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Developing a novel parameter-free optimization algorithm for flood routing

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Abstract

The Muskingum model is a popular hydrologic flood routing method; however, the accurate estimation of Muskingum model parameters is a critical task in the successful and precise implementation of flood routing. Evolutionary and metaheuristic optimization algorithms (EMOAs) are well suited for parameter estimation associated with various complex models including the nonlinear Muskingum model. Among EMOAs, teaching-learning-based optimization (TLBO) is a relatively new parameterless metaheuristic optimization algorithm, inspired by the relationship between teacher and students in a classroom to improve the overall knowledge of a topic in a class. This paper presents an application of TLBO to estimate Muskingum model parameters by minimizing the prediction error of outflow measurements. Several examples evaluate and confirm the successful performance of TLBO for the estimation of Muskingum-routing parameters precisely. The results show TLBO-Muskingum's high

accuracy for estimating accurately Muskingum's parameters based on the Nash-Sutcliffe Efficiency (NSE) to evaluate the TLBO's predictive skill with benchmark problems.

Key words: Teaching-learning-based optimization (TLBO) algorithm; Flood routing; Parameter estimation; Muskingum model; Optimization; Nash-sutcliffe efficiency.

Introduction

Hydrograph routing is a technique used to simulate the changes in the shape of a flood hydrograph as water moves through a river channel or a reservoir. Hydrograph routing methods can be classified into two groups, hydraulic and hydrologic models (Aboutalebi et al. 2016a). Hydraulic models such as HEC-RAS (Hydrologic Engineering Center River Analysis System) and MIKE11 are relatively complex models compared with hydrologic routing models and require solving the continuity, the energy and/or the momentum equations. Hydraulic routing models, in addition, require detailed data on river geometry and Manning's roughness coefficient whose determination is time consuming and expensive. On the other hand, hydrologic routing models, such as the Muskingum model, are popular because of their simplicity, even though hydraulic routing methods are more accurate and have a physically-based foundation. Yet, the calibration of hydrologic models improves their accuracy to acceptable levels (Chow et al. 1988). The Muskingum model features storage-time parameter (K), dimensionless river reach weighting factor (χ), and dimensionless nonlinear flood wave parameter *(m)*. These parameters have been estimated with mathematical techniques and evolutionary or meta-heuristic algorithms (Geem, 2011).

Among the mathematical techniques one can cite the segmented least-squares method (S-LSM) by Gill (1978), univariate least squares (ULS) by Heggen (1984), least squares (LS) by Aldama (1990), the nonlinear least-squares method (N-LSM) by Yoon and Padmanabhan (1993), feasible sequential quadratic programming (Kshirsagar et al., 1995), the Lagrange multiplier (LM) method by Das (2004), the Broyden-Fletcher-Goldfarb-Shannon (BFGS) technique by Geem (2006), the Newton-type trust region algorithm (NTRA) by Sheng et al. (2014). These mathematical techniques, and others not cited, have been applied to provide an estimation of the nonlinear form of the Muskingum model parameters. These techniques are straightforward; yet, they are computationally burdensome and are commonly trapped into local optima. Moreover, the performance of the mathematical techniques frequently depends on the quality of an initial search point: if the initial search point is not near the unknown global solution, there is a high probability that the optimization technique will converge to a local optimum, which is undesired.

Among the evolutionary or metaheuristic optimization algorithms ((EMOAs) one finds the genetic algorithm (GA) by Mohan (1997), harmony search (HS) by Geem et al. (2000) and by Kim et al. (2001), the ant colony algorithm (ACA) by Zhan and Xu (2005), the gray-encoded accelerating genetic algorithm (GEAGA) by Chen and Yang (2007), particle swarm optimization (PSO) by Chu and Chang (2009), the immune clonal selection algorithm (ICSA) by Luo and Xie (2010), the parameter setting free harmony search (PSF-HS) algorithm by Geem (2011), the imperialist competitive algorithm (ICA) by Tahershamsi and Sheikholeslami (2011), multi-objective particle swarm optimization (MOPSO) by Azadnia and Zahraie (2011), differential evolution (DE) by Xu et al. (2012), a combination of the simulated annealing (SA) algorithm and hybrid harmony search algorithm (HHSA) by Karahan et al. (2013), modified honey-bee mating optimization (MHBMO) algorithm by Niazkar and Afzali (2015), the backtracking search algorithm (BSA) by Yuan et al. (2016), PSO for a new form of Muskingum (four-parameter Muskingum model proposed by Easa (2014)) by Moghaddam et al. (2016), hybrid modified honey-bee mating (HMHBM) algorithm by Niazkar and Afzali (2017), bat algorithm (BA) by

