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ORIGINAL ARTICLE

Prediction of total bed material load for rivers in Malaysia: A case study of Langat, Muda and Kurau Rivers

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Abstract A soft computational technique is applied to predict sediment loads in three Malaysian rivers. The feed forward-back propagated (schemes) artificial neural network (ANNs) architecture is employed without any restriction to an extensive database compiled from measurements in Langat, Muda, Kurau different rivers. The ANN method demonstrated a superior performance compared to other traditional sediment-load methods. The coefficient of determination, 0.958 and the mean square error 0.0698 of the ANN method are higher than those of the traditional method. The performance of the ANN method demonstrates its predictive capability and the possibility of generalization of the modeling to nonlinear problems for river engineering applications.

Keywords Alluvial channels · Artificial neural network · Total-sediment load · River engineering · Sediment transport

1 Introduction

Sand and gravel have long been used as aggregate for construction of roads and building. Today, the demand for these materials continues to rise. In Malaysia, the main source of sand

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is from in-stream mining. In-stream sand mining is a common practice because the mining locations are usually near the "markets" or along the transportation route, hence reducing transportation costs.

In-stream sand mining can damage private and public properties as well as aquatic habitats. Excessive removal of sand may significantly distort the natural equilibrium of a stream channel. By removing sediment from the active channel bed, in-stream mines interrupt the continuity of sediment transport through the river system, disrupting the sediment mass balance in the river downstream and inducing channel adjustments (usually incision) extending considerable distances (commonly 1 km or more) beyond the extraction site itself.

In recent years, rapid development in Malaysia has led to an increased demand for river sand as a source of construction material, which has resulted in a mushrooming of river sand mining activities that have given rise to various problems that require urgent action by the authorities. These include riverbank erosion, riverbed degradation, river buffer zone encroachment and deterioration of river water quality. Very often, over-mining occurs, which jeopardizes the health of the river and the environment in general. This study summarizes the results based on field data collected at three river catchments in Malaysia, i.e., the River Langat, the River Muda, and the River Kurau. Fieldwork on selected sites for the three rivers was performed to assess the capacity of the river to convey both water and sediment. Data collection on the bed material was used to characterize the physical characteristics of the sediment responsible for sediment transport, which determines the river response in terms of erosion and deposition. The three rivers clearly have bed material sizes in the sand-gravel range based on the collected data in the present study [13]. This study shows that the measured load can be predicted accurately for Malaysian rivers using the neural networks approach.

The neural networks approach has been applied to many branches of engineering sciences. This approach is becoming a valuable tool for providing civil and hydraulic (river) engineers with sufficient details for design purposes and river-management practices. Motivated by successful applications in modeling nonlinear system behavior in a wide range of areas.

ANNs have been applied in hydrology and hydraulics [14,19]. ANNs have been used for rainfall-runoff modeling, flow predictions, flow/pollution simulation, parameter identification, and modelling nonlinear/ input–output time series [4]. Jain [18] used the ANN approach to establish an integrated stage–discharge–sediment concentration relation for two sites on the Mississippi River in the United States.

Through Jain's study, it was shown that the ANN results were better than those obtained by the conventional technique [18]. Cigizoglu [9,10] employed ANNs to estimate suspended-sediment concentrations and made a comparison between ANNs and sediment rating curves for two rivers with very similar catchment areas and characteristics in northern England. He used only discharge and sediment concentration parameters in his study. He showed that the estimates obtained by the ANNs were significantly superior to the corresponding classical sediment rating curve. Yang et al. [24] used ANN to evaluate total sediment load formulae (where—river and location). Nagy [21] estimated that the natural sediment discharge in rivers in terms of sediment concentration by ANN model yields better results compared to several sediment-transport formulas [3,15,20,23]. Cigizoglu and Kisi [11] developed models of ANN to estimate suspended-sediment. Tayfur and Guldal [22] estimated daily total-suspended sediment in natural rivers by ANN and a nonlinear black box model based upon two-dimensional unit sediment-graph theory (2D-USGT) from precipitation data. The comparison of results revealed that the ANN has a significantly better performance than the 2D-USGT. Recently, Azamathulla et al. [7] used an ANFIS-based approach for predicting the bed load for moderately sized rivers in Malaysia.

