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Estimation of Nonlinear Parameters of Type 6 Hydrological Method in Flood Routing with the spotted hyena optimizer Algorithm (SHO)

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Abstract

In this study, The Spotted hyena optimizer Algorithm (SHO) is used to optimize the parameters of the Non-linear type 6 Muskingum model for flood routing. To evaluate the performance of the SHO in the Non-linear Muskingum models, The Wilson River and the Wye River are applied by many researchers for validation. Moreover, in these studies, the Non-linear Muskingum parameters were estimated by the SHO Algorithm. The SSQ and DPO were considered as objective functions between computed and observed data. According to the results of Wilson river flood, the values of these objective functions for the NL3 model are 128.781, and 0.92 m³/s, and for the NL6 model, are 3.20 and 0.027, respectively. The results of the Wye River flood with the SHO showed that the SSQ and DPO for the NL3 model are 34789.39 and 90.05, and for the NL6 model are 30812.07 and 72.35, respectively. The results show that the proposed algorithm can be applied confidently to estimate the parameter optimal values of the nonlinear Muskingum model. Moreover, this algorithm may be applicable to any continuous engineering optimization problems.

Keywords: Non-linear Muskingum model, Sum of Square Error (SSQ), Spotted hyena optimizer
Algorithm, Flood routing

1. Introduction

Flood means an increase in the water height of a river, and occupation of the riverbanks which lead to damage to the buildings and public installations and causes human and animal casualties.

In some cases, floods can be caused by increasing water height in the lake or the sea, which can have a profound effect on high winds.

Flood routing is a mathematical method for forecasting changes in the volume, velocity and flood waveform in the channel as a function of time, which is of great importance in river engineering, river protection, flow modeling in reservoir and weirs. The problem of flood routing can be solved by hydraulic and hydrological methods depending on the conditions and information available from the river (Ahmed et al., 2019). Hydrological routing is the principle of continuity of flow and described the relationship between the outflow and flood storage along the route, and the results are sufficiently accurate for use in the waterworks. In the other methods, the complex hydraulic principles and laws of unsteady flows were used in the open waterways, which are called hydraulic routing (Hamed et al., 2016).

The Muskingum model is one of the hydrological routing methods first developed by McCarthy (McCarthy, 1938). The method introduced by McCarthy was a linear relationship and did not have the ability to model non-linear relationships between the inflow, outflow and flood storage.

However, Gill (2006) developed a Non-linear version of this method. The important point in using a Non-linear Muskingum method is to determine the appropriate values of its parameters, which are usually determined by trial-and-error or using time-consuming numerical methods. Therefore, using optimization methods to determine these parameters is an excellent solution. The Non-linear hydrological model is presented using equations 1 and 2 (Das, 2004):

$$\frac{ds}{dt} = I_t - O_t \quad (1)$$

$$S_t = K[XI_t + (1 - X)O_t] \quad (2)$$

Where S_t , O_t and I_t denote the values of the flood storage, outflow and inflow at time t , respectively, K is the storage duration to reach the river, which provides the flow time via the river, and X is a weight Coefficient between (0, 0.3).

The standard method for applying the Muskingum model involves two steps including parameter estimation and flood prediction (Das, 2004).

In the first step, the Muskingum parameters are determined using historical input-output data recorded from the river hydrographs. In the second step, the flood is predicted using the Muskingum Routing Equations. A routing plan is suggested, where the relationship between the flood storage and Non-linear weight flow is introduced. In the past studies, five types of Non-linear Muskingum model have been reported (Chow (1959), Gavilan and Hook (1985), Gill (1978), Easa (2013), Haddad et al. (2015)).

In the Muskingum Linear Model by Combining Exponential Parameters with Inflow and Outflow Flood Storage Equation, Nonlinear versions 1 and 2 were obtained in the first and second stages, respectively. Using the weighted storage flow and considering the exponential parameters, the Muskingum version 3 (NL3) model was developed, which was the most widely used model among researchers. The algorithms used in this model can be referred to the Nord algorithm, GOA algorithm, Bat algorithm, SOS algorithm and etc (Ghaleni et al., 2010; Farzin et al., 2018; Khalifeh et al., 2020;).

