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Improving the Muskingum Flood Routing Method Using a Hybrid of Particle Swarm Optimization and Bat Algorithm

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Abstract: Flood prediction and control are among the major tools for decision makers and water resources planners to avoid flood disasters. The Muskingum model is one of the most widely used methods for flood routing prediction. The Muskingum model contains four parameters that must be determined for accurate flood routing. In this context, an optimization process that self-searches for the optimal values of these four parameters might improve the traditional Muskingum model. In this study, a hybrid of the bat algorithm (BA) and the particle swarm optimization (PSO) algorithm, i.e., the hybrid bat-swarm algorithm (HBSA), was developed for the optimal determination of these four parameters. Data for the three different case studies from the USA and the UK were utilized to examine the suitability of the proposed HBSA for flood routing. Comparative analyses based on the sum of squared deviations (SSD), sum of absolute deviations (SAD), error of peak discharge, and error of time to peak showed that the proposed HBSA based on the Muskingum model achieved excellent flood routing accuracy compared to that of other methods while requiring less computational time.

Keywords: bat algorithm; particle swarm optimization; flood routing; Muskingum model

1. Introduction

Floods cause huge economic and social effects on the surrounding environment [1,2], such as breaking levees [3], inundating houses, disrupting transportation systems [4], damaging crops and eroding fertile lands [5]. Thus, flood prediction and flood control are important issues for policy makers and designers [6,7]. Hydrological and hydraulic models are used for flood prediction. The estimation of flood discharge hydrograph at a downstream location given the discharge hydrograph upstream is known as flood routing [8,9]. Hydraulic models based on numerical methods can be used for flood routing, but they involve complex unsteady flow equations [10]. Hydrological models use the spatially lumped continuity equation and a storage equation for flood routing. These models need a small amount of data to predict floods [11]. The Muskingum model is an important hydrological model for flood routing. This model has multiple parameters that should be obtained to accurately predict floods [12], and different versions of the model have been applied for flood routing. One strategy is the optimization method by which the parameters are computed as decision variables [13]. The evolutionary algorithms exhibit a high degree of ability for solving complex optimization problems. These algorithms are efficient, accurate, and flexible [14]. Thus, parameters of the Muskingum model can be computed using evolutionary algorithms.

1.1. Background

Luo and Xie [15] applied the clonal selection algorithm (CLA) to flood routing in China, and CLA decreased the sum of absolute deviations (SAD) by approximately 20% compared to that of the genetic algorithm (GA). The difference between the simulated peak discharge and the observed discharge was small, approximately 0.5 m^3/s. Using the initial values of the Muskingum parameters as decision variables, CLA optimized the objective function to obtain the best parameter values.

The Nelder-Mead simplex algorithm was used for flood routing in the USA [16]. This method obtained the best values for the 3 Muskingum model parameters. Thus, the peak discharges were predicted to be better than those of other nonlinear programming methods.

Barati et al. [17] applied a dynamic wave method for flood routing, and the results indicated that some of the parameters, such as Manning roughness or bed slope, were effective. Thus, accurate determination of these parameters is important for flood routing equations.

Karahan et al. [18] applied hybrid harmony search (HS) and particle swarm optimization (PSO) to estimate the Muskingum parameters and indicated that the computational time for the new hybrid model was less than those of PSO and HS. In addition, peak discharge was estimated with the least difference with the observed discharge.

Fallah-Mehdipour [19] applied PSO, GA and nonlinear programming methods for flood routing and indicated that PSO simulated the flood discharges with lower SAD and sum of squared deviation (SSD) values than those of other algorithms. In PSO, the Muskingum parameters were considered as decision variables.

Easa [20] introduced a four-parameter nonlinear Muskingum model for flood routing and showed that the four-parameter model estimated flood discharge better than the three-parameter model did. The GA was used to obtain the optimal values of the Muskingum parameters.

Nelder-simplex and hybrid PSO were evaluated as new methods to estimate Muskingum parameters [21]. The results showed that the new method decreased the computational time compared to that of the simple PSO and GA. Additionally, there was a small difference between the estimated discharge and the observed discharge.

Honey bee mating (HBM) optimization was used for flood routing by a three-parameter nonlinear Muskingum model for one flood in the USA [22]. Results indicated that the SSQ (sum of squared deviations) and SAD values of the model significantly decreased compared to those of the GA and PSO methods. Additionally, the time of peak discharge was predicted well. The convergence of HBM was faster than those of GA and PSO. A new charged search system (CSS) and PSO hybrid method was used for flood routing based on two- and three-parameter nonlinear Muskingum models [23]. Results indicated that the new evolutionary hybrid algorithm needed a sensitivity analysis for the accurate determination of parameters, and the three-parameter model predicted peak discharge more accurately than GA and HS. Additionally, basing PSO and CSS on more population diversity increased the convergence speed of the algorithm.

A nonlinear Muskingum model that considers lateral flow was used for flood routing [24]. This model used the cuckoo algorithm and predicted peak discharge more accurately than other models. The shuffled frog leaping algorithm (SFLA) based on a three-parameter Muskingum model was used for flood routing [25]. Results showed that the SSD and SAD values for the SFLA were lower than those of the GA, PSO and nonlinear programming methods. Additionally, the correlation coefficient based on the SFA between the observed and estimated discharges was more than those of the GA, PSO and nonlinear programming methods.

A new version of the Muskingum model with nine parameters was used for flood routing in another study [26]. The Karun River in Iran was considered as an important case study for the research. The study showed that the results were better than those of previous Muskingum models, but the new model needed more computational time.

A real-coded adaptive GA was used for flood routing, considering lateral flow along the river reach [14]. The study considered a river in China with important floods. Results indicated that the three-parameter nonlinear Muskingum model based on adaptive GA simulated flood discharges, yielded the least values of SSQ and SAD.

Gene-expression programming (GEP) and the weed algorithm (WA) were used for flood routing [1]. Some important floods in the USA were considered as case studies for the study. The results indicated that GEP had a convergence speed that was approximately 100 times higher than that of WA; in addition, the computed SSD for the estimated discharges was lower than that of WA.

The literature review shows that the evolutionary algorithms have high ability for predicting flood routing, but there are some limitations for these algorithms; they all use the same procedure within the Muskingum model for flood routing. The Muskingum models have parameters with unknown values, and these parameters are applied to the algorithms as decision variables. Computation of the objective function can show the best value for each parameter. In fact, the parameters are input as the initial population to the algorithms, and then, the different operators are applied based on the process of each algorithm [1,10,22]. Basically, there are two major limitations: First, there is no assurance that the computed value for Muskingum's parameters are optimally achieved, second, the convergence rate was relatively high as the required computed values are four parameters.

