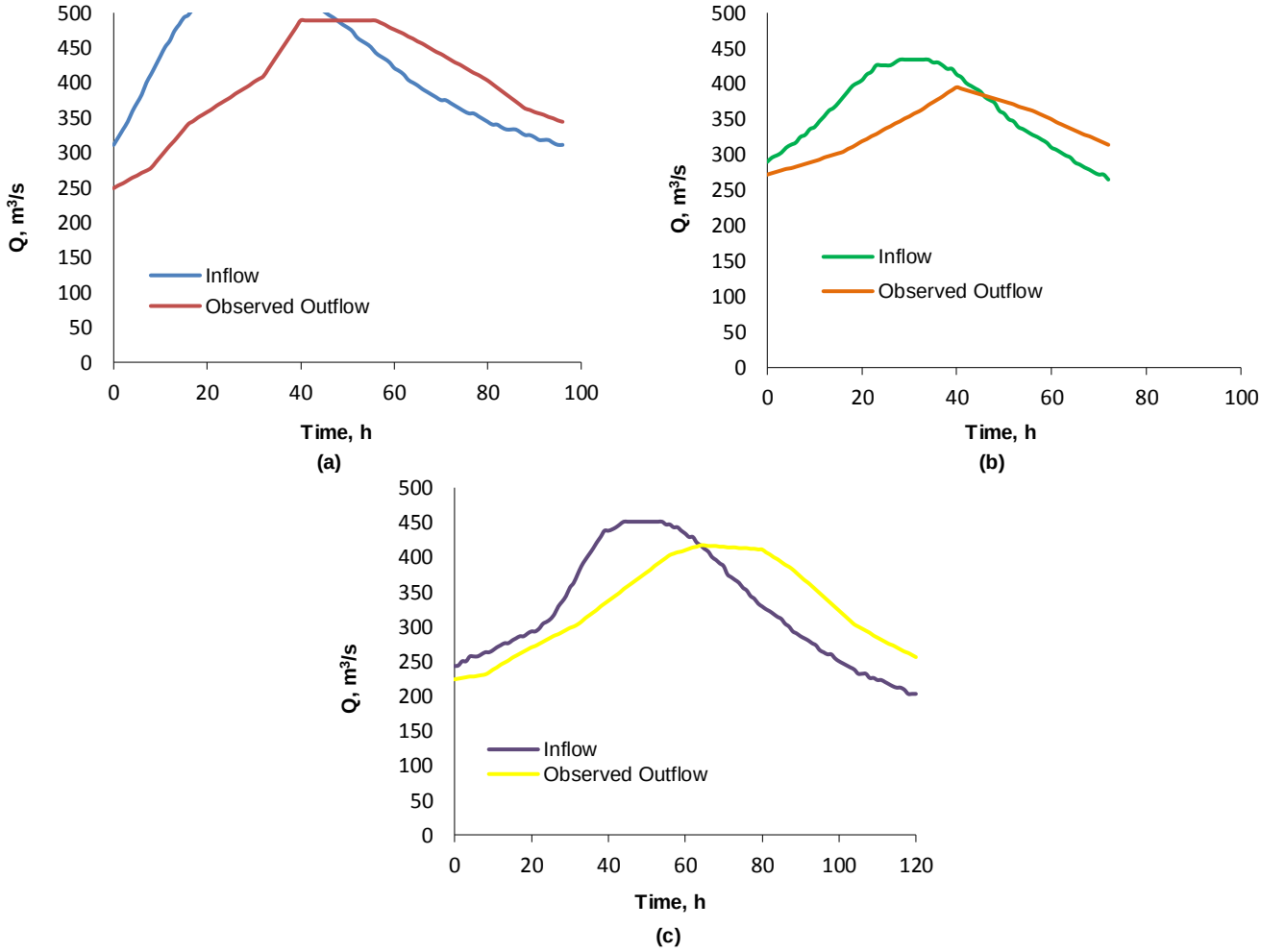

Fig. 1. Observational inflow and outflow hydrographs (a) First flood; (b) Second flood; (c) Third flood.