2 Study area

This study covers three rivers, i.e., the River Langat, the River Muda, and the River Kurau, that have different levels of sand mining activities. River Langat recently has been a major source of sand for construction with the development of Putrajaya. River Muda has a long history of sand mining activity along the upper reach. Less sand mining is ongoing in the River Kurau upstream of the Bukit Merah reservoir.

2.1 River Langat

The River Langat basin occupies the south and southeastern parts of the State of Selangor and small portions of Negeri Sembilan and Wilayah Persekutuan. The basin is bounded on the east by the Main Range and the Straits of Malacca on the west. The basin has diverse topography ranging from mountainous areas in the northeast, low rolling hilly areas in the middle to lowlands in the south-west part of the basin. The geographic location of the basin is shown in Fig. 1(a).

The river system flows through the State of Selangor, Negeri Sembilan, and the Federal Territory of Putrajaya. The main river, the River Langat, has a total length of about 180 km, and it forms one of the four major river systems in the State of Selangor. The River Langat basin (the basin) has a total catchment area of 2,350 km^2 and an average annual flow of 35 m^3/s, and the mean-annual flood is 300 m^3/s. Use of River Langat is not limited to water supply and includes other purposes such as recreation, fishing, effluent discharge, irrigation and even sand mining.

2.2 River Muda

The River Muda is the longest river in the state of Kedah, and it is situated in northern Peninsular Malaysia with its origin in the northern mountainous area of the state adjoining Thailand, as shown in Fig. 1(b). The basin has a drainage area of approximately 4,210 km^2. However, small portions of the catchment lie within the upper boundary of the State of Pulau Pinang. In terms of administrative boundaries, the upper and middle reaches of the basin belong to the State of Kedah, while the downstream of the river forms the boundary between the states of Kedah and Pulau Pinang.

The main channel of River Muda has a length of about 180 km with a slope of 1/2,300 (or 0.00043 m/m) from the river mouth to Muda Dam. The channel width is typically around 100 m and widens up to about 300 m near the river mouth. The channel tends to erode due to sand mining operations, aggravating bank erosion, and river total degradation. Per river surveys in 2000, the shallowest point in the river is located 2.5 km upstream of the river mouth, and it causes difficulty in navigation during low tides. At the upstream end of the River Muda is the Muda Dam, which acts as an extra storage for the Pedu dam. The two dams are part of the irrigation scheme. In general, the River Muda is still in its natural state, with riparian vegetation and flood plains made up of paddy fields along the riverbanks.

2.3 River Kurau

The River Kurau (Fig. 1c) represents the main drainage artery of the basin, draining an area of approximately 682 km^2, which is generally low lying. The river originates partly in the Bintang Range and partly in the Main Range where the terrain in the upper reaches are steep and mountainous. The mid-valley of the river is characterized by low to undulating terrain,