The NL1 and NL2 storage equations were combined and the fourth Non-linear version of the Muskingum (NL4) model was obtained.

Easa (2013) introduced the purpose of developing a Flood Routing Model using the Muskingum method to create a greater degree of freedom. Omid Bozorghad et al. (2015) introduced a Non-linear Muskingum model that modified the structure of the NL4 storage model as NL5. This model has greater degrees of freedom than the standard NL4 and offers 7 nonlinear Muskingum parameters (Haddad et al., 2015).

The NL6 Model was presented to NL5 by adding an improvement coefficient γ , which takes less than and more than one due to the peak flow rate in the outflow hydrograph (Tabari et al., 2018).

According to the mentioned literature, Non-linear 3 was used as the most widely used method and a Non-linear 6 was used as the developed method.

In this paper, the method is based on a powerful nature-inspired intelligent technique called spotted hyena optimizer Algorithm (SHO) to optimize the Non-linear model parameters.

The novelty of this paper is that for the first time in the new nonlinear Muskingum model called Model NL6 with 8 variables, the SHO algorithm was used.

In the present study, first, the performance of the SHO algorithm compared to other meta-heuristic algorithms such as Genetic Algorithm (GA) and Imperialist Competitive Algorithm (ICA) were investigated in the NL3 model for the Wilson River. Thereafter, based on the SHO algorithm, the calculated parameters from the NL3 and NL6 Muskingum models were compared for the Wilson and Kardeh River.

2. Methods

2.1. The Non-linear 3 (NL3) Muskingum Model

The Non-linear Muskingum model version 3 is derived from the following equations.

$$S_t = K[I_t X + O_t(1 - X)]^m \quad (3)$$

$$S_t = K[I_t^m X + O_t^m(1 - X)] \quad (4)$$

Where I_t , O_t and S_t are, inflow, outflow and flood storage, respectively. K is the dimensionless coefficient of storage for the river and I_t is considered a reasonable value close to the time that the flow passes through the entire river, and X is a weight coefficient between (0, 0.5) (Mohan, 1997; Kim et al., 2001; Chu and Chang, 2009).

2.1.1. Method of Estimating Flood Routing Parameters Using NL3 Proposed Model

Using Equation 5, the outflow is obtained (Karahan et al., 2013):

$$O_t = \left(\frac{1}{1-X}\right)\left(\frac{S_t}{K}\right)^{\frac{1}{m}} - \left(\frac{X}{1-X}\right)I_t \quad (5)$$

96 The following equations are derived from the combination of Equations (1) and (3):

$$\frac{\Delta S_t}{\Delta t} = -\left(\frac{1}{1-X}\right)\left(\frac{S_t}{K}\right)^{\frac{1}{m}} + \left(\frac{1}{1-X}\right)I_t \quad (6)$$

$$S_{t+1} = \Delta S_t + S_t \quad (7)$$

97 S_{t+1} is the storage at time $t + 1$. Geem (2006) calculated the flood hydrograph using the above
 98 equations and employed the following algorithm:

99 Step 1: Suppose the initial value for the K , X , and m parameters

100 Step 2: Computing the flood storage (S_t) using equation (3) supposing that the initial outflow is
 101 equal to the inflow ($O_1 = I_1$).

102 Step 3: Computing the ratio of flood storage to the time using equation (6).

103 Step 4: Computing the amount of storage using equation (7).

104 Step 5: Computing the outflow volume using Equation (5).

105 Step 6: Repeat steps 1 to 5.

106 **2.2. The Non-linear 6 (NL6) Muskingum Model Procedure**

107 In this study, the modified version of this model is used which be firstly proposed by Tabari et al.
 108 (2018), called the Non-linear type 6 model (NL6). The NL6 method was originally proposed by
 109 Chow (1959).

$$110 \quad S_{in} = b\left(\frac{I}{a_1}\right)^{\frac{m}{n_1}} \quad (8)$$

$$111 \quad S_{out} = b\left(\frac{O}{a_2}\right)^{\frac{m}{n_2}} \quad (9)$$

112 Where a_1 and n_1 describe the parameters associated with the characteristics of the river upstream
 113 depth-discharge relationship; a_2 and n_2 reveal the characteristics of the downstream depth -
 114 discharge. By substitution of S_{in} and S_{out} , from Eq. (8) and (9) in $S = [XS_{in} + (1-X) S_{out}]^\beta$, the Eq.
 115 (10) is produced.