2.2. Linear Muskingum method

In linear Muskingum method, continuity and storage relations are developed as follows (Chow. 1959; McCarthy. 1938).

$$\frac{dS}{dt} \approx \frac{\Delta S}{\Delta t} = I - O \tag{1}$$

$$S = K[XI + (1 - X)O] \tag{2}$$

Given the continuity of flow and the simplification of Eqs. 1 and 2, we have:

$$O_{j+1} = C_1 I_{j+1} + C_2 I_j + C_3 O_j \tag{3}$$

where, C_1 ،C_2 and C_3 are given as:

$$C_1 = \frac{0.5\Delta t - KX}{K - KX + 0.5\Delta t} \tag{4}$$

$$C_2 = \frac{0.5\Delta t + KX}{K - KX + 0.5\Delta t} \tag{5}$$

$$C_3 = \frac{K - KX - 0.5\Delta t}{K - KX + 0.5\Delta t} \tag{6}$$

$$C_1 + C_2 + C_3 = 1 \tag{7}$$

where, S is storage, I is inflow, O is outflow, t is time, K is storage time constant for the river reach, and X is dimensionless weighting factor that represents the inflow and outflow effects on storage.

2.3. Particle swarm optimization (PSO)

The evolutionary algorithms originate from our environment, inspired by behavior of organisms in nature and their effort for survival. In this algorithm, introduced by (Kennedy and Eberhart. 1995), the hypothesized living organisms (birds or fish) are called particles. Each particle is identified by the following five composition, objective function corresponding to this position, velocity, best velocity experienced, and

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value of objective function corresponding to best experienced position. During the algorithm is run, position and velocity of each particle is built by Equations 8 and 9 based on the information from previous stage:

$$x_j^i[t+1] = x_j^i[t] + v_j^i[t+1] \tag{8}$$

$$v_j^i[t+1] = wv_j^i[t] + c_1 r_1 \left(x_j^{iBest}[t] - x_j^i[t]\right) + c_2 r_2 \left(x_j^{gBest}[t] - x_j^i[t]\right) \tag{9}$$

where, W= inertial factor; r_1, r_2=random vector with uniform distribution in (0, 1); c1, c2= personal learning factor and social learning factor in (0, 1) respectively; x_j^{iBest} =best experienced position of particle, and x_j^{gBest} = best experienced position of whole swarm. These rules of movement are fixed for all particles. At the end, with respect to the specified stopping criterion and through this cooperation, all particles get to the optimal solution of a given problem or defined criteria (DiCesare et al. 2015; Shi and Eberhart. 1998).

In addition, in order to evaluate the optimum values of the X, K, and Δt parameters, the sum of absolute value deviations (SAD) index, defined as Equation (10), was used as the objective function in the PSO algorithm.

$$SAD = \sum_{i=1}^{n} |O_i - Q_i| \tag{10}$$

where, O_i is observed outflow, Qi is routed (computed) outflow. The flowchart used in the present study for optimizing the Δt parameter using the PSO algorithm and the cost function SAD is shown in Fig. 2.