For example, some algorithms such as the GA can become trapped in the local optimums and cannot compute the best values for the parameters [10]. Some literature reviews have reported that some algorithms have immature solutions because the convergence process happens abruptly as with PSO [21]. Some algorithms (e.g., GA [10]) require more computational time for the convergence process, and some algorithms such as Anti Bee Colony and Shark Algorithm need to accurately determine many random parameters, which leads to complex processes for optimization. Thus, the presentation of a better method that could hybridize the advantages of two different methods and hence has the potential to overcome those drawbacks and achieve better results with high convergence rate is necessary. The present study attempts to develop one of the known algorithms based on a hybrid process for the flood routing. The Bat Algorithm (BA) is developed based on the motivation that the algorithm has problems such as trapping in the local optimums and slow convergence, and the algorithm is based on the high ability of bats to perceive sounds [21]. Thus, the PSO is suggested for the hybrid process to improve the BA, and the hybrid process prevents the abrupt convergence of the PSO. The next section presents the innovation and objectives of this study. Then, the optimization methods are explained, and the results and conclusions for three case studies are explained in the following sections.

1.2. Innovation and Objectives

The bat algorithm (BA), as an optimization method, is based on living bats and the powerful ability of bats to receive sounds from their surroundings. It is used widely in different fields of image processing [27], data sensing systems [28], the determination of the seismic safety of structures [29], the design of wireless sensors [30], and water resource management [31]. However, the algorithm has some weaknesses, such as the probability of being trapped in the local optimums and slow convergence in some complex engineering problems, so it is necessary to modify the BA. This paper reports on a hybrid algorithm (HA) based on PSO and BA. The new HA substitutes the weaker BA solution with the best PSO solution, which can prevent trapping in the local optimums and increase the convergence speed. Additionally, with the hybrid model, the BA population diversity and exploration ability increase as the optimal solution is obtained. These improvements are the motivations underlying the introduction of the new HA in this paper. The new HA was used for flood routing by a four-parameter Muskingum model in two case studies. These two case studies have been investigated widely as benchmarks in the literature, so there is comprehensive information for the comparison of the new HA with other evolutionary algorithms. This study used the HA to find the optimal values of the four parameters of the Muskingum model, extracted the output hydrographs for two case studies, and then compared the results with those generated by other types of Muskingum models and other evolutionary algorithms used in previous studies.

2. Methods

2.1. Muskingum Model

The linear Muskingum model is based on the continuity equation and a storage equation [32–34]:

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

$$S_t = K[xI_t + (1-x)O_t] \tag{2}$$

where S_t is the storage (L^3); I_t is the inflow ($L^3 \cdot T^{-1}$); O_t is the outflow ($L^3 \cdot T^{-1}$); K is the storage time constant, which varies from 0 to 30 (T); and x is the weighting factor, which varies from 0 to 0.5. Previous studies have shown that the linear Muskingum model does not perform well for some rivers; thus, nonlinear Muskingum models have been suggested [33]:

$$S_t = K_t[xI_t + (1-x)O_t]^m \tag{3}$$

$$S_t = K[xI_t^m + (1-x)O_t^m] \tag{4}$$

The models of Equations (3) and (4) have an additional parameter (m), and the dimension of K is ($L^{3(1-m)} \cdot T^m$). The current study uses a four-parameter nonlinear Muskingum model based on the model introduced by Easa [20], with a reported high flood routing ability:

$$S_t = K[xI_t^\alpha + (1-x)O_t^\alpha]^m \tag{5}$$

Equation (5) is similar to Equation (3). However, in Equation (5), parameter m is related to the nonlinear form of the storage equation, while in Equation (3), m is related to the linear form of the storage equation. Equation (5) can cover previous equations; that is, if $\alpha = m = 1$, Equation (5) will be the same as Equation (2). If $m = 1 (or) \alpha = 1$, Equation (5) covers Equations (3) and (4). The outflow for Equation (3) is computed as follows:

$$O_t = \left[\left(\frac{1}{1-x}\right)\left(\frac{S_t}{K}\right)^{\frac{1}{m}} - \left(\frac{x}{1-x}\right)\right]^{\frac{1}{\alpha}} \tag{6}$$

Then, Equation (6) is inserted into Equation (1), and the change in storage is computed based on the following equation:

$$\frac{\Delta S_t}{\Delta t} = I_t - \left[\left(\frac{1}{1-x}\right)\left(\frac{S_t}{K}\right)^{\frac{1}{m}} - \left(\frac{x}{1-x}\right) I_t^{\alpha}\right]^{\frac{1}{\alpha}} \tag{7}$$

Finally, the storage for the next step time is computed based on the following equation:

$$S_{t+1} = S_t + \Delta t \tag{8}$$

2.2. Bat Algorithm

The BA is based on the powerful echolocation ability of bats, which can generate loud sounds and receive the echoes of the sounds as they return from the surroundings. The BA is based on the following assumptions [31]:

(1) All bats use echolocation to identify prey and obstacles based on received sound frequencies.
(2) All bats fly randomly with the velocity (v_1) at position (y_1), and the frequency, loudness and wavelength values are f_l, A_0 and λ, respectively.
(3) The loudness changes from a large positive (A_0) to a small positive value ($A_{\min}$).

The sounds generated by bats have a pulsation rate (r_1) that varies from 0 to 1. The value 1 means that the pulsation rate has reached a maximum value, and 0 means that the pulsation rate has reached a minimum value. The velocity, frequency and position are updated based on the following equations [31]:

$$f_l = f_{\min} + (f_{\max} - f_{\min}) \times \beta \tag{9}$$

$$v_l(t) = [y_l(t-1) - Y_*] \times f_l \tag{10}$$

$$y_l(t) = y_l(t-1) + v_l(t) \times t \tag{11}$$

where f_l is the frequency, $f_{\min}$ is the minimum frequency, $f_{\max}$ is the maximum frequency, Y_* is the best position for the bats, t is the time step, $y_l(t-1)$ is the position of the bats at time $t-1$, $v_l(t)$ is the velocity, and β is the random vector.

A random walk is considered as the local search for the BA:

$$y(t) = y(t-1) + \varepsilon A(t) \tag{12}$$

where ε is the random value between -1 and 1; and $A(t)$ is the loudness.

