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APPLICATION OF THE HBMO APPROACH TO PREDICT THE TOTAL SEDIMENT DISCHARGE*

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Abstract– River sediment discharge estimation is a very important process for the water resource management. Sediment discharge is usually calculated either from the direct measurements of sediment concentration or sediment transport empirical equations. Due to several difficulties in applying empirical equations and direct measurements, in this study a general equation is developed to estimate the total sediment load with a good accuracy. An artificial intelligent model based on Honey Bee Mating Optimization (HBMO) is used to estimate the parameters of the proposed equation. The set of variables in the model is based on evaluating some of the existing empirical equations and also the prior researches to find the dominant parameters in the sediment transport formulas. Based on these investigations some parameters such as average flow velocity, water surface slope, average flow depth, median particle diameter, water temperature and width of the rivers are more effective and have been selected as the dominant variables in this research. With consideration of the mentioned variables, this model tries to determine the coefficients and powers of the general equation. Three data sets of different rivers have been chosen to demonstrate the model. The model has been calibrated by 75% of the data and validated by the remaining 25%. To calculate the proposed model efficiency and validity, the results have been compared with two common models. Therefore, the Sediment Rating Curve (SRC) and Non Linear Regression (NLR) models have been applied and the statistical results have been proposed to show the model efficiency.

Keywords– HBMO, total sediment, prediction, mathematical modeling

1. INTRODUCTION

Sediment discharge estimation is required in a wide spectrum of hydraulic problems. The results would be useful in different hydraulic engineering fields such as design of dams, hydraulic reservoirs and channels, maintenance and navigability, reservoir filling, hydroelectric-equipment longevity, protection of fish and wildlife habitats, river aesthetics and environmental impacts assessment. Sediment load carried by rivers may lead to reduction in useful storage of dams and congestion in water inlets [1]. Furthermore, design of stable channels, estimation of aggradation and degradation at bridge piers, prediction of sand and gravel mining effects on river beds and determination of environmental impacts assessment and soil erosion of the basins are affected by sediment load transport [2-4].

For the purpose of analysis, the total sediment load is often divided into two parts: the bed load and the suspended load. The total load is equal to sum of the bed load and the suspended load, but there is an active exchange between the bed load and the suspended load [5]. Therefore, some researchers have attempted to obtain the total sediment load directly, rather than summation of the bed load and the suspended load. Due to the method of sediment determination, the sediment load estimation equations can be categorized into three main groups: direct, indirect and the other methods. In the direct methods,

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determination of the total sediment load is done directly, without making any distinction between the two modes of transport such as Engelund and Hansen's approach [6] and Bagnold's approach [7] which are based on the power concept. Similarly Ackers and White's approach [8] determines the total sediment load on the basis of Bagnold's stream power concept and dimensional analysis. Yang [9, 10] used an analytic power model, and emphasized the stream power available per unit weight of fluid to transport sediment. In the indirect method total sediment load can be obtained by the sum of the bed load and suspended load such as the modified Einstein procedure [11], Chang, Simons and Richardson approach [12], Toffaleti method [13] and Van-Rijn approach [14, 15]. In these methods the hydrodynamics of each mode of transport is not the same. Some other approaches follow the other transport functions such as Laursen [16] who developed a functional relationship between the flow condition and the resulting sediment discharge. Shen, Hung [17] and Brownlie [18, 19] derived a regression equation based on laboratory data. Similarly Karim and Kennedy [20] used nonlinear multiple-regression analysis to derive their equation.

As the scientists have applied different assumptions to develop their formulas, the results come from various formulas not only have differences with one another, but they are also different with the measured quantities. Alonso, Neibling and Foster [21] and Yang [22] compared several conventional methods for calculating total sediment discharge [23]. Results of the researches done by Alonso et al. [21] in 1981 showed that Yang [10], Ackers-White [8], Engelund-Hansen [6] and Laursen [16] formulas have the best agreement with the measured data while the Yalin [24] and Bagnold [7] formulas gave unsatisfactory results [25].

The estimation of sediment discharge is an extremely difficult task because it is closely related to the flow conditions, however the mechanism of their relationship is nonlinear and they have complex interactions to each other [26, 27]. Numerous models for predicting sediment transport discharge are available, however their dependability is often questionable [28, 29]. Furthermore empirical models are not generic and are only applicable for the cases in which they have been developed [22, 30].

These equations are usually based on some simplifying assumptions for flow conditions which seriously affect the calculated values of sediment discharge. Because of the uncertainties involved in the sediment discharge estimation at different flow and sediment conditions, it is difficult to recommend one formula to use in different field conditions. Because of these issues researchers have been looking for simpler, cheaper and easier methods to estimate the sediment load and they have begun to use nonlinear models like artificial intelligent models to solve these problems [31].