Farzin et al. (2018), wolf pack algorithm (WPA) by Bai et al. (2018), shark algorithm (SA) by Farahani et al. (2019), and others. These algorithms have been applied to estimate the three parameters of the nonlinear form of the Muskingum parameters (K , χ , and *m)*. They achieve an acceptable accuracy in the estimation of Muskingum parameters that are near global optima. However, these algorithms must be pre-calibrated to assure their computational efficiency and accuracy. Therefore, the calibration of the three-parameter non-linear Muskingum model with the GA, which has at least four parameters (the number of populations, the mutation and cross-over rates, and the stopping criteria's parameter), turns into a calibration of two sets of parameters, three for the routing model and those of the optimization algorithm. Other limitations of evolutionary algorithms in water resources applications have been discussed in Aboutalebi et al. (2015, 2016a, 2016b and 2016c) and Garousi-Nejad et al. (2016a and 2016b).

This study overcomes the limitations of the mathematical search techniques and the calibration of evolutionary algorithmic parameters by introducing teaching-learning-based optimization (TLBO) (Rao et al., 2011) to estimate the parameters of the nonlinear Muskingum model. TLBO is a metaheuristic search algorithm with the significant merit that it does not involve algorithmic parameters. In other words, its application does not require a pre-calibration process which leads to fast and efficient estimation of parameters. Model outputs obtained with optimization algorithms are highly sensitive to the algorithms' calibrated parameters values, thus implying time-consuming computations to calibrate the algorithmic parameters appropriately. TLBO does not require optimizing algorithmic parameters, which constitutes a significant advantage in the implementation of the nonlinear Muskingum model. TLBO is inspired by the teaching and learning processes that occur in educational environments, such as classrooms. The TLBO's efficiency is assessed by applying it to several benchmark problems, relying on the

Nash-Sutcliffe Efficiency (NSE) as a performance criterion to evaluate the TLBO's accuracy in outflows measurements predictions.

Methods

The Nonlinear Muskingum Flood-routing Model

The relation between stream flow and reach storage is nonlinear. Therefore, the original linear form of the Muskingum flood-routing model has been superseded by the following continuity and nonlinear Muskingum model, respectively (Tung, 1985; Gill, 1978; and Geem 2011):

$$\frac{dS_t}{dt} = I_t - O_t \tag{1}$$

$$S_t = K[\chi I_t + (1-\chi)O_t]^m \tag{2}$$

where S_t, I, and O_t denote the channel storage (with dimension of L^3) of a river reach, rate of inflow with dimension of L^3/T to a river reach, and rate of outflow (with dimension of L^3/T) to a river reach, and respectively, at time t; K = storage-time constant parameter (with dimension of $L^{3(1-m)}T^m$); χ = dimensionless weighting factor river reach; m = dimensionless parameter related to nonlinearity of the flood wave. The following Equation (3) is from Equation (2):

$$O_t = \frac{(S_t / K)^{1/m} - \chi I_t}{1-\chi} \tag{3}$$

Substituting Equation (3) in Equation (1) and taking the derivate of S_t with respect to time produces:

$$\frac{dS_t}{dt} = I_t - \frac{(S_t / K)^{1/m} - \chi I_t}{1-\chi} = \frac{I_t - (S_t / K)^{1/m}}{1-\chi} \tag{4}$$

Equation (4) is an ordinary first-order, nonlinear, differential equation that does not have an analytical solution. Instead, Equation (4) is routinely solved numerically. Regardless of the numerical solution method employed to solve this equation the following conditions are pertinent: (1) the inflow hydrograph I_t is known, (2) the initial inflow equals the initial outflow $O_1(=I_1)$. Assumption (2) and Equation (2) imply that $S_1(=KO_1^m)$. Given values of the Muskingum parameters (K, χ, and m) and applying the numerical discretization of the time derivative in Equation (4), produces a recursive equation for reach storage S_{t+1} as written in Equation (5):

$$S_{t+1} = S_t + \Delta t(\frac{\Delta S_t}{\Delta t}) \qquad t = 1,2,3,... \tag{5}$$

in which Δt is the time step of hydrograph simulation. Therefore, the outflow O_t is calculated with Equation (6):

$$O_{t+1} = \frac{(S_{t+1}/K)^{1/m} - \chi I_{t+1}}{1-\chi} \qquad t = 1,2,3,... \tag{6}$$

The values of the parameters K, χ, and m must be calibrated to achieve accurate outflow predictions with Equation (6). Parameter calibration and hydraulic prediction can be achieved efficiently and accurately with EMOAs. The next section describes TLBO for the estimation of the Muskingum parameters with a novel metaheuristic optimization algorithm.