The pulsation rate and loudness are updated for each level. When the bats find prey, the pulsation rate increases and the loudness decreases for each level. The pulsation rate is updated, based on the following equation:

$$r_l^{t+1} = r_l^0[1 - \exp(-\gamma t)] A_l^{t+1} = \alpha A_l^t \tag{13}$$

where α and γ are the constant parameters. The BA is shown in Figure 1.

2.3. Particle Swarm Optimization

For a d-dimensional search space, the population is formed by $X_i = (x_{i1}, x_{i2}, .., x_{iD})^T$, and the velocity is given by $V_i = (v_{i1}, v_{i2}, .., v_{iD})^T$. The best previous position is given by $P_i = (p_{i1}, p_{i2}, .., p_{iD})^T$, and the g index is used for the global solution. The velocity and the position are updated, based on the following equations:

$$v_{id}^{n+1} = \chi\left[wv_{id}^n + \frac{c_1 r_1 (p_{id}^n - x_{id}^n)}{\Delta t} + \frac{c_2 r_2 \left(p_{gd}^n - x_{id}^n\right)}{\Delta t}\right] \tag{14}$$

$$x_{id}^{n+1} = x_{id}^n + \Delta t v_{id}^{n+1} \tag{15}$$

where d is the number of dimensions, χ is the constriction coefficient, N is the size of the swarm, w is the inertial weight, c_1 and c_2 are the acceleration coefficients, r_1 and r_2 are the random numbers, Δt is the time step, x_{id}^{n+1} is the new position, v_{id}^{n+1} is the new velocity vector, and n is time index.

First, the random population of the swarm is initialized, and then the objective function is computed to determine the local and global leaders. Finally, the velocity and the position are updated, and the cycle continues until the convergence criterion is satisfied.

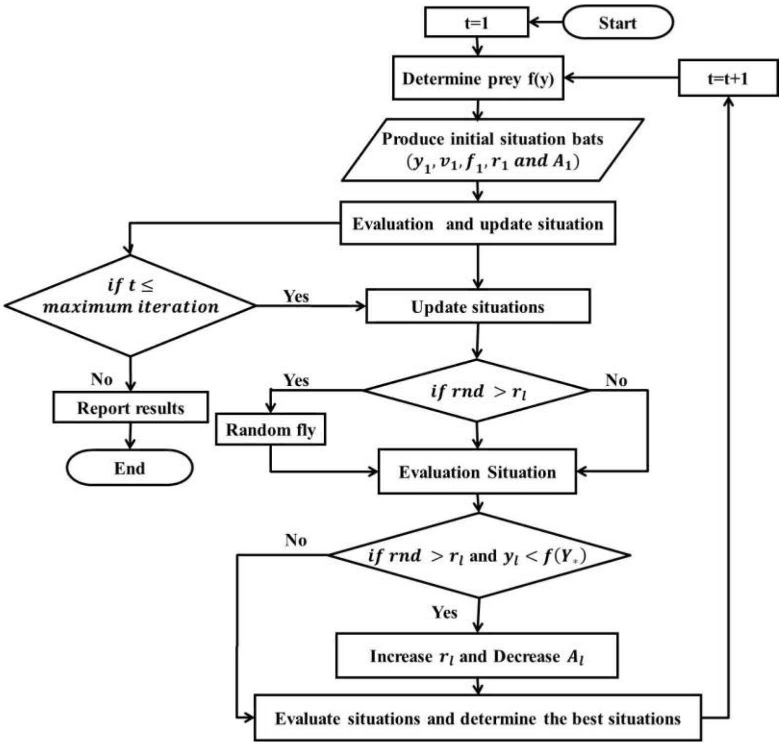

Figure 1. Bat Algorithm procedure.

2.4. Hybrid PSO and BA

The new HA acts based on a communication strategy between two algorithms. The idea of this strategy is that the parallel performance of the two algorithms allows the weaker solutions of one algorithm to be substituted with those of the other algorithm. The parallel structure has subgroups that are based on the division of the population. The subgroups act independently for each iteration. Thus, the objective function is computed for each group, and the weaker solutions of each group are selected and substituted with the better solutions of the subgroups of the other algorithm. The total number of iterations is R, and the total populations is N. Moreover, N_1 and N_2 are equal, i.e., $N/2$. Figure 2 shows the performance of the HA.

The algorithm acts based on the following levels:

(1) The random parameters for both algorithms (PSO + BA) are initialized, and the initial populations for the two algorithms are considered.
(2) The first initial values for the hydrological parameters (K, x, m and α) are considered at the start of the algorithm.
(3) The variation in storage is computed based on Equation (7). The initial outflow is the same as inflow.
(4) The accumulated storage is computed based on Equation (8).
(5) The outflow is computed based on Equation (6).

(6) The time step is compared with the total flood time. If it is less than the total time, the algorithm goes to step 3; otherwise, the algorithm goes to the next level.
(7) The objective function is computed for the two algorithms and all members that can be seen in the algorithms.
(8) The velocity and position for the PSO algorithm are updated based on Equations (14) and (15), and the velocity, frequency and position are updated based on Equations (9)–(11).
(9) The best particles migrate from the PSO algorithm to the BA, and there is a condition for BA similarity. In fact, the specific number of best members for each algorithm is known and is substituted for the worst solutions of the other algorithm.
(10) The convergence criteria are considered. If the criteria are satisfied, the algorithm finishes; otherwise, the algorithm returns to the second step.

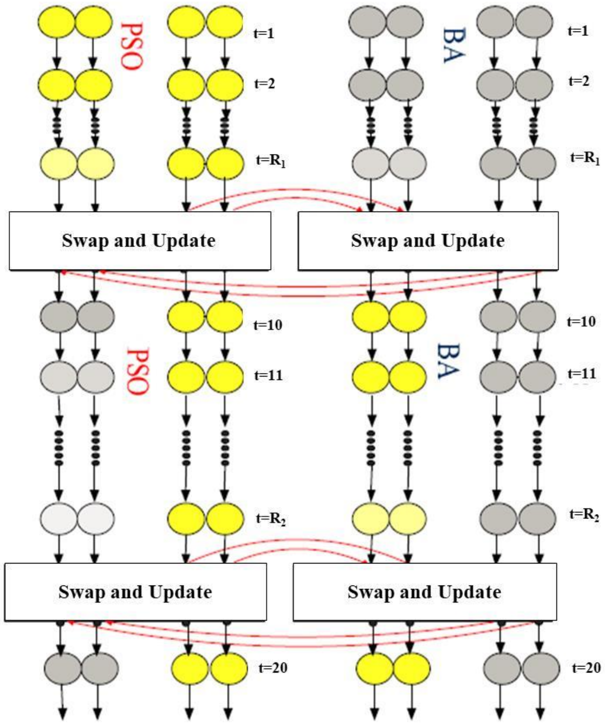

Figure 2. Hybrid algorithm procedure.