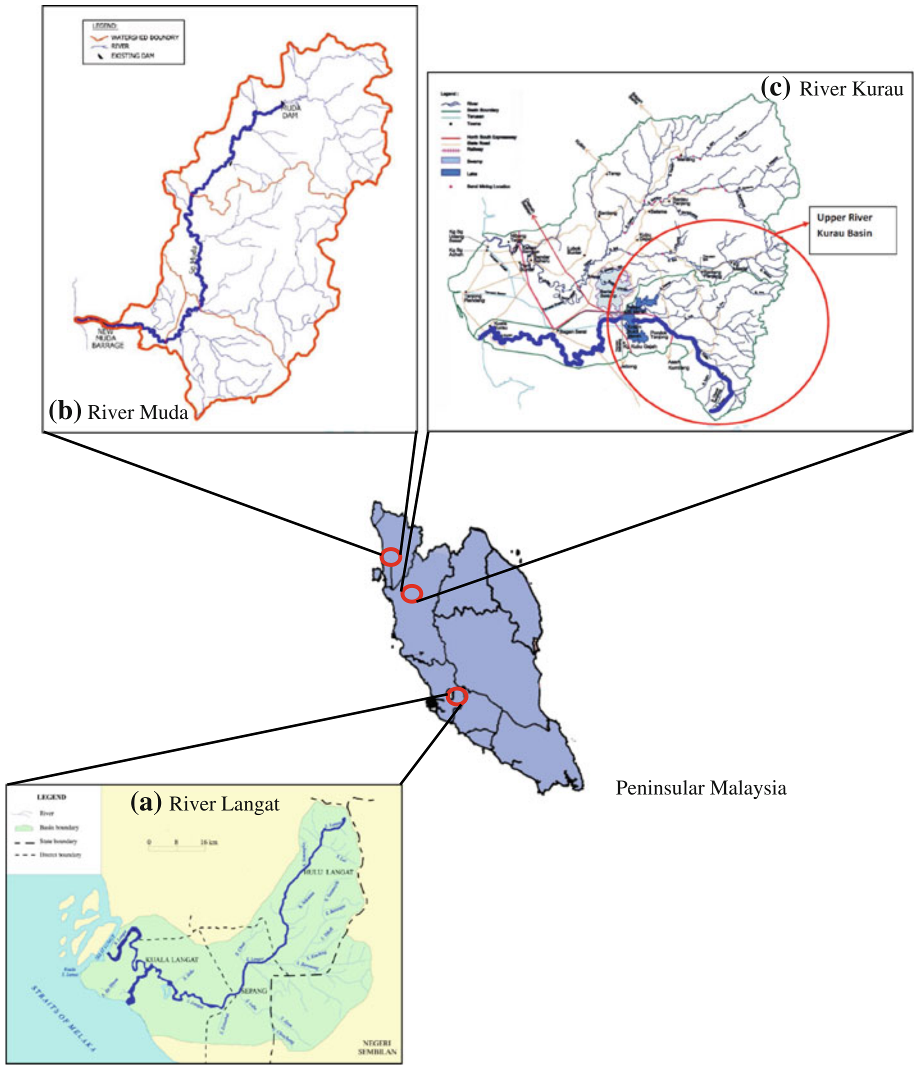

Fig. 1 Study area

which gives way to broad and flat floodplains. Ground elevation at the river headwaters is moderately high, at 1,200 and 900 m in Batu Besar and Batu Ulu Trap, respectively. The slopes in the upper 6.5 km of the river average 12.5%, while those lower down in the valleys are much lower, on the order of 0.25–5%. The River Kurau basin is important as the main water resource for the Kerian Irrigation Scheme as well as the main domestic water supply for the Kerian District and the Larut and Matang District, State of Perak.

A dam was constructed 65 km upstream at the mid section of the rivers to form the Bukit Merah Reservoir. This dam is operated principally to irrigate the paddy areas immediately below the Reservoir. Upstream of the reservoir are two subsystems, namely the Kurau subsystem and the Merah River subsystem. Both drain through undulating to steep terrain. Areas in the former subsystem were developed extensively for tree crop agriculture, while the Pondok Tanjong Forest Reserve forms the main land use of the latter subsystem. Largely rural in

