IOP Conference Series: Earth and Environmental Science

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To cite this article: M A Kadhim *et al* 2022 *IOP Conf. Ser.: Earth Environ. Sci.* **961** 012058

IOP Conf. Series: Earth and Environmental Science **961** (2022) 012058 doi:10.1088/1755-1315/961/1/012058

Evaluation of Flood Routing Models and Their Relationship to The Hydraulic Properties of The Diyala River Bed

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Abstract. In this study, four types of flood routing approaches were studied which give significantly varied results represented by the differences between computed and observed flows and also differ considerably on the friction coefficient and bed slope of the channels. First two approaches use a hydraulic solution to solve the equations of unsteady flow, while the third approach uses the hydrological solution, and the fourth algorithm solves Muskingum approach with seven parameters. All these approaches were run with the same input parameters, the results were compared and tested with four Error Measurement Indices, Sum of Squared Deviations, Error of Peak Discharge, Variance Index, and agreement index. Diyala River was selected for this application. Dynamic wave method gave accurate results, followed by the characteristic method, and then the linear Muskingum-Cunge method, but Symbiotic Organisms Search Algorithm not gave any senses due to change in roughness or bed slope and gave very identical values with recorded outflow in all conditions, which means that the hydraulic solution is better compared to the hydrological solution. The results also showed that the difference between the calculated and observed flows diminished with a decrease in the coefficient of friction and an increase in the bed slope channel.

1. Introduction

Applications of flood routing are based on the use of the unstable flow theory (long waves or surges) or the basic water storage equation. A flood hydrograph is calculated at a given point in a channel based on a known hydrograph of a location at the upstream or downstream and using known channel characteristics and lateral flow or outflow characteristics,([1], [2], [3] and [4]). The analysis of empirical relationships between inflow and outflow is the starting point for flood routing studies. Mathematical methods used for more accurate predictions of flood wave motion have been developed. The development can be divided into two approaches (hydrological and hydraulic approaches), ([5],[6], [7], [8] and [9]).

Hydrological models have the distinction of being less complex than the hydraulic models, but they have some disadvantages as they require configuring observed inflow and outflow hydrographs from a reach to determine the routing parameters at a particular flow section, as well as not taking into account the effects of the back-water impacts from streams, large tributary flows, dams, and bridges, ([10], [11] and [12]). The physical processes of water movement in the natural channels are the basis for hydraulic models,([13] and [14]). A one-dimensional theory of flood wave propagation was developed by Saint Venant,([15], [16], [17] and [18]). The numerical approach, which does not require any radical simplification, is another method for finding solutions to the equations of unsteady flow, ([19] and

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[20]). It replaces the derivatives in partial differential equations with finite differences, [21], making the equations appear as simple algebraic equations. There were issues with account convergence, stability, accuracy, and performance. Despite the fact that the method deals only with simple algebraic equations, the number of equations is enormous, much greater than empirical methods,([22] and [23]).To tackle optimization issues, the Symbiotic Organisms Search Algorithm (SOS) is presented as an evolution optimization model, [24]. This method employs a population-based search that is divided into three stages. The SOS algorithm mimics symbiotic relationships between two species, allowing one to choose the best partner, [25] .
The aim of the research is to prepare an evaluation study of hydraulic models (dynamic wave, the characteristic approaches), hydrological models (linear Muskingum-Cunge approach), and optimization algorithm (SOS) to solve the nonlinear Muskingum approach with seven parameters in flood routing and their relationship to the hydraulic properties of the natural channel basin, and the Diyala river is chosen for its typical flow properties as a case study.

2. Mechanism of the Hydraulic and Hydrological Models

2.1. Dynamic Wave Approach
The implicit nonlinear approximation of the finite difference used to solve the equations of unsteady dynamic flow is referred to as the dynamic wave approach, [21]. This approach has been updated to suit the conditions and objectives of this research. To find results, the procedure uses an implicit finite difference, as shown in figure1.

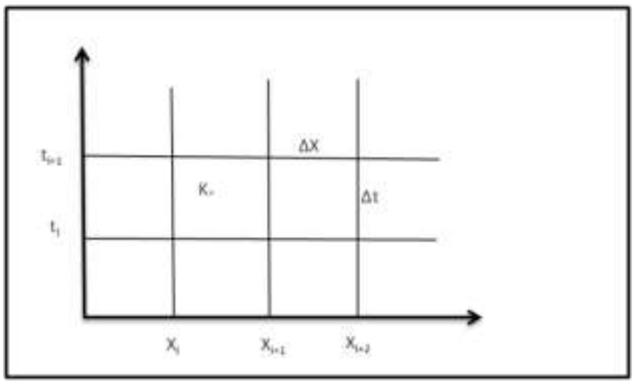

Figure 1. Finite difference approximation method,[21].

$$K = 0.5\beta\left[k_{i+1}^{j+1} + k_i^{j+1}\right] + 0.5(1-\beta)\left[k_{i+1}^{j} + k_i^{j}\right] \quad (1)$$

$$\frac{\partial k}{\partial x} = \frac{\beta}{\Delta x}\left[k_{i+1}^{j+1} + k_i^{j+1}\right] + \left\{\frac{1-\beta}{\Delta x}\right\}\left[k_{i+1}^{j} - k_i^{j}\right] \quad (2)$$

$$\frac{\partial k}{\partial t} = \frac{1}{2\Delta x}\left[k_{i+1}^{j+1} + k_i^{j+1} - k_{i+1}^{j} - k_i^{j}\right] \quad (3)$$

Where β is a weighting factor.