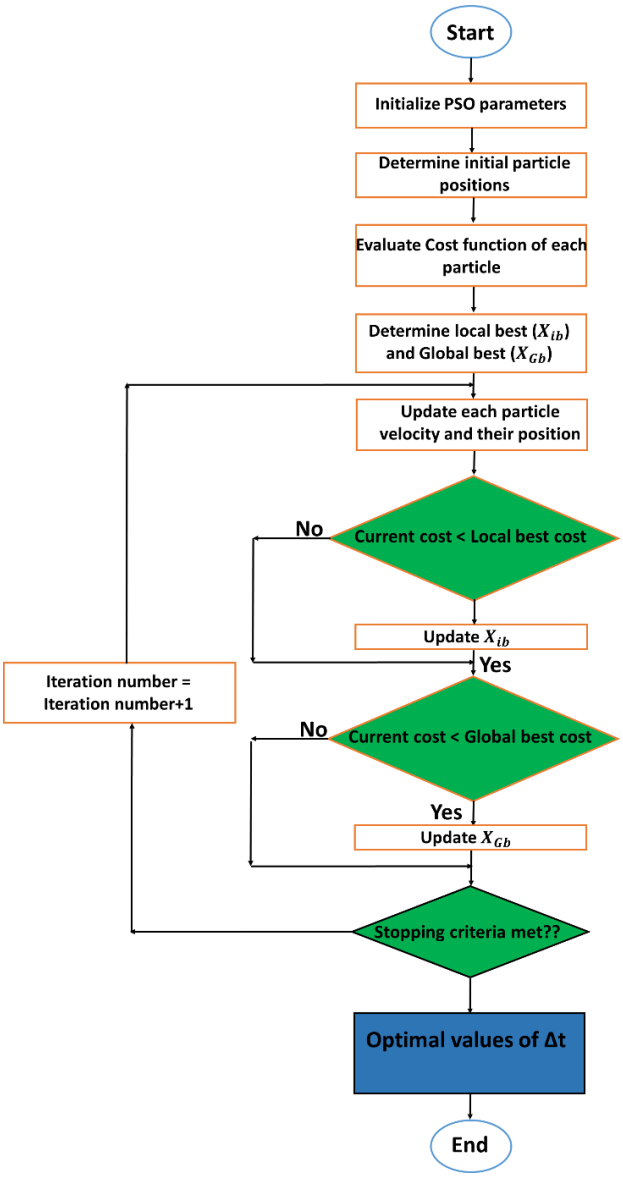

Fig. 2. PSO algorithm flowchart (Bazargan and Norouzi. 2018).

3. Results and discussion

To prevent fatality and financial losses of flood, measures should be taken to control the maximum probable flood. According to equations 4 to 6, the Δt parameter also plays a role in the corresponding calculations and in order to increase the accuracy of the mentioned method, in addition to calculation of the X and K coefficients, the value of Δt must be also optimized (Table 1). In the present study, flood data was used as shown in Fig. 1. The obtained results, as shown in Table 2 and Fig. 3, suggested that if optimized values rather than the time interval between the inflow and outflow hydrograph readings (Δt=1(h)) is used for the Δt parameter, the accuracy of the outflow calculations increased, especially in the peak zone. In other words, if contrary to the previous studies and conventional method of linear Muskingum, in which the Δt parameter is equal to the reading of the inflow and outflow hydrographs, the value of the Δt parameter is optimized using the PSO algorithm, the accuracy of the linear Muskingum method increased, especially in estimating the peak zone of the outflow hydrograph.

Table 1. Optimized parameters of X, K, and Δt.

Flood	X	K, h	Δt, h
First flood	0.075	22.223	0.849
Second flood	0.0001	45.209	0.806
Third flood	0.235	17.673	0.914

To compare the observed hydrographs with the computed hydrographs using the studied methods in the present study, and to determine the

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corresponding error, it is necessary to measure the key characteristics of the observational and computational hydrographs. In order to determine the error in calculation of discharge, the relative error index was used as follows:

$$MRE = \frac{1}{n}\sum_{1}^{n} RE \quad (11)$$

$$RE = \left|\frac{x_0 - x_e}{x_0}\right| * 100 \quad (12)$$

where, MRE is mean of relative error (%), RE is relative error per estimation (%), X_0 is observed value of parameter, Xe is computed value of parameter and n is number of estimation.

Table 2. Obtained results for Δt=1(h) and Δt= Optimized for total and peak zone of floods.

Flood	Δt, h	MRE, % (total flood)	MRE, % (peak zone)
First flood	1	6.03	8.34
	0.849	5.80	5.14
Second flood	1	4.07	2.24
	0.806	3.35	0.44
Third flood	1	3.13	1.99
	0.914	2.80	1.08

In Table 2, the peak zone of the first, second and third floods started at 25, 23, and 42 hours, respectively, and ended at 38, 37, and 58 hours, respectively.