Teaching-Learning-Based optimization (TLBO)

Teaching-learning-based optimization (TLBO) is a meta-heuristic optimization algorithm inspired by the swarm intelligence of a population seeking to change from a current situation to an optimal situation emulating the knowledge improvement of students in a classroom (Rao et al., 2011). The interesting trait of TLBO is that it does not require algorithmic parameters for its implementation other than general parameters ubiquitous to all evolutionary optimization algorithms such as population size and number of iterations. Recall the GA needs crossover and mutation rates, whose values affect the optimization results (Sarzaeim et al, 2018). TLBO does not require any specific parameters. TLBO starts searching for the optimal solution of a well-posed problem with an initial population whose members' scores are the values of the decision variables, such as grades earned by students. TLBO strives to improve the population's quality by means of a "Teaching Phase" and a "Learner Phase" to achieve a solution that is very near the globally optimal solution. A more in-depth description of TLBO can be found in Rao et al. (2011), Rao and Kalyankar (2013), and Sarzaeim et al. (2018).

Linking TLBO to the Muskingum model

Figure 1 depicts the steps of the algorithm applied with TLBO to estimate the Muskingum model parameters. It is seen in Figure 1 the algorithm begins with the generation of the initial population of Muskingum parameters. The flood hydrograph is then simulated with Equations (5) and (6). The values of the objective function for each sequence of scores of earned by the students are calculated following the Muskingum simulation. The third step improves the current population of decision variables (i.e., the estimates of the Muskingum parameters) by calculating the mean value of the objective function and choosing the best solution as the teacher of the population. Afterward, the population of parameters is updated in the teaching phase (by moving the population toward the teachers' sequence of simulated outflows) and the learning phase (i.e., updating the population based on the interaction between the members of the population (students)). The new population of parameters is generated with the modifier operator such that each student (or parameter estimate) starts moving towards the best solution in the population by means of the linear and random base equation (this is the so-called Teacher Phase). In addition, the improvement of the population is guided by the interactions between students using a linear equation based on the difference between their positions (this is the so-called Learner Phase). The Muskingum simulation is repeated with the improved or updated population and the objective function is re-evaluated. A solution is reported whenever the user-specified termination criteria are satisfied. Otherwise the iterations involving improvement of the current population, Muskingum simulation, evaluation of objective functions, and assessment of the termination criteria are continuing until convergence is achieved.

Results and Discussion

The application of the TLBO in estimating the Muskingum model parameters is illustrated with two case studies. The first case study is a benchmark problem based on the data provided by Wilson (1974) and solved by several authors (Gill 1978, Das 2004, Chu and Chang 2009; Barati 2013; Vatankhah 2014; Easa 2015; Bozorg-Haddad et al. 2015) with evolutionary or meta-heuristic algorithms that estimated the nonlinear Muskingum model's parameters.

The second case study is a flood event that occurred in the River Wye in the United Kingdom (NERC, 1975). The objective function adopted to evaluate the optimal values of the Muskingum model's parameters is the maximization of Nash-Sutcliffe Efficiency (NSE), which is a normalized index of error variance (Nash and Sutcliffe, 1970). NSE is a performance metric to evaluate the accuracy of model predictions (Sarzaeim et al. 2017; Hoang et al. 2019) as follow:

$$Max \quad NSE = 1 - \frac{\sum_{i=1}^{N}(O_i - \hat{O}_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \qquad t = 1, 2, 3, \ldots \tag{7}$$

where NSE = Nash-Sutcliffe Efficiency, O_i = observed outflow at time interval i, $\hat{O}_i$ = simulated outflow at time interval i, and $\bar{O}$ = average of observed outflow.

The value of *NSE* illustrates the predictability of hydrological models, which provides a value in the range of $(-\infty,1]$. The closer *NSE* value is to 1, the more accurately the model performs.

The observed data and simulated data calculated with the best solutions for the Muskingum parameters from the TLBO for the first and second case studies are listed in Tables 1 and 2 for each time step (every 6 hours), respectively. Table 3 lists the optimal values of the parameters calculated by TLBO (K, χ, and m) and the values of the *NSE* as the objective function. It is seen in Table 3 the calculated *NSE* equals 0.99 and 0.94 for the first and second case study respectively, which indicates the high accuracy of TLBO algorithm in simulation of Muskingum model's parameters. Recall that the closer the *NSE* is to 1, the more accurate the model prediction is.