The following indexes are used for comparison of the different methods [35–38]:

(1) The sum of the squared deviations between observed and estimated discharges is considered the objective function and is computed based on the following equation:

$$Minimize(SSQ) = \sum_{t=1}^{n} (O_{st} - O_{bt})^2 \quad (16)$$

(2) The SAD between estimated and observed discharges is computed based on the following equation:

$$Minimize(SAD) = \sum_{t=1}^{n} |O_{bt} - O_{st}| \quad (17)$$

(3) The mean absolute error (MARE) between estimated and observed discharges is computed based on the following equation:

$$MARE = \frac{1}{N}\sum_{i=1}^{N}\frac{|O_{bt} - O_{st}|}{O_{bt}} \tag{18}$$

(4) The error for peak discharge (EO) is computed based on the following equation:

$$EO = \frac{\left|O_{peak,bt} - O_{peak,st}\right|}{O_{peak,bt}} \tag{19}$$

(5) The error for peak time is computed based on the following equation:

$$ET = \left|T_{peak,bt} - T_{peak,st}\right| \tag{20}$$

where O_{st} is the simulated discharge, O_{bt} is the observed discharge, $T_{peak,bt}$ is the peak time of observed discharge, $T_{peak,st}$ is the peak time of simulated discharge, and N is the number of data.

3. Case Studies

In this section, brief introduction on the selected case studies have been reported. The first one is the Wilson flood event. The Wilson flood was selected for comparative analysis because it has been widely studied in the literature, resulting in a comprehensive body of information for comparison between the new hybrid method and other methods. This is a benchmark experimental problem that was considered by Wilson [33–37]. The time flood is equal to 120 h, and the peak occurs at a time step of 60 h with a value of 85 cm.

On the other hand, the second case study is the Karahan flood event. The Karahan flood, known as a benchmark problem in flood routing, is based on the 1960 flood of the Wye River in the United Kingdom [14,33–36]. The Wye River from Everwood to Belmont does not have any tributaries, and it has a small lateral flow, which is considered an important problem for flood routing. The flood time is 198 h, and the peak time is at the step time of 102 h.

Finally, the third case study is the Viessman and Lewis flood event. The Viessman and Lewis [39] multi-peak flood hydrograph was also selected as a benchmark study in this research.

4. Results and Discussion

4.1. Wilson Flood

4.1.1. Sensitivity Analysis for Different Algorithms for the Wilson Flood

Tables 1–3 show the inflow and outflow values calculated by different methods. The evolutionary algorithm parameters do not have specific values at the start of the algorithm. Thus, sensitivity analysis was used to obtain the parameters. The objective function selected for this study was SSQ, and the variation in the objective function value was computed for various values of parameters. The best value for each parameter was selected when the objective function value was the minimum. For example, the population size for the HA varied from 20 to 80. When the size was 60, the SSQ value was 4.234 and led to the lowest objective function value. Further, the maximum frequency varied from 3 to 9. When the maximum frequency was 7 Hz, the objective function had the best value. The minimum frequency varied from 0.1 to 0.4, and the best value for the minimum frequency was 0.2. In addition, the maximum loudness varied from 0.2 to 0.8, and the best value based on the objective function value was 0.6 dB. The other parameters are listed in Table 1. For example, the acceleration coefficient varied from 1.6 to 2.2. The best value for this parameter was 2, because the SSQ, which was 4.233, was the lowest. Further, the inertia coefficient varied from 0.3 to 0.9. The best value was 0.7 because the SSQ was 4.234.

Table 1. Sensitivity analysis for hybrid algorithm.

Population Size	Objective Function	Maximum Frequency (Hz)	Objective Function	Minimum Frequency (Hz)	Objective Function	Maximum Loudness (dB)	Objective Function	c_1	Objective Function	c_2	Objective Function	w	Objective Function
20	5.123	3	5.254	1	5.565	0.20	4.999	1.6	5.145	1.6	5.011	0.3	5.133
40	4.789	5	4.884	2	4.987	0.40	4.845	1.8	4.933	1.8	4.987	0.5	4.654
60	4.234	7	4.233	3	4.234	0.60	4.234	2.0	4.234	2.0	4.234	0.70	4.235
80	4.312	9	4.679	4	4.789	0.80	4.565	2.2	4.555	2.2	4.445	0.90	4.512

Table 2. Sensitivity analysis for PSO.

Population Size	Objective Function	c_1	Objective Function	c_2	Objective Function	w	Objective Function
20	5.981	1.60	5.891	1.60	5.954	0.30	5.845
40	5.785	1.80	5.654	1.80	5.878	0.50	5.764
60	5.555	2.0	5.554	2.0	5.554	0.70	5.555
70	5.894	2.2	5.892	2.2	5.891	0.90	5.789

Table 3. Sensitivity analysis for BA.

Population Size	Objective Function	Maximum Frequency (Hz)	Objective Function	Minimum Frequency (Hz)	Objective Function	Loudness (dB)	Objective Function
20	5.765	3	5.812	1	5.911	0.3	5.912
40	5.455	5	5.691	2	5.783	0.5	5.678
60	5.342	7	5.342	3	5.343	0.70	5.343
70	5.694	9	5.611	4	5.455	0.90	5.678

4.1.2. Ten Random Results for Different Algorithms for Wilson Flood

Table 4 shows 10 random results for different algorithms. The average solution for the HA was 4.234, while the average solutions were 5.554 and 5.342 for the PSO algorithm and BA, respectively. Thus, the objective function or error value decreased by 23.71% and 20.7% compared to those of the PSO algorithm and BA, respectively. The computational time for the HA was 20 s, while it was 27 s and 25 s for the PSO algorithm and BA; thus, the computational time decreased by 25% and 20% in the HA compared to those in the PSO algorithm and BA, respectively. Additionally, the coefficient of variation for the HA was smaller than that for the PSO algorithm and BA and was therefore nonsignificant, which implied that the one-run program for the HA was reliable. Figure 3 shows the convergence method for the three algorithms, and it is apparent that the HA converged faster than the PSO algorithm and BA did. In fact, the researchers present the 10 or 15 random solutions to show the variation of solutions. It is apparent that the all runs for the HA are close to the average solution and that all runs are reliable as the final solution. Although the BA and PSO have the solutions that are closest to the average solution, the other factors are important for the selection of the best methods. Table 4 shows that the hybrid method based on soft computing is the best method because the minimum, maximum and average solutions for the 10 results are close to each other. Additionally, the computation time for the HA is less than other methods (based on a PC with an i5 2.4 GHz CPU and 500 GB RAM), and the average of the error objective function based on HA is less than those of the other two methods.