$$116 \quad S = K\gamma[X(C_1 I^{\alpha_1}) + (1 - X)(C_2 O^{\alpha_2})]^\beta \quad (NL5)$$

117 (10)

$$118 \quad K = b^\beta \quad (11)$$

$$119 \quad \alpha_1 = \frac{m}{n_1} \quad (12)$$

$$120 \quad \alpha_2 = \frac{m}{n_2} \quad (13)$$

$$121 \quad C_1 = \left(\frac{1}{a_1}\right)^{\alpha_1} \quad (14)$$

$$122 \quad C_2 = \left(\frac{1}{a_2}\right)^{\alpha_2} \quad (15)$$

123 Where I and O are the inflow and outflow rate (m^3/s), K is the reserve constant which is greater
 124 than 0. X is the dimensionless weight coefficient between 0 and 0.3, indicating the relative
 125 effects of the input and output flow on the reservation. α_1 , α_2 and β are the exponential
 126 parameters, and γ , C_1 and C_2 are the fixed parameters that are greater than zero. The parameter γ
 127 is actually the coefficient determining the linearity and nonlinearity of the output hydrograph
 128 Its value is less than one for single-point flow hydrographs and more than one for multi-point
 129 flow hydrographs. S also indicates the storage volume.

130

131 The NL6 model has 8 parameters including K, X, C₁, C₂, γ, α₁, α₂ and β which is more complex
 132 and accurate compared to the other Non-linear models. These parameters are obtained using
 133 optimization models.

134 2.2.1. Method of Estimating Flood Routing Parameters Using NL6 Proposed Model

135 In this article, Tabari et al (2018) method are used to simulate the flood routing model with
 136 version NL6. The simulation steps of the flood routing in NL6 method are as follows:

137 Step 1: Suppose the initial value of model parameters (K, X, C₁, C₂, α₁, α₂, β, γ).

138 Step 2: Compute the initial flood storage S₀, using equation (16). Permit the initial computed
 139 output flow be equal to initial Observed input flow ($\hat{O}_0=I_0$):

$$140 \quad S_0 = K \gamma \left[X (C_1 I^{\alpha_1}) + (1-X) (C_2 O_0^{\alpha_2}) \right]^{\beta} \quad i = 0$$

141 Step 3: Compute the rate of flood storage volume at time interval t (beginning by i =1):

$$142 \quad \frac{\Delta S_i}{\Delta t} = I_i \left\{ \left[\frac{1}{(1-X)C_2} \right] \left(\frac{S_i}{K\gamma} \right)^{\frac{1}{\beta}} - \left[\frac{1}{(1-X)C_2} \right] \left[(C_1 I^{\alpha_1}) X \right]^{\frac{1}{\alpha_2}} \right\} \quad (17)$$

143 Step 4: Compute the flood storage at time i:

$$144 \quad S_i = \left(\frac{\Delta S_{i-1}}{\Delta t} \right) \Delta t + S_{i-1} \quad (18)$$

145 Step 5: Compute the output flow at time interval i:

$$146 \quad O_i = \left\{ \left[\frac{1}{(1-X)C_2} \right] \left(\frac{S_i}{K\gamma} \right)^{\frac{1}{\beta}} - \left[\frac{1}{(1-X)C_2} \right] \left[(C_1 I_{i-1}^{\alpha_1}) X \right]^{\frac{1}{\alpha_2}} \right\} \quad (19)$$

147 Consider that I_{i-1} rather than I_i is used in Equation. (19), following the method of Geem (2006).

148 Step 6: 1 unit increasing with i and repeat steps (3) to (5) until time N.

3. The Spotted hyena optimizer Algorithm (SHO)

In this article, for the first time, estimating the Non-linear type 3 and 6 is applied by the population-based optimization algorithm and nature-inspired, which is called The Spotted hyena optimizer Algorithm (SHO) (Dhiman and Kumar, 2017). The optimization results demonstrate that the SHO algorithm is very competitive compared to other evolutionary algorithms. The main steps of this algorithm are as follows (Dhiman and Kumar, 2017):