Figures 2 and 3 depict in graphical form the observed and simulated hydrographs for case studies 1 and 2, respectively. The simulated outflow hydrographs correspond to the best estimates of the Muskingum parameters. It is seen in Figures 2 and 3 the overall good fit between observations and predictions. Obviously, the accuracy of the TLBO-Muskingum algorithm's predictability is relatively higher for the first benchmark problem. While, in the second case study, the general accuracy is considerable (*NSE* = 0.94) except for the peak outflow. In this case, the simulated measurement is considerably lower than the observed value, indicating that the model may not able to capture the behavior of Muskingum flood routing for peak flows. In order to tackle this issue, the training phase of the optimization algorithm may need longer time series. Furthermore, applying TLBO to four-parameter Muskingum model may lead to better performance of the flood routing in peak flows, which may be considered for the future works.

Concluding remarks

There are many evolutionary optimization algorithms such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the Firefly Algorithm (FA). These algorithms calculate near optimal solutions for even highly complex problems. Yet, their performance relies on the calibration of algorithmic parameters, for there is no deterministic method for their assignment. The specification of evolutionary algorithmic parameters is commonly guided by experienced gained with similar optimization problems, if available. This paper implemented TLBO to estimate nonlinear 3-Muskingum parameters. TLBO was coupled with a nonlinear Muskingum flood routing model to make optimal predictions of outflow hydrographs by means of K, χ, and m calibration, which is the major challenge in Muskingum application for flood routing purposes. The coupling of TLBO with Muskingum routing bypassed the need for algorithmic optimization parameters, which are not required in TLBO. The results of *NSE* (0.99 and 0.94) demonstrate the effectiveness of TLBO for estimating the parameters values rapidly without requiring recalibrating of the optimizing algorithm parameters. According to the successful of TLBO performance in solving 3-parameter Muskingum model, it is highly recommended to evaluate the TLBO's predictability in solving 4-parameter Muskingum in the future works, which may lead to even better accuracy of Muskingum flood routing.

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Conflict of Interests:

None.

Data Availability Statement (DAS)

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1. Observed and simulated outflows for the first case study.

i	Time (h)	$O_i (m^3 / s)$	$\hat{O}_i (m^3 / s)$	$(O_i - \hat{O}_i)^2$	$(O_i - \bar{O})^2$
0	0	22.00	22.00	0.00	690.26
1	6	21.00	21.77	0.59	743.80
2	12	21.00	19.91	1.20	743.80
3	18	26.00	20.74	27.67	469.07
4	24	34.00	32.41	2.52	203.71
5	30	44.00	48.02	16.15	18.26
6	36	55.00	60.43	29.53	45.26
7	42	66.00	70.44	19.72	314.26
8	48	75.00	78.12	9.76	714.35
9	54	82.00	82.76	0.58	1137.53
10	60	85.00	84.57	0.18	1348.89
11	66	84.00	82.39	2.60	1276.44
12	72	80.00	78.55	2.09	1006.62
13	78	73.00	73.18	0.03	611.44
14	84	64.00	65.84	3.37	247.35
15	90	54.00	57.88	15.06	32.80
16	96	44.00	48.70	22.06	18.26
17	102	36.00	39.31	10.92	150.62
18	108	30.00	30.89	0.78	333.89
19	114	25.00	24.29	0.51	541.62
20	120	22.00	20.03	3.89	690.26
21	126	19.00	19.31	0.10	856.89
sum	-	-	-	169.31	12’222.36

Table 2. Observed and simulated outflows for the second case study.