Table 4. Ten random results for average solutions for Wilson flood.

Run Number	HA	BA	PSO
1	4.234	5.342	5.555
2	4.233	5.348	5.555
3	4.234	5.342	5.555
4	4.234	5.342	5.555
5	4.234	5.342	5.559
6	4.233	5.342	5.560
7	4.234	5.342	5.555
8	4.234	5.342	5.555
9	4.234	5.342	5.555
10	4.234	5.342	5.555
Average	4.234	5.342	5.555
Computational time	20 s	27 s	25 s
Variation coefficient	0.00007	0.0003	0.0004

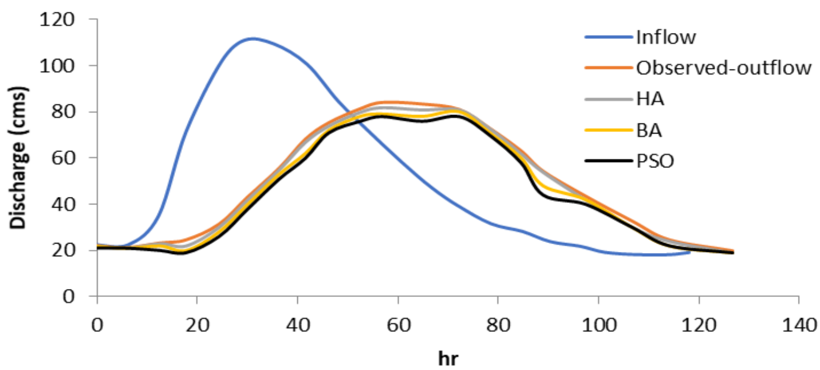

Figure 3. Simulated discharges based on different methods for the Wilson flood.

4.1.3. Discussion of the Wilson Flood Results

Table 5 shows the performance of the HA, PSO algorithm and BA based on the 4PMM (four-parameter Muskingum model). The computed SSQ based on the HA was 4.234, and the HA method decreased the SSQ by 23.7% and 20.74% compared to those of the PSO and BA methods, respectively. The SAD value based on the HA decreased by 25% and 24% compared to those of the PSO algorithm and BA, respectively. The error between the simulated discharge and the observed discharge was shown by the EO, and the minimum value, 0.0111, was related to the HA. Additionally, the three methods predicted the peak time well, with an ET equal to zero. Table 6 compares the performances of different models based on the current research and previous studies. The performance of the HA based on the 4PMM was better than that based on the 3PMM because the error index for the 4PMM HA was lower than that for the 3PMM HA. For example, SSQ and SAD for the 4PMM were 4.234 and 3.125, respectively, while they were 12.25 and 10.95 for the 3PMM. Table 6 shows the performance of GA, HS, and the imperial competitive algorithm (ICA) based on the literature. The highest value of SSQ was related to GA based on the 3PMM; thus, this model had the worst performance. The SAD for the ICA was 23.46, which indicated that this model had the worst performance based on SAD and 3PMM (three-parameter Muskingum model). When the performances of the BA and PSO algorithm based on the 3PMM were compared with that based on the 4PMM, the models based on the 4PMM had the best performance because of their smallest index errors. All the models in Table 6 predicted the peak time well, with an ET value equal to zero. Table 7 shows the inflow and outflow and the peak value for the observed discharge, which was 85 cm when the time was 60 h. The results showed that peak discharge based on the HA was closer to the observed value. Table 8 shows the values of different coefficients for the Muskingum models. Generally, the results showed that the HA based on the 4PMM performed better than the other models did, with an SSQ value that decreased by 65%, 72% and 47% compared to those of the BA (3PMM), PSO algorithm (3PMM) and HA (3PMM), respectively. The values for other indexes supported this trend. Figure 3 shows that the HA based on the 4PMM performed better than the PSO and BA based on the 4PMM during the flood. Additionally, the comparison of results with other research shows the superiority of HA compared to the other algorithms. The honey bee mating algorithm was considered for flood routing [34]. SSQ based on 3PMM was 37.451, while the 3PMM and HA have smaller values for SSQ. Thus, HA has a better performance than HBMO.

Thus, all sections for the HA show the superiority of the method compared to the other methods. Although, the Muskingum method based on four parameters has more parameters than the Muskingum model based on three parameters, it is important to have a simulated hydrograph that matches with the observed flood. This section shows that prediction of peak discharge is the first priority in flood hydrographs. The observed peak in the hydrograph is 85 cm, while the simulated peak discharge is 85.011 cm. Clearly, the new method has good performance for this issue. The method is the best method for flood routing among other evolutionary algorithms because the peak time can be computed accurately. Table 5 shows the peak time predicted based on HA so that there is no delay between the computed time based on HA and the real time. The flood-emergency management authorities can make the best decisions based on the importance of the different projects.

Table 5. Comparison of results based on four-parameter Muskingum model for Wilson flood.

Method	SSQ	SAD	MARE	EO	ET
HA	4.234	3.125	0.012	0.00111	0
PSO	5.555	4.128	0.017	0.00251	0
BA	5.342	4.117	0.015	0.00167	0

Table 6. Comparison of results for Wilson flood.

Method	SSQ	SAD	MARE	EO	ET
GA [40] (Three-parameter Muskingum)	38.230	23.00	0.0912	0.0083	0
HS [40] (Three-parameter Muskingum)	36.780	23.40	0.0878	0.0107	0
ICA [40] (Three-parameter Muskingum)	36.801	23.46	0.0745	0.0105	0
BA (current research) (Three-parameter Muskingum)	12.25	10.95	0.0215	0.0079	0
PSO (current research) (Three-parameter Muskingum)	14.78	12.72	0.0325	0.0081	0
HA (current research) (Three-parameter Muskingum)	8.215	6.515	0.0205	0.0043	0

Table 7. Inflow and outflow for flood routing.