Table 1 Range of field data for three rivers

Study area	Study area		
	River Langat	River Muda	River Kurau
$Q (m^3/s)$	2.75–120.76	2.59–343.71	0.63–28.94
V (m/s)	0.23–1.01	0.14–1.45	0.27–1.12
B (m)	16.4–37.6	9.0–90.0	6.30–26.00
Y_o(m)	0.64–5.77	0.73–6.90	0.36–1.91
$A (m^2)$	8.17–153.57	5.12–278.34	1.43–33.45
R (m)	0.45–3.68	0.55–3.90	0.177–1.349
S_o	0.00065–0.00185	0.00008–0.000235	0.00050–0.00210
T_b (kg/s)	0.027–0.363	0–0.191	0.080–0.488
T_t (kg/s)	0.2860–99.351	0.024–15.614	0.001–2.660
T_j (kg/s)	0.525–99.398	0.099–15.644	0.089–2.970
d_{50} (mm)	0.31–3.00	0.29–2.10	0.41–1.90
Manning n	0.034–0.195	0.021–0.108	0.014–0.066

nature, the River Kurau basin has many riverine villages established from the mid to lower reaches of the river.

3 River conveyance and sediment transport capacity

The data collection program for this study was implemented at three major rivers in Malaysia from 2007 until 2008 to assess the current state of river morphology based on on-site data and to determine the capacity of the river to act as it would naturally. Six study sites were chosen from each river for a detailed analysis of river conveyance and sediment transport capacity.

The surveyed cross sections for the River Muda and the River Langat are single thread channels with the top width ranging between 22.5 and 134.0 m, representing medium-sized rivers, and the top width for River Kurau ranges between 25.8 and 41.0 m, representing a small-medium river. The slopes are between 0.00008 and 0.0021, indicating that the cross sections are still natural. The details of the morphological and hydrological descriptors and range of field data are given in Table 1. The data collection includes flow discharge (Q), suspended load (T_t), bed load (T_b) and water surface slope (S_o). In addition, the bed elevation, water surface and thalweg measurement (the minimum bed elevation for a cross section) were also determined at the selected cross sections. The total bed material load (T_j) is composed of the suspended load and bed load. The total bed material load must be specified for sediment transport, scour, and deposition analysis. Details of the measurement methodology are given in [2]. The measured total bed material rating curves for these six sites at the three rivers are illustrated in Figs. 2–4.

4 Sediment transport equations assessments

A detailed sediment transport study at six sites for each river was conducted and it was found that Yang and Engelund-Hansen equations are able to predict the trend of sediment transport for the three rivers.