(i) Encircling prey

For Encircling prey, the best solution is considered as objective hunting. Search agents or hyenas can identify and improve their position according to this state by identifying. Mathematical modeling of this behavior is shown by Equations (20) and (21):

$$\vec{D}_h = |\vec{B}\vec{P}_p(x) - \vec{P}(x)| \quad (20)$$

$$\vec{P}(x+1) = \vec{P}_p(x) - \vec{E} \cdot \vec{D}_h \quad (21)$$

Where $\vec{D}_h$ displays the distance between the prey and spotted hyena; X indicates the current iteration, $\vec{B}$ and $\vec{E}$ are factor vectors; $\vec{P}_p$ is the location vector of prey; $\vec{P}$ is the location vector of spotted hyena.; $| |$ is the absolute amount, and $(.)$ Is Dot product. The factors vectors are estimated as the following equations:

$$\vec{B} = 2 \cdot \text{rd}_1 \quad (22)$$

$$\vec{E} = 2h \cdot \text{rd}_2 - h \quad (23)$$

$$r_h = 5 - [\text{Iterations} \times (\frac{5}{\text{Max}_{\text{Iteration}}})] \quad (24)$$

Where r_h is the factor that reduced linearly from 5 to 0 during iterations (in two stages of identification and colonization) and rd_1, rd_2 are stochastic vector in the distance 0 to 1.

ii) Hunting

The next step of this algorithm is a hunting strategy that forms a set of optimal solutions against the best search agent and position update.

The following equations are described in this mechanism:

$$\vec{D}_h = |\vec{B} \vec{P}_h - \vec{P}_k|$$

(25)

$$\vec{P}_k = \vec{P}_h - \vec{E} \cdot \vec{D}_h \quad (26)$$

$$\vec{C}_h = \vec{P}_k - \vec{P}_{k+1} + \dots + \vec{P}_{k+N} \quad (27)$$

Where $\vec{P}_h$ defines the position of first best spotted hyena, $\vec{P}_k$ indicates the position of other spotted hyenas. Here, N indicates the number of spotted hyenas which is computed as follows:

$$N = \text{count}_{\text{nos}}(\vec{P}_h, \vec{P}_{h+1}, \vec{P}_{h+1}, \dots, (\vec{P}_h + \vec{M})) \quad (28)$$

Where M is a stochastic vector in $[0.5, 1]$, nos defines the number of solutions and count all candidate solutions, after addition with M , which are far similar to the best optimal solution in a given search space, and $\vec{C}_h$ is a group or cluster of N number of optimal solutions.

(iii) Attacking prey (exploitation)

185 In order to mathematically model this step, the value of the vector h is reduced.

186 Variation in the vector $\vec{E}$ also decreases to change the value of the vector h , which decreases
187 from five to zero in terms of repetition.

188 The mathematical formula for the operation step is as follows:

189
$$\vec{P}(x+1) = \frac{\vec{C}_h}{N} \quad (29)$$

190 Where $\vec{P}(x+1)$ save the best solution and updates the positions of other search agents according
191 to the position of the best search agent.

192 **(iV) Search for prey (exploration)**

193 A group of spotted hyenas search for prey according to their location.

194 At this stage, $\vec{B}$ vector is needed to explore the prey, which provides stochastic values during the
195 iteration process. This mechanism is useful to prevent local optimization until the last iteration
196 and termination of the algorithm after compliance with the criteria. The flowchart in Figure (1)
197 shows the process of this algorithm.

Fig. 1 Flowchart SHO Algorithm. (Dhiman and Kumar, 2017)

4. Statistical evaluation of performance

In order to compare the results of the two methods, a series of indicators or objective functions must be used. These indicators are as follows (Khalifeh et al., 2020):

4.1. SSQ

In this paper, the target function was used to minimize the sum of squares of residuals (SSQ) between observed and computed outputs according to equation (29) to estimate the optimal values of parameters in the Muskingum Non-linear model.

$$MinSSQ = \sum_{t=1}^N (O_t - O_{ct})^2 \quad (29)$$

Where O_t is the output flow measured and O_{ct} is the volume of calculated flood discharge routed at time t , and N is the number of times steps of the flood routing.