Time	Inflow (cm)	Outflow (Observed-cm)	Hybrid Method (cm)	BA (cm)	PSO
0	22	22	22.0	22.0	22.0
6	23	21	22.0	23.0	23.0
12	35	21	21.0	22.5	23.5
18	71	26	25.0	25.0	26.0
24	103	34	34.0	35.0	35.5
30	111	44	43.5	44.0	44.0
36	109	55	54.0	55.0	55.5
42	100	66	66.0	67.0	68.0
48	86	75	74.0	74.0	75.0
54	71	82	81.5	82.0	83.0
60	59	85	85.0011	85.00251	85.00267
66	47	84	84.0	84.0	84.0
72	39	80	81.0	80.5	81.0
78	32	73	74.0	73.0	74.0
84	28	64	64.0	65.0	66.0
90	24	54	54.0	55.0	56.0
96	22	44	44.0	44.0	45.0
102	21	36	36.0	37.0	38.0
108	20	30	30.5	31.0	31.0
114	19	25	25.5	26.2	26.9
120	19	22	23.0	24.0	25.0
126	18	19	20.0	21.0	22.0

Table 8. Extracted coefficients for the four-parameter Muskingum model.

Method	K	x	m	α
HA	0.164	0.2879	3.781	0.4678
BA	0.152	0.2768	3.567	0.4567
PSO	0.144	0.2645	3.123	0.3789

4.2. *Karahan Flood*

4.2.1. Discussion of the Karahan Results

The parameters used for the HA were maximum frequency, minimum frequency, maximum loudness, initial population, acceleration coefficient, and inertia coefficient; which were computed based on sensitivity analysis described in the previous section (maximum frequency: 7; minimum frequency: 3; maximum loudness: 0.95; initial population: 50; acceleration coefficient: 2; and inertial weight: 0.7).

Table 9 compares the performances of different algorithms based on the 4PMM for the Karahan flood. The SSQ of the HA and the 4PMM was 30,235, and the SSQ of the HA decreased by 5.85% and 2.8% compared to those of the PSO algorithm and BA, respectively. The SAD for the HA based on the 4PMM was 625, which were 0.32% and 7.54% lower than those of the PSO algorithm and BA, respectively. The difference between the simulated peak discharge and the observed discharge was nonsignificant; the EO of the HA equaled 0.101, a value that was 7.3% and 6.4% lower than those of the PSO algorithm and BA. The best performance based on MARE was related to the HA, which produced the lowest MARE value. Additionally, the three methods predicted the peak discharge well, with very low EO values. The GA had the worst performance of the methods, as shown in Table 10. The SSQ for the HS method was 39,944, which was the highest SSQ value produced by the models based on the 4PMM and 3PMM. The HA based on the 3PMM performed better than the other methods based on the 3PMM, as the SSQ of the HA decreased by 11.38%, 18%, 7.1%, 3.4% and 6.3% compared to those of the GA, HS, ICA, BA and PSO algorithm, respectively. The HA based on the 3PMM produced the lowest SAD value of all the 3PMM-based models. The performances of the HA, PSO algorithm and BA based on the 4PMM were comparable to the corresponding performances based on the 3PMM, but the 4PMM algorithm performed better than did the 3PMM algorithm. For example, the SSQ values of the HA, PSO algorithm and BA based on the 4PMM were 2.8%, 3.4% and 0.27% lower than those for the HA, PSO algorithm and BA based on the 3PMM, respectively. Table 11 shows the inflow and outflow for different methods and the peak discharge, which was 830 cm when the step time was 96 h. These results show that the discharges estimated by the HA were near to the observed discharges. Table 12 shows the extracted coefficients for different algorithms. Figure 4 shows the HA based on the 4PMM had the best performance during the flood, with a good match between the observed discharges and the discharges estimated by the HA. The general results for this section show that the HA based on 3PMM and 4PMM can predict the peak time well such that the ET parameter for HA based on 3PMM and 4PMM equals zero. Another point is related to the value of predicted discharge such that the EO index shows the ability of the different methods. 4PMM models based on HA, PSO and BA have a better performance: If the EO based on the table equals to 0.701, the EO based on Table 9 and FPMM models is less than 0.701. Although the 3PMM needs less parameters, the time and value peak can be predicted accurately based on 4PMM. Clearly, the importance of the model accuracy to decision makers can be considered in the selection of 3PMM and 4PMM.

Table 9. Comparison of results based on the four-parameter Muskingum model for Karahan flood.

Method	SSQ	SAD	MARE	EO	ET
HA	30,235	625	0.22	0.101	0
PSO	32,119	697	0.25	0.109	0
BA	31,112	676	0.24	0.108	0

Table 10. Comparison of results for Karahan flood.

Method	SSQ	SAD	MARE	EO	ET
GA [40] (Three-parameter Muskingum)	35,123	1980	0.910	0.701	0
HS [40] (Three-parameter Muskingum)	37,944	2161	0.924	0.798	0
ICA [40] (Three-parameter Muskingum)	37,825	2054	0.914	0.787	0
BA (current research) (Three-parameter Muskingum)	32,228	712	0.420	0.115	0
PSO (current research) (Three-parameter Muskingum)	33,229	735	0.454	0.125	0
HA (current research) (Three-parameter Muskingum)	31,125	697	0.254	0.105	0

Table 11. The inflow and outflow for flood routing.

Time	Inflow (cm)	Outflow (Observed-cm)	Hybrid Method (cm)	BA (cm)	PSO (cm)
0	154	102	102.0	102.0	102.0
6	150	140	139.23	138.23	154.2
12	219	169	170.21	171.24	152.1
18	182	190	185.12	183.24	179.4
24	182	209	202.34	200.11	190.9
30	192	218	212.23	198.23	185.4
36	165	210	207.11	192.32	186.9
42	150	194	192.12	189.23	180.2
48	128	172	170.21	169.24	164.1
54	168	149	147.21	146.74	143.7
60	260	136	137.21	139.23	152.8
66	471	228	219.21	212.23	196.3
72	717	303	300.11	298.21	267.3
78	1092	366	358.11	354.23	351.4
84	1145	456	436.32	426.73	431.8
90	600	615	612.21	623.24	617.4
96	365	830	830.101	830.108	830.109
102	277	969	894.12	879.12	836.70
108	227	665	665.101	665.108	665.109
114	187	519	519.21	523.12	549.10
120	161	444	435.68	424.32	416.90
126	143	321	315.23	312.11	305.0
132	126	208	210.21	212.21	221.40
138	115	176	169.21	166.24	163.38
144	102	148	142.12	139.23	131.20
150	93	125	119.21	115.67	110.0
156	88	114	109.21	100.21	96.40
162	82	106	110.21	112.11	89.20
168	76	97	92.21	89.23	82.70
174	73	89	82.12	79.43	76.30
180	70	81	80.23	78.12	73.00
186	67	76	79.14	75.12	69.80
192	63	71	70.14	70.11	66.7
198	59	66	70.23	69.12	62.40

Table 12. The extracted coefficients for the four-parameter Muskingum model.