The continuity equation is classified as a derivative of conservation of mass and momentum, so the equations can be written as follows:

$$F(u,y)\frac{\partial u}{\partial t} + \frac{A}{T}\frac{\partial U}{\partial x} + U\frac{\partial y}{\partial x} = 0 \quad (4)$$

$$G(u,y)\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + g\frac{\partial y}{\partial x} + g\left(S_f - S_o\right) = 0 \quad (5)$$

The finite-differences formula can be used for equations (4) and (5), where I and j denote distance and time phase, respectively.

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2.2. Characteristics Approach

According to the characteristics approach, a flood wave is a disturbance of the free water surface, ([22], and [26]). Any interruption in the flow of the open channel spreads in two directions, upstream and downstream at a certain point. In the x-t plane, a pair of turbulence paths can be plotted to move downstream and upstream from point A at time t = 0. The paths are known as the characteristic lines C_1 and C_2. The region between a pair of C_1 and C_2 and point A at time t > 0 represents the turbulence control range. Inversely, one can describe turbulence that can affect the condition at point D by looking back in time, as shown in figure 2. Solutions of unsteady flow can be found using the concepts of characteristic line, control spectrum, and field, [9].

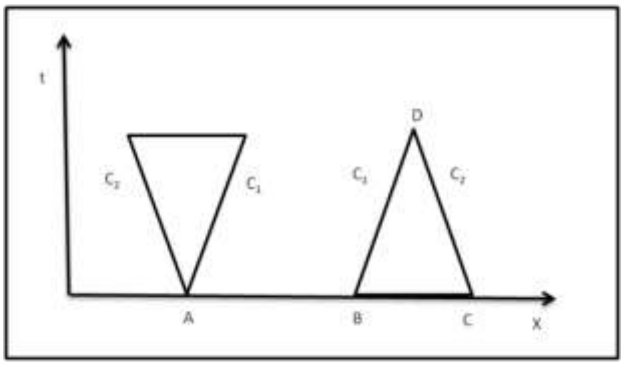

Figure 2. Influence field and domain, [26].

The mathematical definition of the total derivative shows the following:

$$dy = \frac{\partial y}{\partial x}dx + \frac{\partial y}{\partial t}dt \quad \text{or} \quad \frac{dy}{dt}\frac{dy}{dt} + \frac{\partial y}{\partial t} \tag{6}$$

y is a function of x (distance) and t (time). Equation (6) will show the variation of y.

$$\frac{dx}{dt} = u \pm c \tag{7}$$

$$\frac{du}{dt} \pm \frac{1}{c}\frac{dy}{dt} + g(Sf - so) = 0 \tag{8}$$

In which,

$$C = (\frac{gA}{T})^{0.5} \tag{9}$$

Equations (7, 8 and 9) represent the characteristic forms of the unsteady flow equation. In order to find solutions to these equations, the finite difference approximation method is used (either a rectangular grid or a distinct grid of C_1 and C_2).

2.3. Linear Muskingum-Cunge Approach

The Muskingum-Cunge approach ([7], [8], [3] and [17]) is based on mass conservation (i.e., the continuity equation) and the relationship between inflow, outflow, and storage (i.e., storage equation), as follows:

Continuity procedure:

$$\frac{dS}{dt} = I - O \tag{10}$$

Storage equation :

$$S = K\{Ix + (1 - x)O\} \tag{11}$$

which : S = absolute storage within the reach, I = inflow, O = outflow, x= weighing factor,

K= a value related to the time lag or time of the flood wave's transit across the reach, and the storage gradient against the weighted flow curve.
These equations contribute to determining the discharge of the outflow, as follows:

$$O = C_1 O_n^m + C_2 O_n^{m+1} + C_3 O_{n+1}^m \tag{12}$$

$$C_1 = \frac{(\Delta t/_k) + 2x}{(\Delta t/_k) + 2(1-x)} \quad , C_2 = \frac{(\Delta t/_k) - 2x}{(\Delta t/_k) + 2(1-x)} \quad , \; C_3 = \frac{2(1-x) - (\Delta t/_k)}{(\Delta t/_k) + 2(1-x)} \tag{13}$$

Using the kinematic wave equation and assuming a single-value phase discharge relationship, Cunge,([27] and [12]) developed equation (11), finding that K and x can be calculated using the following formulas:

$$K = \frac{\Delta x}{C} \tag{14}$$

$$X = 0.5\left\{1 - \frac{ow}{cso\Delta x}\right\} \tag{15}$$

$$C = \frac{dO}{dA} \tag{16}$$

The main aim of computation in any approach is always to produce an accurate response to match the calculated flow result with the observed flow. The method for determining Δx value influencing Muskingum parameter values, is one attempt to achieve an accurate result. As shown in previous studies ([11], [28] and [29]), that the parameter x varies between 0.0 and 0.5, so the following criteria were established to ensure positive outflow for any positive inflow sequences:

$$X \leq \frac{0.5\,\Delta t}{k} \leq (1 - x) \qquad \text{for } x \leq 0.5 \tag{17}$$

So Δx has to be constrained as follows:

$$\left(C\Delta t - \frac{ow}{cs0}\right) \leq \Delta X \leq \left(C\Delta t + \frac{ow}{cs0}\right) \tag{18}$$

2.4. Symbiotic Organisms Search (SOS) Algorithm

It is one of the presumptive algorithms presented on the basis of interactive behavioral simulation. The use of the SOS as one of the novel met heuristic approaches for estimating parameters of the nonlinear Muskingum model was investigated in this study. To test the proposed algorithm's performance, the results of its implementation were compared to those of other approaches such as the Dynamic wave approach, the Characteristic methodology, and the Muskingum-Cunge attitude. The SOS (figure 3), like other population-based algorithms, produces a population of alternatives periodically in order to identify the best answer in the total range of replies. The SOS algorithm starts with a population known as the ecosystem, [30]. A set of decision variables is randomly created in the search space in the first ecosystem. The degree of compliance with the aim is determined by each living creature as a candidate for the solution associated with a specific fit (the value of the objective function). In each iteration, all met heuristic algorithms use an alternate function to solve a problem and generate a new solution for the next iteration.
The algorithm's overall trend is as follows:
Initialization ⟶ Repetition ⟶ Mutualism ⟶ Commensalism Parasitism ⟶ End procedure after the maximum number of iterations has been reached.