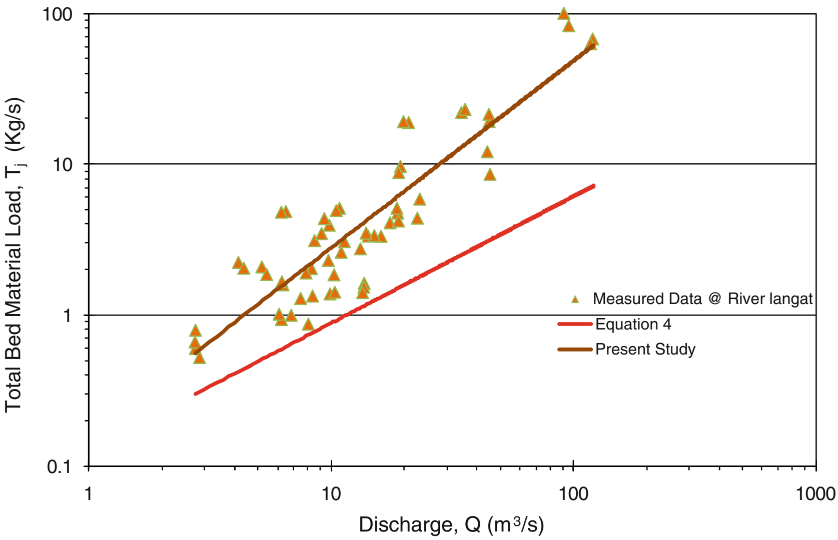

Fig. 2 Comparison of River Langat sediment rating curve for this study and Eq. 4

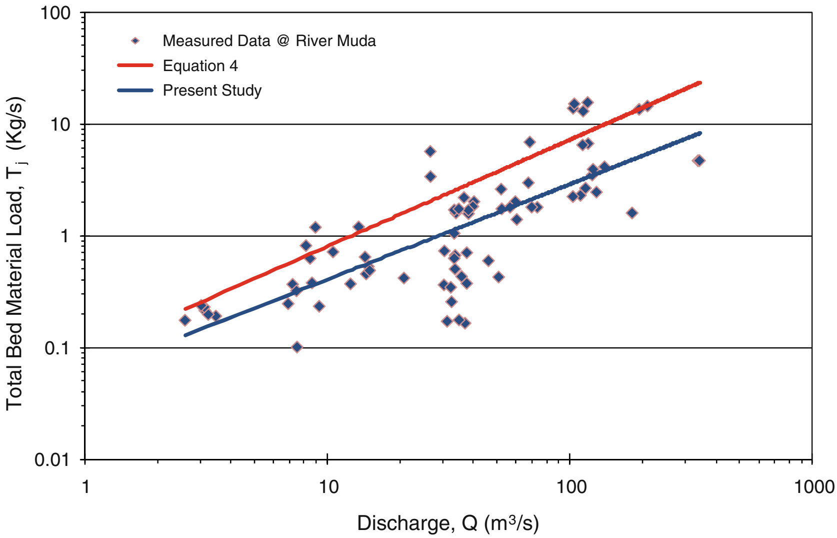

Fig. 3 Comparison of River Muda sediment rating curve for this study and Eq. 4

Yang [23] related the bed material load to the rate of energy dissipation of the flow as an agent for sediment transport. The theory of minimum rate of energy dissipation states that when a dynamic system reaches its equilibrium condition, its rate of energy dissipation is at a minimum. The minimum value depends on the constraints applied to the system. For a uniform flow of energy dissipation due to the sediment transport can be neglected. Yang equation for sand transport is:

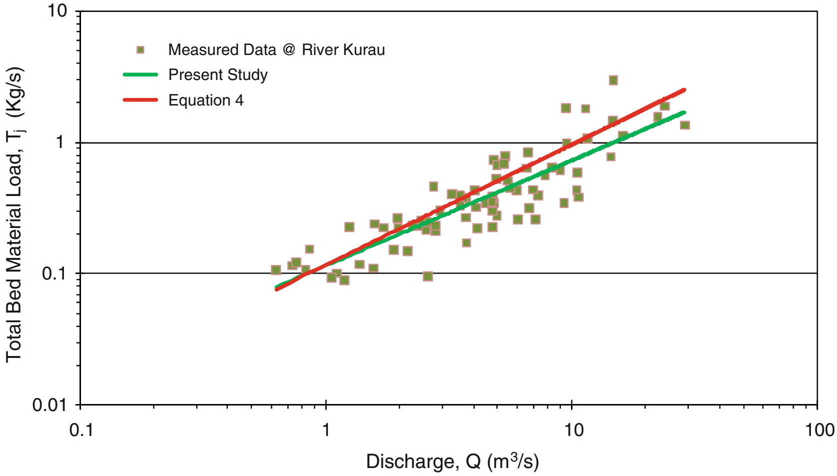

Fig. 4 Comparison of River Kurau sediment rating curve for this study and Eq. 4

$$\log C_{\mathrm{T}} = 5.435 - 0.286 \log \frac{W_{\mathrm{S}} d_{50}}{\upsilon} - 0.457 \log \frac{U_*}{W_{\mathrm{S}}} + \left\{ \left(1.799 - 0.409 \log \frac{W_{\mathrm{S}} d_{50}}{\upsilon} - 0.314 \log \frac{U_*}{W_{\mathrm{S}}} \right) \times \log \left(\frac{V S_{\mathrm{O}}}{W_{\mathrm{S}}} - \frac{V_{\mathrm{C}} S_{\mathrm{O}}}{W_{\mathrm{S}}} \right) \right\} \tag{1}$$

where

$$C_{\mathrm{v}}\,(\mathrm{ppm}) = \frac{C_{\mathrm{t}}\,(\mathrm{ppm})}{S_{\mathrm{S}}}$$