i	Time (hr)	$O_i (m^3 / s)$	$\hat{O}_i (m^3 / s)$	$(O_i - \hat{O}_i)^2$	$(O_i - \bar{O})^2$
0	0	102.00	102.00	0.00	26110.76
1	6	140.00	171.37	984.36	15274.05
2	12	169.00	129.60	1551.97	8946.93
3	18	190.00	219.44	866.95	5415.23
4	24	209.00	189.89	365.35	2979.88
5	30	218.00	180.26	1424.53	2078.29
6	36	210.00	197.97	144.61	2871.70
7	42	194.00	172.79	450.00	4842.52
8	48	172.00	155.64	267.73	8388.40
9	54	149.00	110.41	1489.18	13130.46
10	60	136.00	148.17	148.06	16278.76
11	66	228.00	172.98	3027.29	1266.52
12	72	303.00	251.59	2643.48	1553.29
13	78	366.00	302.30	4057.67	10488.17
14	84	456.00	480.43	596.76	37022.29
15	90	615.00	764.70	22411.35	123490.23
16	96	830.00	801.86	791.78	320822.29
17	102	969.00	741.45	51778.15	497605.76
18	108	665.00	637.53	754.83	161131.40
19	114	519.00	568.66	2465.92	65235.17
20	120	444.00	453.41	88.48	32548.40
21	126	321.00	333.33	152.12	3296.11
22	132	208.00	219.50	132.26	3090.05
23	138	176.00	129.19	2191.33	7671.70
24	144	148.00	112.42	1265.98	13360.64
25	150	125.00	97.45	759.10	19206.70
26	156	114.00	90.45	554.78	22376.64
27	162	106.00	87.21	353.18	24834.05
28	168	97.00	77.42	383.22	27751.64
29	174	89.00	74.86	200.00	30481.05
30	180	81.00	71.03	99.49	33338.46
31	186	76.00	69.17	46.64	35189.35
32	192	71.00	64.23	45.81	37090.23
33	198	66.00	61.68	18.65	39041.11
sum	-	-	-	102’510.99	1’654’208.24

Table 3. Muskingum model parameters and calculated objective functions.

Case study	Muskingum model parameters			Objective function
	K	χ	m	NSE
The first case study	0.0703	0.1895	2.1339	0.99
The second case study	0.0103	0.2221	2.1493	0.94