The main idea of this research is to represent a general equation to estimate the total sediment discharge in rivers. The calculation method is based on an artificial intelligent model in which the sediment and flow conditions are used as the input variables. The method is based on social behavior of bees and named Honey Bee Mating Optimization (HBMO). By this method, it is possible to estimate the sediment discharge of rivers with an acceptable accuracy. This model represents a general equation for the total sediment discharge in rivers, in which the powers and the coefficients of the input parameters vary for different rivers. It should be noted that the difficulties of empirical equations do not appear in this model. Finally, the model will be verified with some data of three rivers in the United States. Field data include average flow velocity, water surface slope, average flow depth, median particle size, water temperature, and width of the rivers. The predictive accuracy of this model is compared with those of some well-known existing models such as Non Linear Regression (NLR) and Sediment Rating Curve (SRC).

2. MATHEMATICAL AND SOLUTION METHODS

A Sediment Rating Curve (SRC) method represents an equation to relate sediment discharge or concentration to stream discharge, which can be used to estimate the sediment loads from the stream flow records. Generally SRC has a power equation form of $Q_s = aQ_w^b$ in which Q_s is the total sediment discharge, Q_w is the water discharge, a and b are the coefficients which will be determined by regression analysis. By applying the SRC method in this research some data will be used to find the unknown coefficients in the calibration process and then the remaining data are applied to test the efficiency of the model for each data set. In this study, the field data published by the Geological Survey of the United States of America has been used to develop a predictive relationship for the sediment problem. These data are taken from three river stations in the United States including Susitna River near Talkeetna, Alaska (1982-1985), Chulitna River below Canyon near Talkeetna, Alaska (1982-1985) and Snake River near Anatone, Wash. (1972-1979) [32]. It is necessary to divide the data set into two categories including calibrating and verifying sets. Table 1 shows some statistical results done on the input data which have been considered as both calibration and verification sets for the SRC model.

Table 1. Statistical analysis for the calibration, verification and all data sets in the SRC model

Statistical Parameters	River	Calibration set		Verification set		All data	
		Q_w (m^3/s)	Q_s (kg/s)	Q_w (m^3/s)	Q_s (kg/s)	Q_w (m^3/s)	Q_s (kg/s)
Min	Susitna	603	7.18	478	3.635	603	7.184
Mean		1362.96	263.13	1329.9	297.825	1279.7143	228.08043
Max		2190	806.8	2610	920.2	2190	718.36
Min	Chulitna	520	87.5	631	50.5	520	87.5
Mean		1036.633	581.2	1176.5	579.11	1022.9048	567.00476
Max		1665	1814	2206	2169	1665	1814
Min	snake	1756	14.249	2400	24.031	1756	14.249
Mean		4037.73	139.56	3118.33	71.0585	3775.0476	119.98867
Max		6010	376.72	3990	167.92	6010	376.72

b) Non linear regression method

Regression based models such as Non Linear Regression (NLR) are simple and easily applicable to solve lots of nonlinear problems [3,33]. This method relates sediment load to flow and sediment conditions through regression equation, which is nonlinear. The regression coefficients are determined by minimizing the sum of square error distances of observation points from the values expressed by the regression equation. The NLR model is trained by the same calibration data sets used for the other models to enable a correct comparison. The models predictive capability is also tested with the same data sets which are not used in the calibration process. Thus the results of the models are comparable. The range of input parameters for calibration and verification of the NLR model has been summarized in Table 2.

Table 2. The range of basic parameters used as input of the NLR model in the calibration and verification processes

Location	Data	Number of measuring stations	Calibration			Number of measuring stations	Verification		
			Minimum	Average	Maximum		Minimum	Average	Maximum
Susitna river Talkeetna, Alaska	Flow velocity (m/s)	25	1.5	2.088	2.7	10	1.2	1.95	2.7
	Width (m)		166	184.36	202		165	181.6	201
	Average depth (m)		1.2	1.728	2.4		1.1	1.72	2.4
	Water surface Slope (m/m)		0.0012	0.0014	0.0018		0.0011	0.0012	0.0014
	Temperature (°C)		0.5	9.82	14.5		3.5	8.25	12.5
	d_{50} (mm)		0.004	0.0667	0.25		0.004	0.0515	0.12
Chulitna river below Canyon near Talkeetna, Alaska	Flow velocity (m/s)	30	1.5	1.9833	2.5	10	1.2	1.99	2.7
	Width (m)		98.5	107.4833	119		101	105.9	120
	Average depth (m)		1.7	2.3667	3.1		1.7	2.45	3.4
	Water surface Slope (m/m)		0.0004	0.0010	0.0015		0.0004	0.0010	0.0012
	Temperature (°C)		1.5	6.1667	16.5		2	4.75	7
	d_{50} (mm)		0.006	0.0474	0.5		0.008	0.0292	0.062
Snake river near Anatone, Wash.	Flow velocity (m/s)	15	1.6	2.3667	2.9	6	1.9	2.1333	2.4
	Width (m)		158	179.3333	192		169	174.5	181
	Average depth (m)		3.5	4.6733	5.4		3.9	4.2833	4.7
	Water surface Slope (m/m)		0.0006	0.0009	0.00112		0.0007	0.0008	0.0009
	Temperature (°C)		8.5	12.1667	17		13	13.6667	14.5
	d_{50} (mm)		0.4	10.42	58		0.4	0.525	0.8

1. Principals of the HBMO method: Honey Bee Mating Optimization (HBMO) is inspired by social behavior of bees consisting of a queen, drones, workers and broods [34]. These four main castes are associated with the different functions in the colony including cooperative work among adults in brood care and nest construction, overlapping of at least two generations and division of labor [35]. The HBMO algorithm simulates the mating process of honey bees that is actually the mating process of the queen [36]. A mating-flight starts with the dance of the queen where the drones follow her and mate with her. In each mating, the sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony [37].