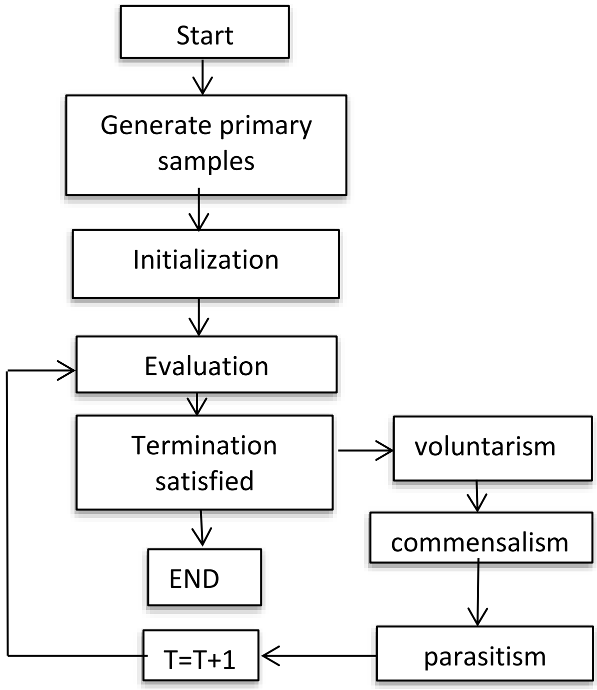

Figure 3. The SOS methodology flow chart, [24].

2.4.1. Model Formulation and Optimization

The Non-linear model of type 5 (NL5) ([31] and [32]) is an enhanced variant of this model. The steps to obtain the NL5 model are outlined below:

$$S_1 = b\left\{\frac{I}{d_1}\right\}^{m/n_1} \tag{19}$$

$$S_o = b\left\{\frac{I}{d_2}\right\}^{m/n_2} \tag{20}$$

Where d_1 and n_1 represent the river's upstream depth–flow relationship, and d_2 and n_2 represent the river's downstream depth–flow parameters, substituted S_I and S_o from equations (14) and (15) in {S = [X S_I + (1-X) S_o)]$^{\alpha}$ }

Simplifying the equation (16) produced,

$$S = k\left[X\left(C_1 I^{\beta 1}\right) + (1-X)\left(C_2 O^{\beta 2}\right)\right]^{\propto}(NL5) \tag{21}$$

Where:

$$K = b^{\propto} \tag{22}$$

$$\beta_1 = {}^{m}/{}_{n_1} \tag{23}$$

$$\beta_2 = {}^{m}/{}_{n_2} \tag{24}$$

$$C_1 = \left({}^{1}/{}_{d_1}\right)^{\beta 1} \tag{25}$$

$$C_2 = \left({}^{1}/{}_{d_2}\right)^{\beta 2} \tag{26}$$

Where:

I, O: inflow and outflow rate (m^3/s)

K: constant which is larger than (0)

X: The dimensionless weight coefficient for the river is between 0 and 0.5, showing the relative impacts of the input and outflow flow.

β_1, β_2 and α: are the zero-valued exponential parameters. Fixed parameters C_1 and C_2 are both zero.

The Non-Linear model of type 5 contains seven parameters: X, K, β_1, β_2, α, C_1, C_2. One of the other non-linear models is more difficult in this regard. Optimization models are used to optimize these parameters.

2.4.2. Simulation Technique for the Proposed NL5 Model

This study employs, [33], to simulate flood routing technique using the NL5 model. The observed inflow, calculated outflow, and computed storage during the i[th] time period in the NL5 model are I_i, Q_i^* and S_i respectively, where (i = 0, 1, 2..., N) represents the simulation time periods. The following are the steps of the proposed NL5 flood simulation model:

1. Assume the seven hydrologic parameters values (X, K, β_1,β_2, α, C_1, C_2):

$$S_o = k\left[X\left(C_1 I^{\beta 1}\right) + (1 - X)\left(C_2 O^{\beta 2}\right)\right]^{\propto} \qquad \text{i=0} \tag{27}$$

2. Calculate the starting storage S_O by setting the initial computed outflow to the same value as the initial observed inflow ($Q_o^* = I_o$):

$$\frac{\Delta Si}{\Delta t} = Ii\left\{\left[\frac{1}{C2(1-X)}\right]\left(\frac{Si}{K}\right)^{\frac{1}{\alpha}} - \left[\frac{1}{C2(1-X)}\right]\left[\alpha\left(C1 I^{\beta 1}\right)\right]\right\}^{1/\beta_2} \tag{28}$$

3. Calculate the storage volume's time rate of change during time period i (beginning with i = 1):

$$S_{I+1} = S_I + \Delta t\left(\frac{\Delta S_i}{\Delta t}\right) \tag{29}$$

4. Calculate the storage at time i
5. Calculate the outflow for period i.:

$$\frac{\Delta Si}{\Delta t} = \left\{\left[\frac{1}{C2(1-X)}\right]\left(\frac{Si}{K}\right)^{\frac{1}{\alpha}} - \left[\frac{1}{C2(1-X)}\right]\left[\alpha\left(C1 Ii - 1^{\beta 1}\right)\right]\right\}^{1/\beta 2} \qquad 30)$$