4.2. DPO

The DPO index to calculate the smallest difference between the measured peak flow and the routed peak flow is as follows:

$$DPO = \text{minimize} |O_p - \hat{O}_p| \quad (30)$$

Where DPO is the absolute value of the difference between the peak output flow measurement and the routed output flow rate, O_p is the measured peak output flow rate and $\hat{O}_p$ is the routed output peak flow rate value.

5. Data preparation

Two cases were investigated in this study. The Wilson River is selected to evaluate SHO Algorithm, and Kardeh River is evaluated to show performance of modified NL6 compared to NL3.

5.1. The first case study _Wilson River (Smooth Single Peak Hydrograph)

The example used in this study was first presented by Wilson (1974). In this example, a non-linear relationship exists between the values of S_t and $[XI_t + (1-X) O_t]$, and it is possible to obtain the performance of various algorithms in calculating optimal values of the Non-linear Muskingum equation parameters. Furthermore, a variety of Meta-heuristic methodologies have been tested in this example. The highest inflow and outflow were 111 and 85 m³/s, respectively (Wilson, 1974).

Applying the NL3 approach to the Wilson River, the optimal values of the three model parameters based on the SHO, GA and ICA algorithms were investigated as shown Table 1. The SHO superiority was determined according to the results of Table 1 and Figure 2, and the routing calculation was also determined according to the Wilson River data in Table 3. Table 2 shows the values of the parameters obtained from the studied algorithms for the Wilson River. Table 4 shows the performance of the proposed algorithms by the statistical parameters including the SSQ and DPO for the Wilson River. As shown in Table 4, the SHO algorithm has a better performance compared to the GA and ICA algorithms. Finally, according to the results, the superiority of the SHO algorithm in Wilson flood routing was determined and as a way to explain the performance of the NL6 method, the results were compared with the NL3 method in Table 5.

Table 1: Values of the parameters obtained from the proposed algorithms for the Wilson River with the model (NL3)

SSQ	m	K	X	Algorithm
128.781	2.154	0.169	0.301	SHO
138.805	1.999	0.33	0.300	GA
130.792	2.10	0.264	0.301	ICA

Table 2: Values of the parameters of the algorithms used for the Wilson River

			Population size	Iteration	Parameter	SHO
			70	1000	Value	
coupling rate	mutation rate	Number of genes	Population size	Iteration	Parameter	GA
0.8	0.02	240	70	1000	Value	
Revolution rate	Solidarity rate	Number of colonists	Population size	Iteration	Parameter	ICA

Figure 2: The output hydrograph is estimated by the algorithms investigated for the Wilson River (NL3 model)

Table 3: Output Hydrograph Values Routed by Algorithms for Wilson River (NL3 Method)

ICA	GA	SHO	Output observation	Input discharge	Time(hr)
			discharge (m³/s)	(m³/s)	
22	22	22	22	22	0
21.784	21.784	21.785	21	23	6
20.00	19.914	20.014	21	35	12
20.195	19.486	20.165	26	71	18
29.975	29.155	29.942	34	103	24
44.566	44.325	44.561	44	111	30
57.104	57.449	57.113	55	109	36

67.515	68.264	67.534	66	100	42
75.576	76.496	75.598	75	86	48
80.424	81.281	80.445	82	71	54
81.504	82.125	81.521	85	59	60
80.285	80.597	80.294	84	47	66
75.871	75.867	75.871	80	39	72
69.817	69.590	69.815	73	32	78
61.811	61.524	61.806	64	28	84
53.418	53.285	53.415	54	24	90
44.140	44.410	44.146	44	22	96
35.341	36.170	36.363	36	21	102
28.315	29.589	28.349	30	20	108
23.417	24.770	23.454	25	19	114
20.239	21.308	20.264	22	19	120
19.486	20.018	19.497	19	18	126

Table 4: Statistical indices investigated for the Wilson River (NL3 model)

SSQ	DPO	Algorithm
128.781	0.92	SHO
138.805	1.5	GA
130.792	1.09	ICA

According to Table 5, two models of NL6 and NL3 were compared with each other based on the SHO. The statistical indices of SSQ and DPO show that the optimization of the observation data is better than the previous method with fewer parameters. Also measuring and calculating hydrographs of the NL6 model, and comparison with the NL3 model for the first case study are shown in Fig. 3. As can be seen, the calculated hydrograph is in a good agreement with the

measured hydrograph. Moreover, the figure shows that the NL6 model with the accuracy of discharge, calculates the peak flood hydrograph, which is an important variable in hydrograph routing. Figure 4 shows the dispersion of observational and simulated data in Wilson River with the coefficient of determination equal to 0.999, which is very high accuracy.