Critical velocity, V_{C} is given by:

$$\frac{V_{\mathrm{C}}}{W_{\mathrm{S}}} = \frac{2.5}{\log \frac{U_*}{V} - 0.06} + 0.06$$

$$R_{e^*} = \frac{U_* d_{50}}{V} = 1.2 - 70$$

$$\frac{V_{\mathrm{cr}}}{W_{\mathrm{S}}} = 2.05 \quad \text{for } R_{e^*} \geq 70$$

where C_{t} is total sand concentration (in ppm by weight), W_{S} is terminal fall velocity, d_{50} is average particle diameter of granular material, υ is kinematic viscosity, U_* is shear velocity, V_{S} is unit stream power, and $V_{\mathrm{C}}S$ is critical unit stream power required at incipient motion, C_{v} is sediment concentration by volume.

Engelund and Hansen [15] applied Bagnold's stream power concept and the similarity principle to obtain the sediment transport equation below.

$$q_{\mathrm{s}} = 0.05 \rho_{\mathrm{s}} V^2 \left[\frac{d_{50}}{g\,(S_{\mathrm{s}} - 1)} \right]^{1/2} \left[\frac{\tau}{(\rho_{\mathrm{s}} - \rho)\, d_{50}} \right]^{3/2}, \tag{2}$$

where q_{s} is total sediment discharge by weight per unit width, V is average flow velocity, S is energy slope, ρ is density of water, ρ_{s} is density of sediment, d_{50} is median particle diameter, g is acceleration due to gravity, and τ is shear stress along the bed.

Table 2 Summary of discrepancy ratio for three rivers using Yang and Engelund-Hansen equations

Location	Total of data	Discrepancy ratio (DR) between 0.5 and 2.0			
		Yang equation		Engelund-Hansen equation	
		Number of data	%	Number of data	%
River Langat	60	30	50.00	31	51.67
River Muda	76	16	21.05	19	25.00
River Kurau	78	33	42.31	38	48.72

The assessment of two existing sediment-transport equations, the Yang [23] and Engelund-Hansen [15] equation, was performed after removing outliers for the 214 sets of data for this study (Table 2). The assessment was based on the average size of the sediment (d_{50}). The performances of the equations were measured using the discrepancy ratio (DR), which is the ratio of the estimated load to the measured load (DR = estimated/measured). A discrepancy ratio of 0.5–2.0 (DR = 0.5–2.0) was used as a criterion in the evaluation of the selected equations. The evaluation using these equations shows that all the existing equations, in most cases, over-estimated the measured values, as shown in Table 2.

5 Multiple linear regression

Ab. Ghani [1] shows that good prediction of sediment transport in pipes could be obtained from simple regression equations. It's therefore decided to keep the form of the equation as simple and as easy to use as possible.

Based on dimensional analysis from previous works [1,21], the proposed function is given as follows:

$$C_{\mathrm{v}} = f\left(\frac{V}{\sqrt{gd_{50}\left(S_{\mathrm{s}}-1\right)}}, \frac{R}{d_{50}}, \frac{B}{y_{\mathrm{o}}}\right), \tag{3}$$

where R is hydraulic radius, and B is water surface width. Utilizing all data from the three rivers in this study, the best equation is given as follows:

$$C_{\mathrm{v}} = 2.42 \times 10^{-5} \times \left(\frac{V}{\sqrt{2g\left(d_{50}\right)\left(S_{\mathrm{s}}-1\right)}}\right)^{0.022}\left(\frac{R}{d_{50}}\right)^{-0.2016}\left(\frac{B}{y_{\mathrm{o}}}\right)^{0.104}. \tag{4}$$

Figures 2–4 show the sediment rating curves for three rivers using Eq. 4.