6. Repeat steps (3)–(5) until the simulation reaches time N. Increment the index I by one ([34];[35]).

2.5. Error measurement Indices

2.5.1. Sum of Squared Deviations (SSD)

In this study, the SSD index is utilized as the objective function. The total squared discrepancies between observed and actual discharges are calculated using the following index, [36] .

$$Min\ (SSQ) = \sum_{t=1}^{N}(Qt - Qct)^2 \tag{31}$$

2.5.2. EP index (Error of peak discharge)

EP index is a metric that quantifies the difference between anticipated and observed discharges, [37].

$$EQ_p = [|Q_o^P - Q_{ro}^P|]/Q_o^P \tag{32}$$

Where:

Q_o^P: observed outflow peaks(m^3/s)

Q_{ro}^P: routed outflow peak (m^3/s)

2.5.3. Varex Q (Variance Index)

This metric displays how close predicted and observed hydrographs are to one other.

$$VarexQ = \left[1 - \frac{\sum(Q_o - Q_{ro})}{\sum(Q_o - Q_{omean})}\right] \times 100 \tag{33}$$

Where (Q_{omean}) is the observed mean discharge, the closer the coefficient is to one, the more accurate the prediction of the flood.

2.5.4. Agreement Index (d)

Based on the following equation, the model's performance is well demonstrated, since the value of the index may fluctuate from 0 to 1, [38].

$$d = 1 - \frac{\sum(Q_o - Q_{ro})^{\wedge}2}{\sum(|Q_{ro} - Q_{av.ob}| - |Q_{ob} - Q_{av.ob}|)} \quad (34)$$

where:

Q_o, Q_{ro}: observed outflow (m^3/s) and routed outflow(m^3/s) respectively

$Q_{av.ob}$: average observed outflow(m^3/s)

3. Study Area

The Diyala River is one of the important water sources in Iraq, and it is characterized by its typical flow characteristics. The southern part of it was chosen for a case study. The aforementioned river is classified as one of the tributaries that flow into the Tigris River, and its estuary point in the Tigris River, located south of Baghdad (the capital of Iraq). The catchment area of the Diyala River is divided into two parts, one in Iran (the neighboring country) and the other in Iraq. The area of Diyala Rive is 33,240 square kilometers with a total length of 574 kilometers, 25% of this area is located in Iran and the majority is in Iraq, figure 4, [39].

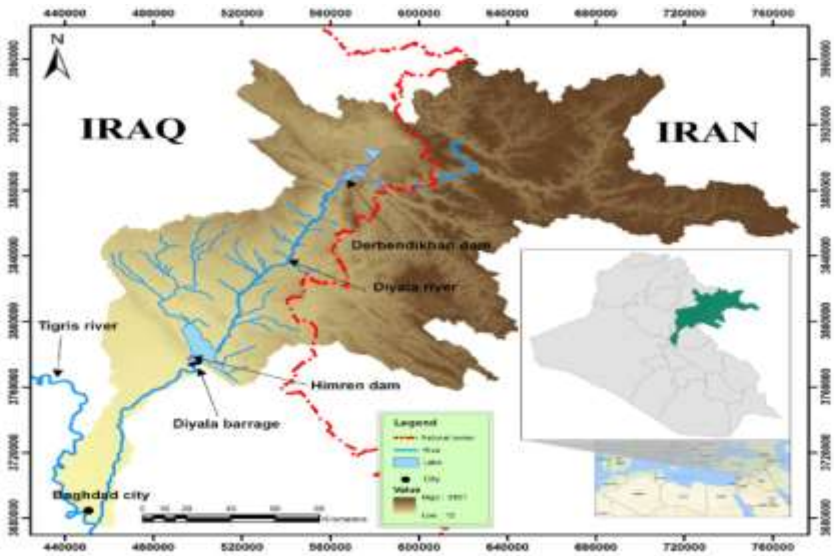

Figure 4. Layout of Diyala River, [39].

The comparison test of the three routes was applied to the flows of the Diyala River, with simulated and observed flows. The computed outflows were compared with each other and the target discharge for each group of bed slope and the Manning's coefficient (n) values. To achieve this, the data of observed flows from the Diyala River for the period from 1993 to 2017 were used, where the general monthly average of these discharges was adopted as shown in table 1, [40], in addition to the slope of the river bed (So) and the Manning's coefficient (roughness) for three locations in the southern part of Diyala River, illustrated in table 2, [41]. The monthly averages of the observed water discharges for the selected period were marked by their regularity, accuracy, and ideality compared to the readings of other time periods.

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Table 1. General monthly average of discharge for Diyala River for the years (1993-2017),([39] and[40]).

Month	October	November	December	January	February	March	April	May	June	July	August	September
Q (m^3/s)	56	101	140	198	273	413	420	220	97	65	57	52

Table 2. Hydraulic properties for several locations in Diyala River, [41].

Location	Location's name	Length of river in the location(km)	Manning coefficient (n)	Bed slope (S_o, cm/km)
A	North of Baquba city	43	0.027	43
B	Center of Baquba city	85	0.089	17
C	South of Baquba city	75	0.038	26

4. Results analysis and discussion

One of the most fascinating and difficult unsteady flow phenomena is flood routing, which involves tracking the complex motion of a flood wave flowing through the channel. It is difficult to estimate the nonlinear Muskingum model parameters via trial and error. Various approaches have been used to estimate these parameters during the last two decades. One of the strategies that have been successful in estimating these parameters is met heuristic techniques. In this study, the nonlinear Muskingum model's parameters were estimated using a search method for symbiotic organisms. To assess the performance of the symbiotic creature search algorithm, the results of its implementation were compared to those of other hydraulics and hydrologic approaches such as a (Dynamic Wave and Characteristics approaches) and hydrological (Linear Muskingum- Cunge approach) models. In order to find the best values of the outflow for the Diyala river, the most accurate and identical of the computed flow with the observed flow were shown. Figures 5,6 and 7 illustrate the ranges of congruence for the hydrographic plans resulting from the computed and observed flows. The statistical indices SSQ, EQP, varex Q, and d were used to assess the algorithms. This shows that the search method for symbiotic organisms is working properly in calculating the values of the nonlinear Muskingum model to find the optimal values of the outflow and more compatible with the calculated outflow with all other methods without any senses to change n and S_o.