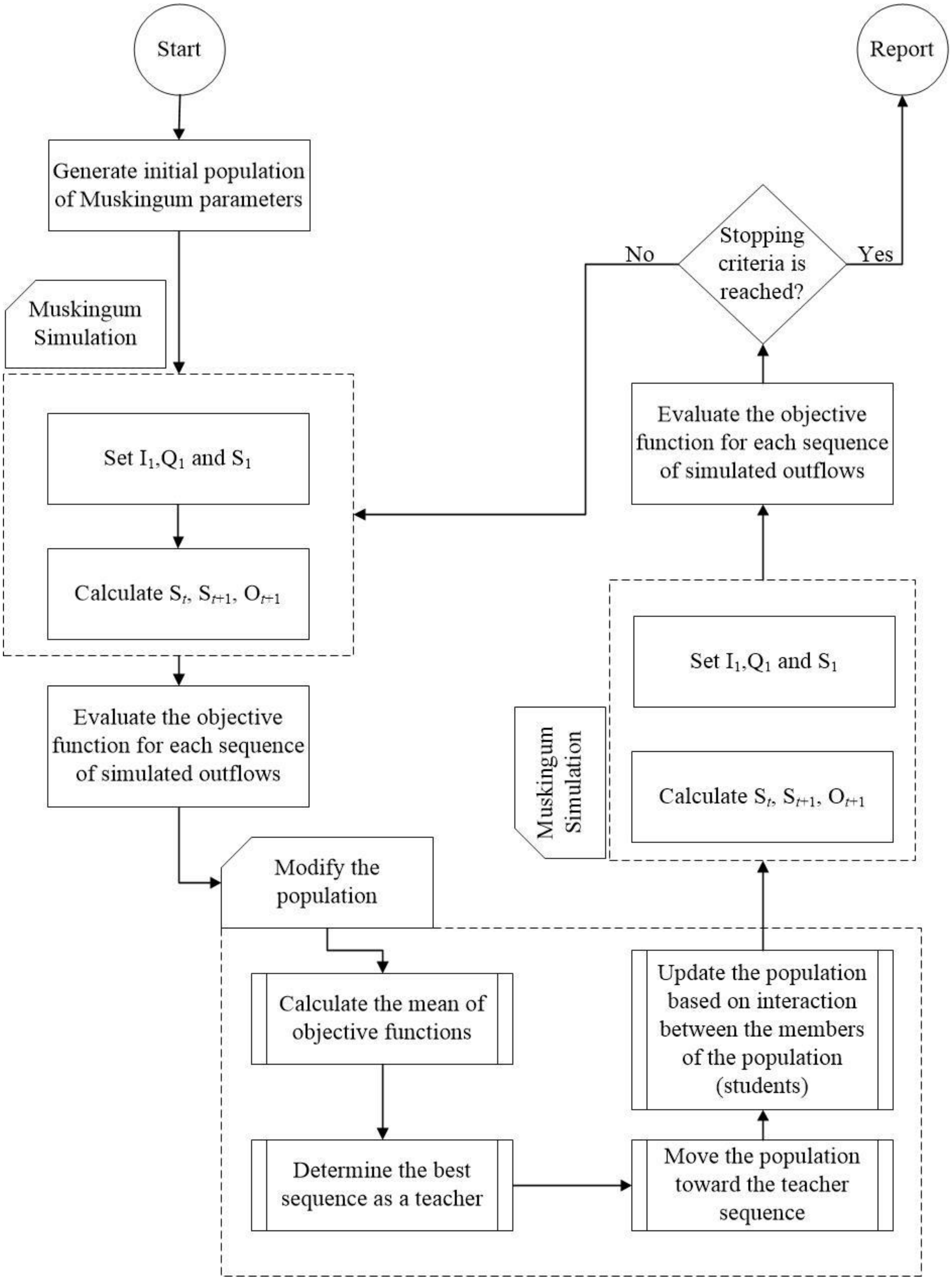

Figure 1. The flowchart the algorithm linking TLBO to the Muskingum model (string: sequence of predictions)

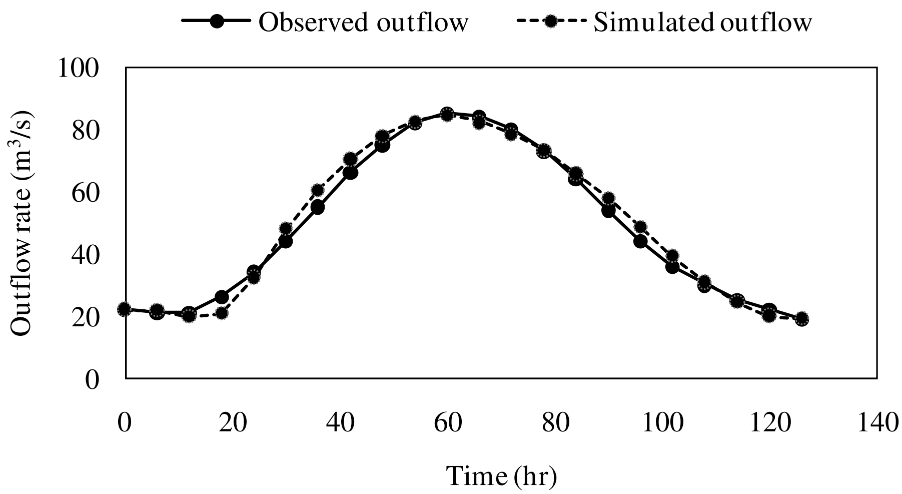

Figure 2. Hydrograph simulated with the parameters calculated by TLBO versus observed hydrograph for the first case study,

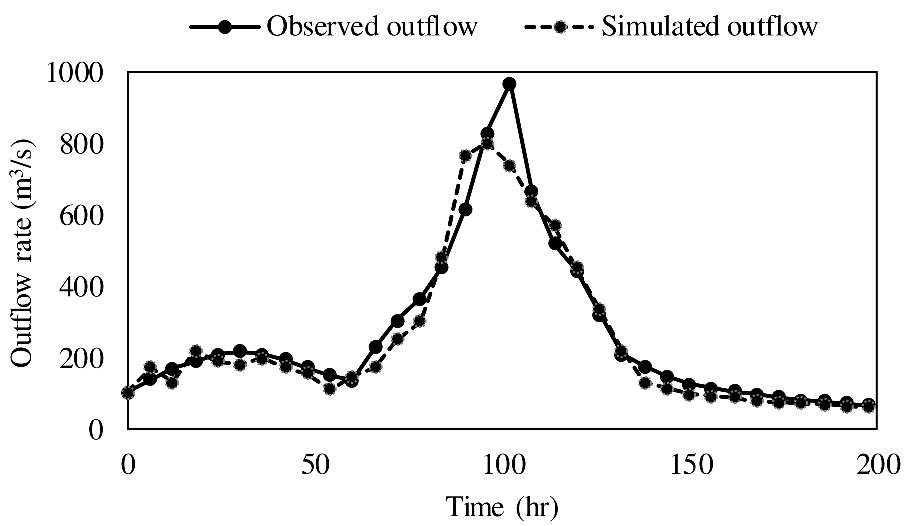

Figure 3. Hydrograph simulated with the parameters calculated by TLBO versus observed hydrograph for the second case study.