Table 5 - Comparison of the results of the first case study

DPO	SSQ	γ	C_2	C_1	β	α_2	α_1	X	K	Algorithm	Model
0.92	128.781	-----	-----	-----	2.154	-----	-----	0.301	0.169	SHO	NL3
0.027	3.20	0.918	0.727	0.593	3.815	0.426	0.701	0.876	0.497	SHO	NL6

Figure 3. Comparison of measured hydrograph and calculated hydrograph obtained with SHO algorithm NL3 and NL6 models

Figure 4 - dispersion of observational and routed data in Wilson River

5.2. The second case study- Wye River (Non-Smooth Single Peak Hydrograph)

The second case study is a flood that occurred on the River Wye in Britain (Nark, 1975).

The 69.75 km stretch of the Wye River from Erwood to Belmont is unbranched and has a very small inflow.

Thus, this flood is a good test case for testing routing methods. The flood was first investigated by O'Donnell et al. (1988) with a linear Muskingum model. This flood is similar to the data reported by Wilson (1974) in that it shows a nonlinear relationship between flow and storage volume. This case study includes Δt equal to 6 hours and $N = 33$.

According to Table 6, the comparison of the NL6 and NL3 models was performed. The values of the SSQ and DPO showed that in the NL6 developed method, optimization of the data is better compared to the previous method with lower parameters. In addition, the measured and

computed hydrographs of the NL6 model and its comparison with the NL3 model for the second case study are shown in Figure 5. It can be seen in Fig. 5 that the calculated hydrograph is in good agreement with the measured hydrograph. Moreover, this figure displays that the NL6 model accurately calculates the discharge peak, which is an important variable in hydrograph routing.

Table 6 - Comparison of the results of the second case study

DPO	SSQ	γ	C_2	C_1	β	α_2	α_1	X	K	algorithm	Model
90.05	34789.39	-----	-----	-----	1.60	-----	-----	0.416	0.075	SHO	NL3
72.35	30812.07	0.9505	0.7735	1.2308	1.399	1.165	1.055	0.4958	0.60008	SHO	NL6

Figure 5. Output Hydrograph Routed by NL3 and NL6 Models for Wye River

6. Results and Discussion

Due to the importance of the flood routing, and the use of linear and non-linear Muskingum model for estimating the outflow hydrograph, many studies have been carried out to increase the accuracy of the model. Accordingly, different relationships with different parameters related to non-linear model storage are proposed.

Since in the previous studies, the output hydrograph error (especially at the hydrograph peak) did not improve, so in this study, the 8-parameter non-linear Muskingum model NL6 was used to improve the computational output hydrograph and its accuracy based on the whale optimization algorithm. By applying the above approach to two case studies, containing single-dimensional hydrograph and optimizing non-linear model parameters by SHO algorithm, the output hydrograph results were calculated and compared with other existing models.

Based on the optimal values of the Muskingum non-linear model parameters and the calculated output hydrographs, for both case studies, the value of all the SSQ and DPO objective functions significantly decreased compared to the other existing models, and the results of output discharge values are improved and brought closer to real values. The SSQ and DPO Objective functions of the NL6 model for the first study is 3.20 and 0.027, respectively, and for the second case study is 30812.07 and 72.35, respectively.

Finally, according to the results of two case studies, both models used in this paper (NL6) and the proposed algorithm have performed well for estimating Non-linear parameters of the Muskingum method.

Accordingly, the approach of this study can be used as a good guide for flood routing in rivers whose measured discharge is natural.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

Whole of datasets and models created or used during the paper are available from the corresponding author by request.

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