The hydrograph computed using the dynamic wave approach gave a great match to the observed outflow values, and this method achieved the required compatibility at the computed peak flow time with the observed flow. Whereas in other approaches applications, it achieved peak flows earlier than the observed outflow time. As a result of the dynamic wave approach achieving the required synchronization condition, the differences between the computed and observed flow were much smaller than what happened in the other approaches.

The results show that the use of hydraulic models to achieve the correspondence between the computed and observed flows as well as the required synchronization at the peak flow is better compared to the hydrological model represented by the linear Muskingum-Cunge approach, as it was difficult to meet the requirements of equations (12) to (17) for a steep bed slope, table 3. The interval remains short enough that Δx can satisfy the condition and ensure positive outflows. So due to the previously mentioned requirements, the Muskingum-Cunge approach failed to obtain an adequate result when applied to a channel with bed slope (So) = 0.0050 and Manning's coefficient (n) =0.035.

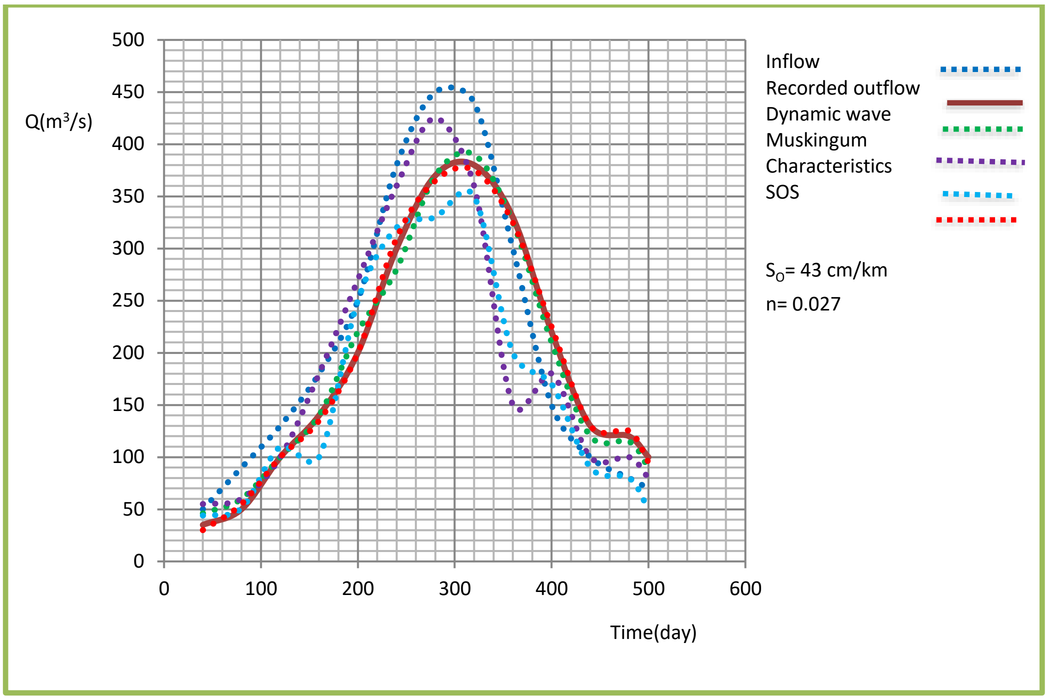

Figure 5. Comparison results to recorded outflow hydrograph with various methods to location (A)

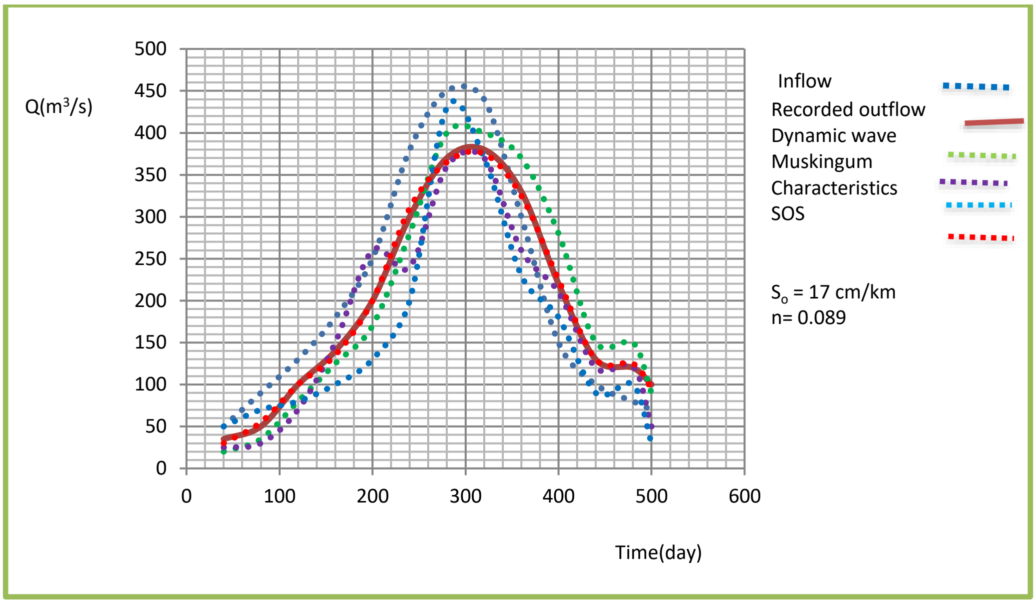

Figure 6. Comparison results to recorded outflow hydrograph with various methods to location (B)

It is also noted that this study confirmed what was stated in previous studies ([6], [7], [8], [16], [3] and [18]) that hydrological models are less complex than hydraulic models, but they also have some defects. Since they require observed inflow and outflow hydrographs from a reach to determine the routing coefficients, they are generally limited in application, backwater effects of tides, major tributary inflow, dams, and bridges are not taken into account.