The drones are the fathers of the colony and amplify their mother's genomes without altering their genetic composition, except through the mutation. Worker bees specialized in brood care and sometimes lay eggs. Broods arise from fertilized (representing the queen or worker) and unfertilized (representing drones) eggs [38]. At the start of the algorithm the queen spermatheca matrix size that corresponds to the maximum number of the queen's mating in a single mating flight must be defined. Each time the queen successfully mates with a drone the genotype of the drone is stored in the queen's spermatheca matrix and a variable is increased by one until the size of spermatheca is reached. Another two parameters must be defined, the number of queens and the number of broods that will be born by all queens. In this implementation of HBMO algorithm, the number of queens is set equal to one and the number of broods is set equal to the number corresponding to the size of the queen's spermatheca matrix. Then the mating flight of the queen begins. At the start of the queen's flight, the queen is initialized with her maximum energy and speed, then returns to her nest when her energy is less than a threshold value and the spermatheca is not full [39]. In order to develop the algorithm, the capability of workers is restrained in brood care and thus each worker may be regarded as a heuristic that acts to improve and/or take care of a set of broods. At the start of a mating flight, the drones are generated randomly and the queen selects a drone using the following annealing function:

$$prob(Q,D) = e^{\left(\frac{-\Delta f}{s(t)}\right)} \tag{1}$$

Where Prob (D,Q) is the probability of adding the sperm of drone D to the spermatheca of the queen, that is, the probability of a successful mating, Δf is the absolute difference between the fitness of drone (D) and the fitness of the queen (Q), and the S(t) is the speed of queen at time "t". After each transition of mating, the queen's speed and energy decline according to the following equations [36]:

$$Speed\,(t+1) = \beta \times Speed\,(t) \tag{2}$$

$$Energy(t+1) = \beta \times Energy(t) \tag{3}$$

where β is the decreasing factor (β=[0,1]).

Initially the speed of the queen is generated at random. At the start of a mating flight, drones are generated randomly and the queen selects a drone using the probabilistic rule [38]. If the mating is successful (i.e. the drone passes the probabilistic decision rule), the drone's sperm is stored in the queen's spermatheca [36]. Workers adopt some heuristic mechanisms such as crossover or mutation to improve the brood's genotype. The fitness of the resulting genotype is determined by evaluating the value of the objective function of the brood genotype [38]. The stages, which have been shown in the flow chart of Fig. 1, are the principles of the HBMO algorithm.

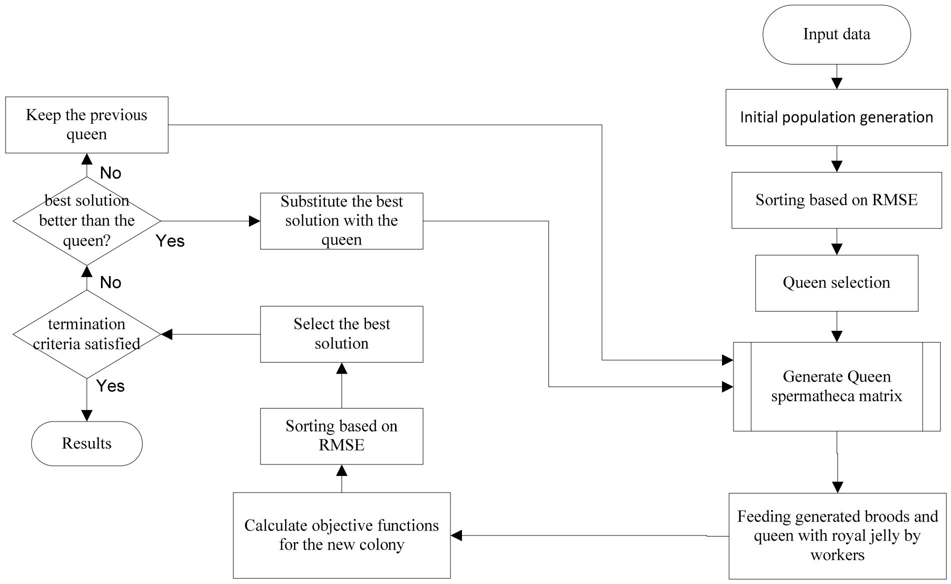

Fig. 1. Flowchart of the HBMO algorithm

The range of input parameters for the calibration and verification of the HBMO model are completely the same as the data sets used for the NLR model.