Figures

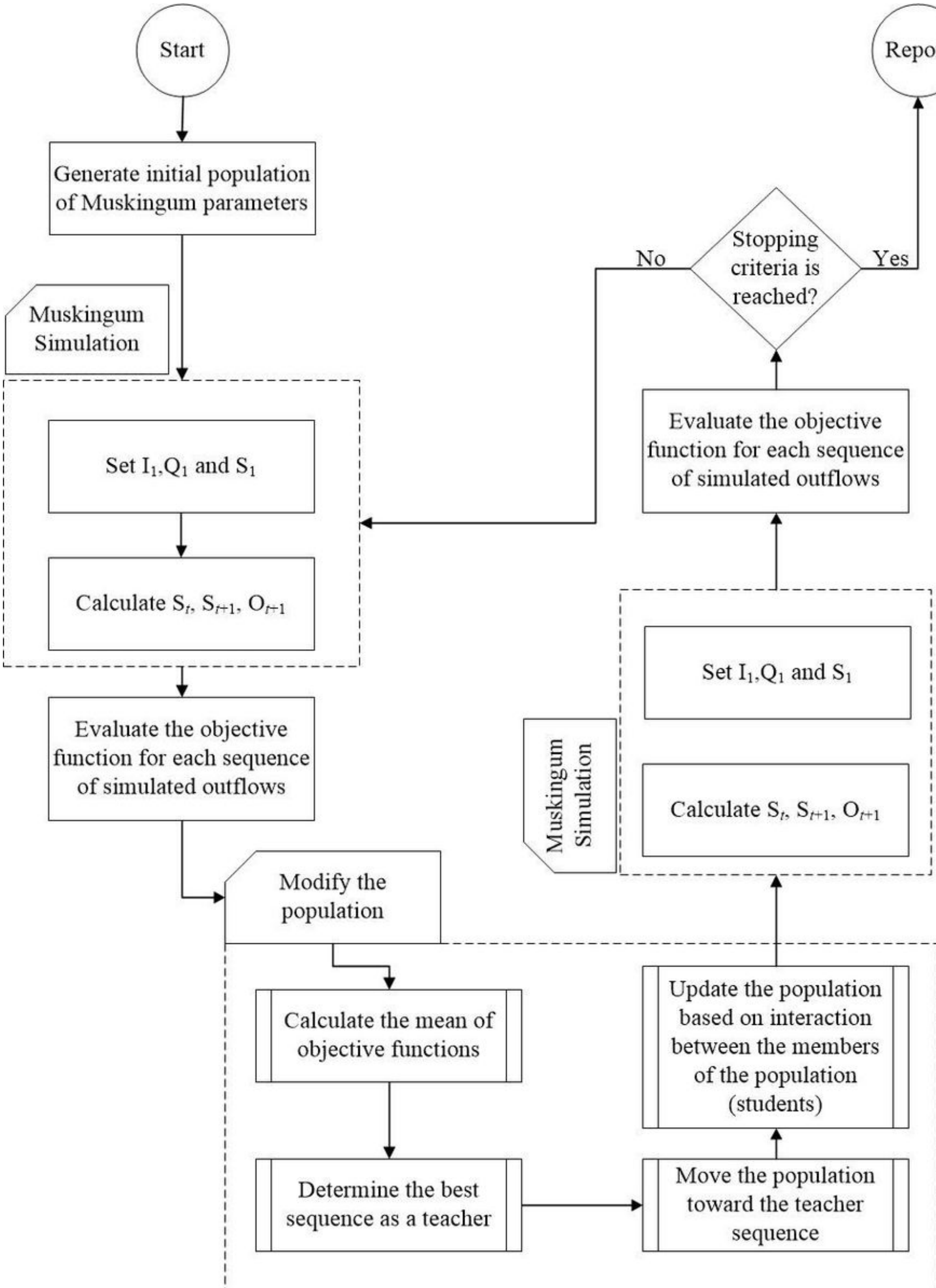

Figure 1

The flowchart the algorithm linking TLBO to the Muskingum model (string: sequence of predictions)