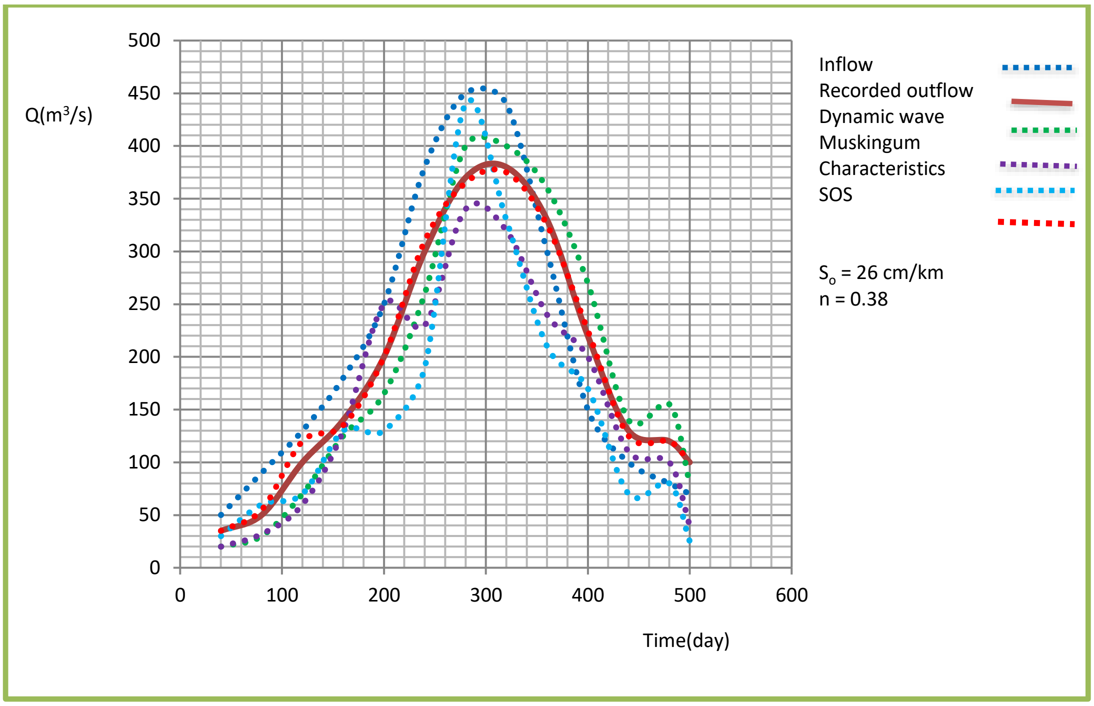

Figure 7. Comparison results to recorded outflow hydrograph with various methods to location (C)

After determining the dynamic wave approach as the best method in flood routing, the effect of both Manning's coefficient (roughness coefficient) and bed slope on this method was studied using different values. The results showed that the difference between the computed and observed flows diminished with a decrease in the coefficient of friction and an increase in the bed slope channel.

5. Conclusion

In this study, the performance of the symbiotic creature search algorithm was used to assess the results of its implementation compared to those of other hydraulics and hydrologic approaches such as a (Dynamic Wave and Characteristics approaches) and hydrological (Linear Muskingum-Cunge approach) models in flood routing and their relationship to the hydraulic properties of the natural channel bed.

The results of the comparison indicated that the use of hydraulic models to achieve compatibility between the calculated and observed flows, as well as the required synchronization at the peak flow, is better than the application of hydrological models. The study showed that the dynamic wave approach achieved a significant match between the calculated flow and the observed outflow values and gave an accurate synchronization of the time of the peak flow with the observed outflow. Also, it is noted that the symbiotic organisms search (SOS) Algorithm did not give any sense due to changes in roughness or bed slope and gave very identical values with recorded outflow in all conditions, which means that the hydraulic solution is better compared to the hydrological solution. The use of the dynamic wave approach showed that the difference between the calculated and observed flows decreases as the Manning coefficient decreases and the channel bottom slope increases.

Table 3. The estimated outflow values for all methods used.