6 ANN schemes

From the above analysis, we have attempted ANN—back propagation schemes for this study. Artificial Neural Network is architecture that fully connects elemental units, called neurons [16]. It draws its power, talent of learning, and generalization through the connectionist network. The ANN is trained to provide a desired response to a specific stimulus (input set). Generalization means that the trained and validated ANN model may produce logical outputs from independent inputs not used in the training and validation stages [16]. The learning process might be supervised or unsupervised; the network may be feed forward or radial based, and so onwards. Hornik et al. [17] stated that multi-layer feed forward

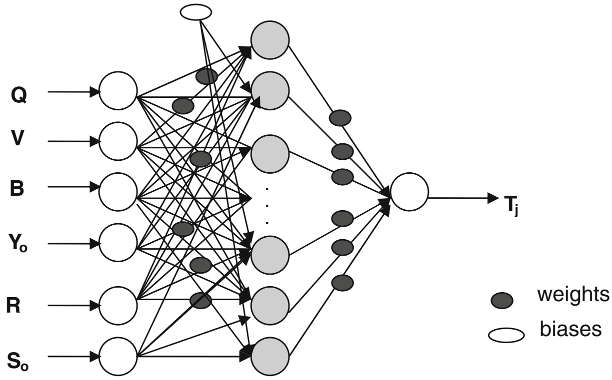

Fig. 5 Feed forward type NN

networks with as few as one hidden layer are indeed capable of universal approximation in a precise and satisfactory sense. They also concluded that if there is any lack of success in applications, the fact may arise from inadequate learning, insufficient numbers of hidden units, or the lack of a deterministic relationship between input and output. In this study, ANNs were developed for sediment data sets, the net work input –output as shown in Fig. 5.

The present ANN structure consists of the input layer (with various numbers of inputs), one hidden layer, and the output layer. The feed-forward calculation starts at the input layer, moves forward to the next layer, and determines the output values for each neuron. Each unit or neuron in the network sums the weighted inputs and a bias passed from the previous layer, and then applies a nonlinear activation function to generate an output.

6.1 Selection of input parameters for the ANN

The selection of the input parameters is a very important aspect of neural network modeling. In order to use ANN structures effectively, input variables in the phenomenon must be selected with great care. This highly depends on the better understanding of the problem. In a firm ANN architecture, in order not to confuse training process key variables must be introduced and unnecessary variables must be avoided. For this purpose, a sensitivity analysis can be used to find out the key parameters. Also sensitivity analysis can be useful to determine the relative importance of the parameters when sufficient data are available. The sensitivity analysis is used to determine the effect of changes and to determine relative importance or effectiveness of a variable on the output. The input variables that do not have a significant effect on the performance of an ANN can be excluded from the input variables, resulting in a more compact network. Then, it becomes necessary to work on methods like sensitivity analysis to make ANNs work effectively [4]. The parameters that affect the total sediment load can be given in a form as: $T_j = f(Q, V, B, Y_o, R, S_o)$ to establish an ANN architecture (Fig. 5).

6.2 Determination of ANN architecture

A total of 214 cross-section averaged load observations were divided into two parts. Seventy percent of the data was reserved for training, the rest for testing. The training data set was