3. GENERAL EQUATION DEFINITION FOR THE SEDIMENT DISCHARGE PROBLEM

The most dominant variables in river hydraulics are water discharge per unit width (q), water depth (D), longitudinal slope (S), bed shear stress (τ), sediment discharge per unit width (q_t), particle's median diameter (d_{50}), sediment and fluid density (ρ_s) and (ρ), kinematic viscosity (ν), acceleration gravity (g) and the particle's fall velocity (ω_0) [22]. By reviewing the conventional sediment discharge equations, it has been found that the dominant parameters in the most sediment transport formulas are average flow velocity (V), water surface slope (S), average water depth (D), median particle diameter (d_{50}) and width (W) of the rivers [25]. Water temperature affects water density and viscosity and subsequently fall velocity of the sediment particles, which is an important factor in the sediment transport will change. Therefore, the water temperature has been considered as a dominant parameter. Because of the inherent complexity and nonlinearity of the sediment phenomenon, a simple linear equation cannot describe the problem. Therefore, a general conventional form of a nonlinear equation has been considered for the problem. Good agreement between the values estimated by the proposed equation and the measured data can support the use of this equation. Therefore, the following nonlinear equation is proposed to estimate the total sediment load in rivers based on the above mentioned dominant parameters which are V, W, D, S, T and d_{50} .

$$C_s = \alpha_1 V^{\beta_1} + \alpha_2 W^{\beta_2} + \alpha_3 D^{\beta_3} + \alpha_4 S^{\beta_4} + \alpha_5 T^{\beta_5} + \alpha_6 d_{50}{}^{\beta_6} \tag{4}$$

In this function the unknown parameters are α_1, α_2, α_3, α_4, α_5, α_6, β_1, β_2, β_3, β_4, β_5, β_6 and they will be determined by the HBMO, NLR and SRC methods. The calibration process will occur using 75% of the data and the resulting equation will be validated using 25% of the remained data in each data set. Validity of the provided methods for each river will be controlled by three different statistical parameters such as Root Mean Square Errors (RMSE), Mean Absolute Errors (MAE) and regressive coefficient (R^2) which are defined below:

$$RMSE = \sqrt{\sum_{i=1}^{n} (C_{S_{measured_i}} - C_{S_{Predicted_i}})^2 / n} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left| C_{S_{measured_i}} - C_{S_{predicted_i}} \right| \tag{6}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(C_{s_{measured_i}} - C_{S_{measured_{mean}}}\right)^2 - \sum_{i=1}^{n}\left(C_{S_{measured_i}} - C_{S_{predicted_i}}\right)^2}{\sum_{i=1}^{n}\left(C_{s_{measured_i}} - C_{S_{measured_{mean}}}\right)^2} \tag{7}$$

In the above formulas C_s is the total sediment load and n is the total number of data.

4. MODELS APPLICATION

a) Application of HBMO algorithm

By considering the mentioned non-linear equation, the objective function in the HBMO algorithm would be:

$$\textit{The objective function} = \textit{Minimize}\ [\, C_s - \alpha_1 V^{\beta_1} + \alpha_2 W^{\beta_2} + \alpha_3 D^{\beta_3} + \alpha_4 S^{\beta_4} + \alpha_5 T^{\beta_5} + \alpha_6 {d_{50}}^{\beta_6}\,] \tag{8}$$

To apply the proposed algorithm for sediment load estimation, the following steps must be considered:

Step1. Determination of the range of algorithm parameters. In this step the range of the following data must be defined. Size of the initial population (N_{ipop}), the speed of the queen at the start of the mating flight (S_{max}), the speed of the queen at the end of the mating flight (S_{min}), the speed reduction factor (β), the number of iterations, the number of workers (N_{Worker}), the number of drones (N_{Drone}), the size of the queen's spermtheca (N_{Sperm}) and the number of broods (N_{Brood}) must be defined at the beginning of the algorithm. The above parameters in this study would be respectively: 1000, 1000000, 1, 0.981, 50, 10, 500, 1500 and 1500. In order to create the initial population at the start of the algorithm, maximum and minimum values of unknown variables have to be defined which act as the state variables in the constraint functions. Table 3 shows the selected range of the mentioned state variables in this study.

Table 3. State variable constraints required for the initial population creation

Unknown variable	α_1	α_2	α_3	α_4	α_5	α_6	β_1	β_2	β_3	β_4	β_5	β_6
Min	0	-10	0	110	-10	-20	0.1	-20	0.1	10	-5	-5
Max	10	0	10	130	20	20	15	3	10	40	3	5

Step2. Input data. It includes average flow velocity (V), water surface slope (S), average water depth (D), median particles diameter (d_{50}), water temperature (T), width (W) of the rivers and total sediment load (C_S).

Step 3. Initial population generation. In this step an initial population will be generated randomly based on the state variables constraints which are defined in Step 1.

$$\textit{Initial Population} = \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_{Nipop} \end{bmatrix} \tag{9}$$

$$X_i = \lfloor x_j \rfloor_{1\times n} = [\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]\ ,\ \mathrm{i}=1,2,\ \ldots\ ,\ N_{ipop} \tag{10}$$

$$x_j = rand \times (x_j^{\max} - x_j^{\min}) + x_j^{\min}\text{; j=1,2, … , n} \tag{11}$$

In the above equations *rand* is the random function generator.