			Estimated outflow (m^3/s)											
			n =0.027, S_o=43 cm/km				n =0.089, S_o=17 cm/km				n =0.38, S_o=26 cm/km			
Time (day)	I(cms)	O(cms)	Dynamic wave	Muski-ngum	charac-	SOS	Dynamic	Muski-	Charac-	SOS	Dynamic	Muski-	Charac-	SOS
0	56	45	46	55	44	30	45	45	35	30	25	20	35	30
40	101	60	60	60	51	55	60	45	45	55	20	20	30	55
80	140	80	100	100	110	100	110	125	130	100	30	32	60	100
120	198	120	140	180	100	135	135	160	110	135	70	60	70	135
160	273	200	220	270	250	200	210	265	240	200	125	130	130	200
200	413	270	280	360	320	310	265	350	340	310	165	250	130	310
240	450	350	370	425	330	365	350	460	430	365	260	230	190	365
280	220	380	390	360	350	375	380	340	300	375	400	340	440	375
320	97	320	325	150	200	325	400	160	230	325	400	320	330	325
360	65	100	210	180	170	225	400	170	190	225	360	240	210	225
400	150	220	120	100	90	130	170	120	120	130	270	200	170	130
440	100	130	115	100	80	125	130	110	100	125	140	110	70	125
480	80	120	90	80	50	120	75	60	45	120	155	100	80	120
500	70	100	50	30	30	100	45	35	30	100	80	40	25	100
SSD			4.995	22.42	21.05	2.112	5.221	22.52	21.03	2.012	5.001	22.11	20.13	2.725
EQ_p			0.0004	0.001	0.001	0.000	0.0005	0.002	0.001	0.000	0.0004	0.001	0.001	0.000
Verx			96.85	90.45	91.02	98.91	95.95	90.00	91.52	98.91	96.85	90.56	92.12	98.92
d			0.95	0.91	0.92	0.98	0.94	0.89	0.92	0.985	0.94	0.89	0.93	0.99

6. References

[1] Bautista E, Strelkoff T S and Clemmens A J 2003 General characteristics of solutions to the open-channel flow, feedforward control problem *J. of Irri. and Drain. Engi.* **129** 2 129–137 DOI:10.1061/(asce)0733-9437(2003)129:2(129)

[2] Chen X Y, Chau K W and Busari A O 2015 A comparative study of population-based optimization algorithms for downstream river flow forecasting by a hybrid neural network model *Engi. Applications of Artificial Intelligence* **46** 258–268 DOI:10.1016/j.engappai.2015.09.010

[3] Latt Z Z 2015 Application of feedforward artificial neural network in Muskingum flood routing: A black-box forecasting approach for a natural river system *Water Resources Management* **29** 14 4995–5014 DOI:10.1007/s11269-015-1100-1

[4] Perumal M and Price R K 2013 A fully mass conservative variable parameter McCarthy-Muskingum method: Theory and verification *J. of Hydrology* **502** 89–102 DOI:10.1016/j.jhydrol.2013.08.023

[5] Akbari G and Firoozi B 2011 Characteristics of recent floods in persian gulf catchment *World Rese. J. of Civil Engineering* **1** 1 7-14

[6] Barati R 2013 Application of excel solver for parameter estimation of the nonlinear Muskingum models *KSCE J. of Civil Engineering* **17** 5 1139–1148 DOI:10.1007/s12205-013-0037-2

[7] Chu H J 2000 The Muskingum flood routing model using a neuro-fuzzy approach *KSCE J. of Civil Engineering* **13** 5 371–376 DOI:10.1007/s12205-009-0371-6

[8] Karahan H, Gurarslan G and Geem Z W 2013 Parameter estimation of the nonlinear Muskingum flood-routing model using a hybrid harmony search algorithm. *J. of Hydrologic Engineering* **18** 3 352–360

[9] Kucukkoc I and Zhang D Z 2016 Integrating ant colony and genetic algorithms in the balancing and scheduling of complex assembly lines *International J. of Advanced Manufacturing Technology* **82** 1– 4 265–285 DOI:10.1007/s00170-015-7320-y

[10] Al-Humoud J M and Esen I I 2006 Approximate methods for the estimation of Muskingum flood routing parameters *Water Resources Management* **20** 6 979–990 DOI:10.1007/s11269-006-9018-2

[11] Karahan H 2008 Solution of weighted finite difference techniques with the advection-diffusion equation using spreadsheets *Computer Applications in Engineering Education* **16** 2 147–156 DOI:10.1002/cae.20140

[12] Yang R, Hou, B, Xiao W, Liang C, Zhang X, Li B and Yu H 2020 The applicability of real-time flood forecasting correction techniques coupled with the Muskingum method *Hydrology Research* **51** 1 17–29 DOI:10.2166/nh.2019.128

[13] Bazargan J and Norouzi H 2018 Investigation the effect of using variable values for the parameters of the linear Muskingum method using the Particle Swarm Algorithm (PSO) *Water Resources Management* **32** 14 4763–4777 DOI:10.1007/s11269-018-2082-6

[14] Ehteram M, Mousavi S F, Karami H, Farzin S, Singh V P, Chau K W and El-Shafie A 2018 Reservoir operation based on evolutionary algorithms and multi-criteria decision-making under climate change and uncertainty *J. of Hydroinformatics* **20** 2 332–355 DOI:10.2166/hydro.2018.094

[15] Akbari G and Firoozi B 2010 Implicit and Explicit numerical solution of Saint-Venent equations for simulating flood wave in natural rivers *5th National Congress on Civil Engineering,* May 4-6 2010 vol 1 (Ferdowsi University of Mashhad, Mashhad, Iran) p 2–8

[16] Kim J H, Geem Z W and Kim E S 2001 Parameter estimation of the nonlinear Muskingum model using Harmony Search *J. of the American Water Resources Association* **37** 5 1131–1138 DOI:10.1111/j.1752-1688.2001.tb03627.x

[17] Niazkar M and Afzali S H 2016 Application of new hybrid optimization technique for parameter estimation of new improved version of Muskingum model *Water Resources Management* **30** 13 4713–4730 DOI:10.1007/s11269-016-1449-9