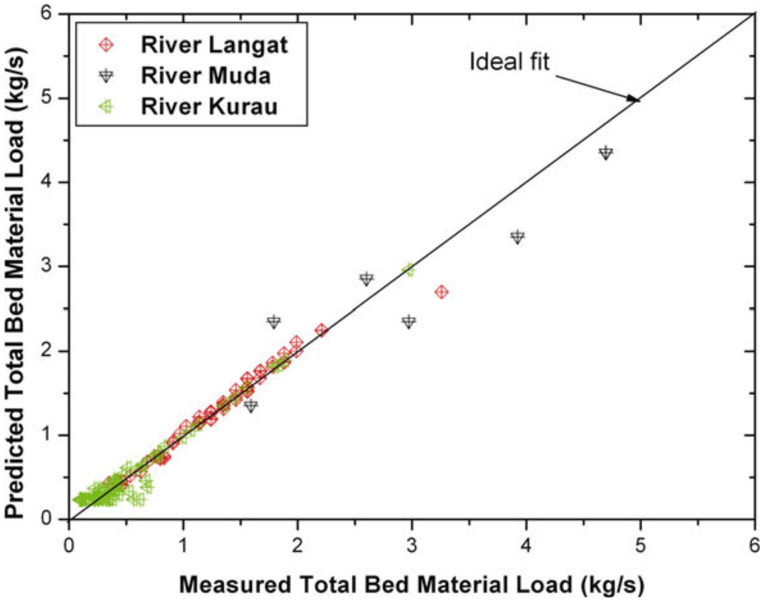

Fig. 6 Observed versus predicted Sediment load ANN—BFG (inputs: eight hidden neurons)

used to determine the best weights and biases for the network. The testing data pattern was used to measure the generalization performance of the selected model [16]. Data for each set were selected randomly but statistical consistency between the sets was ensured. The division of data is a complex task [8]. The data from all rivers were uniformly distributed among the training and test data sets.

The logistic function, which is used in all layers of the proposed network, is constrained between 0 and 1. Thus, the entire data set was rescaled so that one predictor did not dominate the model [12]. There are many different alternative standardization methods used to create data with zero mean and unit standard deviation, but herein, for all ANN models, the input(s) and the output were rescaled between 0.0 and 1.0. Researchers [5–7] used ANN techniques in modeling have used many different criteria to evaluate model performance. There is no generally accepted standard for the assessment of ANN performance. A common procedure is the use of the root-mean-square error (RMSE) and the coefficient of determination R^2 when evaluating the goodness of fit of models. After selecting the model and the network type, the outputs predicted on the basis of the trained and the validated weight bias matrices were compared with the three traditional total sediment load discharge models.

Because there is no specific method to determine the network structure, it was found that the best model representing the total load phenomena is in the form of the ANN *(6,10,1)*. The number of neurons in the hidden layers was determined through a trial-and-error approach. The ANN model was shown in Fig. 5 dimensional input parameters and one desired result, i.e., the sediment load. The model was trained using 150 data sets and tested with the remaining 64 data sets. The input 8, 1 hidden layer with 10 hidden nodes and 1 output, the trained network yields satisfactory performance with $R^2 = 0.958$ for BFG scheme (Fig. 6). The other schemes were attempted and presented in Table 3.

Table 3 Error measures for different ANN schemes

ANN schemes	Iteration number (Epoch)	Coefficient of determination, R^2	Mean square error
BFG	2000	0.958	0.070
CGF	1000	0.717	11.788
CGP	1200	0.694	12.567
OSS	600	0.746	10.457
LM	40	0.959	0.075
GDA	120	0.656	12.845
GDX	150	0.704	12.689
RP	200	0.813	5.678
SCG	80	0.876	1.234
CGP	1500	0.699	12.678
Yang [23]		0.722	10.376
Engelund–Hansen [15]		0.623	12.735

7 Conclusions

Total load transport in rivers is a complex phenomenon. The nature and motivation of traditional total load models differ significantly. These approaches are normally able to make predictions within about one order of magnitude of the actual measurements. To overcome the complexity and uncertainty associated with total-load estimation, this research demonstrates that an ANN model can be applied for accurate prediction of total-load transport. A feed forward-back propagated (BFG) ANN model with one hidden layer with 10 hidden neurons was found to perform adequately. The ANN model was able to successfully predict total load transport in a great variety of fluvial environments, including both sand and gravel rivers. Also, the ANN prediction of mean total load was in almost perfect agreement with the measured mean total load. The high value of the coefficient of determination ($R^2 = 0.958$) implies that the ANN model provides an excellent fit for the measured data. These results suggest that the proposed ANN model is a robust total load predictor. This study demonstrates a successful application of the ANN modeling concept to total load sediment transport. Despite having five index parameters, the conclusion that only eight parameters are required to predict total load, is in agreement with previous works [24]. The value of the ANN approach is that the nonlinear function need not be the same for all fluvial environments. The genetic programming will be used to predict sediment load in the future with more database.

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