Step4. Nonlinear function calculation. In this step the nonlinear sediment function (equation 4) is calculated for each member X_i by using the measured values of V, W, D, S, T and d_{50} and is then compared with the measured total sediment load, C_s for N_{ipop} times. Then the RMSE would be determined for these calculated and measured values.

Step5. Sorting. The initial population must be sorted increasingly based on the calculated values of RMSE in order to separate different castes of the colony.

Step6. Queen selection. The member who has the minimum RMSE or the first member in the above sorted population matrix can be considered as the queen (X_{best}).

Step7. Queen speed generation. The queen speed is generated randomly with the following equation:

$$S_{Queen} = rand \times (S_{\max} - S_{\min}) + S_{\min} \tag{12}$$

Step8. Drones population selection. The population of drones (N_{Drone}) will be selected from the sorted initial population.

$$Drone\ population = \begin{bmatrix} D_1 \\ D_2 \\ \dots \\ D_{N_{Drone}} \end{bmatrix} \tag{13}$$

$$D_i = \lfloor d_j \rfloor_{1\times n} = [\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]\text{ , i=1,2, … , }N_{Drone} \tag{14}$$

The second member till the $N_{Drone}{}^{th}$ member in the sorted matrix provided in step 5 will form the drone population matrix.

Step9. Queen's spermatheca matrix generation (mating flight). At the start of the mating flight, the queen flies with her maximum speed. A drone is randomly selected from the population of drones. The mating probability is calculated based on the objective function values of the queen and the selected drone. A number between 0 and 1 is randomly generated and compared with the calculated probability. If it is less than the calculated probability, the drone's sperm is stored in the queen's spermatheca and the queen speed is decreased. Otherwise, the queen speed is decreased and another drone from the population of drones is selected until the queen reaches her minimum speed or the queen's spermatheca is full. If SP_i is the i^{th} sperm in the queen's spermatheca, then its matrix will be generated as follows:

$$prob_i = e^{-\frac{|RMSE_{Queen} - RMSE_{Drone}|}{S^i_{Queen}}} \qquad \text{i= 1, 2, …, } N_{Drone} \tag{15}$$

$$Spermatheca\ \ Matrix = \begin{bmatrix} SP_1 \\ SP_2 \\ \dots \\ SP_{N_{Sperm}} \end{bmatrix} \tag{16}$$

$$SP_i = \lfloor sp_j \rfloor_{1\times n} = [\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]\text{ , i=1,2, … , }N_{Sperm} \tag{17}$$

Step10. Broods population generation. In this paper as described above the breeding process in the original HBMO is implemented.

Step11. Improvement of the selected broods with the royal jelly by workers. By implementing the heuristic functions and mutation operators the brood population can be improved. For this reason a number (equal to or less than N_{worker}) of individuals are randomly generated around the ith brood. Then the value of the objective function is evaluated for each individual. The best individual among these generated broods will be replaced with the ith brood.

Step12. Objective function calculation and sorting. In this step the objective functions are calculated and then sorted for the new population as mentioned in the steps 4 and 5.

Step13. Termination and criteria checking. The termination criteria will be checked in this step. If all criteria are satisfied the algorithm will be finished, else N_{best} individuals must be selected among the broods matrix. They will be considered as the new population and the algorithm must be started again until all the convergence criteria are met.

The calibration parameters, α_1, α_2, α_3, α_4, α_5, α_6, β_1, β_2, β_3, β_4, β_5, β_6 which have been calculated using 75% of the data in each data set are summarized in Table 4.

Table 4. Estimated parameters for the sediment transport function, HBMO

River	Calibration parameters (coefficients (α) , powers (β))					
Susitna River	α_1	α_2	α_3	α_4	α_5	α_6
	0.24062	-9.5049	5.4452	118.73	16.268	19.321
	β_1	β_2	β_3	β_4	β_5	β_6
	7.3125	-15.241	5.5331	39.001	0.38869	3.8685
Chulitna River	α_1	α_2	α_3	α_4	α_5	α_6
	10	-0.051687	0.37258	129.41	16.011	20
	β_1	β_2	β_3	β_4	β_5	β_6
	4.7319	-1.2063	7.2119	28.565	-5	0.35064
Snake River	α_1	α_2	α_3	α_4	α_5	α_6
	0.32745	-8.6505	0.40131	110	-6.0506	-0.0034552
	β_1	β_2	β_3	β_4	β_5	β_6
	6.5797	-8.3596	0.76127	36.184	-3.0911	2.2423

b) Application of NLR model

For the sediment estimation problem, the dependent variable C_s is affected by the independent variables V, W, D, S, T and d_{50} by the highly nonlinear equation (4). Considering this equation, NLR analysis is used to estimate the unknown parameters which are the coefficients and the powers of the equation. In this study, the regression coefficients were determined using the ordinary least square method. Table 5 gives the simulation results of the NLR method for the rivers.