[18] Ali-Askari O K and Shayannejad M 2016 Flood routing in rivers by Muskingum'S method with new adjusted coefficients *International Water Technology J*. **6** 3 189–194 http://iwtj.info/wp-content/uploads/2017/02/ID-55.pdf
[19] Perdikaris J, Gharabaghi B and Rudra R 2018 Evaluation of the simplified dynamic wave, diffusion wave and the full dynamic wave flood routing models. *Earth Science Research* **7** 2 14 DOI:10.5539/esr.v7n2p14
[20] Price R K 2009 Volume-conservative nonlinear flood routing *J. of Hydraulic Engineering* **135** 10 838–845 DOI:10.1061/(asce)hy.1943-7900.0000088
[21] Moghaddam M A 2011 Development of dynamic flood wave routing in natural rivers through Implicit Numerical Method *American J. of Scientific Research* 14 14 6–17
[22] Barbetta S, Moramarco T and Perumal M 2017 A Muskingum-based methodology for river discharge estimation and rating curve development under significant lateral inflow conditions *J. of Hydrology* **554** 216–232 DOI:10.1016/j.jhydrol.2017.09.022
[23] Mazzoleni M, Noh S J, Lee H, Liu Y, Seo D J, Amaranto A, Alfonso L and Solomatine D P 2018 Real-time assimilation of streamflow observations into a hydrological routing model: effects of model structures and updating methods *Hydrological Sciences J.* **63** 3 386–407 DOI:10.1080/02626667.2018.1430898
[24] Cheng M Y and Prayogo D 2014 Symbiotic organisms search: a new metaheuristic optimization algorithm *Computers and Structures* **139** 98–112
[25] Tejani G G, Savsani V J and Patel V K 2016 Adaptive symbiotic organisms search (SOS) algorithm for structural design optimization *J. of Computational Design and Engineering* **3** 3 226–249
[26] Ferrick M G 2005 Simple wave and monoclinal wave models: River flow surge applications and implications *Water Resources Research* **41** 11 1–19 DOI:10.1029/2004WR003923
[27] Alhumoud J M and Almashan N 2019 Muskingum method with variable parameter estimation *Mathematical Modelling of Engineering Problems* **6** 3 355–362 DOI:10.18280/mmep.060306
[28] Pei J Z, Su Y X and Zhang D H 2017 Fuzzy energy management strategy for parallel HEV based on pigeon-inspired optimization algorithm *Science China Technological Sciences* **60** 3 425–433 DOI:10.1007/s11431-016-0485-8
[29] Yadav B, Perumal M and Bardossy A 2015 Variable parameter McCarthy-Muskingum routing method considering lateral flow *J. of Hydrology* **523** 489–499 DOI:10.1016/j.jhydrol.2015.01.068
[30] Tejani G G, Pholdee N, Bureerat S, Prayogo D and Gandomi A H 2019 Structural optimization using multi-objective modified adaptive symbiotic organisms search *Expert Systems with Applications* **125** 425–441
[31] Haddad O B, Hamedi F, Orouji H, Pazoki M and Loáiciga H A 2015 A re-parameterized and improved nonlinear Muskingum model for flood routing *Water Resources Management* **29** 9 3419–3440
[32] Tejani G G, Savsani V J, Bureerat S and Patel V K 2018 Topology and size optimization of trusses with static and dynamic bounds by modified symbiotic organisms search *J. of Computing in Civil Engineering* **32** 2 4017085
[33] Geem Z W 2006 Parameter estimation for the nonlinear Muskingum model using the BFGS technique *J. of Irrigation and Drainage Engineering* **132** 5 474–478.
[34] Farzin S, Singh V P, Karami H, Farahani N, Ehteram M, Kisi O, Allawi M F, Mohd N S and El-Shafie A 2018 Flood routing in river reaches using a three-parameter Muskingum model coupled with an improved bat algorithm *Water* **10** 9 1130
[35] Mohammad G M, Haddad O B and Ebrahimi K 2010 Optimization nonlinear Muskingum model's parameters by simulated optimization Nord algorithm *J. of Water and Soil* **24** 908–919
[36] Haddad O B, Hamedi F, Fallah-Mehdipour E, Orouji H and Marino M A 2015 Application of a hybrid optimization method in Muskingum parameter estimation *J. of Irrigation and Drainage Engineering* **141** 12 4015026

IOP Conf. Series: Earth and Environmental Science **961** (2022) 012058 doi:10.1088/1755-1315/961/1/012058

[37] El-Shafie A, Mukhlisin M, Najah A A and Taha M R 2011 Performance of artificial neural network and regression techniques for rainfall-runoff prediction *International J. of Physical Sciences* 6 8 1997–2003

[38] Ehteram M, Binti Othman F, Yaseen Z M, Abdulmohsin A H, Falah A M, Najah A A, Shahid S P, Singh Vand El-Shafie A 2018 Improving the Muskingum flood routing method using a hybrid of particle swarm optimization and bat algorithm *Water* **10** 6 807

[39] Al-Ansari N 2013 Management of water resources in Iraq: perspectives and prognoses *Engineering* **5** 6 667–684

[40] Iraqi Ministry of Water Resources 2017 *Water discharges of the Tigris and its tributaries and the Euphrates for the water years (1993-2017)* (Iraqi Ministry of Water Resources/ Planning and Follow-up Department/ Environmental Policy Division)

[41] Aydin M and Ereker F 2009 Water scarcity and political wrangling: Security in the Euphrates and Tigris basin *Facing Global environmental change engineering* (Springer) pp 603–613 DOI:10.1007/978-3-540-68488-6_44.

[42] Singh, H., Singh, J., Sharma, S., Dwivedi, S. P., & Obaid, A. (2021). Comparative Performance of Copper, Graphite, Brass and Aluminium/Graphite- Based Different Tool Electrodes for Optimizing the Material Removal Rate during Die-Sinking EDM of Stir-Casted, Al6061/SiC-MMCs for Sustainable Manufacturing and Energy Applicatio. Journal of Green Engineering, 11(1), 922-938.