Method	K	x	m	α
HA	0.610	0.404	3.781	1.125
BA	0.578	0.311	2.896	1.112
PSO	0.578	0.309	2.789	1.105

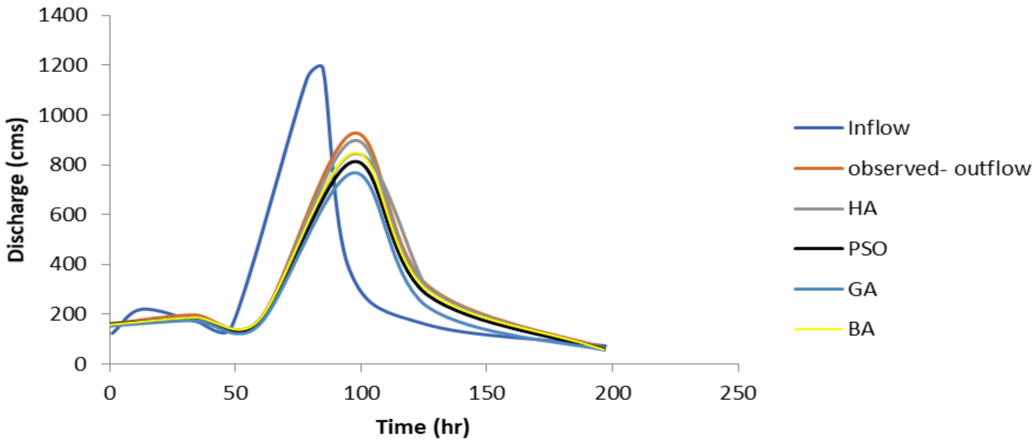

Figure 4. Simulated discharges by different algorithms for Karahan flood.

4.2.2. Ten Random Results for Karahan Flood

Table 13 shows the averages of 10 random results for different methods. The average solution of the HA was lower than that of the PSO algorithm and BA. Additionally, the computational time for the HA was 17% and 29% lower than those for the BA and PSO algorithm, respectively. Additionally, the coefficient of variation for the HA was a small value, which proved that the HA based on one computer program run can be reliable, producing high-quality solutions. Table 13 helps determine the best decision based on time, value of objective function and variation coefficient. The least value for the error objective function is provided by the HA based on the least value of the error objective function. Additionally, the least probable time is related to the HA, and all the runs for the HA have the smallest probable variations. Thus, the method encourages the decision makers to select HA based on the mentioned indexes. Additionally, Table 14 shows the sensitivity analysis for the HA and 4PMM model. The best population size for the HA is 60, and the best value for the maximum frequency and minimum frequency is 7 and 3. Other parameters can be seen in Table 14.

Table 13. Investigation of different methods for Karahan flood.

Run Number	HA	BA	PSO
1	30,235	31,112	32,119
2	30,237	31,117	32,119
3	30,235	31,112	32,119
4	30,235	31,112	32,119
5	30,235	31,112	32,119
6	30,235	31,112	32,119
7	30,237	31,112	32,122
8	30,235	31,117	32,112
9	30,235	31,112	32,119
10	30,235	31,112	32,119
Average	30,235.4	31,113	32,119
Computational time	19 s	23 s	27 s
Variation coefficient	0.00002	0.00005	0.00007

4.3. Discussion of the Viessman and Lewis Flood Results

The Viessman and Lewis Fi [39] multi-peak flood hydrograph was selected for this section. Table 15 shows the performances of different models in analysing the Viessman and Lewis flood. The results were compared with those of the WA in the literature, and this is a synthetic problem [33–37]. The highest SSQ for this flood, 73,312, was produced by the WA based on the 3PMM. The HA based on the 4PMM performed better than did the other models. The SSQ, SAD and MARE values of the HA based on the 4PMM had the lowest values. The BA based on the 4PMM performed better than did the WA and PSO algorithm based on the 3PMM. For example, the SSQ of the BA based on the 4PMM was 47,224, which was 14%, 3.8%, 16.72% and 35% lower than those of the PSO algorithm (4PMM), BA (3PMM), PSO algorithm (3PMM) and WA (3PMM), respectively. Additionally, the HA, PSO algorithm and BA based on the 4PMM outperformed the PSO algorithm, BA and HA based on the 3PMM. Figure 5 shows that the estimated discharge of the HA based on the 4PMM matched the observed discharge during the flood well. Furthermore, Table 16 shows the sensitivity analysis for the 4PMM and HA. The best size population for the HA is 60 because it has the least value for the objective function. The maximum loudness for the HA is 0.60, and the other parameters can be seen in Table 16. The comparison of results with other research studies shows the superiority of 4PMM and HA. For example, one study considered flood routing based on improved PSO based on correction of Wight inertia and a Muskingum flood with two parameters. The MARE index is 0.911, while the MARE for the HA and 4PMM is 0.794. HA acts better than the improved PSO and the Muskingum model with two parameters [34].

Moreover, Table 17 shows the 10 random results for different methods, and it can be seen that the value of the error objective function for the 4PMM and HA is less than PSO and BA. Additionally, the computational time based on HA and 4PMM is less than those of other methods. The solution for the HA is high quality because the variation coefficient is small compared to those of the other methods.

Table 14. Sensitivity analysis for Karahan flood.

Population Size	Objective Function	Maximum Frequency (Hz)	Objective Function	Minimum Frequency (Hz)	Objective Function	Maximum Loudness (dB)	Objective Function	c_1	Objective Function	c_2	Objective Function	w	Objective Function
20	34,231	3	33,278	1	32,278	0.20	31,124	1.6	32,112	1.6	32,114	0.3	31,127
40	32,278	5	32,211	2	31,112	0.40	30,298	1.8	31,214	1.8	31,289	0.5	31,119
60	30,235	7	30,235	3	30,235	0.60	30,235	2.0	30,235	2.0	30,235	0.70	30,235
80	31,112	9	31,265	4	31,112	0.80	30,236	2.2	31,112	2.2	31,112	0.90	30,254

Table 15. Evaluation of different methods for Viessman and Lewis flood.