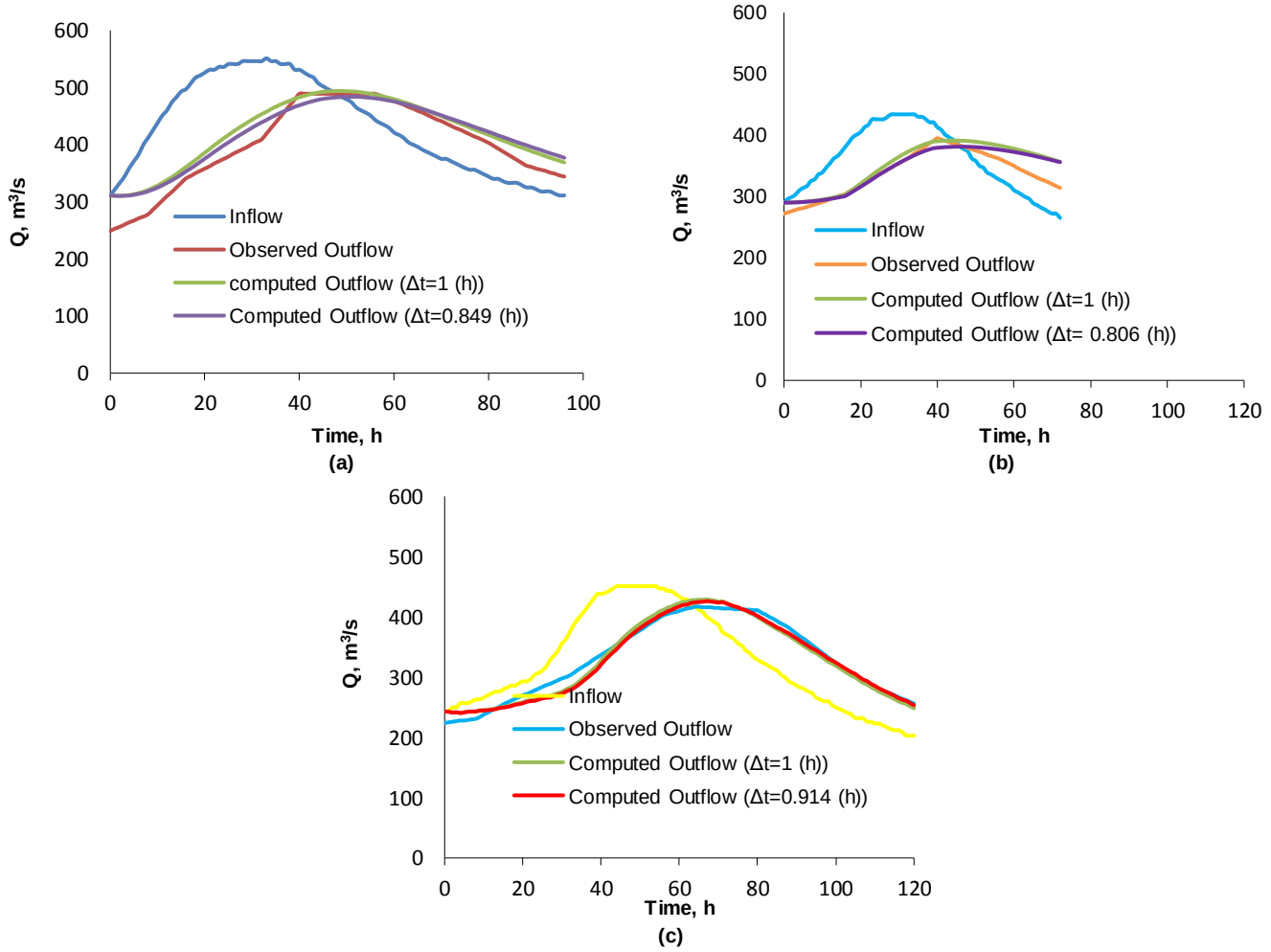

Fig. 3. Observational and computational discharges (a) First flood; (b) Second flood; (c) Third flood.

4. Conclusions

In general, the results of the present study include: 1) If only the X and K coefficients are calculated, the MRE of the peak zone for the first, second and third floods would be equal to 8.34, 2.24 and 1.99 %, respectively. However, by using the optimized Δt value, the corresponding error decreased to 5.14, 0.44 and 1.08 %. In other words, the presented method reduced the calculation error of the peak zone of the first, second and third floods by 38, 80 and 46 %, respectively. 2) The MRE values of the total flood using the proposed and the conventional methods for the first flood were equal to 5.80 and 6.03 %, respectively. The corresponding values for the second flood were equal to 3.35 and 4.07 %, respectively. The corresponding MRE values for the third flood were equal to 2.80 and 3.13 %, respectively.

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