Table 5. Estimated parameters for the sediment transport function, NLR

River	Calibration parameters (coefficients (α) , powers (β))					
Susitna River	α_1	α_2	α_3	α_4	α_5	α_6
	4.4405	-8.98E-15	1.4697	4	-33.187	0.83532
	β_1	β_2	β_3	β_4	β_5	β_6
	4.5499	6.2575	7.2534	4	-0.19999	23.748
Chulitna River	α_1	α_2	α_3	α_4	α_5	α_6
	-7784.9	1.856	0.95825	-0.073252	7600.5	0.73188
	β_1	β_2	β_3	β_4	β_5	β_6
	-0.0060484	1.1763	6.5673	-1.0467	-0.0012951	-0.88283
Snake River	α_1	α_2	α_3	α_4	α_5	α_6
	-31.059	-0.47161	2.2043	-52101	1.3031	0.72122
	β_1	β_2	β_3	β_4	β_5	β_6
	-0.88891	1.0812	3.0773	1.4853	0.98713	0.87449

c) Application of SRC model

SRC model determines the sediment discharge (Q_s) based on the water discharge (Q_w) by using the equation in the form of $Q_s = aQ_w^b$ in which Q_w is the input variable and Q_s is the output. The SRC was fitted to the calibration data and the results in Table 6 have been obtained.

Table 6. Estimated equation for the sediment transport function, SRC

River	Susitna	Chulitna	Snake
SRC Equation	$Q_s=0.0001Q_w^{1.992}$	$Q_s=0.00019251Q_w^{2.1374}$	$Q_s=1.621e\text{-}009Q_w^{3.0007}$

5. RESULTS AND DISCUSSION

In order to compare the accuracy of the models, the resultant equations by the HBMO, NLR and SRC models have been applied to the same data which were not used in the calibration process. The calculated total sediment loads based on the three models in comparison with the measured values for the verification data of the three mentioned rivers are shown in Figs. 2-4.

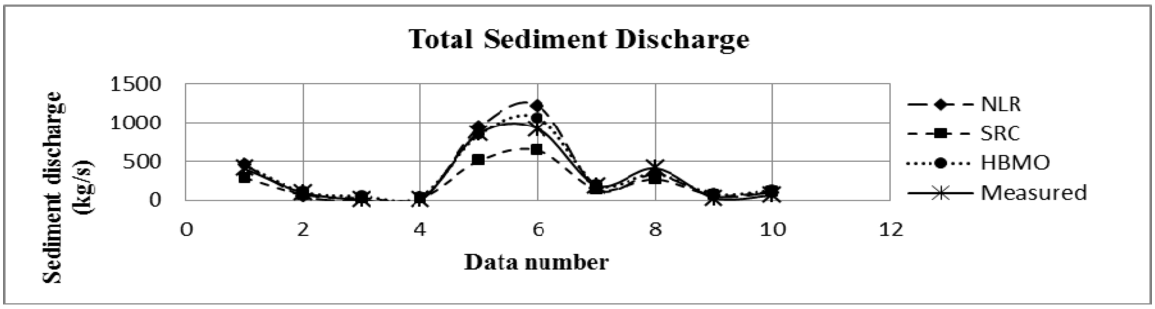

Fig. 2. Observed and estimated sediment discharge by the HBMO, NLR and SRC methods; Susitna River

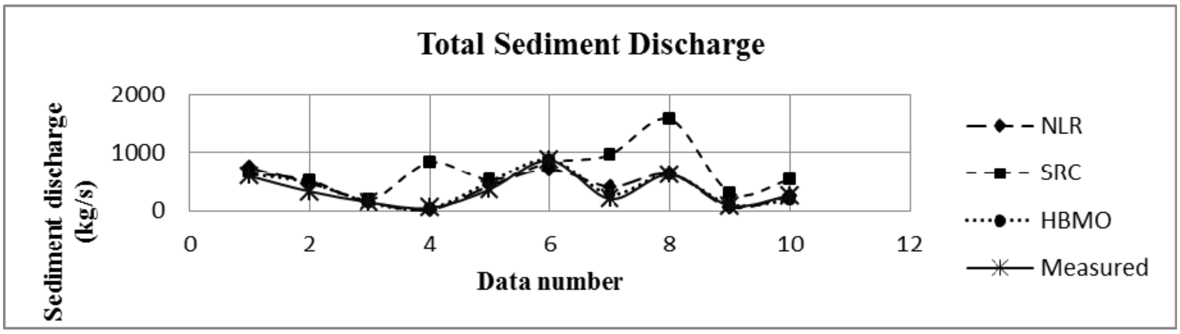

Fig. 3. Observed and estimated sediment discharge by the HBMO, NLR and SRC methods; Chulitna River