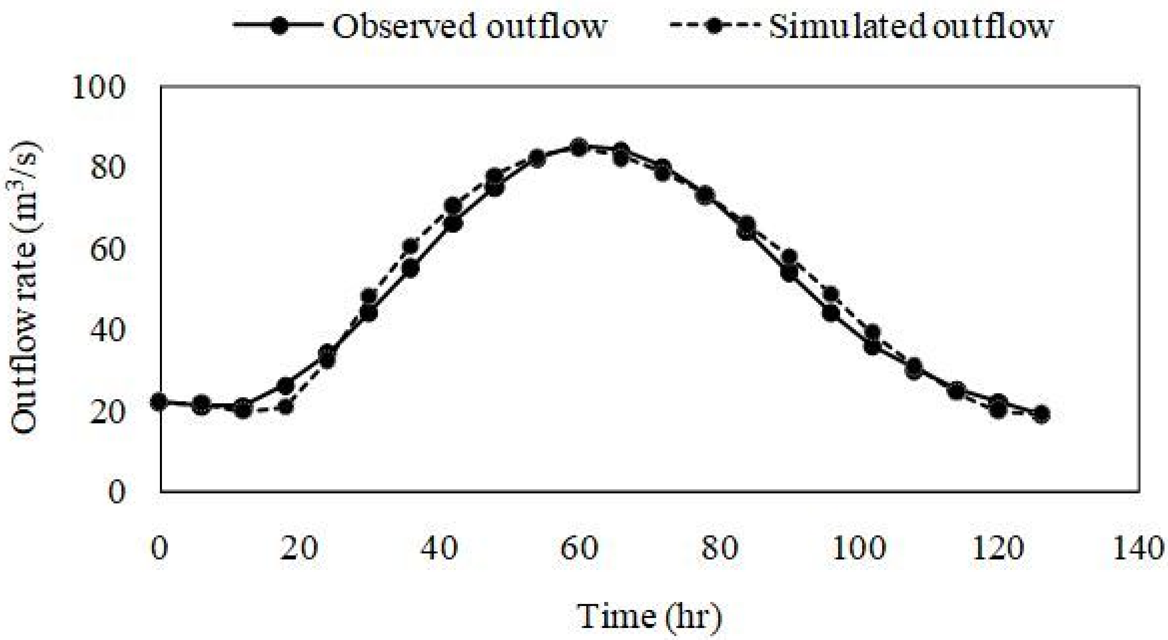

Figure 2

Hydrograph simulated with the parameters calculated by TLBO versus observed hydrograph for the first case study,

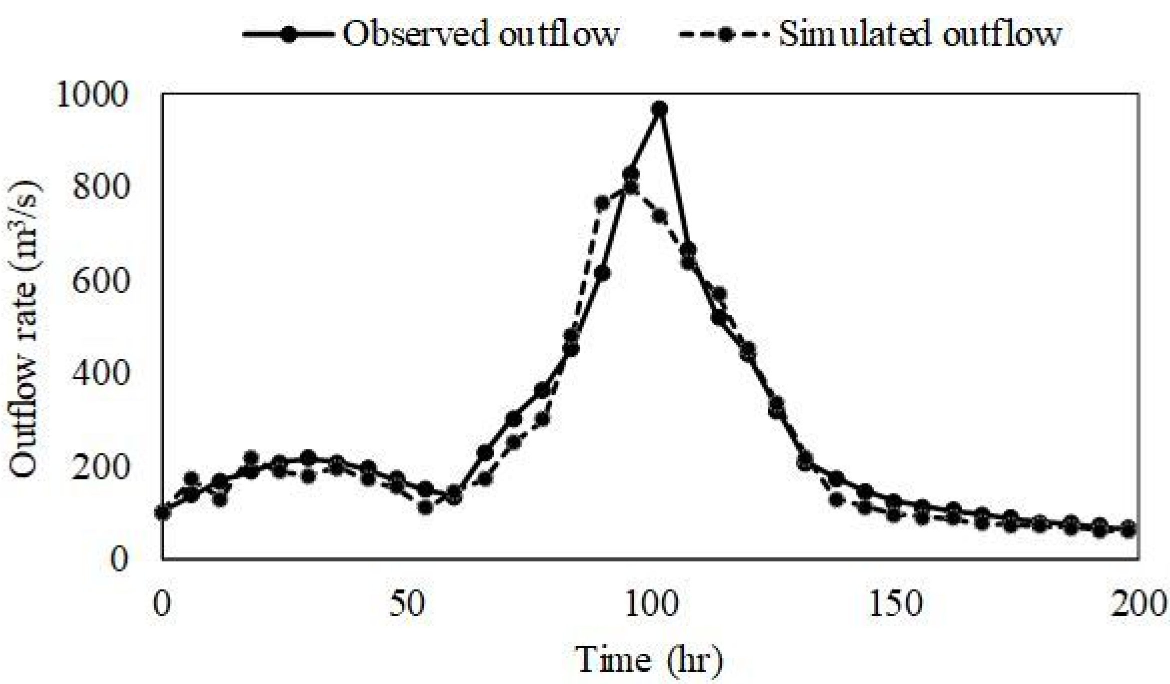

Figure 3

Hydrograph simulated with the parameters calculated by TLBO versus observed hydrograph for the second case study.