Method	SSQ	SAD	MARE	EO	ET
HA (4PMM)	45,225	998.24	0.794	0.111	0
PSO (4PMM)	55,124	1012.22	0.812	0.209	0
BA (4PMM)	47,224	1001.14	0.798	0.118	0
HA (3PMM)	48,225	1002.23	0.812	0.115	0
PSO (3PMM)	56,712	1014.45	0.867	0.288	0
BA (3PMM)	49,112	1009.23	0.724	0.202	0
WA (3PMM)	73,312	1037.25	0.994	0.488	0

Table 16. Sensitivity analysis for Viessman and Lewis flood.

Population Size	Objective Function	Maximum Frequency (Hz)	Objective Function	Minimum Frequency (Hz)	Objective Function	Maximum Loudness (dB)	Objective Function	c_1	Objective Function	c_2	Objective Function	w	Objective Function
20	47,229	3	47,312	1	49,278	0.20	46,124	1.6	47,119	1.6	48,124	0.3	48,119
40	46,214	5	47,001	2	47,112	0.40	45,298	1.8	46,224	1.8	47,211	0.5	47,015
60	45,225	7	45,225	3	45,225	0.60	45,225	2.0	45,225	2.0	45,225	0.70	45,225
80	49,112	9	45,287	4	48,112	0.80	47,119	2.2	46,179	2.2	46,117	0.90	46,119

Table 17. Investigation of different methods for Karahan flood.

Run Number	HA	PSO	BA
1	45,225	55,124	47,224
2	45,226	55,124	47,226
3	45,225	55,127	47,224
4	45,225	55,124	47,224
5	45,225	55,124	47,224
6	45,225	55,124	47,224
7	45,225	55,124	47,224
8	45,225	55,124	47,224
9	45,225	55,124	47,224
10	45,225	55,124	47,224
Average	45,225	31113	47,224
Computational time	15 s	17 s	19 s
Variation coefficient	0.000004	0.000006	0.00005

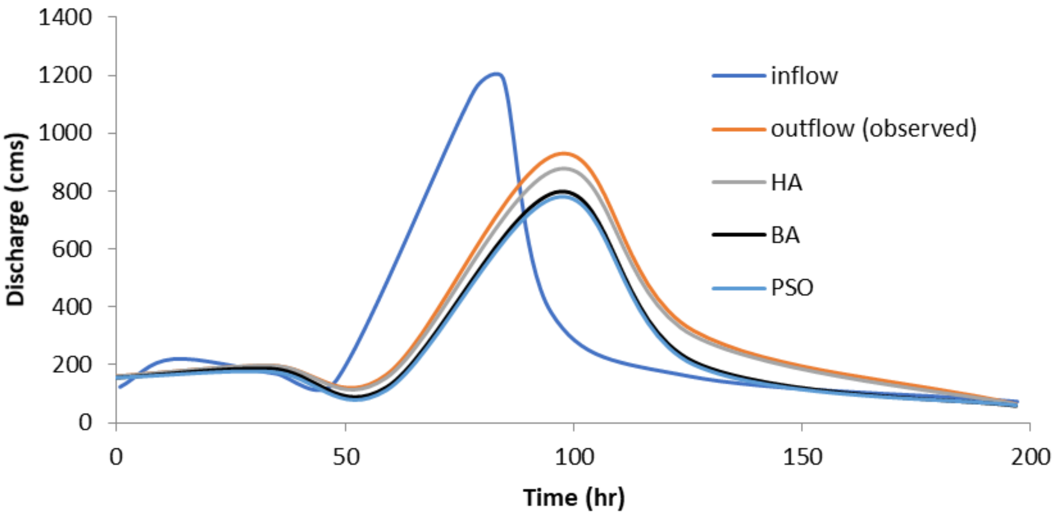

Figure 5. Extracted hydrograph for Viessman and Lewis flood based on 4PMM.

5. Conclusions

The present study considers flood routing based on the new hybrid BA and PSO algorithm. The new algorithm is based on the substitution of the weaker BA solutions with PSO. The structure of the new HA, with the elimination of the weaker BA solutions, enables the escape from local optimums. Three case studies that are benchmark studies in the flood routing field were used in this study, and the 4PMM was selected for analysis. For the Wilson flood case study, the computational time of the HA method was 25% and 20% lower than those of the PSO algorithm and BA methods, respectively. The SSQ computed by the HA was 4.234, which was 23.7% and 20.74% lower than those computed by the PSO algorithm and BA, respectively. Generally, the Wilson flood results showed that the HA based on the 4PMM performed better than the other models, with an SSQ value 65%, 72% and 47% lower than those of the BA (3PMM), PSO algorithm (3PMM) and HA (3PMM), respectively; the values of the other indexes agreed with this result. The results for the Karahan flood case study showed that the performances of different models based on the BA, PSO algorithm and HA with the 4PMM were better than those of the same models with the 3PMM. In the Karahan flood case study, the HA based on the 3PMM performed better than the other methods based on the 3PMM did, with an SSQ value that was 11.38%, 18%, 7.1%, 3.4%, and 6.3% lower than those of the GA, HS, ICA, BA and PSO methods, respectively. For the Viessman and Lewis flood case study, the SSQ, SAD and MARE of the HA based on the 4PMM were the lowest. The HA based on the 4PMM performed better than did the BA and PSO based on the 3PMM. The results indicated that the HA based on substitution of weaker solutions of each algorithm with the strong solutions can decrease the computational time, and the chance of obtaining the best solutions increased significantly. With the new strategy, there is no problem with trapping in the local optimums because the elimination of weaker solutions can lead to exits from the local optimums.

However, the HA based on the 4PMM had the best performance of all the models, suggesting that it should be used in future studies with other advanced Muskingum models and more parameters, such as 7- or 9-parameter Muskingum models, to evaluate the skill of HA for flood routing prediction modelling.

Author Contributions: A.E.-S. and V.P.S. initiated the research point of the hydrological problem and supervised the study. M.E. collected the data and performed the modeling. M.B.A.M., A.N.A. and M.F.A. handled the writing up of the introduction and methodology. The analysis of the modeling outcomes have been handled by F.B.O., S.S., Z.M.Y., H.A.A. and M.E.; Z.M.Y. and H.A.A. organized the whole manuscript and managed the paper submission and revision.

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