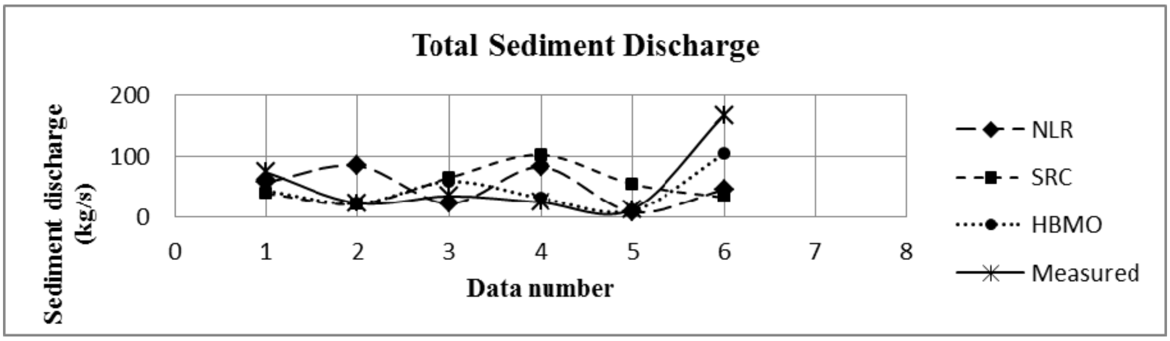

Fig. 4. Observed and estimated sediment discharge by the HBMO, NLR and SRC methods; Snake river

It is clear from Figs. 2-4 that the HBMO model shows a better agreement with the measured values than the NLR and SRC models.

The statistical analysis curves of the models are shown in Figs. 5-7. They show the correlation of the measured and estimated values by the three methods.

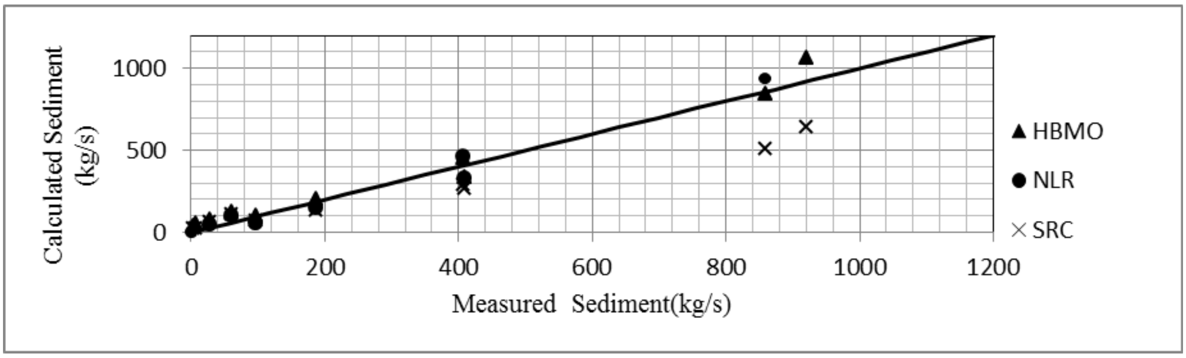

Fig. 5. Measured sediment discharge versus calculated values by the HBMO, NLR and SRC models; Susitna river

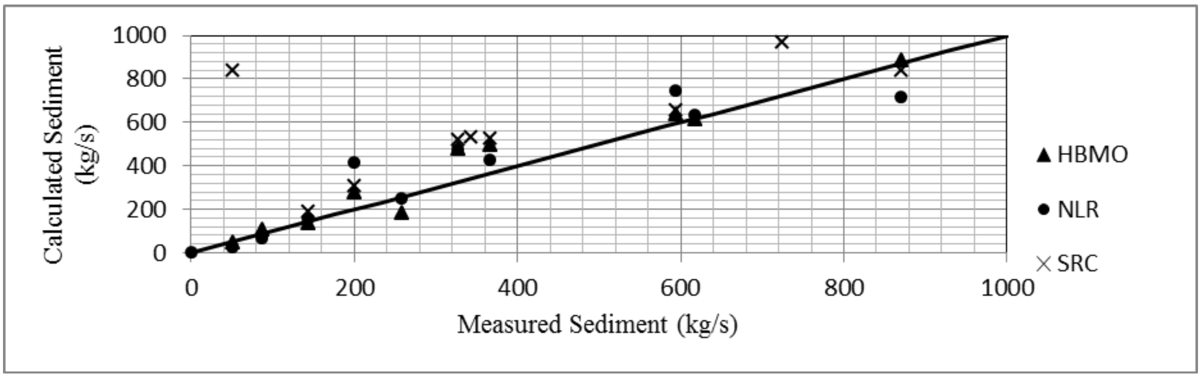

Fig. 6. Measured sediment discharge versus calculated values by the HBMO, NLR and SRC models; Chulitna river

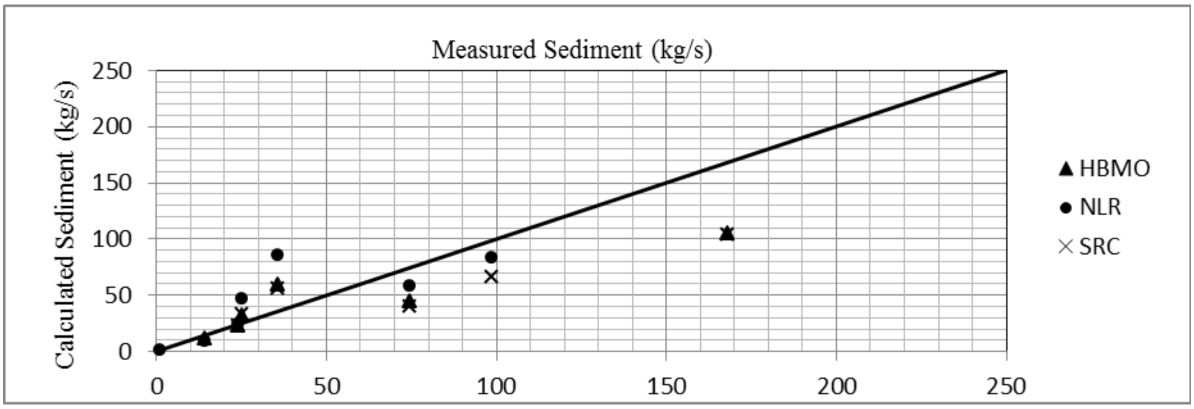

Fig. 7. Measured sediment discharge versus calculated values by the HBMO, NLR and SRC models; Snake river

As seen from the scatter-plots, the HBMO estimations are much closer to the measured values than those of the SRC and NLR methods.

In Table 7 the statistical results of the HBMO model are compared with the NLR and SRC models. In this table Root Mean Square Errors (RMSE), Mean Absolute Errors (MAE) and determination coefficient (R^2) parameters have been used to evaluate the accuracy of these models.

Table 7. R^2, MAE and RMSE values in the sediment prediction by the three models for the verification process

River	Model	R^2	RMSE (kg/s)	RMSE (t/day)	MAE(kg/s)	MAE(t/day)
Susitna River	HBMO	0.9645	61.866	5345.2	49.7	4294.1
	NLR	0.89649	105.64	9127.3	67.741	5852.8
	SRC	0.77306	156.42	13515	109.1	9426.4
Chulitna River	HBMO	0.91669	72.734	6284.2	52.24	4513.5
	NLR	0.81756	107.63	9299.5	80.289	6937
	SRC	0.68597	327.23	28273	233.94	20212
Snake River	HBMO	0.67711	23.808	2057	17.78	1536.2
	NLR	0.39319	33.817	2921.8	26.829	2318
	SRC	0.56282	30.232	2612	21.199	1831.6

According to the data proposed in Table 7, the HBMO model has improved the statistical parameters in comparison with the results of the NLR and SRC methods.

A comparison of the prediction accuracy of the models has shown that the application of the proposed general equation with the HBMO model is more accurate in predicting the sediment and its performance is better than the NLR and SRC models. Although the NLR model provided some reasonable results with this equation, it is not as accurate as the HBMO results. The SRC model has relatively low R^2 and has provided relatively poor load estimation in comparison with the proposed model. The lower performance of the SRC model shows that the water discharge is not the sole parameter to describe the sediment problem and it may be applied where detailed measured data are not available. Because of the inherent complexity and nonlinearity of the sediment phenomenon, the performance of the common regression models (i.e., NLR and SRC) was not suitable. Therefore, these techniques are not adequate in view of the complexity of the problem. The main advantages of using the proposed equation with HBMO model are its flexibility and ability to model nonlinear relationships. The HBMO model simulates the problem with an acceptable accuracy in spite of nonlinear properties of the objective function.

Several factors must be considered in evaluating and analyzing the total sediment load data such as length of the records, number of the observations, accuracy of the measuring instruments and also accuracy of the data collections. These factors seriously affect the results of analysis. A less accurate measurement may lead to more error in the estimation process which can be seen in the sediment estimation for Snake river.

6. CONCLUSION

This research proposes a new model for the total sediment load estimation in rivers based on a new general equation and a heuristic search method (HBMO). It was developed to estimate the total sediment load with a good accuracy in different rivers with consideration of dominant factors. The set of variables in the model is based on evaluating some of the existing empirical equations and also the prior researches to find the dominant parameters in the sediment transport formulas. Based on these investigations some parameters such as average flow velocity, water surface slope, average flow depth, median particle diameter, water temperature and width of the rivers are more effective and have been selected as the dominant variables in this research. To calculate the proposed model efficiency and its validity, the results have been compared with the other common models. Therefore, the Sediment Rating Curve (SRC) and Non Linear Regression (NLR) models have been applied and the statistical results show the model efficiency. Overall, the simulation results on three different rivers show that the HBMO and NLR models seem to be more efficient than the SRC model. However the form of the proposed equation for HBMO and NLR models are different from that in the SRC model. Also, the difficulties of empirical equations do not appear in this model. The accuracy of the HBMO model was compared with those of NLR and SRC models. The comparison results show that the HBMO generally performs better than the NLR and SRC models. The main advantage of using the proposed equation with the HBMO model is its flexibility and ability to model the nonlinear behavior of the sediment discharge in different rivers. Mathematically, the HBMO could be treated as a universal estimator in conjunction with the general equation for the sediment load calculation. This model can become a good estimator with great potential due to the ease of application and simple formulation in different rivers.

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